Development and application of electricity load profiles for long-term forecasting and flexibility assessment

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Abstract

The advancing defossilisation of the energy system requires far-reaching interventions and their sound planning to ensure an efficient, safe and sustainable system transformation. The application of electricity demand models with high temporal and spatial resolution is a key element for evaluating different transformation pathways. As a literature review reveals, however, models and data describing electricity demand are only available in very fragmentary or outdated form. This thesis addresses this research gap and focuses on the development, validation, exemplary application and evaluation of subsector load profiles. The potential benefit is evident: subsector load profiles serve as generic profiles which allow to model national or regional power systems. They are used for demand forecasting, for the planning and design of power generation plants and for the procurement of energy. Moreover, they can be used to analyse efficiency and demand side flexibility potentials of individual subsectors – a field of increasing relevance in the scientific literature. There are multiple fields of application for electricity load profiles spanning across all steps of the value chain. Addressing different research gaps, this thesis is divided into six modules.

The first module presents the development of 32 subsector load profiles (TUB BLP) from the sectors of industry as well as commerce, trade and services (CTS). Based on a large number of real metered load profiles, the subsector load profiles are developed using multiple regression and then validated using real data and literature-based load profiles (e.g. VDEW standard load profiles). The performance of the regression model approach is also compared with the model quality of a feed-forward artificial neural network. The accuracy of the subsector load profiles varies between subsectors, which is due to the underlying explainable variance in the data and the subsector-specific heterogeneity. Overall, however, a comparison with real metered load profiles shows in the vast majority of cases a very reasonable model performance according to Lewis' benchmark as well as a mostly significantly higher mapping accuracy of the developed TUB BLP compared to available standard load profiles. In combination with a description of the load characteristics and the demand drivers, the TUB BLP of each subsector were made freely available for further scientific use.

In the second module, the TUB BLP are used and evaluated in the Python-based application *disaggregator*. The *disaggregator* allows the modelling of electricity demand in Germany in high temporal and spatial resolution. Using demand drivers, the annual electricity consumption from the industrial, commercial and residential sectors is disaggregated to subsectors and counties. Subsequently, the annual electricity consumption is converted into electricity load profiles of quarter-hourly resolution using subsector load profiles. On the one hand, standard load profiles and generic load profiles are used as subsector load profiles; on the other hand, the TUB BLP developed in the first module are used. The model results of the different load profile approaches are compared with real data at federal and county level. It is shown that the *disaggregator* can reproduce the load behaviour at both federal and county level in a good to very good approximation. In addition, it can be seen that the use of TUB BLP significantly improves the load modelling compared to standard load profiles. There are various possible explanations for remaining structural deviations in the model results: In addition to a possible inaccuracy of the residential profile used, some important subsectors could not be modelled in a distinguished manner in the form of TUB BLP due to a lack of data.

In the third module, an engineering-based approach is developed for modelling technology-specific load profiles of five CTS subsectors. Due to the increased sophistication and effort of the engineering-based approach, this approach is applied in modules 3-5 to only five relevant subsectors out of the original 32 considered in module 1. These five subsectors of offices, trade, accommodation, hospitals and education account for about 62 % of the electricity consumption of the CTS sector. Occupancy profiles are developed based on international and national standards (ISO, DIN, SIA), which are converted into load profiles for each application technology in conjunction with technology-specific simultaneity profiles. By means of a literature-based annual electricity demand, a subsector-specific scaling of the load profiles is then carried out. A comparison of the engineering-based subsector load profiles with the TUB BLP developed in the first module allows the adjustment of the weighting of international and national standards as well as individual assumptions to increase the accuracy of the model. As a result, technology-specific load profiles for five subsectors are presented, which represent essential load characteristics and form the foundation for the modelling steps of the next two modules.

In the fourth module, the previously developed technology-specific load profiles of five subsectors are projected to the year 2035 with the help of literature-based scenarios. In addition to the efficiency development of the individual application technologies, a technology shift from night storage heaters to heat pumps with a corresponding profile change is also taken into account. It can be seen that the resulting (cumulative) load profiles alter in some subsectors. The projected load profiles of some subsectors show more pronounced load peaks. The energy consumption shares of individual technologies also change, which in turn influences the load flexibility potentials in the fifth module.

In the fifth module, technical demand side flexibility (DSF) potentials of the above five CTS subsectors are quantified in high temporal and spatial resolution. The DSF potentials are specified per subsector and application technology (air conditioning, ventilation, process cooling, space heating and hot water) for the years 2018 and 2035 and described in terms of minimum/maximum switchable loads, minimum/maximum shiftable energy quantities, shift duration and temporal availabilities. The five subsectors are responsible for about 74 % of the technical DSF potential of the entire CTS sector. A comparison with literature values underlines the plausibility of the chosen approach. The high switchable loads identified for the subsectors offices and trade, as well as the temporally stable shiftable energy quantities of hospitals and accommodation, can make a cost-effective contribution to the reduction of the residual load, the avoidance of grid bottlenecks and the integration of renewable energies in the overall system.

In the last module, the beneficial applicability of developed subsector load profiles is demonstrated in two use cases: In the first use case, the substitution of old standard load profiles by newly developed TUB BLP is assessed for the electricity procurement and balancing group management. Therefore, the model outputs of the *disaggregator* (once using standard load profiles only, once using TUB BLP) are priced on the spot market, simulating a specific procurement strategy. Any model deviations that arise between the *disaggregator* output and real reference loads are considered by the imbalance settlement price. The assessment comfirms that the total costs from procurement and balancing energy are significantly reduced for the entire system by using TUB BLP (and replacing standard load profiles) in the outlined case. However, the assessment also shows that arbitrage profits, which result from short-term trading or imbalance settlement, are smaller in the majority of cases through the application of TUB BLP. These unilaterally generated arbitrage profits result in an incentive, especially for distribution system operators in the synthetic load profile procedure, to continue to use partially outdated standard load profiles and not to switch to new, more accurate subsector load profiles. In the second use case, the flexibility potentials identified in the engineering-based modelling approach are economically evaluated in their use for peak load reduction. For this purpose, Germany's residual load in 2018 is compared with the temporally high-resolution DSF potentials in order to determine the maximum peak load reduction through load shifting. Technical restrictions of the load reduction potentials and shiftable energy quantities are taken into account. The maximum peak load reduction is evaluated with the annual power costs for gas turbine power plants that can be replaced by using the CTS DSF potentials. These cost savings are compared with the estimated costs for exploiting the DSF potentials. It is shown that commercial DSF offers a considerable cost saving potential reducing necessary peak load capacity. In addition, other use cases promise further economic benefits.

Kurzfassung

Die voranschreitende Defossilisierung des Energiesystems erfordert weitreichende Eingriffe und deren fundierte Planung, um eine effiziente, sichere und nachhaltige Systemtransformation zu gewährleisten. Die Anwendung von Stromnachfragemodellen in zeitlich und räumlich hoher Auflösung stellt einen entscheidenden Baustein dar, um verschiedene Transformationspfade zu bewerten. Wie eine Literaturauswertung zeigt, liegen die Stromnachfrage beschreibende Modelle und Daten jedoch nur sehr lückenhaft oder veraltet vor. Die vorliegende Dissertation setzt an dieser Forschungslücke an und fokussiert auf die Entwicklung, Validierung, Anwendung und Bewertung von wirtschaftszweigspezifischen Lastprofilen, sogenannten Branchenlastprofilen (BLP). Der potenzielle Nutzen liegt auf der Hand: branchenspezifische Lastprofile dienen als generische Profile, mit denen sich nationale oder regionale Stromsysteme modellieren lassen. Sie werden für Bedarfsprognosen, für die Planung und Auslegung von Stromerzeugungsanlagen und für die Beschaffung von Energie verwendet. Darüber hinaus können sie zur Analyse von Effizienz- und Flexibilitätspotenzialen einzelner Branchen verwendet werden - ein Bereich, der in der wissenschaftlichen Literatur zunehmend an Bedeutung gewinnt. Die Anwendungsfelder für Stromlastprofile sind vielfältig und erstrecken sich über alle Stufen der Wertschöpfungskette. Die vorliegende Dissertation gliedert sich in sechs Module, die jeweils unterschiedliche Forschungslücken adressieren.

Im ersten Modul wird die Entwicklung von 32 Branchenlastprofilen (TUB BLP) aus den Sektoren Industrie sowie Gewerbe, Handel, Dienstleistungen (GHD) vorgestellt. Basierend auf einer Vielzahl real gemessener Lastgänge werden die Branchenlastprofile mittels multipler Regression entwickelt und anschließend anhand von Realdaten sowie mit literaturbasierten Lastprofilen (z.B. mit VDEW Standardlastprofilen) validiert. Die Modellgüte des regressionsanalytischen Ansatzes wird zudem mit der Modellgüte eines vorwärtsgerichteten künstlichen neuronalen Netzes verglichen. Die Abbildungsgenauigkeit der Branchenlastprofile variiert zwischen den Wirtschaftszweigen, was auf die in den Daten zugrundeliegende erklärbare Varianz sowie auf die wirtschaftszweigspezifische Heterogenität zurückzuführen ist. Insgesamt zeigt sich im Vergleich mit real gemessenen Lastprofilen jedoch in der überwiegenden Mehrzahl der Fälle eine nach Lewis‘ Benchmark sehr passable Modellgüte sowie eine gegenüber verfügbaren Standardlastprofilen meist deutliche höhere Abbildungsgenauigkeit der entwickelten TUB BLP. In Verbindung mit einer Beschreibung der Lastcharakteristika und der Einflussgrößen wurden die TUB BLP jedes Wirtschaftszweigs zur weiteren wissenschaftlichen Nutzung frei zugänglich zur Verfügung gestellt.

Im zweiten Modul werden die TUB BLP in der Python-basierten Anwendung *disaggregator* eingesetzt und evaluiert. Der *disaggregator* erlaubt die zeitlich und räumlich hochaufgelöste Modellierung der Stromnachfrage in Deutschland. Anhand von energienachfragebestimmenden Größen werden dabei statistische Jahresstromverbräuche der Sektoren Industrie, GHD und Haushalte auf Wirtschaftszweige und Landkreise disaggregiert. Anschließend werden die jährlichen Stromverbräuche mittels wirtschaftszweigspezifischen Lastprofilen in Stromverbrauchsverläufe von bis zu viertelstündlicher Auflösung überführt. Als wirtschaftszweigspezifische Lastprofile werden einerseits Standardlastprofile und generische Lastprofile eingesetzt; andererseits werden die im ersten Modul entwickelten TUB BLP eingesetzt. Die Modellergebnisse der unterschiedlichen Lastprofilansätze werden mit Realdaten auf Bundes- und Landkreisebene verglichen. Es zeigt sich, dass der *disaggregator* das Lastverhalten sowohl auf Bundes- als auch auf Landkreisebene in guter bis sehr guter Näherung widergeben kann. Zudem zeigt sich, dass die Verwendung von TUB BLP gegenüber Standardlastprofilen die Lastmodellierung deutlich verbessert. Für verbleibende strukturelle Abweichungen in den Modellergebnissen kommen verschiedene Erklärungsansätze infrage: Neben einer möglichen Ungenauigkeit des verwendeten Haushaltsprofils (ZVE-Profil) konnten einzelne wichtige Wirtschaftszweige aufgrund von Datenmangel nicht differenziert in Form von TUB BLP abgebildet werden.

Im dritten Modul wird ein ingenieursbasierter Ansatz zur Modellierung technologiespezifischer Lastgänge von fünf Wirtschaftszweigen des Sektors GHD entwickelt. Aufgrund der höheren Komplexität und des höheren Aufwands des ingenieurbasierten Ansatzes wurde dieser Ansatz in den Modulen 3 bis 5 auf fünf relevante Wirtschaftszweige von den ursprünglich 32 in Modul 1 betrachteten angewandt. Diese fünf Wirtschaftszweige Büroähnliche Betriebe, Handel, Beherbergung, Krankenhäuser und Schulen bilden etwa 62 % des Stromverbrauchs des Sektors GHD ab. Auf Basis internationaler und nationaler Standards (ISO, DIN, SIA) werden Anwesenheitsprofile entwickelt, die in Verbindung mit technologiespezifischen Gleichzeitigkeitsprofilen in Lastprofile je Querschnittstechnologie überführt werden. Mittels Anwendungsbilanzen erfolgt anschließend eine wirtschaftszweigspezifische Skalierung der Lastprofile. Ein Abgleich der wirtschaftszweigspezifischen Lastprofile mit im ersten Modul entwickelten TUB BLP erlaubt die Anpassung der Gewichtung der internationalen und nationalen Standards sowie einzelner Annahmen zur Erhöhung der Abbildungsgenauigkeit. Im Ergebnis werden technologiespezifische Lastprofile für fünf Wirtschaftszweige vorgestellt, die wesentliche Lastcharakteristika abbilden und die die Ausgangsbasis für die Modellierungsschritte der nächsten beiden Module bilden.

Im vierten Modul werden die zuvor entwickelten technologiespezifischen Lastprofile der fünf Wirtschaftszweige mithilfe literaturbasierter Szenarien in das Jahr 2035 fortgeschrieben. Neben der Effizienzentwicklung der einzelnen Querschnittstechnologien wird dabei auch ein Technologiewechsel von Nachtspeicherheizungen zu Wärmepumpen mit entsprechender Profiländerung berücksichtigt. Es zeigt sich, dass sich das resultierende (Summen-)Lastprofil je Wirtschaftszweig ändert. So weisen die fortgeschriebenen Lastprofile einzelner Wirtschaftszweige stärker ausgeprägte Lastspitzen auf. Auch ändern sich die Energieverbrauchsanteile einzelner Technologien, was wiederum Einfluss auf die Identifikation von Lastflexibilisierungspotenzialen im fünften Modul hat.

Im fünften Modul werden technische Lastflexibilisierungspotenziale der fünf genannten Wirtschaftszweige des Sektors GHD in hoher zeitlicher und räumlicher Auflösung quantifiziert. Die Lastflexibilisierungspotenziale werden je Wirtschaftszweig und Technologie (Klimakälte, Lüftung, Prozesskälte, Raumwärme und Warmwasser) für die Jahre 2018 sowie 2035 angegeben und bezüglich minimal/maximal schaltbarer Lasten, minimal/maximal verschiebbarer Energiemengen, der Verschiebungsdauer und zeitlicher Verfügbarkeiten beschrieben. Die fünf Branchen verantworten etwa 74 % des technischen Lastflexibilisierungspotenzials des gesamten Sektors GHD. Ein Vergleich mit generischeren Potenzialerhebungen aus der Literatur unterstreicht die Plausibilität des gewählten Ansatzes. Die im Ergebnis identifizierten hohen Lastflexibilisierungspotenziale der Wirtschaftszweige Bürobetriebe und Handel sowie die zeitlich stabilen verschiebbaren Energiemengen der Krankenhäuser und der Beherbergung können einen kostengünstigen Beitrag zur Reduktion der Residuallast, der Vermeidung von Netzengpässen und der Integration erneuerbarer Energien im Gesamtsystem leisten.

Im letzten Modul wird die vorteilhafte Anwendbarkeit der erstellten Branchenlastprofile in zwei Anwendungsfällen unter Beweis gestellt. Im ersten Anwendungsfall wird die Substitution von veralteten Standardlastprofilen durch neu entwickelte TUB BLP für die Strombeschaffung und das Bilanzkreismanagement untersucht. Dazu werden die Modelloutputs des *disaggregator* (einmal nur mit Standardlastprofilen, einmal mit TUB BLP) auf dem Spotmarkt bepreist und damit eine bestimmte Beschaffungsstrategie simuliert. Etwaige Modellabweichungen, die sich zwischen dem *disaggregator* -Output und den realen Referenzlasten ergeben, werden durch den regelzonenübergreifenden einheitlichen Bilanzausgleichsenergiepreis (reBAP) berücksichtigt. Die Analyse kommt zu dem Ergebnis, dass die Gesamtkosten aus Beschaffung und Ausgleichsenergie durch die Anwendung von TUB BLP (und dem Ersatz von Standardlastprofilen) im skizzierten Fall deutlich für das Gesamtsystem reduziert werden. Allerdings zeigt die Abschätzung auch, dass Arbitragegewinne, die sich über den

kurzfristigen Handel oder Ausgleichsenergieabruf ergeben können, in der Mehrzahl der Fälle kleiner ausfallen durch die Anwendung von TUB BLP. Diese einseitig erwirtschafteten Arbitragegewinne ergeben insbesondere für Verteilnetzbetreiber im synthetischen Lastprofilverfahren einen Anreiz, weiterhin teilweise veraltete Standardlastprofile zu verwenden und nicht auf neue, bessere Branchenlastprofile umzustellen. Im zweiten Anwendungsfall werden die im Rahmen des ingenieursbasierten Modellansatzes identifizierten Flexibilitätspotenziale im potenziellen Einsatz zur Spitzenlastreduktion ökonomisch bewertet. Dabei wird die Residuallast Deutschlands im Jahr 2018 mit den zeitlich hochaufgelösten Flexibilitätspotenzialen gegenübergestellt, um die maximale Spitzenlastreduktion durch Lastverschiebung zu ermitteln. Technische Restriktionen der Lastreduktionspotenziale sowie verschiebbarer Energiemengen werden berücksichtigt. Die maximale Spitzenlastreduktion wird bewertet mit den jährlichen Leistungskosten für Gasturbinenkraftwerke, die durch den Einsatz der GHD-Lastflexibilisierungspotenziale ersetzt werden können. Diesen Kosteneinsparungen werden die geschätzten Kosten zur Hebung der Lastflexibilisierungspotenziale gegenübergestellt. Es zeigt sich, dass GHD-Lastflexibilisierungspotenziale ein erhebliches Kosteneinsparungspotenzial aufweisen durch die Reduktion notwendiger Spitzenlastkapazitäten. Zudem versprechen zusätzliche Anwendungsfälle weiteren ökonomischen Nutzen.

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List of Abbreviations

AC	Air conditioning
AGEB	Working group on energy balances (German: Arbeitsgemeinschaft Energiebilanzen)
AGS	Official municipality key (German: Amtlicher Gemeindeschlüssel)
ARegV	Incentive Regulation Ordinance (German: Anreizregulierungsverordnung)
BAFA	German Federal Office for Economic Affairs and Export Control (German: Bundesamt für Wirtschaft und Ausfuhrkontrolle)
BDEW	German association of energy and water industries (German: Bundesverband der Energie- und Wasserwirtschaft e.V.)
BLP	Subsector load profiles (German: Branchenlastprofile)
BMWi	German Federal Ministry of Economics and Energy (German: Bundesministerium für Wirtschaft und Energie)
BNetzA	German Federal Network Agency (German: Bundesnetzagentur)
BRP	Balance responsible party
CTS	Commerce, Trade and Services
Destatis	German Federal Statistical Office (German: Statistische Bundesamt)
DIN	German Industry Standard (German: Deutsche Industrienorm)
DSF	Demand Side Flexibility
DSO	Distribution system operator
EinsMan	Feed-in management (German: Einspeisemanagement)
EnWG	German Energy Act (German: Energiewirtschaftsgesetz)
FEC	Final energy consumption
ICT	Information and communication technologies
ISO	International Organisation for Standardisation
LV	Low voltage
MV	Medium voltage
NABEG	Grid Expansion Acceleration Act (German: Netzausbaubeschleunigungsgesetz)
PP	Power plant
PV	Photovoltaic
reBAP	Imbalance settlement price (German: regelzonenübergreifender einheitlicher Bilanzausgleichsenergiepreis)
RES	Renewable energy systems
RLM	Registering power measurement (German: registrierende Leistungsmessung)
SGD	Stochastic gradient descent
SIA	Swiss society of engineers and architects
SLP	Standard load profiles

StromNZV	regulation on electricity feed-in to and consumption from electricity supply grids (German: Stromnetzzugangsverordnung)
TSO	Transmission system operator
TUB BLP	Group of 32 subsector load profiles (BLP) developed at TU Berlin
VDEW	German Association of the electricity industry (German: Verband der Elektrizitätswirtschaft e.V.), Predecessor organisation of BDEW
WZ 2008	German Classification of Economic Activities – WZ corresponds to a specific subsector (German: Wirtschaftszweig)

1. Introduction

In view of today's intensifying challenges like climate change and the phase-out of nuclear energy, the German 'Energiewende' is profoundly transforming the energy landscape. Against the background of growing international ambitions, e.g. through the Paris Climate Agreement, the German federal government strives to become climate neutral by 2045 (Bundesregierung, 2021). As depicted in the government's energy concept (Bundesregierung, 2010), there are two central strategies in order to achieve self-defined goals: the expansion of renewable energies and the increase in energy efficiency. These central strategies are aimed towards specific goals, e.g. reaching 80 % renewable energy share of gross electricity consumption (SPD, Bündis 90/Die Grünen, FDP, 2021, p. 56) as well as the reduction of primary energy consumption for 30 % in the year 2030[1] (BMWi, 2021, p. 12).

The transition of a formally centralized energy system supplied by conventional and dispatchable power plants towards a system with high shares of intermittent and distributed renewable energy systems poses considerable challenges to the system planning and operation. In this regard, the assessment of different transformation pathways requires models of high temporal and spatial resolution. While comprehensive high-resolution models and data are already available for the generation side, the demand side is less well represented (Gotzens et al., 2020, p. 1). However, the electricity demand has been and will be a critical factor in the electricity system (Wietschel et al., 2011a). Hence, it is essential to assess the structure and predictability of the demand side in high temporal and spatial resolution. Until recently, there were no openly available models which are able to depict the sector-specific final energy demand in high temporal and spatial resolution in Germany. Existing projects are of closed access and thus intransparent, still ongoing or lacking in extent or detail (Fraunhofer ISI, 2019), (ifeu GmbH et al., n.d.), (Umweltbundesamt, 2014), (Fraunhofer ISE, 2020), (Fischer, 2019). The recent BMWi[2]-funded research project DemandRegio was targeted to fill this research gap: The project sought to develop models which enable a depiction and forecast of subsector-specific final energy demands in Germany in high spatial and temporal resolution (Gotzens et al., 2020, p. 1). The project's results are the foundation for various relevant research questions about, for instance, energy storage and network expansion requirements, business model developments, sector coupling, efficiency as well as demand side management potentials.

As part of the research project DemandRegio, the final energy demand of two sectors has been closely analysed and modelled: the industrial as well as the commerce, trade and services (CTS) sector, with a final energy consumption (FEC) of 750 TWh (28.9 % of total FEC) and 401 TWh (15.5 % of total FEC)[3], respectively (Umweltbundesamt, 2019). The regional mapping of final energy demand follows a top-down approach, which requires the collection and harmonization of various federal and regional statistics. The final energy demand has been regionally disaggregated using the energy consumption of individual subsectors (Destatis, 2019), the number of employees of individual subsectors (FfE and Bundesagentur für Arbeit, 2019) and – as a more detailed complement – a regionally specific energy consumption of industrial subsectors (FfE, 2019). In order to transform this regionally disaggregated annual energy consumption to a temporally resolved energy load, two approaches have been adopted: an engineering-based approach and a real data-based approach. The former requires detailed information about the underlying processes or applications and their specific energy consumption patterns and is potentially subject to a high degree of ambiguity. In contrast, the latter requires real metered load data comprising the aggregation of underlying processes and applications with their aggregated energy consumption patterns.

[1] As compared to the primary energy consumption in the year 1990.
[2] Germany's Federal Ministry of Economics and Energy (BMWi)
[3] As of 2017, the total final energy consumption of Germany amounts for 2.591 TWh.

Building on the research project DemandRegio, the present thesis aims to develop and apply subsector load profiles in the sectors of industry as well as CTS in Germany. In addition, this thesis seeks to project selected load profiles to the year 2035 and derive demand side flexibility potentials. The following research questions will be addressed:

(1) How can the electricity load profiles of selected industrial and CTS subsectors be (a) modelled and (b) projected, and what is their electricity demand pattern?
(2) How do newly developed subsector load profiles perform in their application within the electricity demand modelling in high spatial and temporal resolution?
(3) What is the current and future technical demand side flexibilization potential of five relevant CTS subsectors?
(4) What is the estimated economic value of (a) applying these newly developed subsector load profiles and (b) the identified demand side flexibilization potentials?

Facing significant requirements in the quantity and quality of underlying load data, data collection poses a major challenge in the present thesis. Based on collected real load data, statistical as well as machine learning methods will be applied in order to identify relevant demand drivers and to generate typical subsector load profiles. Ensuring compatibility and usability of results, the definition of subsectors will be mainly based on the classification of economic subsectors by Destatis (Destatis, 2008) and consumer groups defined by the working group on energy balances ("AGEB," 2019). The coverage of subsectors will be restricted to available data. A number of 32 newly developed profiles can be validated or at least checked for plausibility by comparison with national and international subsector load profiles as well as by comparison with aggregated load data of different regional entities. In an extension, five engineering-based subsector load profiles will be developed and assessed with regards to demand side flexibility potentials. Results will be openly published, enabling the scientific community to use (and complement) the demand models in further research projects.

Up to now, a systematic literature research indicates a significant interest in the field of energy demand modelling of single facilities or regions, due to an increase in numbers of publications in the international scientific community (Verwiebe et al., 2021b, p. 2) (see chapter 2.3.1). The particular development of subsector load profiles, however, seems to be given less attention to in scientific literature (see chapter 2.3.3), which could result from the immense data requirements mentioned above. A recent analysis and survey have revealed, that there is distinct need for open data in the German energy sector, particularly for demand data in high temporal and spatial resolution (see chapter 2.1), which also gets confirmed by Behm et al. (2020, p. 15). Outdated standard load profiles form the industry standard, but are associated with structural deviations (see chapter 2.3.2) (Ecke and Kauffmann, 2013; Hinterstocker et al., 2014, pp. 1–2; Spiegel, 2018, pp. 796–797). This identified gap for demand data is being addressed by DemandRegio as well as the present thesis. The potential benefit is evident: subsector load profiles serve as generic profiles which allow to model national or regional power systems. They are used for demand forecasting, for the planning and design of power generation plants and for the procurement of energy (Schellong, 2016a, p. 375). Moreover, they can be used to analyse efficiency and demand side flexibility potentials of individual subsectors – a field of increasing relevance in the scientific literature (see chapter 2.3.5) (Gartner et al., 2019; Gils, 2015; Langrock et al., 2015). There are multiple fields of application for electricity load profiles spanning across all steps of the value chain (see chapter 2.2.4).

This thesis is structured as follows. Chapter 2 will introduce the theoretical foundation for the energy demand modelling research. Relevant literature in the field of energy demand modelling will be introduced and research gaps identified. The conceptual background of chapter 2 will help to determine the scope of the present thesis, with regards to the energy demand sectors modelled, the techniques and methodologies used as well as the temporal and spatial resolution applied. Chapter 3 will depict the methodology and research design of this thesis, introducing the six individual modules and their interplay. Chapter 4 will lay out the detailed steps of analysis of each individual module, specifying the database, data processing and modelling procedures. Chapter 5 will present the results of each individual module, starting with 32 subsector load profiles (chapter 5.1), as well as the application and evaluation of these newly developed subsector load profiles in the *disaggregator* tool (chapter 5.2). Next, engineering-based and application-specific subsector load profiles of five CTS subsectors will be introduced (chapter 5.3) and projected into the year 2035 (chapter 5.4). The current and projected engineering-based load profiles will then be used to derive technical demand side flexibility potentials within these subsectors (chapter 5.5). Lastly, the application of newly developed subsector load profiles and identified demand side flexibility potentials will be assessed economically in two separate contexts (chapter 5.6). The results are discussed in chapter 6. A conclusion of all modules will be given in chapter 7, and chapter 8 will give an outlook for potential future research opportunities.

2. The Modelling of Energy Demand

The defossilisation of the energy system and the associated increasing integration of intermittent renewable energy sources requires a fundamental transformation on the technological, regulatory and economic level. In order to ensure a transition as smooth and efficient as possible, stakeholders from politics, science and industry apply energy system models that enable the depiction of a complex reality and thus ensure rational decision-making. Central investigations relate to the effects of different energy and climate policy instruments, for instance (Götz et al., 2013). In view of evolving boundary conditions, technological developments, increasing computing power and available data, model approaches are constantly being further developed (Dodds et al., 2015). In addition to model approaches, the quality and availability of input data is a crucial precondition to generate reliable results that form an adequate basis of decision-making. In recent years, there have been various research projects investigating the implications of intermittent electricity generation by renewable energy sources. However, the electricity demand has been and will be a critical factor in the electricity system and is at the heart of energy system modelling (Wietschel et al., 2011a). Energy demand modelling provides the foundation for a variety of subsequent analyses regarding grid expansion and storage requirements, efficiency potentials, demand side management potentials and sector coupling, to name but a few. The present thesis seeks to fill some research gaps in demand side modelling, which are elaborated from the literature review in chapter 2.3.

The next chapters will introduce to the basics of energy demand modelling and will describe underlying concepts and literature. It is structured as follows: In order to demonstrate the need for open energy data in general and energy demand data in particular, chapter 2.1 will introduce the data landscape of the German energy system, summarizing the findings of a previous publication (Seim et al., 2019). Chapter 2.2 will further elaborate on the topic of energy demand modelling by defining central terms and concepts (chapter 2.2.1), introducing the balancing group system (chapter 2.2.2) as well as the concept of demand side flexibility (chapter 2.2.3) and the diverse fields of applications of energy demand modelling (chapter 2.2.4). The current research literature on the topic will be described in chapter 2.3 and relevant research gaps will be identified. Some of these research gaps will be addressed by the present thesis. In the chapter 2.4, relevant units of analysis for the energy demand side will be introduced, i.e. the definition and prioritization of economic (sub-)sectors and consumer groups (chapter 2.4.1) as well as the conceptual basis and implications of process technologies and cross-sectional application technologies (chapter 2.4.2). Chapter 2.5 will introduce the main techniques and methods used for the electricity demand modelling of this thesis.

2.1. The Data Landscape of the German Energy System

As mentioned beforehand, a reliable and complete database is essential for energy system modelling and the related decision-making process in the transformation of the energy system. However, the collection and pre-processing of input data ties up a considerable part of scientific resources, as required data might be distributed among multiple data owners, tedious to process, publicly inaccessible or partly inaccurate (Wiese et al., 2019). A well-organized and up-to-date energy system database is built on years of preparatory work and represents a competitive advantage for scientific institutions or consulting companies. This fact stands in the way of the universal dissemination of energy data and leads to a concentration of data and models for particular scientific issues at established institutes, which regularly make use of internal data for central system analyses (Seim et al., 2019). Nevertheless, there is a number of good reasons that promote more open structures (Hülk et al., 2018; Morrison, 2018; Pfenninger, 2017):

- „Improved quality of science […] [by transparency and reproducibility of results],
- Increased productivity through collaborative burden sharing" (Pfenninger et al., 2017),

- Building societal confidence in a transparent energy system research.

As a consequence, the debate on open data and open source projects in the German energy system research is gaining momentum (Morrison, 2018; Pfenninger et al., 2017). In the course of this, an investigation into the data landscape of the German energy system was conducted by Seim et al. (2019), addressing the following research questions:

1. What information is available about which actors and elements of the energy sector?
2. What are the data needs of the community?
3. What are the obstacles to using the information?

The article reviewed the relevant legal situation and described existing information flows in the German energy sector. Subsequently, a data classification system was developed which enabled the systematic analysis of data platforms and data sources. In addition, a survey was conducted, directed at energy system actors, to complement the research and answer the above questions. The paper identified and classified 22 relevant data platforms and 279 data sources across different energy carriers and steps of the value chain based within the German energy sector.

Both within the data research and in the survey, an increased need for energy generation and demand data of high temporal and spatial resolution for the electricity and heat sector could be identified. While spatially and temporally resolved production data can be approximated by fundamental models, the data situation on the energy demand side looks insufficient, given the heterogeneity of the demand sectors. In the field of networks, the gas sector seems to be of particular interest, since the data situation appears complex and incomplete due to the grid operator structure. Figure 1 lists the main reasons of restricted access due to the above-mentioned survey.

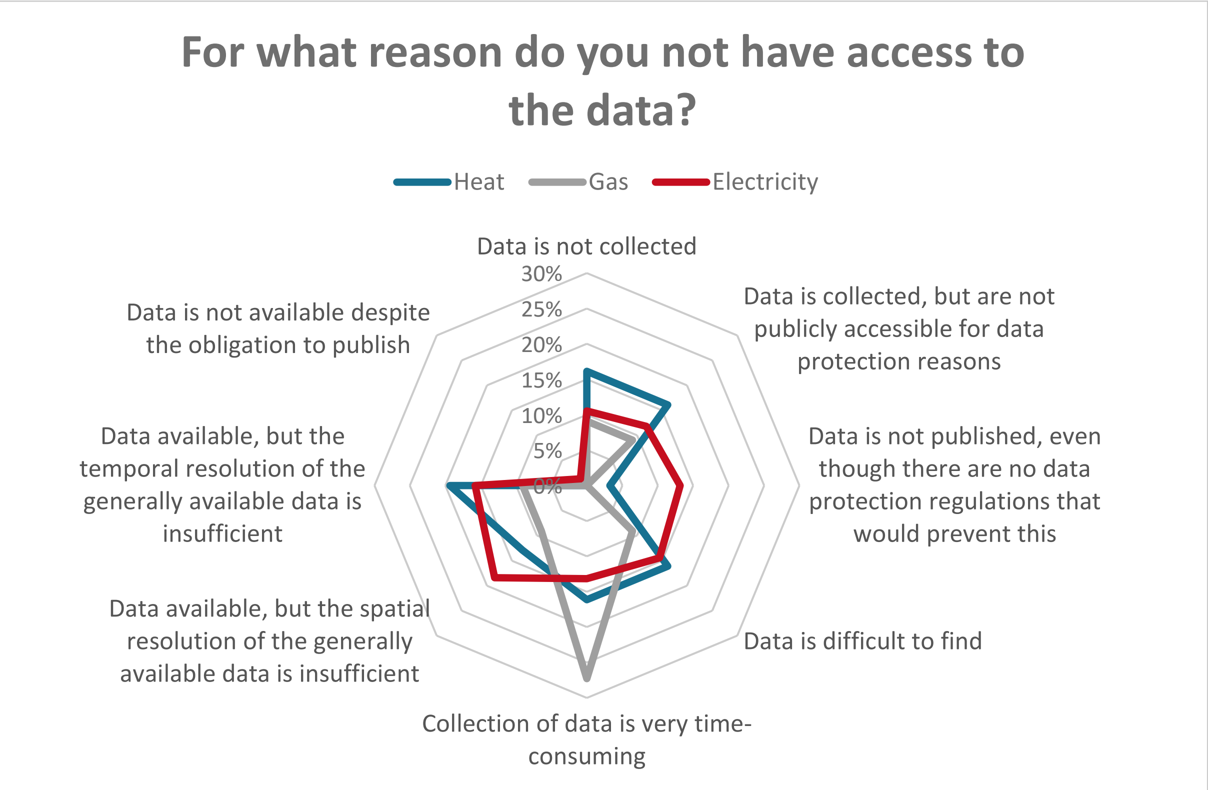

Figure 1: Survey result to the question for what reason there is no access to required data. Diagram by author, adapted from Seim et al. (2019)

According to Figure 1, data might not be collected in the first place, such as building energy certificates. Even when data is collected, it is oftentimes not publicly accessible, which is according to some survey participants, due to data protection reasons. In many cases, data is difficult to find and hence time-consuming to collect. Also, the spatial and/or temporal resolution of a significant share of data appears to be insufficient. The reasons for a limited usability of the data as a major obstacle are manifold and have also been discussed elsewhere (Hirth et al., 2018b; Pfenninger et al., 2017). Although some data is publicly available, it is oftentimes distributed in heterogeneous or non-machine-readable form and is sometimes incorrect (Wiese et al., 2019). The issue of inadequate licensing is also a well-known problem (Morrison, 2018, p. 50; Wiese et al., 2019, p. 404) and leads to the fact that data may either not be used or that modelers operate in a legal grey area. The study also revealed, that public as well as private data providers do not always grant licenses.

Overall, some of the gaps identified in the areas of energy generation, network and demand data with high temporal and spatial resolution could stem from data protection requirements as well as business and trade secrets. While data protection has played only a minor role so far, according to Morrison (2018, p. 61) this could change in the future with models of increasingly high resolution and the corresponding mapping of the consumption side, for instance.

Among central implications for policy makers, the question was raised, whether the issues of data protection requirements and business secrets, particularly in the case of identified data gaps of the demand side, could be encountered with an orchestrated data platform by the federal network agency, similar to their transparency efforts in the SMARD database. Demand data could be collected, processed and provided in an aggregated, anonymous form. Moreover, the need to enhance funding for open source-/ open data research projects was emphasized.

The above mentioned publication of Seim et al. (2019) was aimed to address some of the above limitations, by making transparent and analysing the most important data sources within the German energy landscape. Moreover, by providing openly accessible load profile data in high temporal and spatial resolution, the present thesis seeks to overcome some of the above identified data gaps. Applying this thesis' load profile modelling procedures, potentially sensitive company load data can be averaged and turned into usable load profiles, mapping the characteristic demand patterns of particular subsectors.

2.2. Relevance of Energy Demand Modelling

The energy demand modelling and forecasting has in the past been of particular importance for utilities and large industrial companies. On the one hand, energy demand forecasts are *the* crucial input to the design and scale of energy infrastructure (e.g. generators, grids, storages), on the other hand they help to optimize the procurement, trade and utilization of energy (Schellong, 2016b, pp. 375–379). Nowadays, in the course of the ongoing energy system transformation and digitalization, the field of energy demand modelling and forecasting appears to become more relevant for a wider audience. The need for system decarbonization and associated trends (e.g. increasing energy efficiency, system flexibilization requirements, behavioural changes as well as technological advancements) will profoundly affect energy demand characteristics. The energy demand side, in turn, has a large influence on all other energy system actors. The demand and its changing characteristics is thus a central element in energy system models, which are applied to enable informed decision making to identify robust, efficient and socially acceptable transformation pathways (Wietschel et al., 2011a). Despite its relevance, the current model and data landscape for the German energy demand side is regarded largely insufficient, as shown in the previous chapter 2.1. Existing or previous projects are of closed access (Fraunhofer ISI, 2019; ifeu GmbH et al., n.d.), have a specific sectoral focus (Fraunhofer ISE, 2020), are outdated (VDEW, 1999) or lack in extent or detail (Fischer, 2019; Prognos AG et al., 2014; Umweltbundesamt, 2014). As part of the BMWi-funded research project DemandRegio, the present thesis strives to fill this gap.

In order to consolidate the relevance of energy demand modelling, chapter 2.2 is structured as follows: Chapter 2.2.1 will introduce central terms and concepts in the modelling of energy demand. Chapter 2.2.2 will introduce the German balancing group system as an important field of application for subsector load profiles. Chapter 2.2.3 will introduce the concept of demand side flexibility, which will become increasingly relevant in the future energy system. Lastly, chapter 2.2.4 will further elaborate on additional fields of application for energy demand modelling.

2.2.1. Introduction to Central Terms and Concepts

In the following, central terms and concepts within the energy demand modelling literature will be introduced, from the terms energy demand, energy consumption and load profiles (chapter 2.2.1.1); factors influencing the energy demand, i.e. so-called demand drivers (chapter 2.2.1.2); the temporal horizon and the temporal resolution of energy demand models (chapter 2.2.1.3); the spatial resolution (chapter 2.2.1.4) as well as the level of detail of energy demand models (chapter 2.2.1.5). These central terms and concepts will help to define the methodological scope of this thesis. In addition for scope determination, energy demand sectors as well as techniques and methods will be elaborated further in later chapters 2.4 and 2.5.

2.2.1.1 Energy Demand, Energy Consumption and Load Profiles

According to VDI 4661, **energy demand** is defined as the “final energy to be used in order to perform a defined energy service […] for defined boundary conditions” (*VDI 4661*, 2014, p. 15); boundary conditions being weather conditions, for example. In contrast, the quantity of energy consumed “in order to cover energy demands under real conditions” is defined as **energy consumption** (*VDI 4661*, 2014, p. 15). Depending on boundary conditions, the energy consumption can deviate from the calculated energy demand (Schellong, 2016b, p. 322). These boundary conditions are determined by a variety of demand influencing factors, which are also referred to as demand drivers (see chapter 2.2.1.2).

The **load profile** depicts the pattern of electrical, gas or heat load consumed in high temporal resolution[4] over a certain time period (Schellong, 2016b, p. 375). Load profiles commonly depict the load patterns of individual processes/consumers or of a group of processes/consumers. Due to the partial compensation of load fluctuations (as reflected by the simultaneity factor[5]), a group of consumers tends to show a much more smoothed load profile as compared to an individual consumer (Boßmann, 2015, p. 64). Load profiles play an important role in the energy system, as they are used for a broad range of different purposes (Schellong, 2016b, p. 375) (see chapter 2.2.4 for details). Using electrical load profiles in this thesis, patterns of electricity consumption (with specific boundary conditions) serve as model input in order to derive patterns of electricity demand (in dependence of boundary conditions). Here, the term *load profile* is used for the *electrical* load only, to describe both the input data (electricity consumption) as well as the resulting subsector load profiles (electricity demand).

Since the liberalisation of the electricity markets in 1998 and the accompanying obligation of grid operators to grant non-discriminatory access to all suppliers, knowledge of a customer's load profile is of particular importance (Schellong, 2016b, p. 377). While large consumers are obliged to registering power measurement (RLM), the load profile of small consumers with an annual electricity consumption of less than 100,000 kWh is to be accounted for using a simplified method with **standard**

[4] In Germany, electrical load profiles are commonly measured in 15-min intervals, gas and heat in hourly intervals.
[5] Sometimes also referred to as “diversity factor” (German: Gleichzeitigkeitsfaktor)

load profiles (SLP) (*StromNZV*, 2020 § 12). In Germany, SLP have been introduced for households, commercial branches and agriculture (VDEW, 1999). These SLP differentiate according to type day (working day, Saturday and Sunday) as well as season (winter, transitional period and summer). SLP approximate the load profile for consumers which are not metered individually. They were created as average load profiles using real load data metered between the years 1981 and 1998. SLP are always only a rough approximation of the actual load profiles of the groups they represent. As they explicitly depict group behaviour, they are in most cases unsuitable to satisfactorily represent the behaviour of a concrete individual customer (VDEW, 1999, p. 42). In any case, representing the load characteristics of 20 to 40 years ago, standard load profiles appear to have structural deviations and are not accurate anymore (Gerblinger et al., 2014, p. 3; Hinterstocker et al., 2014, p. 1; Sohns, 2015, p. 17; Spiegel, 2018, pp. 796–797). However, SLP are still widely used. Related literature will be reviewed in chapter 2.3.2.

2.2.1.2 Demand Drivers

The energy demand is essentially determined by the nature and dimension of the system. Specifically, most electricity load data exhibit large fluctuations while showing distinct and recurring patterns over time. Those patterns can be traced back to factors influencing the electricity demand, namely demand drivers. These interdependencies are complex and it is almost impossible to depict all demand drivers adequately in larger systems. Hence, modelling as a simplified representation of reality is therefore indispensable in order to examine quantitative and qualitative interactions within the system (Schellong, 2016b, pp. 322–328).

In a recent literature review by Verwiebe et al. (2021b) , a number of 419 articles in the energy demand modelling literature has been analysed with regards to multiple features, such as demand drivers used. A selection of relevant insights of this review is introduced in chapter 2.3.1, while most relevant demand drivers identified in the literature review are listed in Table 1.

Table 1: Demand drivers for energy consumption, based on Verwiebe et al. (2021b, pp. 4–5).

Demand driver	Examples
Historic energy demand	Historic load, electricity, heating, cooling or natural gas demand
Weather data	Outside temperature, atmospheric pressure, cooling and heating degree days, humidity, solar radiation, wind speed
Calendar data	Time of day, day of week, month, holidays, bridge days, seasons, workday, working hours, operating time of appliance
Demographic or economic data	Economic indicators: GDP, GNI, level of production, income, import and export level of a region
Technical system data	demographic indicators: human development indices, population, number of dwellers/ buildings/ residences, age, sex, education, infant mortality
Usage or behavioural data	Appliance data: equipment installed, number of appliances, efficiency, material properties, air change ratio, flow rate, outlet/ inlet temperatures, rated power of equipment, impedance
Energy prices	building data: floor space, number of bedrooms, transmission factor, building type, age of building, efficiency rating, geometry of building, status of refurbishment, window area, building material, indoor temperature, indoor humidity

In varying combinations, these demand drivers serve as explanatory variables and predictors in electricity demand models. Depending on the context, methodology and the temporal horizon of electricity demand forecasts, different demand drivers are deployed. Table 2 classifies some of these demand drivers according to their strength of influence on electricity demand forecasts, depending on their temporal horizon (short to long-term). The temporal horizon gets further specified in the next chapter 2.2.1.3.

Table 2: Demand drivers for electricity consumption and their strength of influence depending on temporal horizon of forecasts. +++ strong influence, ++ moderate influence, + weak influence, - no influence, based on Schellong (2016a, p. 327)

Demand driver	**Temporal horizon of forecast**		
	Short-term	**Mid-term**	**Long-term**
Temperature	+++	++	-
Solar radiation	+++	+	-
Precipitation	+	-	-
Wind	++	+	-
Sunshine duration	+	+	-
Effective cloud coverage	++	+	-
Week day	+++	++	+
Holiday	+++	++	+
Bridge days	+++	++	+
Seasons	+++	+++	+++
GDP	+	++	+++
Production schedules	+++	++	++
Energy intensity	++	++	++
Energy efficiency	+++	+++	+++
Energy prices	+	++	+++
Energy policy	-	+	++
Climate change	-	-	++

The most dominant demand drivers for electricity consumption are weather variables, particularly temperature and solar radiation, as well as calendar data, from day types to seasons. Moreover, production schedules and energy efficiency values are regarded very influential. For very long-term forecasts, economic output figures like GDP or energy prices are considered very important.

2.2.1.3 Temporal Horizon and Temporal Resolution

The temporal horizon of an energy demand model reflects the time span that is covered by the modelling effort, and typically ranges from short-term over mid-term to long-term forecasts. In the scientific literature, the following distinction is widely used (Verwiebe et al., 2021b, p. 5):

- Long-term (>= 1 year)
- Mid-term (> 1 day and < 1 year)
- Short-term (<= 1 day)

The temporal resolution reflects the scale of time steps that are described by the modelling effort, and typically ranges from seconds, minutes, 15-minute or hourly intervals, days, months to one year.

As found in the literature review, short-term electricity modelling efforts tend to exhibit a higher temporal resolution in the scientific literature, whereas long-term electricity models are associated with a lower temporal resolution. In the German electricity system, electrical loads are typically metered and accounted for at 15-minute intervals. Therefore, a large extent of existing electrical load data in Germany is associated with a quarter-hourly resolution.

2.2.1.4 Spatial Resolution

The spatial resolution of an energy demand model indicates the scale of regions which are described, reaching from a country to a sub-country regional level (e.g. county), to a building level or to the appliance, to name a few examples (Verwiebe et al., 2021b, p. 27). In order to uniquely identify a spatial unit, the official municipality key (German: Amtlicher Gemeindeschlüssel (AGS)) can be used for Germany. The AGS is not a number, but a sequence of digits. The first two digits indicate the federal state, the first five digits correspond to the county key (German: Landkreisschlüssel) (Gotzens et al., 2020, p. 7), which can also be displayed in an eight-digit notation:

Example.:

06 535 009	Homberg (Ohm)
06 535 000	Vogelsbergkreis
06 535	Vogelsbergkreis
11 000	Berlin
11 000 000	Berlin

For areas in the Member States of the European Union, the NUTS (French: Nomenclature des unités territoriales statistiques) system is used, which makes regional units identifiable and comparable even across national borders. A table published by Forschungsstelle für Energiewirtschaft (FfE, 2020) enables the mapping of NUTS code to the AGS code of German counties.

In the electricity load forecasting, the spatial resolution of the modelled unit has influence on the stochastic properties of the underlying load profile, which in turn significantly affects the forecast quality. For example, the national load has significantly less variance than the load of an industrial consumer due to the high aggregation of consumers and the associated mutual compensation of load fluctuations. Modelling the national load is thus associated with a much smaller forecast error as compared to modelling an industrial consumer (Verwiebe et al., 2021b, p. 29).

2.2.1.5 Level of Modelling Detail

According to Flatau (2019, p. 21), energy models can be classified into black, grey and white box models, based on their level of modelling detail. In a black box model, the focus is on the input and output variables without considering the inner system behaviour. Black box models are also called descriptive models and are mainly used when the real relationships cannot be depicted. Instead of causal relationships between the input and output variables, these are described with empirical relations. In contrast, the focus of white box models is on the exact imitation of reality. White box models are also called causal models, as the internal behaviour of a system is described, for example, based on physical or chemical laws. The quality of the results of a model increases with increasing causality. Grey box modelling is a hybrid form of the above extremes, white box and black box modelling. Only the components of a system relevant for an investigation are modelled. The depth of consideration is based on the individual needs of the user. Consequently, both causal and empirical model relations can be used (Flatau, 2019, pp. 21–22).

2.2.2. Balancing Group System

In the following chapter, the balancing group system and its actors are being introduced on the basis of Figure 2. For technical reasons of frequency conservation and limited capacity of electricity storage, generation and consumption in the electricity grid must be balanced at all times (Schellong, 2016b, p. 376). For that purpose, each control area is subdivided into **balancing groups**, which commercially ensure the balancing of generation and consumption (BNetzA, 2021a). All suppliers and consumers are assigned to a balancing group. As a virtual account of generation and consumption, balancing groups are managed by the **balance responsible party (BRP)**, which is responsible to balance quarter-hourly amounts of electricity being fed into or taken from the grid and which bears the commercial responsibility for deviations within its group (*StromNZV*, 2020 § 4 (2), (3)). The BRP will procure electricity based on its customers' forecasted load profiles (**4.**). In order to account for smaller consumers with less than 100,000 kWh annual electricity consumption, every distribution system operator (DSO) provides SLP (**3.**) to all BRPs registered within its network area (**2.**) (*MaBiS*, 2020, p. 65). Hence, the load profiles and forecasts of individual consumers are the central parameters enabling the BRP to efficiently procure electricity. All generators within that balancing group must meet the electricity demand at all times. If the required and supplied amounts of electricity diverge over all balancing groups in a control area, the transmission system operator (TSO) must compensate these net deviations by supplying control energy. Incurring costs for control energy are allocated (**10.**) according to who caused the deviations using the imbalance settlement price (reBAP)[6] (BNetzA, 2020, p. 212; Schellong, 2016b, p. 19). In Germany, the TSO also takes the role of the **balancing group coordinator**, whose responsibility is to balance the control area by technical means and to settle all balancing group accounts.

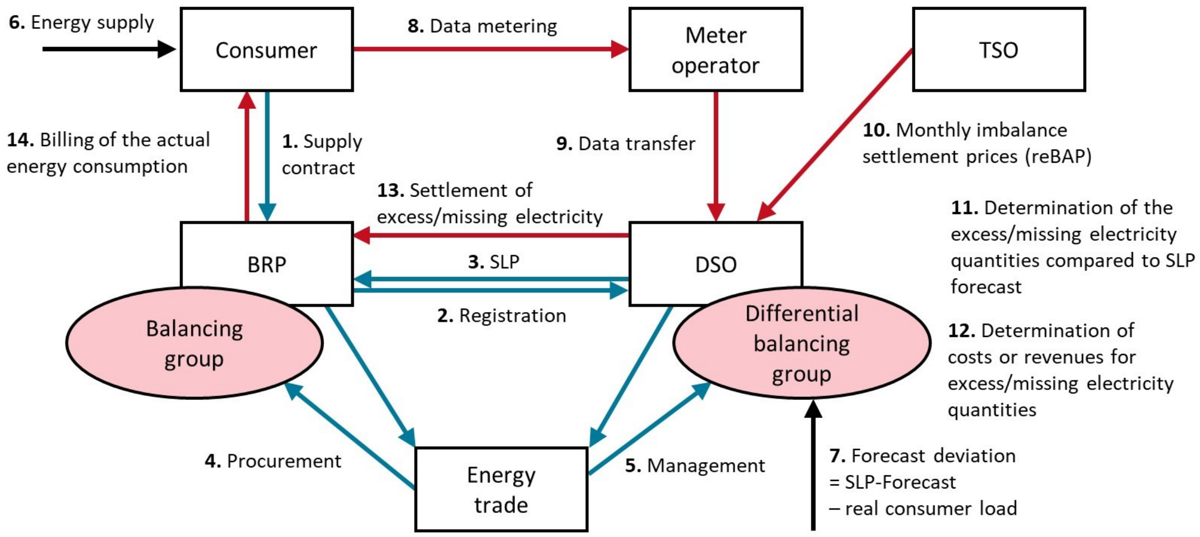

Figure 2: Schematic representation of balancing group system processes for the electricity supply of an SLP consumer. The colours indicate whether processes take place before (blue), during (black) or after (red) the electricity supply. Diagram by author, adapted from Gerblinger et al. (2014, p. 2)

Using SLP, there will inherently be deviations in procured and consumed electricity for related consumers (see chapter 2.3.2). According to StromNZV § 12 (3), a DSO is obliged[7] to record these SLP deviations in a **differential balancing group**. In contrast to the balancing group, DSO differential balancing groups are not purely virtual accounts but relate to the DSO's actual physical balancing area. In differential balancing group time series, the DSO is obliged to exclusively record and annually publish the quarter-hourly deviations of all those smaller consumers who are accounted for using SLP (*StromNZV*, 2020 § 12 (3)). In addition to SLP deviations, the differential balancing group time series will also encompass potential forecast errors from profile-based generation systems (like photovoltaic (PV) modules) (MaBiS, 2020, p. 12).

The responsibility and the commercial risk for managing these SLP-based deviations is assigned to either DSO or BRP according to the load profile procedure, which is determined by the DSO (Sohns, 2015, p. 18). There are two options:

- Synthetic load profile procedure (DSO responsible)
- Analytic load profile procedure (BRP responsible)

[6] In German: regelzonenübergreifender einheitlicher Bilanzausgleichsenergiepreis (reBAP)
[7] DSOs with less than 100 000 customers connected to their distribution network are exempt from the obligation.

Depending on the responsibility, the DSO or the BRP are required to actively manage their portfolio (**4./5.**): Predictable deviations in the consumption behaviour of SLP-based consumers must be accounted for and reduced as accurately as possible. This particularly includes the short-term trading of quarter-hourly electricity amounts in the (intraday) spot market (BNetzA, 2013, p. 2). Excess electricity is to be sold and missing electricity is to be bought. Remaining deviations (**7.**) will be priced with the reBAP (**10.**).

After the end of a contract year, the actual energy consumption of a customer is metered (**8.**) and transferred (**9.**) to the DSO by the meter operator. Furthermore, the DSO receives the monthly reBAP from the respective TSO, which is used to price SLP forecast deviations (**10.**). In the next step, the DSO determines the excess or missing electricity quantities of a customer with regard to the SLP (**11.**) as well as the costs or revenues incurred for this (**12.**). In order to price excess or missing electricity quantities, spot market prices of the twelve previous months will be used (and not the reBAP). The costs or revenues determined on the basis of a customer's excess or missing electricity quantities are then billed by the DSO to the supplier (**13.**). Based on the actual energy consumption, the BRP can send the final invoice for the respective billing year (**14.**) (Gerblinger et al., 2014, p. 2).

As the reBAP is associated with high fluctuations and penalty payments may occur in case of large deviations, DSOs (or BRPs) are incentivized to accurately forecast and procure. As Koch and Maskos (2019) described, there might be opposing incentives to deviate from a balanced portfolio under certain circumstances (passive balancing), but this is actually not allowed by German law (*StromNZV*, 2020 § 4 (2)), (Tennet, 2019). For the efficient management of balancing groups, the remaining load (of SLP consumers) is a central parameter (Sohns, 2015, p. 18). It can be calculated daily after delivery, according to:

Remaining load *= + import from neighbouring balancing areas*
+ total load (total infeed)
- export to neighbouring balancing areas
- loads of metered consumers
- grid losses

The remaining load comprises the sum of the real quarter-hourly electricity load of all SLP customers. In the synthetic load profile procedure, the DSO will forecast the remaining load and buy or sell anticipated deviations (**5.**) to the SLP electricity quantities procured by BRPs (**4.**). In the analytic load profile procedure, the DSO will split the remaining load according to customer group and BRP. This split is being provided to the BRP who will likewise use the split to forecast and compensate deviations to SLP electricity quantities already procured. In both cases, the remaining load is a central parameter and essentially deviates from inaccurate SLP (Sohns, 2015, p. 18).

2.2.3. Demand Side Flexibility

The decarbonisation of the energy sector is associated with various challenges. The central strategy for emissions reduction is the expansion of fluctuating renewable energy system (RES), such as wind and solar. In addition, other end-use sectors that are difficult to decarbonise will increasingly be electrified in the course of the energy transition, referred to as *sector coupling*[8] in literature (von Roon, 2017). In order to make efficient use of fluctuating renewable electricity and ensure power system reliability, system flexibility is necessary in order to mitigate potential mismatches in supply and demand (IRENA, 2019, p. 7). The demand for flexibility will largely depend on the RES share and the technology mix (Nicolosi and Burstedde, 2021, p. 72). Among major options to offer flexibility are

[8] A comprehensive definition of *sector coupling* can be found in Wietschel et al. (2018)

flexible generators, flexible storage facilities, the expansion of electricity grids and demand side flexibility. These flexibility options are considered to have priority if they are either more cost-efficient and/or socially more acceptable (Fürstenwerth and Waldmann, 2014, p. 39).

According to Seidl et al. (2016, p. 9), demand side flexibility (DSF) is an increasingly important flexibility option in the German energy system. IRENA (2019) defines demand-side flexibility “as a portion of the demand […] that could be reduced, increased or shifted in a specific period of time to: 1) facilitate the integration of [fluctuating RES] by reshaping load profiles to match [fluctuating RES], 2) reduce peak load and seasonality and 3) reduce electricity generation costs by shifting load from periods with high price of supply to periods with lower prices” (IRENA, 2019, p. 7). According to Ladwig (2018, pp. 14–15), demand side flexibility can be subdivided into three categories. In the first two categories, load increase and load reduction (also load shedding), the load will be increased or reduced without any load compensation at an earlier or later point in time. A load increase can be provided, for example, through Power-to-Gas or Power-to-Heat facilities at times of excessive electricity in the system. In times of an electricity deficit in the system, load shedding can be provided by energy intensive industry processes like the electric arc furnace or the chlor-alkali electrolysis. The third category is load shifting, which is associated to the shifting of loads to earlier or later times to better match the fluctuating RES generation or grid infrastructure restrictions. Applications and processes which are coupled to heat or cold storage systems, such as night storage heaters, are particularly suitable for this purpose (Ladwig, 2018, pp. 14–15). In this thesis, the technical potential for load shifting of selected commercial subsectors will be analysed, considering application-specific maximum and minimum loads as well as time-related availability restrictions.

The shedding, increasing and shifting of load is supposed to contribute to smoothing the residual load curve and avoid situations of grid congestion. The residual load can be defined as the difference between actual power demand and the feed-in of inflexible and non-dispatchable renewable generators (Schill, 2014, p. 65). The residual load has to be balanced by means of (conventional or renewable) flexible generation or storage technologies. In the future, the residual load will be subject to strong changes. In particular, the further expansion of RES will lead to an increase in short-term fluctuations. According to Weinert et al. (2018, p. 151), demand side flexibility will be required to smooth the residual load in the following situations:

- High demand coinciding with low electricity generation from wind and PV: leads to residual load peaks and is most likely to be observed in the early evening on winter working days.
- Surplus of renewable electricity generation coinciding with low electricity demand: leads to low, possibly negative residual load peaks and is most likely to occur at midday on summer weekends.
- Load peaks due to new applications, e.g. electric vehicles or air conditioning (AC): in the long-term, growing load peaks due to uncoordinated demand patterns (e.g. simultaneous charging of a large number of electric vehicles in the early evening after the last journey) (Weinert et al., 2018, p. 151).

By smoothing and reducing peak load hours of the residual load profile, demand side flexibility can partially reduce the need for peak load generation technologies, such as gas turbines, and efficiently ensure system stability (Boßmann, 2015, p. 212). In times of a negative residual load, demand side flexibility can also avoid grid congestion and make efficient use of the excess electricity by shifting demands or increasing loads, particularly to avoid the curtailment of fluctuating RES (Ladwig, 2018, p. 15).

From a regulatory perspective, §13 of the German Energy Act (“EnWG,” 2021) specifies a cascade of measures for the operational management and maintenance of system security in case of an impending grid congestion. In addition to grid switching measures to relieve electricity lines, another option is using so-called redispatch measures, imposed by the TSO. Redispatch measures reduce power plant capacities at one location and increase them at another location. If these measures are not sufficient, the TSO may impose adjustments to electricity feed-ins and withdrawals (§13 (2) EnWG). This also affects RES and CHP plants, the electricity feed-in of which can then be reduced or curtailed. The reduction of the grid feed-in of these plants initiated by the TSO is referred to as feed-in management (German: Einspeisemanagement (EinsMan)). In order to reduce overall costs, a further development of the regulation will shortly come into force with so-called *Redispatch 2.0*. In *Redispatch 2.0*, conventional and renewable generation plants will be considered in one step and controlled simultaneously in a cost-efficient manner, instead of the previous cascade of Redispatch and subsequent EinsMan. This will presumably result in increased curtailment of renewable generation plants within the framework of grid stabilisation measures, insofar as these can be curtailed more efficiently (Interconnector, 2021).

Due to the existing grid topology and the expansion of fluctuating RES, situations of grid congestion will increasingly appear, especially along the transport routes from the wind parks in the north to load centres in the south of Germany (Beucker et al., 2020b, pp. 11–12). Already in the past decade, the curtailed energy due to EinsMan measures multiplied, from 74 GWh in 2009 to 6.482 GWh in 2019 (BNetzA, 2021b, p. 149). Until now, the TSOs have mainly relied on large power plants and the curtailment of renewable electricity to eliminate bottlenecks. DSF, however, has hardly been used so far. Even the amendment to the German Grid Expansion Acceleration Act (German: Netzausbaubeschleunigungsgesetz (*NABEG*, 2021)), which came into force in May 2019, continues to exclude flexible consumers for the purpose of redispatch. In general, the principle "use instead of curtail" should apply to the renewable electricity generated, if the DSF can be used inexpensively. To give an example of application, the WindNODE research project has worked on the development of a flexibility platform for the north of Germany, to prepare the market-based utilization of DSF (Beucker et al., 2020b, pp. 11–12).

From an economic point of view, the consideration of further DSF potentials in the process of grid congestion management is particularly interesting if more expensive flexibility options can be substituted or the use of renewable electricity can be increased. For this, the saved costs must at least compensate for the costs of further development and operation of a future flexibility platform. The frequency of use of the flexibility and the required capacity can vary greatly depending on the location of the plant and the local situation in the electricity grid and must be assessed individually (Beucker et al., 2020a, p. 25). In any case, recent studies found that demand side flexibility can significantly reduce the grid expansion that would otherwise be necessary in the future (Agora Verkehrswende et al., 2019, p. 10; Kaul et al., 2019, p. 193).

2.2.4. Fields of Application for Electricity Demand Modelling

Since electricity can only be stored to a limited extent and with losses, electricity trading, transport and generation must follow the temporal fluctuations in electricity consumption (Schellong, 2016b, p. 376). For that reason, the fields of application for electricity demand modelling are manifold and span across all stages of the electricity system value chain. In order to investigate the various fields of application, Morozov (2019) conducted a structured literature search in her bachelor thesis at TU Berlin. Within the field of electricity load forecasting, the analysis identified 13 different fields of application for energy demand models employed by six different actors. Table 3 summarizes the results and illustrates the widespread use of energy demand models highlighting their relevance across all steps of the energy supply chain.

Table 3: Fields of application for energy demand modelling across different energy system actors, adjusted from Morozov (2019). Morozov adjusted the methodology from Verwiebe et al. (2021b) in order to narrow down the analysis to the 100 most cited papers from 2010 onwards to 2019, of which 72 were found suitable based on additional exclusion criteria.

Field of application	Energy producer	Trader	Grid operator	Energy provider	Consumer	Government
Planning and operation	■		■	■	■	■
Cost minimization	■	■	■	■	■	■
Energy policy						■
Planning of Generation	■					
Security of Supply			■	■		
Maintenance and services	■		■			
Procurement/Trading	■	■	■	■	■	
Balancing	■		■	■		
Expansion planning	■		■	■		
Energy efficiency measures			■		■	■
Pricing policy		■				
Building and facility management					■	
Microgrids			■			

In this thesis, subsector load profiles are developed, validated and applied in long-term electricity demand models. In this context, especially the liberalisation of the electricity market and the obligatory non-discriminatory grid access of all suppliers requires the knowledge of customer-specific load profiles (Schellong, 2016b, p. 377). Complementary to the above literature review, Schellong lists the following fields of application for electricity load profiles in high temporal resolution. Electricity load profiles, as developed in this thesis, can be used for:

- Planning and design of energy generation plants for electricity, heat and gas (dimensioning depending on peak load, also considering sector coupling technologies)
- Power plant resource planning for heat and electricity generation (dispatch)
- Simulation of time-dependent power consumption for smaller consumer groups without registering power measurement (RLM) (cf. chapters 5.1, 5.2, 5.3, 5.4)
- Calculation of grid fees for electricity transmission and distribution
- Portfolio management (structured electricity procurement in the liberalised energy market) (cf. chapter 5.6)
- Balancing group management for the organisation of customer-supplier relationships to cover the electrical energy demand (cf. chapter 5.6)
- Load management (avoidance or shifting of peak loads in electricity demand) (cf. chapter 5.5)
- Demand-side management (temporal control of electricity demand to smooth the load curve) (cf. chapter 5.5) (Schellong, 2016b, pp. 378–379)

Particularly for the future planning of the electricity system, there are specific fields of application for load profiles. Load profiles and energy demand forecasts are a central input for the electricity network development plan, which is updated every second year by the four German TSOs in collaboration with the Federal Network Agency (*NEP Strom*, 2021, pp. 12–13). More specifically, load profiles can be used to forecast demand and to estimate future technical DSF potentials as well as storage requirements (Seim et al., 2021a), as will be described later in this thesis (cf. chapters 4.5, 4.6). Forecasted load profiles can help to forecast bottlenecks in the electrical grid, which can also help to adjust market signals of a future flexibility platform and avoid grid extension.

On a microeconomic level, load profiles can serve as a subsector specific benchmark to consultancy firms estimating energy efficiency potentials in related subsectors. Also, they are an important input in the planning and simulation of local district energy concepts or microgrids that strive for a low carbon and self-sufficient energy supply.

Regarding future applicability of load profiles, the smart meter rollout and the associated increase in temporally high-resolution load data might change or complement some of the above fields of application, like the balancing group system introduced in chapter 2.2.2. Recently, however, the smart meter rollout was temporarily stopped for some utilities because certified gateways allegedly did not meet the legal requirements (Dierks, 2021). Also, smart meter rollout in Germany is not expected to be completed before the year 2032 (*MsbG*, 2020 § 29), (Dena, 2016). In any case, there will be a need for aggregate subsector load profiles to forecast the load behaviour of a variety of customers on a broad measurement basis (Gerblinger et al., 2014, p. 3).

The above considerations show that energy demand modelling in general and subsector load profiles in particular have a wide range of possible applications. The subsector load profiles developed in this thesis may be able to fill some of the existing data gaps in the German energy system for some of the application purposes listed above.

2.3. Current Research – Literature Review

In the following, the current state of research for this thesis will be introduced. Particularly, relevant literature and common concepts will be discussed. Moreover, the following chapters highlight in which way the present thesis fits into current research and addresses identified research gaps. Chapter 2.3.1 will present the main findings of an international literature review conducted and published in Verwiebe et al. (2021b). The subsequent chapters 2.3.2 to 2.3.5 will predominantly focus on national literature and current research with regards to the application and performance of standard load profiles (chapter 2.3.2), the development of subsector load profiles (chapter 2.3.3), the forecasting of load profiles (chapter 2.3.4) and the literature on demand side flexibility potentials (chapter 2.3.5).

2.3.1. International Literature Review on Energy Demand Modelling

In a process of capturing the current state as well as trends in the scientific field of energy demand modelling, a systematic literature review was conducted in Verwiebe et al. (2021b). As energy demand is a crucial input factor for sound energy system and infrastructure planning, the discipline of energy demand modelling has a long tradition (Debnath and Mourshed, 2018, p. 310). In view of increasing requirements and higher data availability, energy demand modelling has recently become even more relevant in the scientific literature. As found in Verwiebe et al. (2021b, p. 4), the number of related articles indexed on “Web of Science” increased tenfold in the last decade. For these articles, the wide research spectrum can be differentiated according to the modelled energy carriers, the methodological approaches, the temporal horizon or the spatial resolution, to name but a few (Debnath and Mourshed, 2018; Hong and Fan, 2016). As part of the research project DemandRegio, the literature review aimed to provide a “systematic and replicable analysis of a high number of articles [on energy demand modelling] regarding the utilized techniques as well as associated input data, accuracy, and spatio-temporal resolution across different energy carriers and sectors.” (Verwiebe et al., 2021b, p. 3)

Some of the literature review's insights also help to inform and contextualize the present approach of developing subsector electricity load profiles. In total, a number of 419 articles from the years 2015 to 2020 was reviewed with regards to the above-mentioned features. As found in the review and displayed in Figure 3, electricity is the most modelled and investigated energy carrier, by far exceeding natural gas or thermal energy. This not only underlines the value and significance of electricity for the overall energy system; it also underlines both rigorous requirements of balancing electricity supply and demand at all times as well as the associated high availability of data. This leads to a high interest in sophisticated models and data (Verwiebe et al., 2021a, p. 13). Likewise, for this thesis, significance and data availability are among the very reasons for the focus on modelling electricity (as opposed to natural gas or heat).

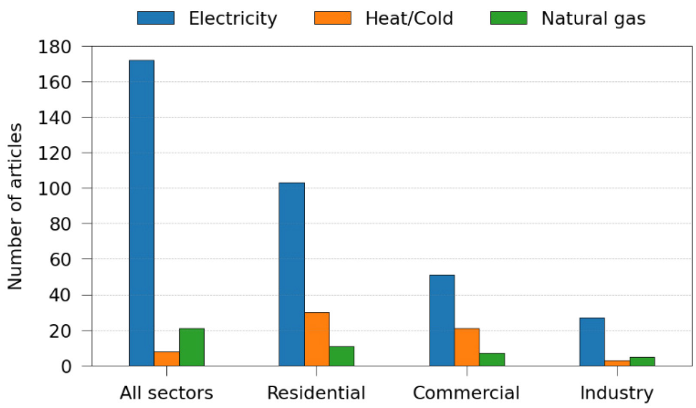

Figure 3: Number of published articles by sector and energy carriers. Used from Verwiebe et al. (2021c, p. 7859)

Regarding the consumer group focus, Figure 3 depicts the number of published articles by sector and energy carriers. As can be seen, most reviewed articles are not limited to a single sector. Rather, energy demand of an entire region is modelled, comprising all sectors. A sectoral focus on the electricity demand of the CTS and the industrial sector is less common within reviewed articles, despite their high electricity demand and significance (Verwiebe et al., 2021b, p. 32). The reason why these two sectors are underrepresented may be due to the sensitivity of business-related data (Wei et al., 2019, p. 7) as well as the heterogeneity of these sectors (Seim et al., 2019, pp. 4, 17). In view of these barriers, the present thesis seeks to fill this research gap by modelling the load behaviour of various industrial and CTS subsectors.

The techniques of reviewed articles are manifold, but machine learning and statistical approaches are among the most popular techniques employed, which is also in line with a literature review by Debnath and Mourshed (2018). The dominant use of machine learning and statistical approaches goes back to their flexibility and performance in a variety of contexts (Verwiebe et al., 2021b, p. 9). Particularly, linear and logistic regression are popular within statistical approaches, whereas artificial neural networks (ANN) are most applied approaches within machine learning techniques (Debnath and Mourshed, 2018, pp. 300–301). Since engineering-based techniques require high amounts of data and effort, they are used less frequently in the electricity demand modelling (Verwiebe et al., 2021b, p. 8). The above findings inform the present thesis' choice to apply multiple (linear) regression for the development of subsector load profiles. As a complement, ANN will be used to benchmark the multiple regression approach. Due to data and time requirements, engineering-based load profiles will only be developed for a selection of subsectors, in order to derive further insights with regards to the projection of load profiles and the identification of DSF potentials.

The temporal and spatial properties represent their level of detail for the modelling task. It was found in the review that the temporal horizon of reviewed articles spans evenly distributed from short-term, over medium term to long-term modelling tasks. Likewise, the temporal resolution of reviewed articles covers a spectrum from sub-hourly, hourly, daily or above-daily time steps (Verwiebe et al., 2021b, p. 27). The combination of a long-term forecasting horizon and sub-hourly resolution, however, is found less frequently within reviewed articles. Developing and forecasting subsector load profiles, the present thesis aims to also address this research gap: the provision of tools for the long-term electricity load forecast in high temporal resolution. Regarding the spatial resolution of reviewed papers, regional and country level energy demands are investigated more intensely compared to the appliance level (Verwiebe et al., 2021b, p. 27). This finding is in line with Wei et al. (2019, p. 7), who attribute this fact to the difficulty of data acquisition for smaller spatial entities.

Further insights of the literature review will be discussed where helpful in the course of this thesis. Particularly, the accuracy of reviewed papers and its dependency on the spatial resolution will be presented in chapter 2.5.5.

2.3.2. Standard Load Profiles

For more than 20 years now, the VDEW SLP have been used for the electricity procurement and the billing practice of non-power metered customer groups (cf. chapter 2.2.1.1). They were created as average load profiles, using 607 commercial, 332 residential and 260 agricultural load profiles in hourly and quarter-hourly resolution metered in the years between 1981 and 1998 (VDEW, 1999, pp. 15–16). The consumer groups were clustered using a fuzzy logic algorithm, yielding one average residential load profile (H0), seven commercial (G0 – G6) and three agricultural (L0 - L2) load profiles (VDEW, 1999, pp. 24–25). These SLP distinguish between working day, Saturday, Sunday as well as the seasons summer, winter and transition period. Figure 4 exemplifies two normalized VDEW SLP (H0, G1) in the winter period.

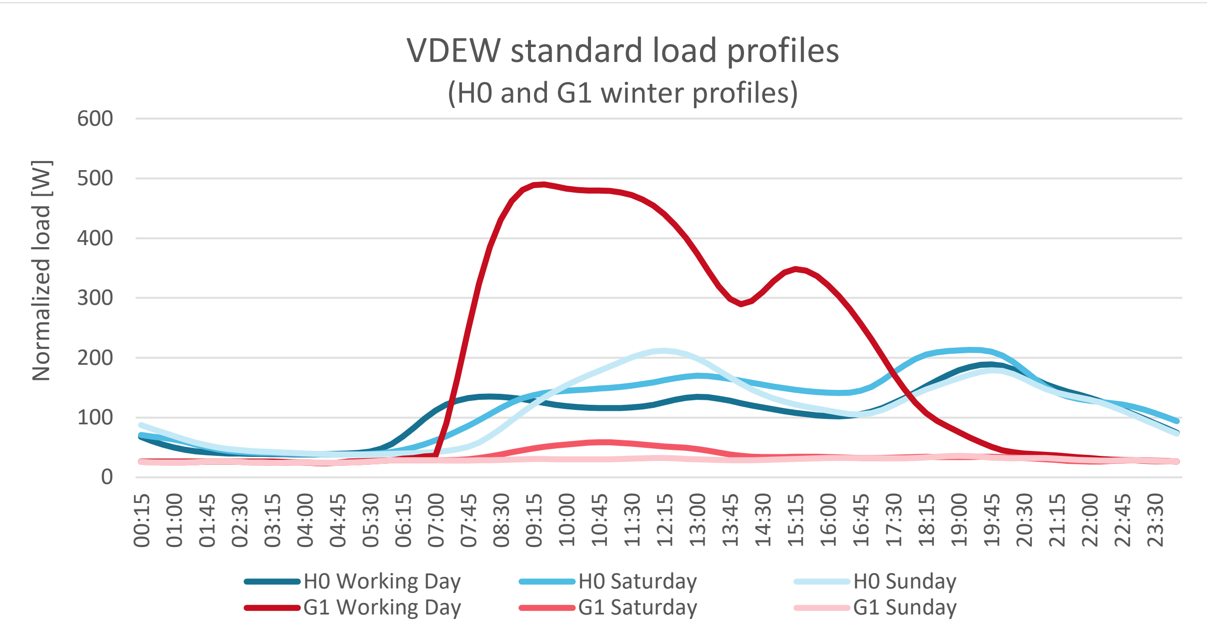

Figure 4: Exemplary illustration of two VDEW SLP (H0 and G1) in winter period. Diagram by author, based on BDEW (2021).

In addition to these consumer group SLP, standardised load profiles for specific interruptible and highly temperature-dependent loads (e.g. night storage heating, heat pumps) were created by VDEW. Based on technical parameters of the modelled system, basic load profile structures can be determined and adapted to the real conditions by form factors. These profiles were developed using real load data from the years 1998 to 2001, consisting of metered data from about six apartment buildings, 36 individual measurements from the domestic and commercial sector, as well as heating measurements from 75 individual customers (Schieferdecker et al., 2002, pp. 3, 23).

Representing the load characteristics of 20 to 40 years ago, SLP are associated with structural deviations. These deviations and the underlying drivers can be found in literature. Comparing the residential SLP (H0) with smart meter load profiles of Austria, Hinterstocker et al. (2014, pp. 1–2) identify significant deviations that might be traced back to behavioural changes, efficiency improvements as well as climatic developments. Similarly, both Gerblinger et al. (2014, p. 3) and Spiegel (2018, pp. 796–797) find that particularly the increasing share of PV self-generation and decentralised battery systems leads to forecast deviations using SLP, increasing the balance price risk for the BRP or DSO. As Sohns (2015, p. 17) points out, SLP are naturally associated with deviations which can lead to higher demands for imbalance settlement, resulting in higher costs for connected customers. These deviations affect both residential and commercial load profiles, as internal research indicated (Seim et al., 2021b, pp. 1–2). These deviations of non-power metered customer groups are typically captured in differential balancing group time series, which have to be recorded by DSOs, according to StromNZV § 12 (3) (cf. chapter 2.2.2). For Stadtwerke Hagenow, Figure 5 depicts the differential balancing group time series in a heatmap. As can be seen exemplary, the DSOs tend to largely underestimate electricity demands of small customers over the night time and in morning hours, while overestimating the electricity demand during the day. Using SLP, the differential balancing group time series of other DSOs exhibit similar deviations (Ecke and Kauffmann, 2013).

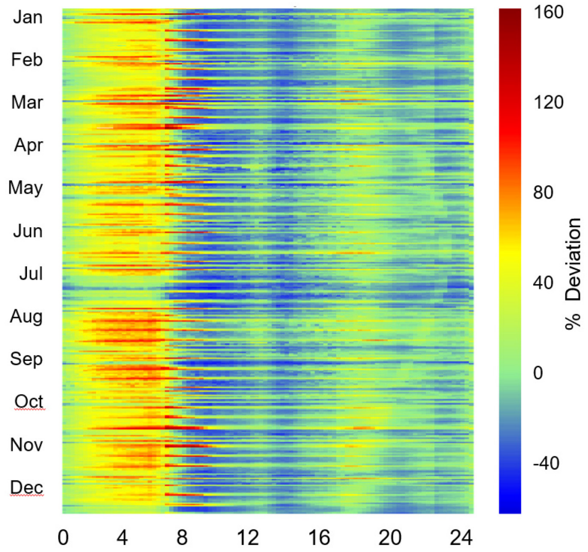

Figure 5: Heatmap illustration of a differential balancing group time series according to StromNZV § 12 of Stadtwerke Hagenow (2016), illustration by author.

Despite their structural deviations, these SLP are still widely used in research projects and as a benchmark for mapping the electricity demand of small customers – due to the lack of alternatives. In the research project DemandRegio, SLP have been used both in the *SLP only* and the *BLP application* approach in order to map the German electricity demand in high temporal and spatial resolution. In the *BLP application* approach, SLP were partially replaced by newly developed subsector load profiles (Gotzens et al., 2020, p. 154), which will be further introduced in this thesis. In a separate context, SLP have been commonly used in order to assess the demand side management potential of Germany (Heitkoetter et al., 2020, p. 7; Ladwig, 2018, p. 47; Steurer, 2017, p. 49). According to an analysis by Beuker (2018), residential SLP were used by 87 % of all 46 DSOs analysed. As remaining 54 DSOs did not publish sufficient information or data for the analysis, the share of DSOs using SLP is likely even higher. Further, multiple studies used SLP to simulate residential electricity consumption in the quantitative assessment of RES in decentralised power systems (Moshövel et al., 2015, p. 568; Seim et al., 2017, p. 9; Waffenschmidt, 2014, p. 89). Due to the lack of demand data in high temporal resolution, as discussed in chapter 2.1, the above examples only represent a fraction of research that had to resort to SLP.

2.3.3. Subsector Load Profiles

Recent alternatives to the use of SLP are either of closed access or very specific with regard to the mapping of individual subsectors. Kunze and Fichtner (2010, pp. 64–67) generated representative load profiles for the subsectors offices and retail food, based on 1,549 metered quarter-hourly load profiles of the years 2004 and 2005, using a fuzzy C-means algorithm. Outside the German context, Dolman et al. developed ten subsector load profiles for the commercial building sector in Great Britain (office buildings, education, health etc.) by averaging 226 half-hourly electricity demand profiles (Dolman et al., 2012, p. 64). Afterwards, application-specific sub-loads were approximated assuming that each follows the profile shape of the total load. Sub-loads were refined by assumptions (where available) to subsequently derive the technical demand side potential (Dolman et al., 2012, p. 21). Although these load profiles were developed for the commercial sector of Great Britain, they are still used in German research due to lack of alternatives. For example, the German Agency for Energy Efficiency (German: Bundesstelle für Energieeffizienz) used and cited these load profiles as the only data basis for application specific load profiles in the CTS sector (Weinert et al., 2018, pp. 114–117). In a different research project, Peter (2013, p. 8) used individual industrial and commercial load profiles in order to model decentralised structures based entirely on RES in the year 2050. The measured load profiles of 20 sites were not published. Gobmaier (2013, p. 47) generated synthetic load profiles for various industrial and commercial subsectors as well as application technologies. Although resulting load profiles have not been published, the applied multiple regression methodology inspired this thesis. Jakob et al. (2014) generated subsector-specific load profiles of the CTS sector for Germany and other European countries, using a bottom-up approach based on application and standards-based occupancy profiles. These profiles are not publicly available. In the GEKLES model, Schlomann et al. presented application specific load profiles for the banking and administration sector. Related application specific energy demands were determined based on the results of a broad survey in 2,000 commercial sites between the years 2006 and 2012, supplemented by research and internal data (Schlomann et al., 2015, pp. 64, 67). In a different research project, Weißmann et al. (2016) developed load profiles for the subsector of schools for further application in the energy assessment in local districts. The profiles were developed by averaging the load data of 12 schools of the year 2014 according to school type, season and type of day (i.e. workday, weekend). In the project “Teilenergiewerte”, Hörner et al. (2016, p. 22) measured application-specific load profiles in 75 non-residential buildings. Only the cumulative average load profiles for a low and high-tech office building were published. More recently, Behm et al. developed national electricity load profiles using artificial neural networks. Based on historic data for Germany from 2006 to 2015 provided by ENTSO-E, calendrical as well as weather information was used to generate synthetic load profiles for “much-needed” long-term electricity load predictions for European countries (Behm et al., 2020, pp. 1, 15). In order to create an overview of hardly available demand data, the HTW has created a portal where measured and synthetic load profiles can be made available collectively (HTW Berlin, n.d.).

Most developed load profiles from the research projects discussed above are either not published, too specific or too general in order to sufficiently map the subsector electricity demand in Germany in high temporal resolution. Notwithstanding, there are models capable of such tasks: the combination of the FORECAST model and the eLOAD model by Fraunhofer ISI is employed in central projects assessing the German energy system, such as the electricity grid development plan, the development of national long-term energy scenarios as well as national energy demand statistics (Elsland et al., 2016, pp. 17–19; Pfluger et al., 2017a, p. 21; Rohde, 2019, p. 2). In eLOAD, application-specific load curves are deduced from the system load curve of the base year using a partial decomposition approach. For the long-term forecast, these application-specific load curves can be scaled by projected application-specific annual electricity demands in FORECAST. The models are based on more than 500 hourly load profiles from different types of industrial, commercial and residential appliances or processes, historic load curves as well as application-specific demand side flexibility parameters (Fraunhofer ISI, 2019). However, both cross-sectoral models are of closed-access and thus cannot be used for replication or validation purposes.

The need for demand data has been described in chapter 2.1, while multiple fields of application for electricity load profiles have been identified in the former chapter 2.2.4. By providing openly accessible, up-do-date and accurate subsector load profiles, this thesis aims to close the identified research and data gap.

2.3.4. Load Profile Projections

In the international literature, the long-term projection of electricity consumption usually focuses on the *annual* electricity consumption of individual cross-sectional application technologies or sectors (Verwiebe et al., 2021a, p. 19). If at all, the temporal resolution of annual electricity demands is oftentimes achieved by applying current-state load profiles, as is the case for the research project DemandRegio (Gotzens et al., 2020, pp. 58–60). However, major technology shifts like the electrification of the heat or transport sectors will not only have significant effects on the total annual electricity demand but also on its load profile (Elsland et al., 2016, p. 18). In the German context, there are only few research institutions that engage in projecting the electricity load profiles with regards to their potential future shape. Even current commercial and industrial load profiles are hardly publicly available (HTW Berlin, n.d.; Seim et al., 2019, p. 17). In the eLOAD model, however, Elsland et al. extrapolate load profiles into 2030 or 2035, taking into account efficiency advances and technology shifts, such as the partial electrification of the heat and transport sectors (Elsland et al., 2016). For the regionalisation of loads, a distinction is made between the four demand sectors (households, CTS, industry and transport). While the effects on load profiles of individual technologies or sectors are described, the underlying data and load profiles are not publicly available, as mentioned in chapter 2.3.2. ZIRIUS has also dealt with the projection of load profiles in the project "Lastprofilwandel", but only for an exemplary pilot analysis for the mobility sector (Prehofer et al., n.d.). Here, too, the resulting profile was not published.

This thesis seeks to address this research gap by developing plausible load profiles of selected commercial subsectors for the year 2035 based on application-specific load profiles from Böckmann et al. (2021) and a scenario-based projection of application-specific annual electricity demands from Pfluger et al. (2017b). Using these bottom-up simulation models allows the mapping of structural changes and is therefore suitable for long-term energy forecasts (Wietschel et al., 2011a, pp. 43–44). The methodology and results of the load profile projection for respective commercial subsectors have already been published in Seim et al. (2021a).

2.3.5. Demand Side Flexibility Potentials

In a recent literature review, Kochems (2020) compiled and systematically analysed the studies on technical DSF potentials. The review concludes that data gaps on DSF potentials are particularly prevalent in the CTS sector, although considerable load shifting potentials can be identified there. Among Kochems' conclusions, two can be highlighted for the present thesis: firstly, closing the research gap of DSF potentials within the CTS sector is suggested. Secondly, it is recommended to focus future research on application-specific load shifting potentials across all sectors. These application-specific assessments can reduce uncertainties associated with the quantification of potentials found in current literature (Kochems, 2020, p. 12).

This thesis seeks to close these research gaps by identifying technical load flexibility potentials in high temporal and spatial resolution, using application-specific load profiles of key commercial subsectors (Böckmann et al., 2021). The methodology and results of technical demand side flexibility potentials for respective commercial subsectors have already been published in Seim et al. (2021a). Existing approaches (Gils, 2015; Heitkoetter et al., 2020; Ladwig, 2018; Steurer, 2017) differ from this thesis' approach in the use of (partly incorrect) standard load profiles (cf. chapter 2.3.2) or highly simplified profile assumptions.

2.4. Energy Demand Sectors

In order to define the scope of this thesis, the German energy demand sectors will be characterized briefly with regards to their demand structure as well as existing subsector classification systems (chapter 2.4.1). Going from subsectors to sub-loads in chapter 2.4.2, process and application technologies will be distinguished from each other to form the conceptual basis for the bottom-up modelling referred to in future chapters 2.5.4 and 4.4. Chapter 2.4.1 is based on a previous publication in Gotzens et al. (2020, pp. 62–65).

2.4.1. Depiction of Relevant Economic Subsectors

In national energy statistics, the energy demand side is commonly divided into four consumption sectors: the transport sector; the industrial sector; the residential sector as well as the sector of commerce, trade and services (CTS). In the year 2018, the final energy consumption (share) in Germany amounted to 751 TWh (30.1 %) for the transport sector, 736 TWh (29.5 %) for the industrial sector, 636 TWh (25.5 %) for the residential sector and 375 TWh (15.0 %) for the sector CTS. Figure 6 depicts the final energy consumption of Germany by sector, application and energy carrier. For the latter three sectors, (natural) gas and electricity are the predominant final energy carriers, providing mainly process heat, space heat and hot water (natural gas) as well as mechanical energy, computational power of information and communication technologies (ICT), process cooling and lighting (electricity). In contrast, the transport sector is mainly supplied by mineral oil products, providing mechanical energy ("AGEB," 2019).

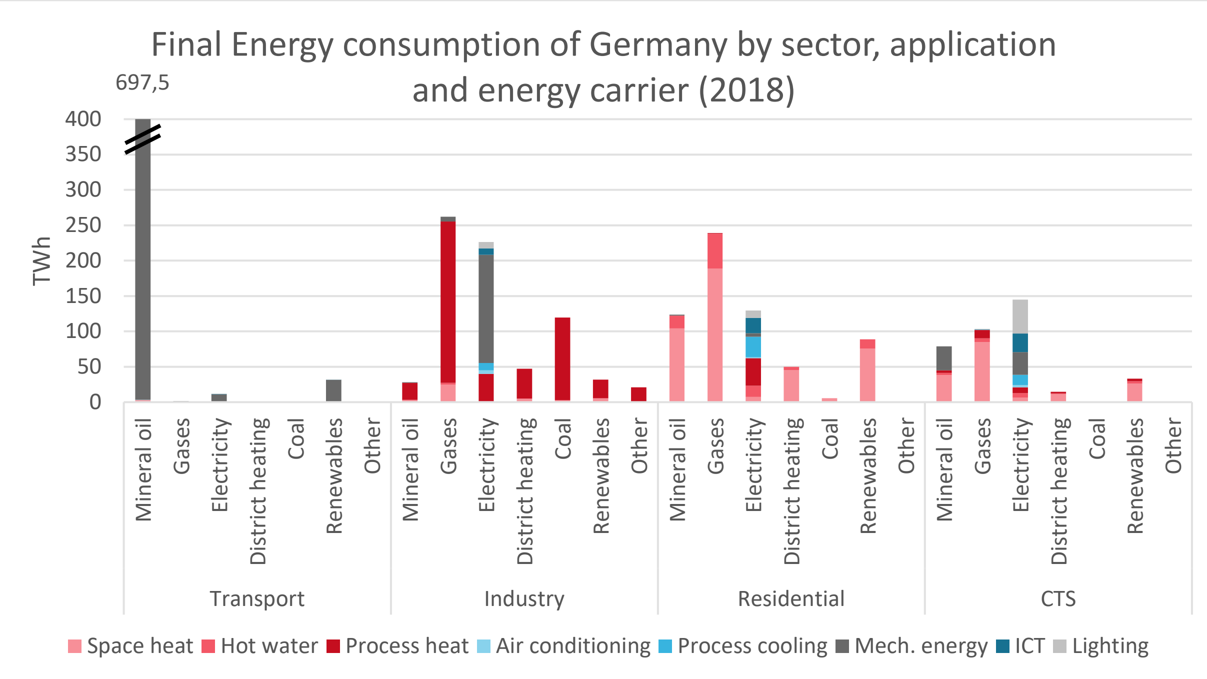

Figure 6: Final energy consumption of Germany by sector, application technologies and energy carriers in the year 2018. Depiction by author, based on AGEB (2019). (Electricity – includes renewable electricity; ICT – Information and communication technologies; Renewables – mainly biomass; Other – thermal utilization of waste materials, as well as waste heat; Mechanical energy includes ventilation, pumps, electric motors, compressed air systems and others)

In the course of the energy transition, electrical energy is of particular relevance, due to its accessible decarbonization potential. In previous years, the share of renewable energies increased strongly in the electricity sector, due to the expansion of proven technologies like wind turbines and PV systems. In contrast, the share of renewable energies in the provision of process and space heat as well as in the transport sector has increased only little or insignificantly in the same time period. The electrification of the heat and transport sector is hence being fostered and referred to in literature as sector coupling (von Roon, 2017). Despite the promising expansion of renewable energies in the electricity sector, there are particular challenges associated to the characteristics of the electricity system (Schellong, 2016b, p. 376), i.e.

- the system requirement to keep electricity generation and consumption in balance at all times,
- the intermittent character of renewable electricity generation and inflexible consumption,
- as well as the fact that electricity can hardly be stored in large quantities.

In view of the above considerations, this thesis puts a major focus on modelling the electricity demand of the industry and CTS sectors, as they exhibit high shares of electricity consumption; and as there is a general lack of information with regards to their demand patterns, mainly due to the previously described lack of data and their heterogeneity.

In order to take into account the sectors' heterogeneity, the industrial and CTS sector should be subdivided into smaller energy consumer groups, i.e. subsectors. Existing subsector classifications in the relevant literature can be found in the Working Group on Energy Balances (AGEB)[9] (Ziesing et al., 2019), in Fleiter et. al (2013) as well the *German Classification of Economic Activities (WZ 2008)* by the Federal Statistical Office (Destatis, 2008), which will be briefly introduced in the following. All three classification schemes can be mapped to each other to a certain extent.

Energy statistics form an important statistical information base for energy policy and serve as the basis for further considerations and measures within the Federal Government's Energy concept. Collected by various authorities and actors, the energy statistics are structured, standardized and merged into a consistent picture by AGEB (Ziesing et al., 2019). Among its central outputs are the *Anwendungsbilanzen,* i.e. annual reports specifying the subsectoral energy consumption for different application technologies ("AGEB," 2019). In the industrial, residential and CTS sector[10], AGEB specifies the electricity demand for 29 consumer groups, depicted in Figure 7 (p. 24). As can be seen, the electricity consumption amounted to about 129 TWh annually in the residential sector, which corresponds to about 25 % of the total electricity consumption. Further relevant subsectors are the basic chemical industry (47.4 TWh/a), offices (29.8 TWh/a), trade (22.6 TWh/a) and many more.

Building upon the existing AGEB consumer group classification, Fleiter et al. (2013) added another level of detail for the industry sector, analysing 63 energy-intensive industry processes. Regarding their electricity consumption, Figure 8 (p. 24) illustrates the 21 most relevant industry processes in Germany, which are associated with an annual electricity consumption of more than 1 TWh. While energy saving potentials of those processes are being discussed, information for load profile characteristics are not being provided (Fleiter et al., 2013).

[9] AGEB (German: Arbeitsgemeinschaft Energiebilanzen)

[10] According to Schlomann et al. (2015, p. 2), the sector CTS is distinguished from the industry sector by the number of employees: Commercial enterprises with a maximum of 19 employees, commercial buildings and premises of a commercial nature, trading companies as well as private and public service companies and facilities are assigned to the CTS sector. Agriculture, military services and stationary energy consumption by German Railways and airports are also included.

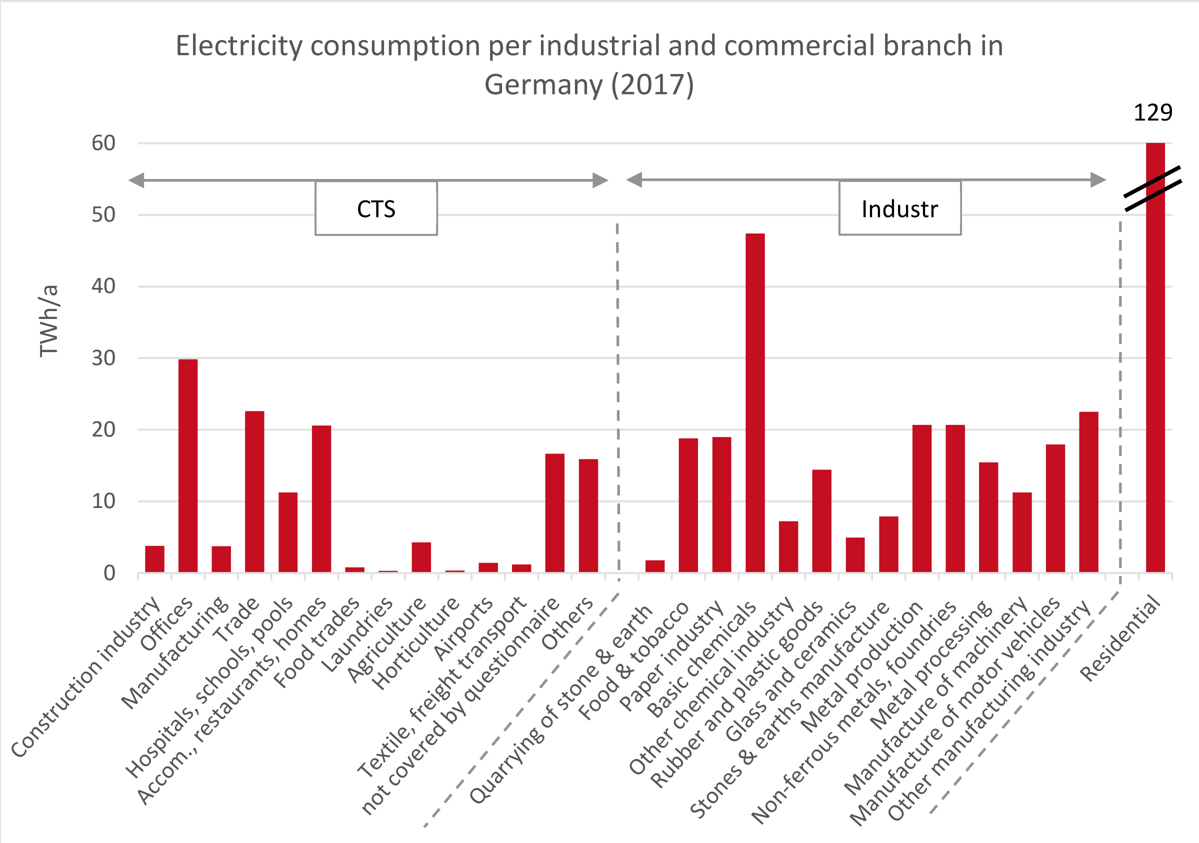

Figure 7: Classifying industrial, commercial and residential subsectors: Electricity consumption per subsector in Germany of the year 2017. Up-to-date subsector-specific data is not available for the CTS sector. Depiction by author, based on (Geiger et al., 2019, p. 19; Rohde, 2019, p. 18; Schmidt et al., 2019, p. 13).

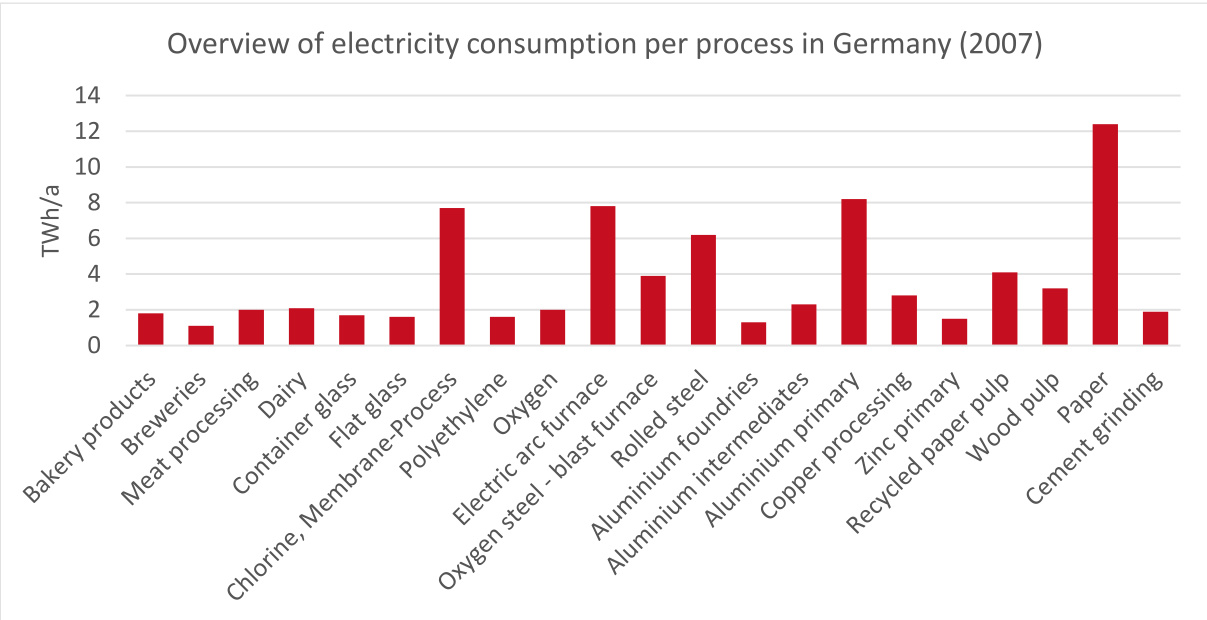

Figure 8: Classifying energy-intensive processes in Germany: electricity consumption for all energy-intensive processes with an annual electricity consumption of more than 1 TWh. Depiction by author, based on (Fleiter et al., 2013).

In contrast to the two literature examples above, the *German Classification of Economic Activities (WZ 2008)* by the Federal Statistical Office (Destatis, 2008) does not set a particular focus on energy statistics but on socio-economic statistics associated to economic activities. This classification forms the basis for the statistics on production values, production factors used (labour, inputs, energy, etc.)

and financial transactions of each subsector. The German classification (WZ 2008) has also been harmonized to some degree to match the European (NACE[11]) and global (ISIC[12]) classification schemes. In the current edition of WZ 2008, a subdivision of subsectors is made at five levels of detail. In ascending level of detail, these are:

- Sections (of which 21), coded with one letter.
- Divisions (of which 88), coded numerically with two digits
- Groups (of which 272), coded numerically with three digits
- Classes (of which 615), coded numerically with four digits
- Subclasses (of which 839), coded numerically with five digits

The literature discussed above (AGEB, Fleiter et al. (2013), WZ 2008) presents existing subsector classification schemes in Germany which could serve as a reference to define consumer groups for the generation of subsector load profiles. For the purpose of the present thesis, defined consumer groups should

- be as homogeneous as possible with regards to their electricity consumption patterns,
- match to existing statistics to enable the scaling of results, and
- exhibit a sufficient level of detail with regards to data availability.

Despite the distinct focus on energy statistics of AGEB and Fleiter et al., particularly industrial consumer groups are declaredly associated with heterogenous structures or technologies (“AGEB,” 2019, p. 11). The heterogeneity of electricity consumption can be even more pronounced for the classification WZ 2008, where groups are assigned based on production factors, inputs, production processes, intermediate or final products and services (Destatis, 2008). However, the most important benefit of the WZ 2008 classification is its compatibility to other socio-economic statistics, which allows for the scaling of any subsector specific results on a county-level (AGS) throughout Germany. In the course of this thesis, *divisions* from the classification WZ 2008 will therefore be used to define subsectors. The inherent heterogeneity in this classification cannot be avoided and will be addressed in the discussion of results.

As indicated in chapter 1, the compatibility of WZ 2008 to other socio-economic statistics enables a regional mapping of the electricity demand by using the electricity consumption of individual subsectors (Destatis, 2019), the number of employees for individual subsectors (FfE and Bundesagentur für Arbeit, 2019) and a regionally specific energy consumption of industrial subsectors (FfE, 2019). The detailed methodology of the regional mapping of electricity demand is presented in Gotzens et al. (2020, pp. 75–79). Naturally, those subsectors with high energy consumption are to be investigated as a priority.

2.4.2. Process Technologies and Application (Cross-sectoral) Technologies

In addition to subsectors, the energy demand can be further divided into sub-loads of the underlying energy consuming technologies. Depending on their scope of application and specificity, energy consuming technologies can be divided into two groups, which eventually provide energy services: process technologies and cross-sectoral application technologies.

Process technologies are technologies that are very specific to a certain (industrial) sector, product or production process. These include, for example, the paper machine, the cement mill or the chlorine-alkali-electrolysis, which are only applied in that particular subsector. These very diverse industrial

[11] NACE – Statistical Classification of Economic Activities of the European Community

[12] ISIC – International Standard Industrial Classification

processes lead to a heterogeneous technology structure with a large number of different energy consumers. The mapping of this heterogeneous technology structure is therefore complex and involves high data requirements. Chapter 2.4.1 introduced several energy-intensive process technologies and their respective energy demand (Fleiter et al., 2013, pp. 46–49). As indicated by their name, *process* technologies are oftentimes closely related to the manufacturing process, i.e. the central process in the value creation within the manufacturing industry. These manufacturing processes are subject to (stochastic as well as scheduled) fluctuations and depend on production schedules, which are mostly unknown to modelers, which complicates the energy demand modelling of process technologies.

In contrast to process technologies, application technologies are widely used mass products across subsectors. These technologies mostly consume electrical energy only, and comprise lighting, ICT, ventilation, air conditioning, pumps, electric motors as well as compressed air systems. While the individual application (e.g. lighting) might only account for a limited share of the total energy consumption in a subsector, their cross-sectoral application makes them relevant energy consumers from the perspective of the overall system (Fleiter et al., 2013, p. 21). Figure 6 (page 22) displays the final energy consumption of these application technologies. Application technologies are particularly dominant in the CTS sector. Besides their relevance as energy consumers, the temporal availability and regional distribution of application technologies qualify them for load shift interventions. This is particularly relevant because the use of application technologies does oftentimes not directly interfere with the manufacturing process – in contrast to process technologies (Schellong, 2016b, p. 407).

Among energy demand modelling methods, the distinction of process and application technologies particularly concerns engineering-based bottom-up modelling approaches, which exhibit the respective technological detail (Fleiter et al., 2011, p. 3100). Using physical parameters, engineering-based models are characterized by the detailed depiction of a system's technological equipment enabling the realistic simulation of the system's behaviour as a function of various framework parameters. In view of the above-mentioned technological heterogeneity, data requirements of bottom-up models can quickly become very high and inexpedient. This is all the more challenging because (application-specific) energy demand data is rarely accessible, let alone metered separately (Seim et al., 2019, p. 17). Chapter 2.5.4 will further elaborate on engineering-based models.

2.5. Techniques and Methods of Energy Demand Modelling

As presented in a recent literature review (Verwiebe et al., 2021b), there is a variety of techniques and methods in the realm of electricity demand forecasting. Similar to existing literature (Debnath and Mourshed, 2018, p. 299), the techniques of reviewed articles were classified according to the following five categories: statistical, machine learning, metaheuristic, stochastic/fuzzy/grey, and engineering-based techniques. Due to an increasing development of hybrid approaches, the boundaries are not always clear. As indicated in chapter 2.3.1, this thesis applies a combination of statistical, machine learning and engineering-based approaches for their flexible applicability, their widespread use and performance. The following chapters will introduce these specific techniques used in this thesis, i.e. a multiple regression and quantile regression approach for the development of subsector load profiles (chapter 2.5.1 - 2.5.2); an ANN approach as a benchmark model (chapter 2.5.3); and an engineering-based approach to develop sub-load profiles for selected CTS subsectors (chapter 2.5.4). Auxiliary methodologies to evaluate and validate model performances are introduced in chapters 2.5.5 and 2.5.6. Other techniques frequently applied in the energy demand forecasting literature are briefly contextualized by Verwiebe et al. (2021b, chapter 3) and partially introduced in Backhaus et al. (2016).

2.5.1. Multiple Regression

The following introduction to multiple regression has partially been published in Gotzens et al. (2020, chapter 4.5.3.1) and is based on the introduction from Backhaus et al. (2016).

Multiple regression analysis is a flexible and universally applied technique used to quantitatively describe the influence of several independent variables x_j on a dependent variable y within complex systems and to estimate or predict values of the dependent variable y. In the quantitative determination of dependencies of individual demand drivers x_j on the energy consumption, regression analysis compares favourably with the black box character of artificially intelligent methods. The regression function can be described in the following mathematical form (1)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_j x_j \tag{1}$$

y	estimation of dependent variable
β_0	intercept
$\beta_{1,2,\ldots,j}$	regression coefficient
$x_{1,2,\ldots,j}$	independent variable
J	number of independent variables

The multiple regression analysis can only map linear dependencies in their functional dependence on the model parameters. However, this only refers to the functional dependence of the regression parameters β_j, but not to variables x_j, which in turn can be integrated within nonlinear functions with $x_j = f(x)$ (Backhaus et al., 2016; Schellong, 2016b).

In this thesis, the electrical load forms the dependent variable y to be predicted, while demand drivers x_j are used as independent variables. As optimization criterion of the regression analysis the minimization of the residual variables e, thus the deviation of actually observed y to determined estimated values $\hat{y}$ of the dependent variable is considered, as represented in formula (2):

$$e_i = y_i - \hat{y}_i \qquad , i = 1, 2, \ldots n \tag{2}$$

$$\sum_{i=1}^{n} e_i^2 \rightarrow \min! \tag{3}$$

$$\sum_{i=1}^{n} |e_i| \rightarrow \min! \tag{4}$$

y_i	–	observed value of the dependent variable Y for x_i
$\hat{y}_i$	–	determined extmated value of Y for x_i
n	–	number of observations

Typically, regression analysis uses the minimization of squared residuals, the so-called Ordinary Least Squares (OLS) method, as shown in formula (3). The goal of regression is to determine those values of the regression parameters $\beta_0, \beta_1 \ldots \beta_j$ that fulfill the optimization criterion. An alternative, but mathematically more complex criterion to handle is the minimization of the absolute values of the residual variables (formula (4)). The latter is used in modified form in the Quantile Regression, introduced in the next chapter.

2.5.2. Quantile Regression

The following introduction of Quantile regression has partially been used in the DemandRegio final report (Gotzens et al., 2020, chapter 4.5.3.2). Quantile regression is a promising supplement to multiple regression in the present thesis. On the one hand, it can be used to generate prediction intervals that provide information about the accuracy, distribution and variance of the prediction. On the other hand, it is more flexible compared to some model assumptions, which limit the multiple regression analysis. While multiple regression analysis predicts the conditional expected value by applying the least squares method, quantile regression aims at estimating conditional quantiles (e.g. the median). The Quantile Regression is therefore less susceptible to outliers (Koenker and Hallock, 2001). A comprehensive description of quantile regression can be found in Koenker (2005). Formula (5) represents the typical optimization criterion of Quantile Regression (Fitzenberger, 2019, p. 407):

$$\sum_{i=1}^{N}[\theta * \overbrace{I(y_i > x_i'\beta_\theta)}^{\text{Residuals are positive}} + (1-\theta) * \overbrace{I(y_i < x_i'\beta_\theta)}^{\text{Residuals are negative}}] * \underbrace{|y_i - x_i'\beta_\theta|}_{\text{Absolute Deviation}} \rightarrow \min! \qquad (5)$$

- θ – Quantile
- I – Indicator function
- x_i' – variable x at position i as vector
- β_θ – regression coefficient of the θth Quantile

For $\theta = 0.5$ (median), positive and negative residuals are equally weighted, i.e. the sum of the absolute values of the residuals is minimized, analogous to formula (4). If the residuals are positive (or negative), the absolute deviation is multiplied by the quantile value θ (or the residual term $1 - \theta$). Figure 9 illustrates the resulting weighting of the residuals in case of the 0.75 quantile ($\theta = 0.75$, also "upper quartile"). If $\theta = 0.75$, positive residuals (1) are weighted higher (0.75) than negative residuals (2) (0.25). The shown example shows that point (1) is more strongly weighted than point (2) for the 0.75 quantile of y at the position $X = X_i$. In the concrete case, the higher weighted small distance (1/3 * 0.75) is compensated by the weaker weighted larger distance (1 * 0.25). In the minimization process, those values of the regression parameters are determined which are decomposed by quantile-weighted negative and positive residuals into equal parts after the transformation.

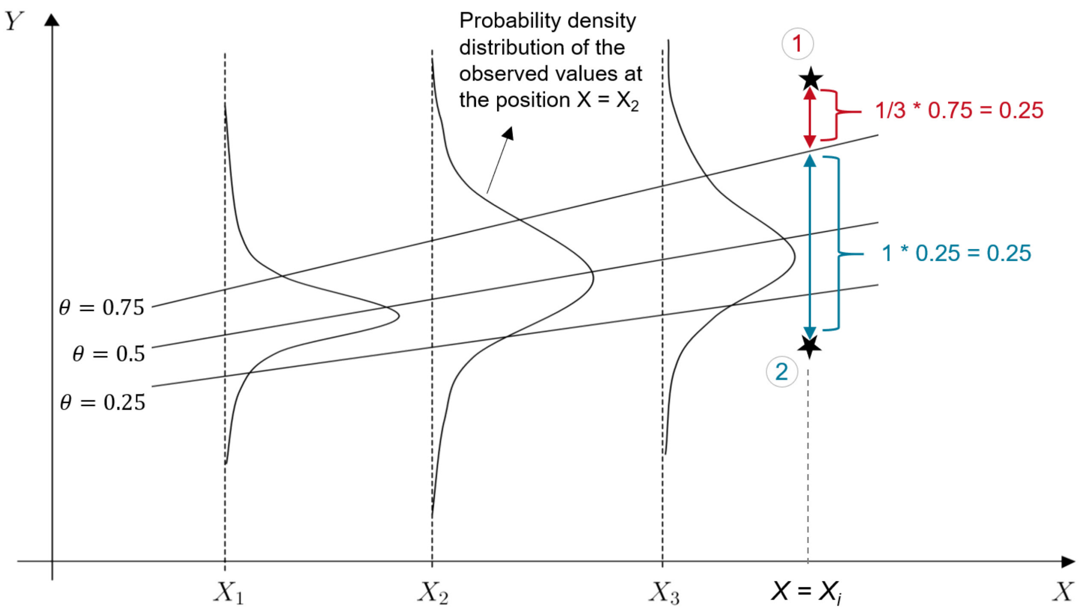

Figure 9: Variance of the conditional distribution of Y as a function of X and the corresponding weighting of the residuals in the case of the 0.75 quantile. Adjusted representation based on Fitzenberger (2019, p. 411).

2.5.3. Artificial Neural Networks

In reality, dependencies between variables are often very complex. The complexity not only becomes apparent in the large number of (partly interdependent) variables, but also the fact that relationships between variables are often of non-linear nature. In such cases, artificial neural networks (ANNs) are advantageous, as the user does not necessarily have to make an assumption about the relationship between variables. Rather, the application of ANN allows to autonomously determine correlations between (a large number of) variables through a training process. Given a large number of observations, ANN can replace classical multivariate analysis methods, such as forecasts (e.g. multiple regression) or cluster analyses (Backhaus et al., 2016, p. 604). Their potential and flexibility in the context of load forecasting is demonstrated by the high level of research interest in the international literature (Debnath and Mourshed, 2018, p. 303; Verwiebe et al., 2021b, p. 6).

The working principle of ANN is based on processes in the nervous system of humans and animals. It attempts to reproduce biological learning via suitable mathematical operations, whereby very good results can be produced (Backhaus et al., 2016, p. 604). The basic structure of ANN can be illustrated by Figure 10. Each ANN consists of an input layer, one or more hidden layers and an output layer. The exemplary structure in Figure 10 shows an input layer with four neurons (1-4), two hidden layers with three and two neurons (5-7, 8-9) and an output layer of three neurons (10-12). The input layer maps all empirically collected variables[13] (in the present case: all demand drivers for the electricity demand modelling), which then cause activation of the neurons on the two hidden layers (Backhaus et al., 2016, p. 604). The output layer captures actual predictions Y' of the target values Y. The loss function compares these predictions with the actual target values and determines a loss score, which is a measure of how accurate the ANN predicts the expected target values. The optimizer uses the loss scores to adjust the weights of selected neurons. The weights of the layers that have been learned through a so-called stochastic gradient descent (SGD) procedure contain the knowledge of the ANN (Chollet, 2018, pp. 86–87).

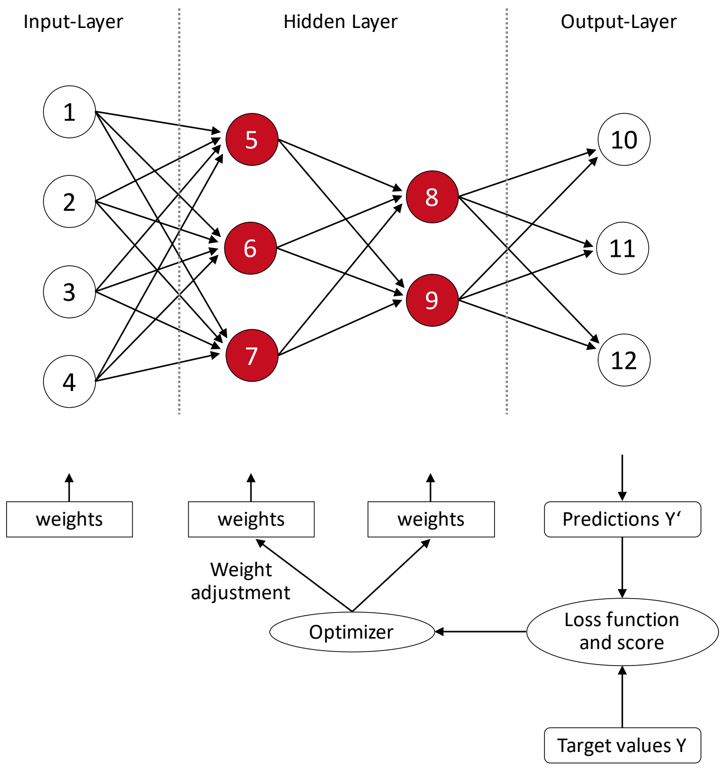

Figure 10: Basic structure of a neural network, including the loss function and the optimizer. Diagram by author, based on Backhaus et al. (2016, p. 605) and Chollet (2018, p. 86).

According to Backhaus et al. (2016, p. 605), the basic principle of information processing in the hidden layer neurons can be illustrated as follows: first, the signals arriving at a neuron are condensed into a net input value for the neuron. This condensing step of incoming information is achieved by the so-called propagation function. In the simplest case, the propagation function is defined as a sum function that calculates the net input value from the sum of the weighted input signals. Within the neuron, this

[13] In scientific literature dealing with ANN, input variables are also referred to as features (Chollet, 2018, p. 38).

net input value is then processed according to an activation function, which determines the neuron's degree of activation. In the simplest case, the degree of activation is a binary value (0 – deactivated, 1 – activated). Both the weights of the propagation function and the threshold parameter of the activation function can be changed and adjusted by the learning process of the network until the output neurons can represent the empirically measured target values as well as possible. This training procedure of continuously adjusting weights requires a large number of observations in order to effectively train the neural network (Backhaus et al., 2016, p. 605). Further details on different principles of information processing (feedforward, backpropagation etc.) are explained in Backhaus et al. (2016, pp. 607–608).

The topology of the network, i.e. the number of layers and nodes, is an important property for the given modelling task, as are the choice of learning rate, the loss function, the optimizer and potential penalty functions which prevent overfitting. These properties must be set and adapted to the modelling problem to achieve the best possible results. They are called hyperparameters to distinguish them from the actual weight parameters of the individual layers and nodes. Hyperparameters cannot be estimated from real data. Rather, they must be first set manually and optimized with the help of a heuristic (Feurer and Hutter, 2019, p. 4). Fine-tuning these hyperparameters is a major focus of machine learning research (Chollet, 2018, pp. 133, 157).

2.5.4. Engineering-based techniques

In the energy demand modelling, two fundamentally different methodological approaches can be distinguished: top-down and bottom-up energy demand modelling, the latter also called engineering-based modelling.

Top-down modelling approaches describe a procedure that is directed from "top" to "bottom". The analysis is carried out on the basis of aggregated historical data, which includes energy demand patterns, macroeconomic relationships and trend curves. Accordingly, the top-down approach is of econometric character (Wietschel et al., 2011a, p. 43). The strength of the top-down approach is its fairly easy application for long-term forecasting. However, due to its dependence on historical data, potentially incomplete and inefficient structures are carried forward in energy demand forecasts. Moreover, structural shifts in energy demand patterns cannot be readily incorporated.

Bottom-up modelling approaches, in contrast, are based on the idea of modelling from "bottom" to "top". With regard to the energy demand modelling, "bottom" refers to the detailed analysis of individual subsectors, technologies or production processes. The detailed and subsector-specific energy demand patterns can then be scaled to the "top", yielding a total and representative energy demand for the whole (sub)sector. The bottom-up approach thus starts at a specific level and aims towards the general (Wietschel et al., 2011a, p. 44). Its strength lies in the flexibility of mapping structural shifts within individual subsectors and technologies due to its level of detail, making it a suitable approach for the long-term forecasting of electricity demands (Wietschel et al., 2011a, p. 48). Due to the high degree of detail, drivers and causes of change can be well identified and investigated. Adjustments resulting from technological shifts can thus also be incorporated in the process without having to regenerate the entire model (Kavgic et al., 2010, p. 1684). On the other hand, there is an extensive need for data on subsector specific energy demands, technologies and processes, which is necessary for a realistic representation of the system. Depending on the scope of the system, e.g. the subsector to be depicted, data requirements can quickly become very high and inexpedient (Fleiter et al., 2011, p. 3109; Iqbal and Kutt, 2018, p. 2). Despite their high data requirements, bottom-up approaches can be of particular use where only little historic load data is available (Verwiebe et al., 2021b, p. 7). In addition to their capacity to model the above mentioned technological shifts, bottom-up models can be used to identify DSF potentials and model the effects of efficiency gains (Jakob et al., 2014, p. 1).

Due to the level of technological detail that bottom-up models often exhibit, these approaches are also referred to as engineering-based models (Verwiebe et al., 2021b, p. 7). In contrast to ANN, engineering-based methods can mostly be classified as a white box model approach (cf. chapter 2.2.1.5), as they attempt to model the reality of a given system as accurately and in as much detail as possible using physical input factors (Flatau, 2019, pp. 21–22). Common examples comprise models on the level of industrial processes or 3D building simulations. Further, residential loads can be simulated in an engineering-based model sometimes referred to as load profile generator. Here, behavioural data of time of use surveys (Destatis, 2021) are linked to the utilization of household appliances in order to model the load behaviour of individual or multiple households (Swan and Ugursal, 2009; Ziegler et al., 2020, p. 2). As found by literature review (Verwiebe et al., 2021b, p. 7), engineering-based models are widely used in practice, despite their limited visibility in scientific articles on energy demand modelling. This might go back to the data and labour requirements in the application of engineering-based models. The level of detail and the system boundaries significantly determine the required data effort. The scope should therefore be set carefully to balance the costs and benefits.

2.5.5. Model Performance and Prediction Accuracy

In order to assess the model performance of the different approaches and to evaluate the reliability of subsector load profiles, performance measures are used in the research literature. The following elaboration on model performance measures has partly been published in the DemandRegio final report (Gotzens et al., 2020, chapter 4.5.3.1). For a global check of the model performance, the coefficient of determination (R^2) is particularly often used for statistical models. The coefficient of determination relates the variance explained by the regression model to the total variance. As a normalized quantity, it has a value range between zero and one. The closer the coefficient of determination is to one, the better the regression model described by it is, i.e. the larger the proportion of the declared variance compared to the total variance (cf. formula 6).

$$\mathrm{R}^2 = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\hat{\mathrm{y}}_{\mathrm{i}} - \bar{\mathrm{y}})^2}{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y}_{\mathrm{i}} - \bar{\mathrm{y}})^2} = \frac{\text{explained variance}}{\text{total variance}} \qquad (6)$$

$$\mathrm{R}_{\mathrm{adj}}^2 = \mathrm{R}^2 - \frac{\mathrm{J} \cdot (1 - \mathrm{R}^2)}{\mathrm{n} - \mathrm{J} - 1} \qquad (7)$$

$\bar{y}$ – mean of the dependent variable Y
$\hat{y}_i$ – determined estimated value of Y for x_i
J – number of independent variables
$n - J - 1$ – number of degrees of freedom

As a modification, the adjusted coefficient of determination (R_{adj}^2) is also used, which takes into account the size of the sample and the number of regressors. With the R_{adj}^2, the simple R^2 is reduced by a correction quantity which is the larger the smaller the number of degrees of freedom or the larger the number of independent variables (cf. formula 7). Thus, R_{adj}^2 can also decrease in contrast to R^2 by the inclusion of further independent variables.

However, the above performance measures only say something about how well the estimated model fits the observed values (Backhaus et al., 2016). In addition to R^2 and R_{adj}^2, there are other performance measures more frequently used in energy demand modelling that describe the average deviation of the model estimate from the actual observed values: the mean absolute percentage forecast error (MAPE) and the normalized root-mean-square error (nRMSE) (Debnath and Mourshed, 2018, p. 310).

$$\text{MAPE} = \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \qquad (8)$$

$$\text{nRMSE} = \frac{\text{RMSE}}{y_{max} - y_{min}} = \frac{\sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}}{y_{max} - y_{min}} \qquad (9)$$

The MAPE corresponds to the average absolute percentage error and is widely used mainly because of its simplicity and transparency. However, a major weakness in the application of MAPE is the handling of very small load values close to (or equal to) zero. The occurring deviations ($y_i - \hat{y}_i$) in the numerator are weighted significantly higher in the denominator (y_i) for low load values, which leads to a distortion. Still, MAPE is the most used performance measure in the power industry (Hong and Fan, 2016, p. 933).

In contrast, the RMSE fits well to the optimization criterion of the OLS method, since the average squared residuals are included in the error measure. The root function ensures that the order of magnitude of the forecast and the error measure are equal. The normalization step allows a comparison of the nRMSE performance measures between load forecasts of different orders of magnitude. Similar to the OLS method, the nRMSE assigns higher weights to outliers – but equally so to positive and negative outliers. This avoids an error distortion towards load values of small amounts as in the case of MAPE (Vandeput, 2018). On the other hand, in normalization, the nRMSE shows a sensitivity in the difference between the maximum and minimum load value.

Benchmarking these performance measures is very difficult, not only because there are multiple performance measures used in literature (Debnath and Mourshed, 2018, p. 310). As found in a literature review (Verwiebe et al., 2021b, p. 29), the model performance is largely affected by particular use-cases and the underlying data (Fallah et al., 2018, p. 26). More specifically, the spatial resolution had a much stronger influence on the model accuracy than the applied technique or temporal resolution. A greater spatial resolution is associated with a higher level of detail which proved to result on average in higher MAPE values. The prediction of an individual appliance or site is associated with higher (i.e. worse) MAPE values as compared with a prediction of the national energy consumption (Verwiebe et al., 2021b, p. 29). In the context of this thesis, the models to develop subsector load profiles exhibit a high spatial resolution (i.e. individual company sites), which in case of high fluctuations might negatively affect model performance values. In addition, combining individual site-specific models to a subsector load profile further increases heterogeneity, which further deteriorates MAPE values. Thus, the model performance of subsector load profiles has to be evaluated in context.

Table 4: Lewis's benchmark for model performance evaluation

MAPE	**≤ 10 %**	**10 % - 20 %**	**20 % - 50 %**	**≥ 50 %**
Evaluation	Highly accurate	Good	Reasonable	Inaccurate

The above-mentioned limitation in the benchmarking of performance measures for energy demand models has to be taken into account. Nevertheless, the Lewis's benchmark (Lewis, 1982) has been used to evaluate model performances in the energy demand forecasting literature (Wei et al., 2019, p. 8). According to Lewis's benchmark, the classification shown in Table 4 was made.

2.5.6. Cross Validation

Since the values realized at the time of the forecast are in the future and therefore not yet known, ex-post forecasts are used in the validation of the energy demand models. For this purpose, the available data is broken down into so-called training data, validation data and test data. Training data serve as a reference section for estimating the model and validation data for testing the quality of the model (Backhaus et al., 2016, p. 147). A further separation in test data is only necessary if different model configurations are to be weighed against each other and an overfitting of the model to the underlying data is to be avoided. The considerations on cross validation have already partially been published in the DemandRegio final report (Gotzens et al., 2020, chapter 4.5.3.4).

A central problem of the above-mentioned data decomposition into training, validation and test data is the associated reduction of the data basis for model generation. In the literature on energy demand forecasting using machine learning methods, the k-fold cross validation has become established. It is a formalized statistical procedure to use the existing database as efficiently as possible, to reduce systematic errors in model selection and to calculate robust error measures for the models. In the k-fold cross-validation, data are decomposed into k disjunctive subsets of the same size. Each subset is used once as validation data set and the remaining k-1 data is used as training data set. The mean value of the error measures of all k subsets is used as a cross-validated error measure. Usually values like 5 or 10 are used for k (Wollschläger, 2014, p. 493).

The example in Figure 11 illustrates the procedure of the 5-fold cross validation (k = 5). The whole sample (all data) is divided into training and validation data in the ratio 80/20. This division is done within five different model runs (splits), where the training and validation data are divided into five disjunctive subsets (Fold 1 to Fold 5), four parts of which are used as training data (blue) and one part as validation data (light red). In the five different model runs (5 splits), model estimates of the regression function are made on the basis of the respective training data (blue) and the quality of the forecast is determined in relation to the validation data (light red). In this way, the forecast quality of the model can be determined for each separate split against an unknown data set. The quality parameters from the five separate regression analyses are then averaged (Pedregosa et al., 2011).

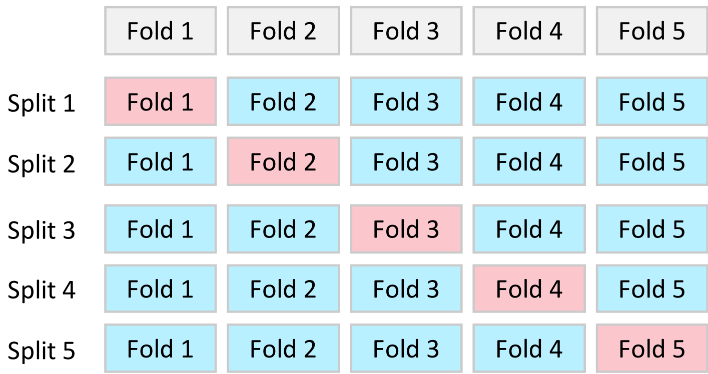

Figure 11: Data decomposition of the 5-fold cross-validation into training data (blue) and validation data (light red), diagram by author, based on Pedregosa et al. (2011).

By splitting the data into smaller subsets, repeated model estimation and validation, the influence of prominent, non-representative conditions (e.g. unusual weather influences) in the data can be reduced by averaging the effects and the generalizability of the models can be assessed in terms of a robust measure of quality.

For artificial neural networks, the potential overfitting of the model is a particular challenge. This is due to their adaptability and complexity. In order to avoid potential overfitting of the model, it may be necessary to carry out the model parametrisation (particularly of hyperparameters) with the help of k-fold cross validation and to subsequently check the model quality on a test data set that has been completely separated in advance (scikit-learn developers, 2021). Figure 12 illustrates the extended scheme of cross-validation of artificial neural networks, with preserving a test data set.

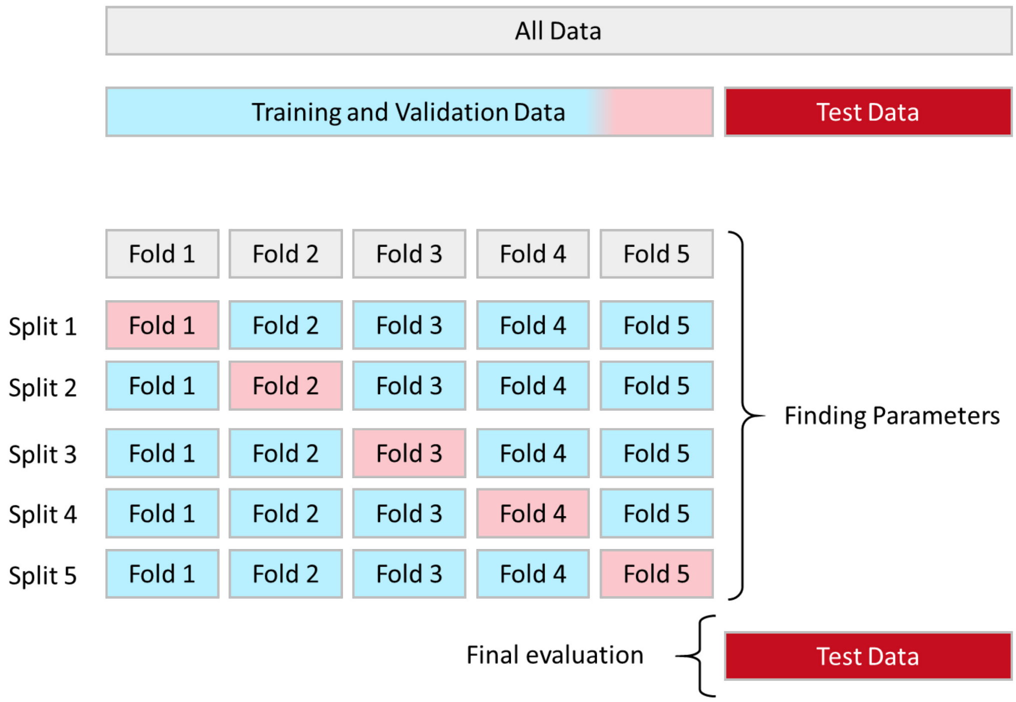

Figure 12: Data decomposition of the 5-fold cross-validation into training data (blue), validation data (light red) and test data (dark red). Diagram by author, based on Pedregosa et al. (2011)

3. Methodology

The methodology developed and applied in this thesis consists of six modules that build on each other. The interaction of these modules is depicted in Figure 13. Each module's results contribute to answering the research questions (RQ 1-4) posed in chapter 1 and fill the various research gaps identified in chapter 2.3.

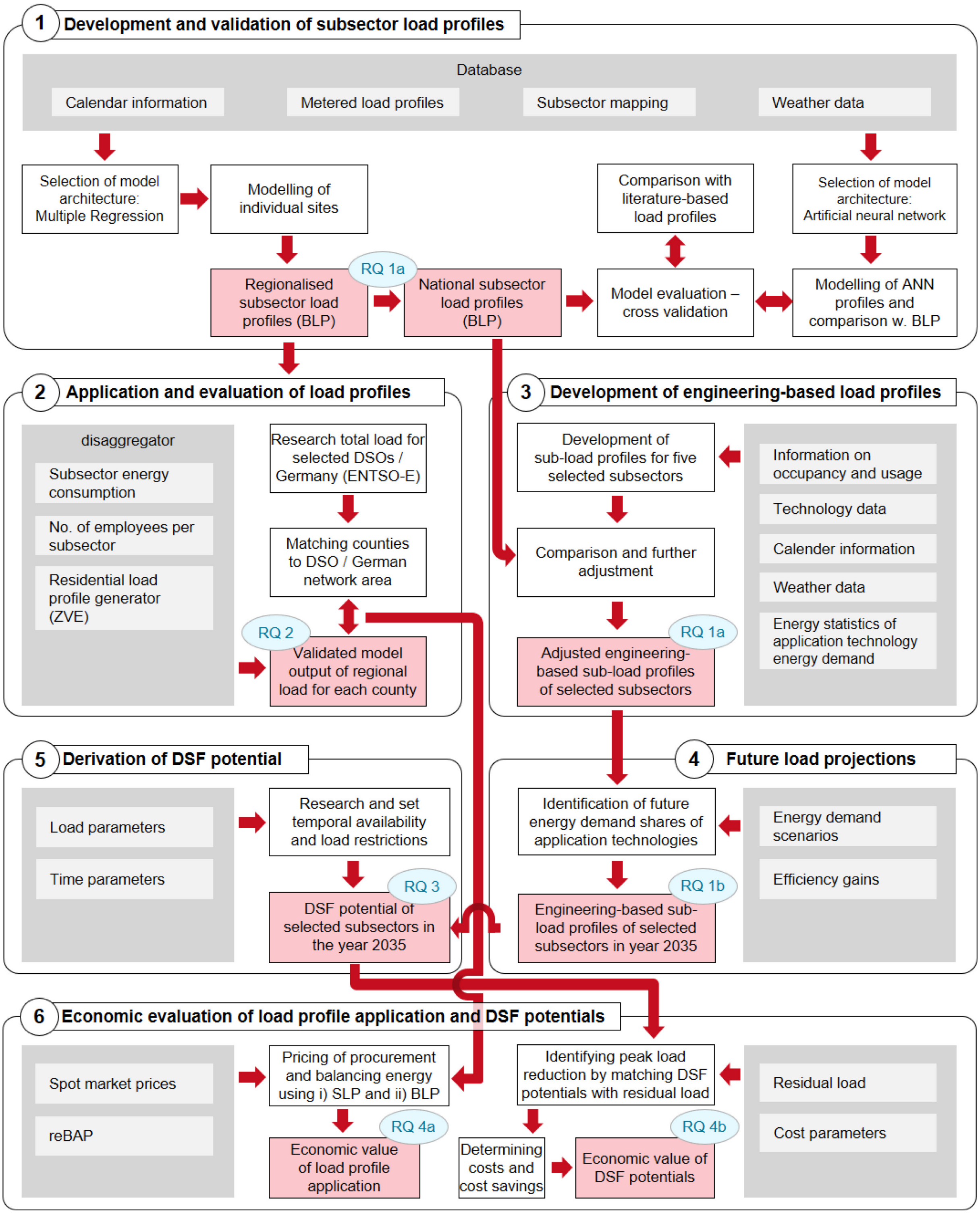

Figure 13: Research design of this thesis, covering six modules and their interaction. Grey boxes indicate external input data, white boxes indicate the main process steps and red boxes indicate (interim) results. Blue ellipses allocate research questions. Diagram by author.

In **module 1**, electric subsector load profiles (BLP[14]) of 32 industrial and CTS subsectors[15] are developed based on 1,049 metered load profiles. Initially, metered load profiles are mapped to subsectors and complemented with demand drivers in high spatial resolution (i.e. for each individual county). A multiple regression approach is chosen to create i) regionalised as well as ii) nationally averaged subsector load profiles. Besides being one of the most dominant and respected techniques within the (long-term) energy demand modelling literature (Debnath and Mourshed, 2018, p. 300; Verwiebe et al., 2021b, p. 31), multiple regression has the ability to reveal cause-and-effect relationships (grey box model, chapter 2.2.1.5) (Backhaus et al., 2016, p. 64). Moreover, multiple regression can be supplemented by quantile regression, which enables the depiction of prediction intervals that provide information about the accuracy, distribution and variance of the prediction. The multiple regression approach used has been adapted from Gobmaier (2013). As a benchmark, the results of the multiple regression approach are compared to an ANN modelling approach, a performant technique which enjoys great popularity within the research community (cf. chapter 2.5.3) and which can be considered a black box model. All load profiles are developed in 15-min resolution. The spatial scope encompasses Germany for national subsector load profiles, and will be resolved to county-level (German: Landkreis) for regionalised subsector load profiles. In addition to modelling subsectors, all individual sites are modelled in order to determine the forecast quality and heterogeneity within a subsector. The validation of subsector load profiles is examined in two steps:

- the internal validation using a 5-fold cross validation approach
- the comparison of subsector load profiles with the VDEW SLP, analysing their performance to model underlying metered load profiles.

In **module 2**, newly generated regionalised subsector load profiles are applied in the DemandRegio tool *disaggregator* in order to model the regional load for each county (Verwiebe et al., 2020). In the applied *BLP application* approach, 32 subsector load profiles replace the corresponding VDEW SLP. The new subsector load profiles are compared to the VDEW SLP used in the *SLP only* approach of the disaggregator. The results of both approaches yield regional load profiles which are compared and validated separately using the total load profile of selected DSOs and the ENTSO-E load for several years. Remaining structural deviations between modelled and actual DSO/ENTSO-E load are explained for both the *SLP only* and the *BLP application* approach. The methodology and results of the first two modules have also been partially published in Gotzens et al. (2020) and Seim et al. (2021b).

Module 3 presents a separate bottom-up approach to model engineering-based load profiles for five main CTS subsectors, i.e. *offices*, *trade*, *accommodation*, *hospitals* and *education*. Due to the increased sophistication and effort of the engineering-based approach, this approach is applied in modules 3-5 to only five relevant subsectors out of the original 32 considered in module 1. These five subsectors are responsible for about 62 % of the total CTS electricity demand. Böckmann (2021) developed and applied the engineering-based approach to model sub-loads for application technologies based on information of occupancy and usage, technological specifications, calendar and weather data as well as annual energy demands for application technologies from national statistics. These engineering-based load profiles are compared and adjusted using the corresponding subsector load profiles of the first module. The methodology and the results of module 3 have also been published in Böckmann et al. (2021). In contrast to the multiple regression and ANN used so far, the engineering-based approach can be considered a white box model (cf. chapter 2.2.1.5), which is a precondition for projecting the

[14] In the following, sometimes also referred to as TUB BLP (TUB – Technische Universität Berlin), to distinguish from other load profiles.
[15] See chapter 5.1, page 74 for a list of subsectors modelled.

future load behaviour of selected subsectors and identifying DSF potentials in the two subsequent modules.

In **module 4**, engineering-based load profiles are projected into the year 2035. Using literature-based energy demand scenarios (Pfluger et al., 2017b), future energy demand shares of application technologies are identified and mapped to selected CTS subsectors. Technology changes (from night storage heating to heat pumps), economic developments and efficiency improvements are considered.

In **module 5**, current and future technical DSF potentials are derived based on engineering-based load profiles for the above-mentioned five CTS subsectors. Based on literature research, the temporal availability and load restrictions for DSF measures are set for each application technology and subsector. As a result, technical DSF potentials are identified in high temporal and spatial resolution for the years 2018 and 2035. The five subsectors account for approximately 74 % of DSF potentials within the CTS sector. The methodology and results of modules 4 and 5 have been introduced in Seim et al. (2021a).

Module 6 lists two possible procedures for estimating the economic value of utilizing subsector load profiles. In the first procedure, model deviations from module 2 are further analysed for potential significance in the balancing group system. As some DSOs might still use SLP to actively manage their portfolio of small consumers, the electricity procurement of a hypothetical balancing group is simulated: the modelled electricity load output of both *disaggregator* approaches using a) SLP and b) BLP is procured on the spot market, whereas identified model deviations are priced with imbalance settlement prices. Potential cost differences of both approaches are compared and discussed, yielding an indication of the value of applying TUB BLP. In the second procedure, DSF potentials of high temporal resolution from module 5 are further analysed for their economic value. While there are different fields of application (and thus economic valuations) of DSF, the present analysis focuses on the assessment of a possible peak load reduction accessing DSF potentials. Specifically, the possible reduction in required peak load capacity (i.e. gas turbine power plant capacity) resulting from load shifting potentials was determined. This calculated monetary saving was adjusted by associated exploitation costs of DSF potentials in order to determine an economic value. While this economic evaluation cannot be considered conclusive for either procedure, it provides indicative insights into possible values and evaluation approaches.

The classification of the above sketched research design is of hybrid character in many regards: the development and application of subsector load profiles has elements of both a top-down and a bottom-up approach. As sketched in chapter 2.5.4, subsector load profiles are modelled based on individual companies and sites, which can be scaled up to county or national level. The national subsector energy demand is regionalized to county level using demand drivers from energy statistics (top-down). The development of engineering-based load profiles for selected CTS subsectors in module 3 is a bottom-up approach, which benefits significantly from fine-tuning through already existing aggregated subsector load profiles. Results of engineering-based models of module 4 and 5 are also scaled up using spatially-resolved demand drivers. In this way, the spatial scope of the present thesis touches several levels, i.e. from individual sites or application technologies up to the county or national level. The temporal horizon of all modules can be classified as long-term load modelling, covering annual load profiles which can be projected to the year 2035 or even further into the future. However, long-term load forecasts from literature are usually associated with a much lower temporal resolution, most times depicting monthly or annual forecasts (Verwiebe et al., 2021a, p. 19). By combining top-down and bottom-up approaches, the author seeks to make efficient use of available but limited data, address research gaps and generate robust insights which can be transferred to different levels of the overall system (Wietschel et al., 2011a, p. 48).

4. Implementation

A model is a simplified representation of reality that reduces the complexity of real dependencies and influences. In modelling, there is a conflict of objectives between simplicity (and the associated applicability) and complexity (completeness) (Backhaus et al., 2018, p. 63). How closely a model represents reality and how complex it is depends on the objective and data availability. In this thesis, the author seeks to develop subsector load profiles using multiple approaches and apply these load profiles in different contexts. In analogy to the VDEW SLP (cf. chapter 2.2.1.1), the objective is thus not to model individual consumers with reference to their load fluctuations and peaks. Rather, the load behaviour of a group of similar consumers is to be modelled realistically. It follows that selected approaches and demand drivers are not aimed at developing *the* best prediction of a specific company, but rather at selecting a sufficiently good procedure that is appropriate for all subsectors.

The following chapter describes in detail the implementation of the methodology introduced in the previous chapter 3. First, the database for all modules is being introduced in chapter 4.1, sorted by individual modules. Afterwards, a detailed description of the modelling and analysis steps for each individual module is given, starting with the development and validation of subsector load profiles (chapter 4.2), and followed by the application and evaluation of these created subsector load profiles (chapter 4.3). In the next step, the development of engineering-based load profiles is being introduced (chapter 4.4). Chapter 4.5 elaborates on how these engineering-based load profiles are projected into the future. Chapter 4.6 lays out how DSF potentials can be quantified using these engineering-based load profiles. The procedure of how newly developed subsector load profiles are assessed economically, is being presented in chapter 4.7.

4.1. Database

The following chapters introduce the database that is relevant for this thesis. The database description of module 1 (chapter 4.1.1) is very similar to the one used in the DemandRegio project, and thus partially relates to Gotzens et al. (2020, chapter 4.2.7). The engineering-based approach to model sub-loads for application technologies (module 3, chapter 4.1.3) has already partially been described in Böckmann et al. (2021). Moreover, the description of data requirements for the projection of future loads (module 4) as well as the derivation of DSF potential for selected commercial subsectors (module 5) (both chapter 4.1.4) have been introduced in Seim et al. (2021a). The database description of module 6 is described in chapter 4.1.5. After the database of the individual modules has been described below, the implementation of the different model approaches is presented in chapters 4.2 to 4.7.

4.1.1. Data Requirements for Developing of Subsector Load Profiles (Module 1)

The development of subsector load profiles (TUB BLP) mainly requires a database of metered load profiles, weather data and calendar data. Due to the limited data availability, which has already been discussed in chapter 2.1 and chapter 2.3.3, the collection of data consumed a considerable amount of time. The collection of real load profile data was mainly driven by the following channels (Gotzens et al., 2020, p. 74):

- Data acquisition by telephone
- Student theses
- Frankfurt (Main) Energy Management (“Energiemonitoring der Stadt Frankfurt am Main,” n.d.)
- Student consultancy project
- Pilot programme “Einsparzähler” by the German Federal Office for Economic Affairs and Export Control (BAFA) (Bundesamt für Wirtschaft und Ausfuhrkontrolle (BAFA), n.d.)

Figure 14 illustrates the database for metered load profiles that were collected in the context of this thesis. Customer groups are depicted according to AGEB (cf. chapter 2.4.1, Figure 7). A similar depiction using the WZ 2008 classification can be found in appendix A.1.1. Furthermore, appendix A.2.3 lists the available data for specific subsector load profiles. It can be seen that a large share of the German electricity consumption can be covered by metered load profiles. However, significant data gaps persist.

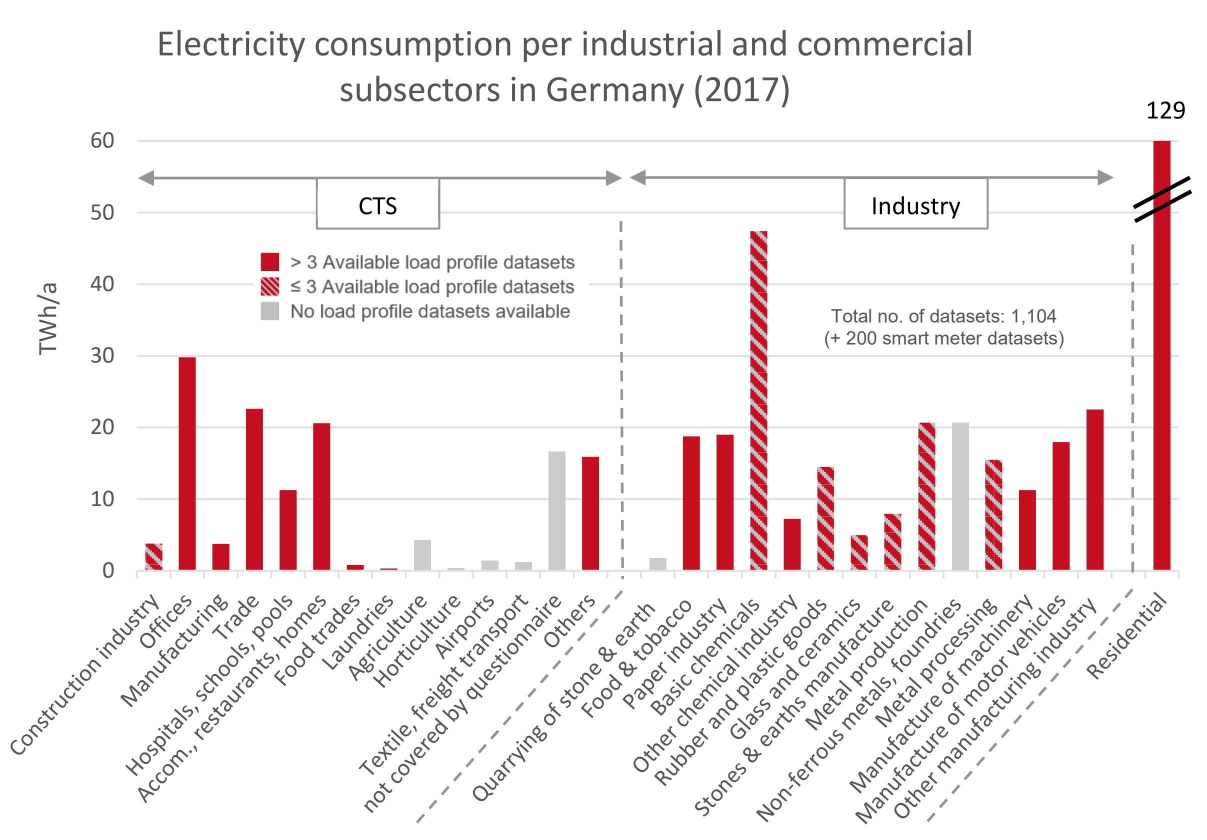

Figure 14: Database of real load profile data according to AGEB consumer groups, indication of electricity consumption 2015. One data set corresponds to the electricity load profile of one year. Depiction by author, based on (Geiger et al., 2019, p. 19; Rohde, 2019, p. 18; Schmidt et al., 2019, p. 13).

In addition to metered load profiles, weather data and calendar data were used as demand drivers for all forecasting techniques, i.e. multiple regression, ANN and the engineering-based approach. Table 5 lists all demand drivers for the development of subsector load profiles, valid values and their data type.

Table 5: Demand drivers for the development of subsector electricity load profiles

Demand driver	Values	Data type
Time (hour)	{00:00, …, 23:00}	Categorical
Time (quarter hour)	{00:00, …, 23:45}	categorical
Weekday	{Mon, …, Sun}	Categorical
Month	{Jan, …, Dec}	Categorical
Holiday	{1,0}	Boolean
Temperature	$\mathbb{R}$	Numerical
Solar radiation	$\mathbb{R}_+$	Numerical

County-specific data for ambient temperature and solar radiation were imported from the DemandRegio database (“DemandRegio – opendata.ffe.de,” n.d.). Calendar data was imported using Python-based libraries such as the *Germanholidays* package.

The plausibility of developed subsector load profiles (TUB BLP) was checked by comparison with further literature-based load profiles, namely VDEW SLP (BDEW, 2021) and De Monfort load profiles (Dolman et al., 2012). In addition to determining the profiles’ performances, structural deviations of all load profiles were depicted and compared with differential balancing group time series of DSOs (cf. chapter 2.2.2): Energienetze Berlin, NRM Netzdienste Rhein-Main GmbH and Stromnetze Hamburg. These DSOs were selected because the collected metered consumer load profiles most frequently originated from their grid areas. The differential balancing group time series were obtained as obligatory publication from the websites of the respective DSOs. Only the time series’ structures were compared to structural deviations of load profiles, the level is ignored.

4.1.2. Data Requirements for Applying and Evaluating Subsector Load Profiles (Module 2)

Regionalised subsector load profiles were applied using DemandRegio tool *disaggregator* in order to model the regional load for each county. The *disaggregator* is capable of mapping the electricity demand following a top-down approach, using the energy consumption of individual subsectors (Destatis, 2019), the number of employees of individual subsectors (FfE and Bundesagentur für Arbeit, 2019) and a regionally specific energy consumption of industrial subsectors (FfE, 2019). A detailed description of the methodology and database for the *disaggregator* tool can be found in Gotzens et al. (2020, chapter 4) or in Verwiebe et al. (2020).

In the *SLP only* approach within this thesis, annual county-specific electricity demands derived by the *disaggregator* tool were resolved temporally using VDEW SLP (BDEW, 2021) and generic shift load profiles (Gotzens et al., 2020, chapter 4.4.2), yielding regional load profiles. In the *BLP application* approach, subsector load profiles (TUB BLP) partially replaced these SLP and generic load profiles, where available. Both approaches used the ZVE load profile, developed in the DemandRegio project (Gotzens et al., 2020, chapter 3.4.2) and available in the *disaggregator* tool. For error analysis, the ZVE profile was replaced by an average load profile of smart meter data, the raw data of which was published in Beyertt et al. (2020). Regional load profiles of both approaches (*SLP only* / *BLP application*) were compared and validated separately with the total load profile of selected DSOs and the ENTSO-E load for several years.

The data published by ENTSO-E (“ENTSO-E,” 2021) was submitted by TSOs in advance. In order to be able to use the TSO data for the model validation, the published data was aggregated to a German-wide total load profile. The comparison of model output (county level) and DSO total load (network area) can only be made for those DSOs whose network area is largely identical to the county area. Using ene’t data (2018), 26 DSOs with matching network areas were identified, 10 of which published usable data. The data of two further DSOs could be collected by request, whereas the dataset of one DSO was inconsistent. Remaining DSOs were contacted several times, but no further data was provided. Table 6 presents the collected DSO data as well as their regional county scope. As can be seen in the below table, identified DSO-county matches are restricted to independent cities only.

Table 6: List of DSO-County matches, based on works by Tobias Schmid (FfE) and Held (2020), with addtions by the author.

DSO	County	AGS	Years
WSW Wuppertal	Kreisfreie Stadt Wuppertal	05124	2017, 2019
KNS/TWL Ludwigshafen am Rhein	Kreisfreie Stadt Ludwigshafen am Rhein	07314	2017, 2019
SWE Netz Erfurt	Kreisfreie Stadt Erfurt	16051	2017, 2019
EVB Eisenach	Kreisfreie Stadt Eisenach	16056	2017, 2019
DO-Netze Dortmund	Kreisfreie Stadt Dortmund	05913	2017, 2019
Stadtwerke Bochum	Kreisfreie Stadt Bochum	05911	2018, 2019
SWB Bielefeld	Kreisfreie Stadt Bielefeld	05711	2017, 2018
Netz Lübeck GmbH	Kreisfreie Stadt Lübeck	01003	2017, 2019
Stadtwerke Straubing	Kreisfreie Stadt Straubing	09263	2017, 2018
SÜC Energie und H2O GmbH	Kreisfreie Stadt Coburg	09463	2017
Stadtwerke Kaiserslautern	Kreisfreie Stadt Kaiserslautern	07312	2017, 2018, 2019

The processing of DSO data is intricate, as the distribution grid usually consists of several voltage levels. The lower voltage levels draw power from the upper level. If the load profiles of all voltage levels were summed up, these shares would be counted twice. In her bachelor thesis, Held (2020) developed a procedure to calculate the net load and avoid double counting, which considers further data published by the DSO and is presented below.

Figure 15 (p. 42) shows an example of the distribution grid of a DSO whose network comprises the medium-voltage level (MV), the transformer level from medium voltage to low voltage (MV/LV) and the low-voltage level (LV). For this DSO, the procedure for determining the net load is explained below following Held (2020).

The net load corresponds to the total consumption (CNS) by final consumers from the distribution grid.

$$net\ load_{DSO} = \sum_i CNS_i = CNS_{MV} + CNS_{MV/LV} + CNS_{LV} \tag{10}$$

The system boundaries 1 are being crossed by feed-ins (FI), consumption, grid losses (LS) and withdrawals (WDR) from the upstream transformer grid. The following balance (11) can be obtained for the net load in this distribution grid area:

$$\begin{aligned} net\ load_{DSO} &= \sum_i CNS_i = \sum_i (FI_i - LS_i) + WDR_{up} = \\ &= FI_{MV} + FI_{MV/LV} + FI_{LV} - LS_{MV} - LS_{MV/NV} - LS_{LV} + WDR_{up} \end{aligned} \tag{11}$$

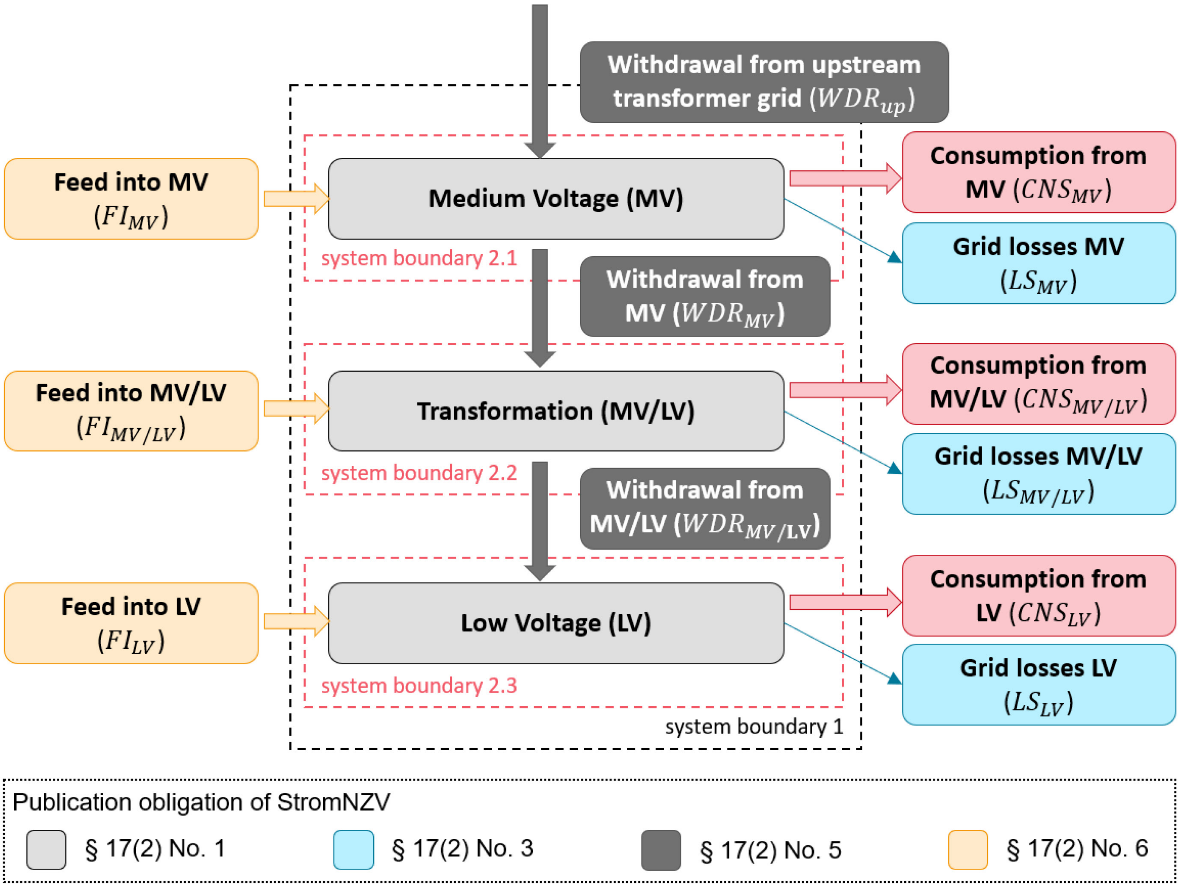

Figure 15: Electricity flows in the distribution grid broken down by voltage levels. Depiction adapted from Held (2020, p. 18)

Alternatively, the net load can be calculated by balancing systems 2.1 to 2.3 and subsequently summing up. For these systems, the published load profile (LP_i) of the respective voltage level according to § 17 (2) No. 1 StromNZV (2020) must correspond to the sum of all outflows of this system, i.e. $LP_i = CNS_i + LS_i + WDR_i$. For the low voltage level (system 2.3), there is no downstream level. Consequently, there is no withdrawal from this level ($WDR_{LV} = 0$). Solving equation (12) for consumption (CNS) from each level and summing up returns:

$$net\ load_{DSO} = \sum_i CNS_i = \sum_i (LP_i - LS_i - WDR_i) = \\ = LP_{MV} + LP_{MV/LV} + LP_{LV} - LS_{MV} - LS_{MV/LV} - LS_{LV} \\ - WDR_{MV} - WDR_{MV/LV} \qquad (12)$$

In some cases, the load profiles of the DSOs published in accordance with §17 (2) No. 1 StromNZV (2020) have already been adjusted for grid losses. In this case, the term "$-LS_i$" in the above equations is dropped.

4.1.3. Data Requirements for Developing Engineering-based Load Profiles (Module 3)

The engineering-based approach to model sub-loads for application technologies for five commercial subsectors has been developed in the master thesis of Böckmann (2021). Underlying data requirements have been published in Böckmann et al. (2021), where detailed information can be found. The engineering-based load profiles were developed based on information on occupancy and usage, technology data, calendar information, weather data, and annual energy demands for application technologies from national statistics.

The occupancy profiles generated in this approach were derived from the provisions of three standards, which exhibit different levels of details: the international guideline ISO 18523-1:2016(E) (2016) and the Swiss guideline SIA 2024:2015 (2015) provide hourly occupancy profiles per building and characteristic zone as a proportion of full occupancy. In addition, ISO 18523-1:2016(E) (2016) provides information on profiles of lighting as well as equipment and distinguishes between type days. Finally, DIN V 18599-10:2018-09 (2018) documents usage and operating times. These were defined as the start and end times of the duration of use (Böckmann et al., 2021, p. 4).

The technology data used in this engineering-based approach can be divided into characteristic load profiles and further literature-based assumptions on consumption behaviour. Characteristic load profiles indicate typical consumption patterns and operating times of application technologies. These can depend on the type day (working day, weekend) and the temperature. The second category of technology-specific assumptions manipulates the load profile of an application technology, like the specification of lighting depending on opening hours (Böckmann et al., 2021, p. 4). A detailed summary of literature used for technology-specific assumptions can be found in Böckmann et al. (2021, appendix A, Table 3).

Calendar information and weather data was derived similar to the first module (chapter 4.1.1), using the DemandRegio database ("DemandRegio – opendata.ffe.de," n.d.) as well as the respective Python libraries. In contrast to the subsector load profiles of the first module, however, the engineering-based model framework only distinguishes type days (weekday, Saturday, Sunday/Holiday).

Information on annual energy demands for application technologies per subsector was extracted from existing energy statistics. The most recent data on the electricity consumption of all application technologies per subsector was derived from Schlomann et al. (2015, p. 8) and represents the year 2013. For the year 2018, Rohde (2019, p. 9) published energy demand statistics which only show the total consumption of the application technologies for the whole sector. Accordingly, the annual consumption for 2018 had to be approximated using the subsector shares from Schlomann et al. (2015, p. 8) (Böckmann et al., 2021, p. 4).

4.1.4. Data Requirements for Future Load Projections (Module 4) and Derivation of Demand Side Flexibility Potential (Module 5)

Energy consumption scenarios can be used to quantify technology- and sector-specific development paths and to transfer them to technology-specific load profiles of selected subsectors. In the sector CTS, the most important drivers of the energy consumption scenarios are employees, electricity prices, energy reference areas, energy efficiency improvements and implicit discounting rates of the companies (Pfluger et al., 2017b, p. 63).

There are different scenario studies in the literature that model the CTS sector (Böckmann, 2021; Kemmler et al., 2020; Repenning et al., 2015; Schlesinger et al., 2014; Zipperle, 2019). Due to the required granularity, i.e. the technology share of electricity consumption per sector, this thesis used the long-term scenarios of the study commissioned by the BMWi from Fraunhofer ISI, Consentec GmbH and the Institute for Energy and Environmental Research Heidelberg (IFEU) (Pfluger et al., 2017b). Using these energy consumption scenarios allowed to determine future annual electricity demands by application technology and scenario for the whole CTS sector (Pfluger et al., 2017b, pp. 68, 71). Annual energy demands of the baseline scenario (German: Basisszenario) and reference scenario (German: Referenzszenario) were used and interpolated for the year 2035. While the reference scenario represents an exploratory phase-out of the clean energy transition, the normative baseline scenario achieves long-term climate and energy policy goals of the German government's energy concept (Bundesregierung, 2010) at the lowest possible cost, with an 80 % greenhouse gas reduction by 2050 (Seim et al., 2021a, p. 5). Details of the scenario conception can be found in Pfluger et al. (2017b). Selected framework assumptions of both scenarios regarding employees, energy reference area and efficiency improvements are shown in Pfluger et al. (2017b, pp. 63–64).

The disaggregation of projected application electricity demands to individual subsectors was weighted by subsector-specific shares of future energy reference areas, which were extracted from the same study (Pfluger et al., 2017b, p. 64). These disaggregated annual electricity demands could then be used in combination with the bottom-up approach of Böckmann et al. (2021) applied in module 3: all application sub-load profiles could be scaled for each application technology and subsector, using weather data of 2018 ("DemandRegio – opendata.ffe.de," n.d.) and calendar data of 2035. The integration of recognised scenarios into the bottom-up engineering approach enables the development of plausible future load profiles (Jakob et al., 2014, p. 12).

In the assessment of the technical DSF potential, this thesis applied the methodology introduced by Kleinhans (2014), which is further elaborated in Seim et al. (2021a, chapter 2.2). Only the engineering-based load profiles in high temporal resolution, taken from module 3 and 4 (years 2018 and 2035), allowed a solid assessment about temporal availabilities and maximum capacities of flexible loads. Application technologies suitable for load shifting include ventilation, air-conditioning, process cooling as well as space heating and hot water (Heitkoetter et al., 2020, p. 9; Klobasa, 2007, pp. 69–78; Ladwig, 2018, p. 23). The modelled durations for shifting load peaks of each application technology were taken from similar data (Heitkoetter et al., 2020, p. 9; Ladwig, 2018, p. 23).

4.1.5. Data Requirements for Economic Evaluation of Load Profile Application (Module 6)

The economic evaluation of load profile application is divided into two use cases. In the first use case, the influence of newly developed TUB BLP (module 1) on electricity procurement and balancing group management is assessed. For this purpose, the *disaggregator* model outputs for Germany and 11 DSOs (module 2) were used to assess a potential procurement strategy on the Day-Ahead spot market, using standardised auction products of the European Power Exchange in hourly resolution (EPEX SPOT, 2021). Model deviations were priced using the reBAP (TransnetBW GmbH, 2021). In the second use case, the residual load for Germany was determined using data published on ENTSO-E Transparency Platform (2021). The residual load was matched to DSF potentials identified in module 5. Cost data for gas turbine power plant (PP) capacity as well as DSF exploitation were found in current literature (Heitkoetter et al., 2020, p. 9; Konstantin, 2017, p. 248).

4.2. Development of Subsector Electricity Load Profiles

In the first module, subsector load profiles were developed for selected industrial and CTS subsectors. As for its widespread use and flexibility within the energy demand modelling literature, multiple regression was chosen as the main technique, to create regionalized and nationally averaged subsector load profiles. The following chapter 4.2.1 describes this process in detail, i.e. the individual steps to select a multiple regression configuration (chapter 4.2.1.1), to conduct site-specific regression and correlation analyses (chapter 4.2.1.2), to create a subsector load profile by averaging of site-specific models (chapter 4.2.1.3), to evaluate the models' performances (chapter 4.2.1.4), and to compare developed subsector load profiles with existing literature-based load profiles (chapter 4.2.1.5). As a supplementing methodology, quantile regression was applied (chapter 4.2.2) in order to generate prediction intervals that provide information about the accuracy, distribution and variance (heterogeneity) of the prediction. The multiple regression was benchmarked by an ANN-based regression model (chapter 4.2.3), in order to evaluate the robustness of both techniques as well as their performance. In order to enable comparison, the ANN approach was conducted very similarly to the multiple regression approach with regards to input data.

4.2.1. Multiple Linear Regression (MLR) Model

In the following chapter, the creation of subsector load profiles using a multiple regression approach is presented. The procedure was developed in the DemandRegio research project. The below description largely corresponds to the descriptions in the final report (Gotzens et al., 2020, chapter 4.5.2).

For the creation of the model, a uniform procedure was developed for all subsectors to enable a direct comparison between the various subsectors. In addition, this uniform procedure facilitates the reproducibility and extension of the results, thus acknowledging a central criticism of current scientific literature (Hong and Fan, 2016, p. 934). Hence, the uniform procedure does not aim at an optimal but rather a sufficiently good result for each individual subsector with regard to the model quality. Figure 16 (p. 45) gives an overview of the procedure.

The original data described in chapter 4.1.1 served as model input data. Site-specific load profiles of companies from several subsectors and years were linked with site-specific calendar and weather data, i.e. ambient temperature and solar radiation. The first step within the modelling procedure was to determine a model configuration for the multiple regression, which was applied uniformly across all subsectors. Using this model configuration, a company-specific regression analysis was performed in the second step to obtain load models and regression coefficients of the individual companies. These individual models were then combined to form a subsector load profile in the third step. In analogy to the use of VDEW SLP (cf. chapters 2.2.1.1 and 2.3.2), these subsector load profiles can be regionalized by means of regional calendar data and scaled by means of regional electricity demands. In addition, regional weather data can be included.

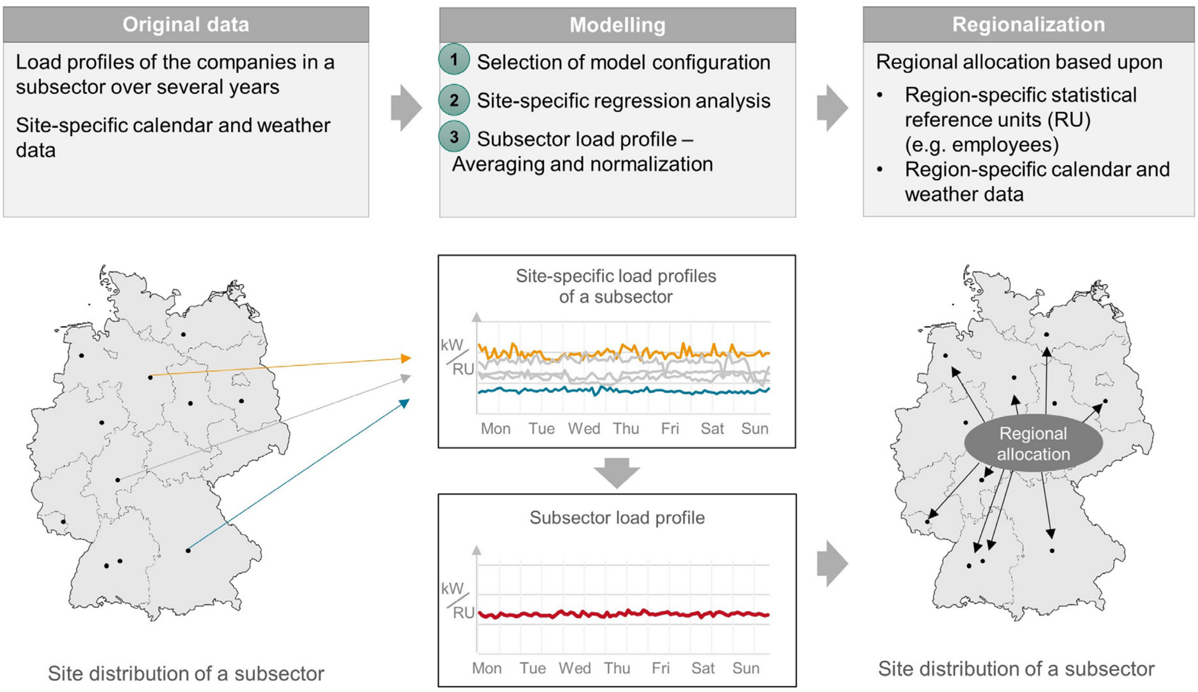

Figure 16: Research Design in the creation of industry load profiles. Diagram by author, adapted from Gotzens et al. (2020, p. 85)

Figure 17 illustrates the individual steps of the modelling procedure in more detail, which will be explained in the following chapters.

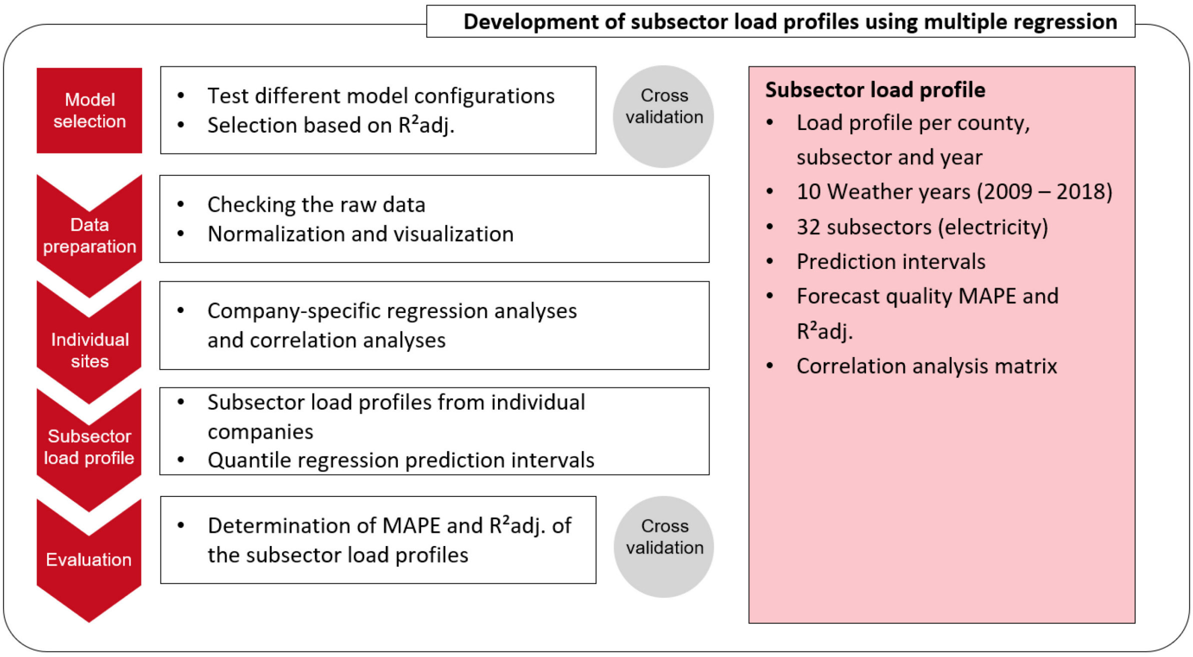

Figure 17: *Individual steps for creating subsector load profiles. Diagram by author, adapted from Gotzens et al. (2020, p. 93)*

Firstly, the selection of model configuration for the multiple regression will be introduced (chapter 4.2.1.1). The subsequent chapter 4.2.1.2 describes the data preparation and the implementation of site-specific regression analyses. Chapter 4.2.1.3 presents the creation of subsector load profiles by means of averaging of site-specific models. The last step in the process of subsector load profile development is the model evaluation introduced in chapter 4.2.1.4. The evaluation of generated subsector load profiles is determined using the performance measures of R^2_{adj} and MAPE. The model evaluation of the multiple regression approach is very similar to the evaluation of ANN-based load profiles in order to enable direct comparison. As output, load profiles for 32 subsectors, for 401 counties and 10 weather years have been generated using the multiple regression approach. In addition, prediction intervals were generated by quantile regression. Performance measures were determined using 5-fold cross validation. Correlation analysis matrices give an indication as to the relevance of demand drivers for individual subsectors.

4.2.1.1 Selection of the Multiple Regression Model Configuration

The multiple regression model was determined empirically by comparing a selection of possible configurations using three sample locations. Cross validation (cf. chapter 2.5.6) was used for selecting the model configuration of sample locations, which avoids overfitting of the model and ensures a robust identification of the model's performance. The data set of the sample locations was decomposed in advance by a reproducible random seed into training or validation data (80 %) and test data (20 %). The latter decomposition into test data is particularly necessary in the application of artificial neural networks in order to avoid their tendency to overfit, which in the case of statistical regression analysis should only be of minor importance. Nevertheless, the different model configurations were checked for comparison by means of both validation data and test data.

Table 7 (p. 47) shows the tested model configurations for one of the sample locations (here: Bürgeramt Zeil 3, ("Energiemonitoring der Stadt Frankfurt am Main," n.d.)) each in linear (y) and logarithmic form log(y), their cross-validated performance measures MAPE, R^2_{adj} and nRMSE, the number of independent variables k and the required computing time on a machine Intel® Core™ i7-5960X CPU, 3.00GHz, 128 GB RAM.

Table 7: Test statistics of different model configurations using the example of the office building Bürgeramt Zeil 3. Highlighted in light red is the selected model configuration. Table adapted from Gotzens et al. (2020, p. 94)

	Modell configuration	MAPE [%]		R^2_{adj}		nRMSE [%]		k	Computing time [s]	
	y | log(y) ~	**y**	**log(y)**	**y**	**log(y)**	**y**	**log(y)**		**y**	**log(y)**
1	β_0+holiday+C(month):C(weekday)+C(hour)	32.4	22.0	0.71	0.79	14.8	12.7	108	0.6	0.6
2	β_0+holiday+C(month)+C(weekday)+C(quart)	32.4	21.9	0.71	0.79	14.8	12.7	114	0.6	0.6
3	β_0+holiday+C(month):C(weekday)+C(quart)	32.4	21.9	0.71	0.79	14.8	12.6	180	0.8	0.8
4	β_0+holiday+C(month)+C(weekday):C(hour)	9.9	8.5	0.93	0.94	7.1	6.4	180	0.8	0.8
5	β_0+holiday+C(month)+C(weekday):C(hour)+tp	9.9	8.5	0.93	0.94	7.1	6.4	181	0.9	0.9
6	β_0+holiday+C(month)+C(weekday):C(hour)+sr	9.9	8.5	0.93	0.94	7.1	6.4	181	0.9	0.9
7	β_0+holiday+C(month)+C(weekday):C(hour)+tp+sr	9.9	8.5	0.93	0.94	7.1	6.4	182	0.9	0.9
8	β_0+holiday+C(month)+C(weekday):C(hour)+C(quart)	9.9	8.4	0.93	0.95	7.0	6.3	275	1.3	1.3
9	β_0+holiday+C(month)+C(weekday):C(hour)+C(quart)+tp+sr	9.9	8.3	0.93	0.95	7.0	6.2	277	1.3	1.4
10	β_0+holiday+C(month):C(hour)+C(weekday)	32.2	21.9	0.70	0.78	14.8	12.7	295	1.3	1.3
11	β_0+holiday+C(month)+C(weekday):C(quart)	9.7	8.3	0.93	0.94	7.0	6.3	684	3.3	3.3
12	β_0+holiday+C(month):C(quart)+C(weekday)	33.0	22.4	0.62	0.72	15.2	13.0	1159	6.3	6.4
13	β_0+holiday+C(month):C(weekday):C(hour)	9.1	8.2	0.91	0.92	6.8	6.4	2017	16.0	16.9

For each model configuration, five regression analyses were initially performed according to the principle of 5-fold cross-validation based on reproducible, randomly distributed training and validation data (see chapter 4.2.1.4). The corresponding cross-validated performance measures from five runs were averaged and used as decision criteria to select a configuration (see MAPE, R^2_{adj} and nRMSE, Table 7). In addition to the cross-validation, the model was then parameterized using a complete training data set to check a prediction against the test data set and thus exclude a potential overfitting of the regression model.

In the final selection of the model configuration for electricity load profiles, a balance between forecast quality and model complexity was emphasised. In addition, the two weather variables, ambient temperature and solar radiation, should be part of the model to be able to check potential load dependencies. In this respect, the following model configuration (cf. Table 7, No. 7) has proven suitable for subsector load profiles for considered sample locations:

$$log(y) = \beta_0 + holiday + C(month) + C(weekday){:}\,C(hour) + tp + sr \qquad (13)$$

In this model configuration, holidays, months (1 - 12), weekdays (1 - 7) and daily hours (1 - 24) were each included as categorical variables in the form of binary variables.[16] In contrast, temperature and solar radiation data were included as continuous variables. The categorical variables of the weekdays and the daily hours were connected with each other, so that in total 167 variables were included (Monday-0:00, Monday-1:00, ..., Sunday-22:00, Sunday-23:00). The connection of the two variables is expressed by the colon sign. In these narrow categories of binary time and calendar variables, a certain degree of multicollinearity is unavoidable, as Wissmann and Toutenburg (2007, pp. 10–15) were able to show. However, these interdependencies did not influence the model output. They merely provided

[16] The mapping of n categories in regression analysis requires the inclusion of only n-1 binary variables, since the remaining category results from a combination of remaining binary variables. This avoids perfect multicollinearity, also called "dummy trap" in the context of categorical variables. In regression analysis, twelve months are thus represented by 11 categorical variables.

a certain degree of uncertainty in the assessment of the impact strength of individual independent variables on the load.

In an extended version, the above configuration was supplemented by a binary variable for production schedules or company holidays ($prod\_holiday$) for some subsectors, in order to account for related load fluctuations. Production schedules and company holidays were determined either endogenously from the available load data (e.g., in the case of WZ 17 *manufacture of paper*) or exogenously by school holiday schedules (in the case of WZ 85 *education*). Formula 14 shows the resulting configuration:

$$log(y) = \beta_0 + holiday + C(month) + C(weekday){:}\,C(hour) + tp + sr + prod\_holiday \quad (14)$$

Due to the fact that the process in the case of WZ 17 *manufacture of paper* is largely independent of weekdays and times of day, a simple distinction was made between production and downtimes based on the metered load profile. By means of process-endogenous binary variables, those times were declared as production downtimes in which the load value fell below a previously determined threshold value of 17.7 % on average.[17] In this way the model could be parameterized efficiently despite the apparently stochastic fluctuations in the production schedule. In order to derive the subsector load profile for WZ 17, representative downtimes were used.

In selected companies of other industries, clearly definable periods with very low load levels have been identified, which could be traced back to company holidays. Company holidays of this type exhibit a recurrent structure in summer or winter time. In this case, these periods were manually declared as company holidays by means of the binary variable $prod\_holiday$. In order to derive the load profile for such subsectors, vacation periods were averaged over the entire subsector in order to generate a representative load profile.

4.2.1.2 Site-specific Regression Analyses and Correlation Analyses

For data preparation purposes, the metered load profiles were first standardized in format and assigned to an economic subsector according to the classification WZ 2008. The load profiles were then imported into a Python script and checked for missing values. Zero-values were considered as outliers and removed from the data set, assuming they are caused by meter connection failures or scheduled disconnections (Zufferey et al., 2018, p. 109). The normalization of the load data was based on the respective annual total value. Subsequently, the county-specific weather data was imported from the DemandRegio database ("DemandRegio – opendata.ffe.de," n.d.). Corresponding solar radiation and outdoor temperature data were assigned to each company site via respective county. Before the actual regression, the normalized load data of the individual operating sites were visually checked for anomalies, data errors and outliers. In addition, this visual inspection helped to identify heterogeneity within a subsector with regard to the load patterns.

In order to quantify the calendrical, temporal and weather-related interrelationships of the load in a specific subsector, a site-specific correlation analysis was carried out. In addition to the independent variables "Holiday", "Temperature" and "Solar radiation", time and calendar variables for the correlation matrix were clustered according to the following scheme[18]:

- *Workday* – corresponds to all working days (Monday - Friday)
- *Early* – early shift, corresponds to the hours from 06:00 - 14:00

[17] The threshold value was determined in a company-specific manner by optimizing the regression analytical results for each site. 17.7 % is the average of the determined company-specific threshold values.

[18] The clustering of time and calendar variables according to the above scheme is intended to make the dependencies clearer. In the model, time and calendar variables are integrated in more detail (see formulas 13 and 14). In the definition of summer and winter times, the existing classification according to (Bundesverband der Energie- und Wasserwirtschaft, 2000) was chosen for comparability.

- *Late* – late shift, corresponds to the hours from 14:00 - 22:00
- *Night* – night shift, corresponds to the hours from 22:00 - 06:00
- *Office* – office working hours, corresponds to the studies from 09:00 - 17:00
- *Summer* – corresponds to the days from 15.05. - 14.09.
- *Winter* – corresponds to the days from 01.11. - 20.03.

Subsequently, the site-specific correlation coefficients were averaged to obtain an indication of the intersectoral correlations. Figure 18 shows an example of the averaged correlation matrix of the subsector *offices* (WZ 64-71):

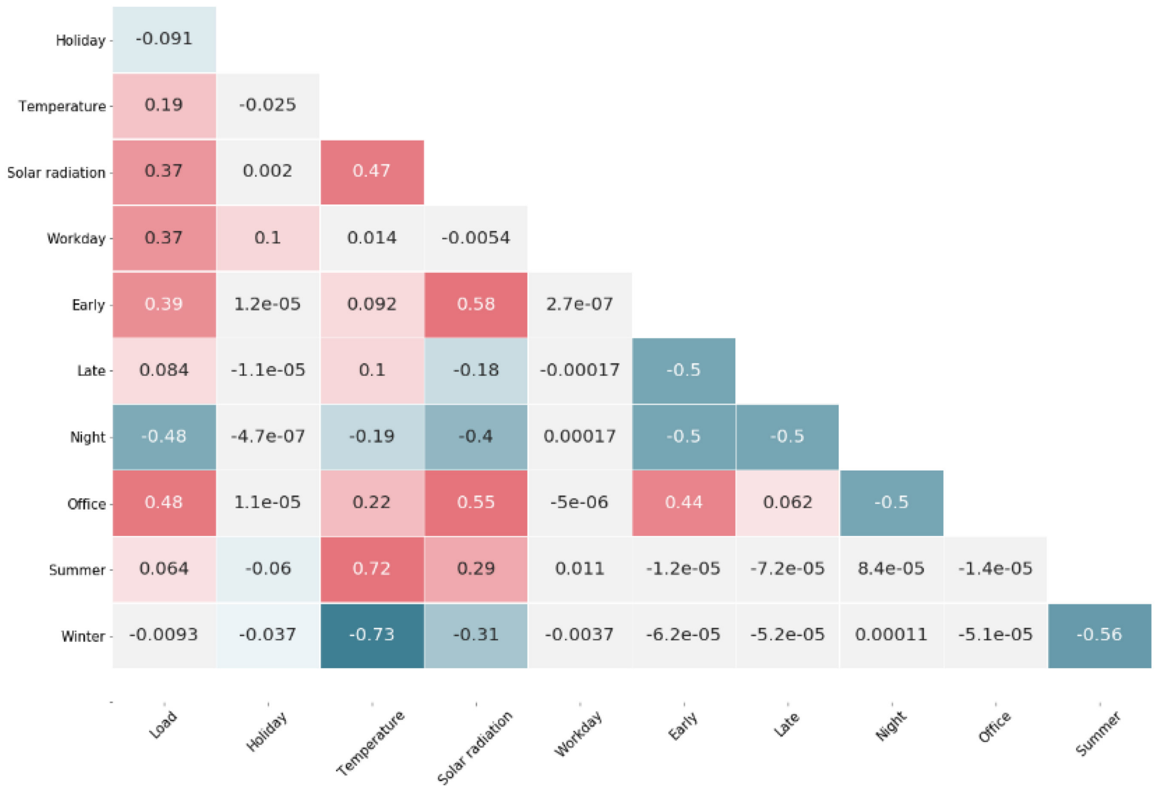

Figure 18: Averaged correlation matrix of the subsector offices *(WZ 64-71). Diagram by author, figure adapted from Gotzens et al. (2020, p. 97)*

As shown in Figure 18, especially the weather variables show some dependencies to each other as well as to time and calendar variables. This concerns on the one hand the mutual dependence between outdoor temperature and solar radiation (0.47). On the other hand, there are dependencies between outdoor temperature and season (0.72 and -0.73) as well as between solar radiation and time of day, e.g. the early shift (0.58). These mutual dependencies do not influence the forecast result. They only provide a certain degree of uncertainty in the assessment of the influence of individual independent variables (clusters) on the load. This means, for example, that the influence of the outside temperature can be partially overlaid by seasonal (in the model: monthly) influences. A complete separation of these influences cannot be achieved. In this respect, the first column of the correlation matrix, which quantifies the dependence of the load on individual influencing factors, is to a certain extent indicative. Particularly, these correlations have explanatory value in the comparison of different subsectors.

Following the correlation analysis, the regression analysis was performed. First, all load values were logarithmised. The regression analysis itself was performed using *Statsmodels*, an econometric and statistical Python package (Seabold and Perktold, 2010). After the regression analysis, the logarithmic load values were transformed back and the load values were linearly smoothed.

In the next step, site-specific regression coefficients could be combined to form an average subsector load profile. Using subsector load profiles, a prediction was made for each individual location, whereby the model was parametrized by corresponding calendar and weather conditions. These predictions were compared to the real data and subjected to a visual check for validity, whereby possible structural artefacts and outliers were investigated. By means of cross-validation, the performance measures of the subsector load profile were determined using unknown data. The procedure of the cross validation in case of the subsector load profile is explained in chapter 4.2.1.4. For the evaluation of the validity and robustness of the subsector load profiles the performance measures of the site-specific and the subsector load profile models were compared. Any outliers were checked and removed from the data set if necessary. In order to obtain a reliable picture of the subsector models' validity, outliers were only removed in exceptional cases, for example if the data did not fit the subsector.

4.2.1.3 Creating a Subsector Load Profile

A subsector load profile was created by averaging the regression coefficients of the site-specific regression analyses within a subsector. These subsector load profiles can be parameterized and scaled regionally in the same way as SLP, also considering weather variables. Figure 19 illustrates the process.

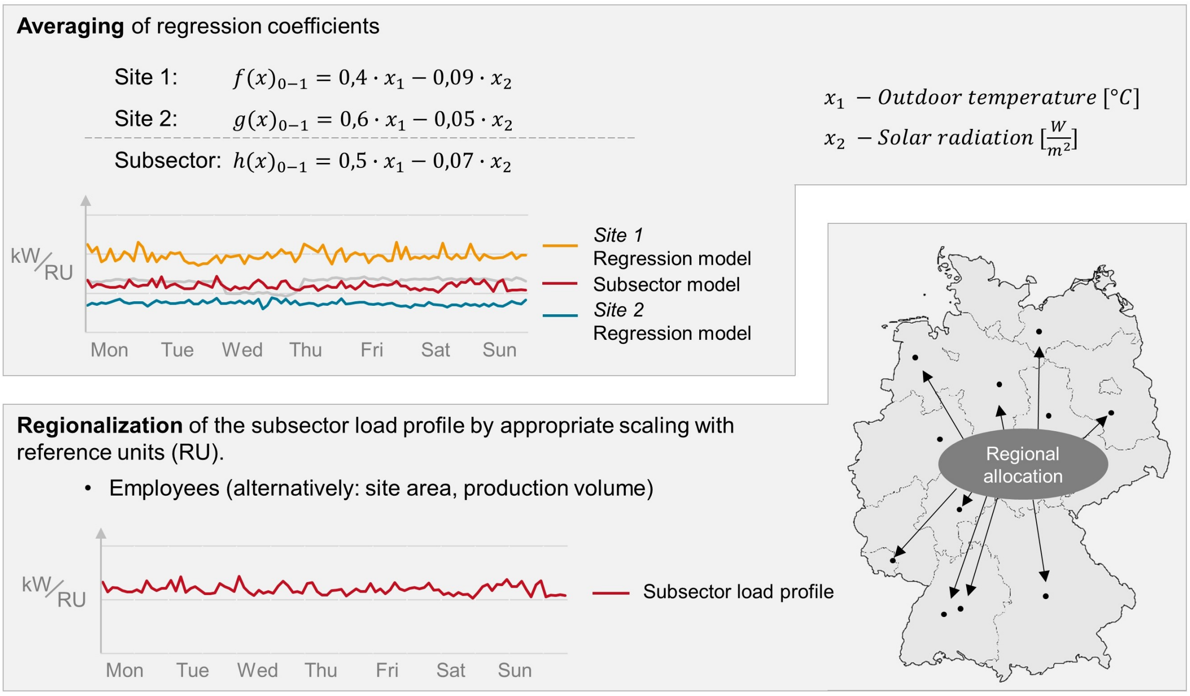

Figure 19: Schematic representation of averaging and regionalization in the creation and application of subsector load profiles. Diagram by author, adapted from Gotzens et al. (2020, p. 99)

The region-specific parameterization and scaling of the subsector load profiles allows a direct individual comparison of the subsector load profile with the respective real data, which was used for plausibility checks and for validation of the subsector load profile by means of cross-validation. As mentioned above, a detailed description of the validation of the subsector load profiles can be found in the following chapter 4.2.1.4. Figure 20 illustrates the visual comparison of the subsector load profile with respective real metered load profiles for the plausibility and structure check using the example of *offices*.

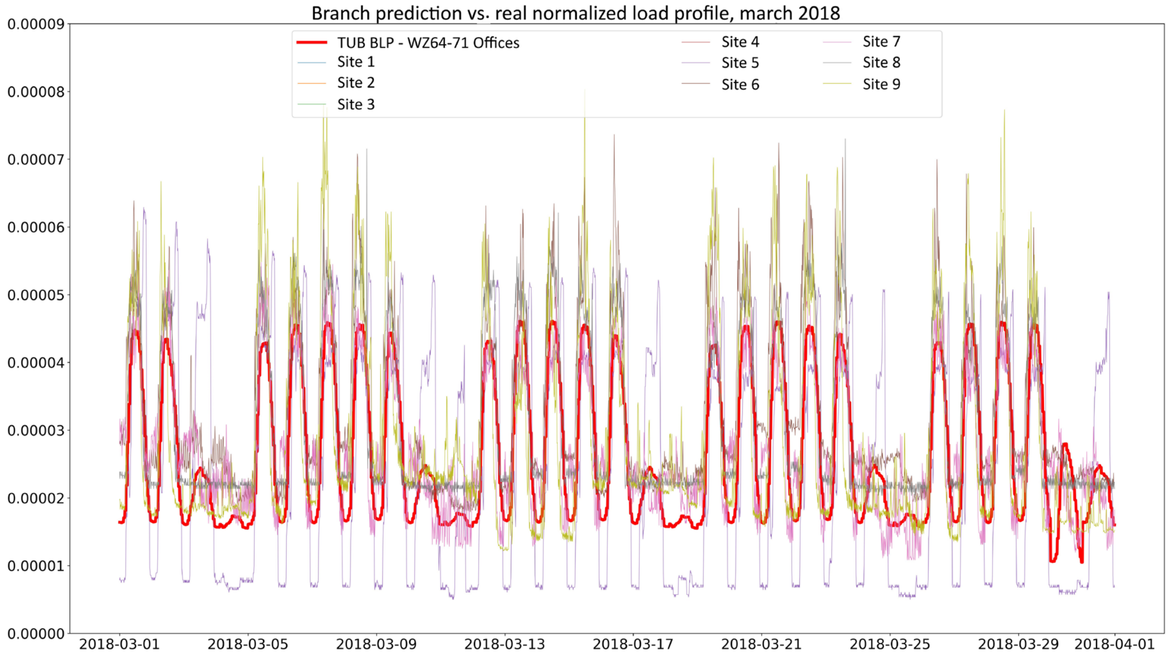

Figure 20: Visual inspection of the subsector load profile by comparison with the underlying real data (all standardized). Diagram by author, adapted from Gotzens et al. (2020, p. 99)

The comparison of the subsector load profile (red) with the underlying real data illustrates the tendency of the model to depict the average pattern. The subsector load profile represents characteristic patterns over time, whereby the deep load valleys of office site 5 or the load peaks of office site 9 are not captured.

Due to their heterogeneity, selected subsectors were divided into several sub-models. This could only be done if sufficient data was available. The economic subsector WZ10 *manufacture of food products* was divided into the following sub-models:

- meat processing (32 %)
- milk processing (28 %)
- bakeries (24 %)
- production of confectionery (11 %)
- coffee production (5 %)

The subsector load profile WZ10 *manufacture of food products* was created from the weighted sub-models. The weighting (percentages in brackets) was determined based on the power consumption shares from table 43531,001 of JEVI (2015, on request) (see Gotzens et al. (2020, section 2.3.2.3)).

Similarly, the subsector WZ47 *retail trade* was divided into the following two sub-models:

- retail non-food (78 %)
- retail food (22 %)

The weighting (percentages in brackets) was determined based on the proportion of employees subject to social security contributions in both subsectors, using the publication of the Federal Employment Agency (see Gotzens et al. (2020, section 2.3.3.2)). Figure 21 illustrates the averaging of both sub-models for the entire subsector load profile on the basis of an average week.

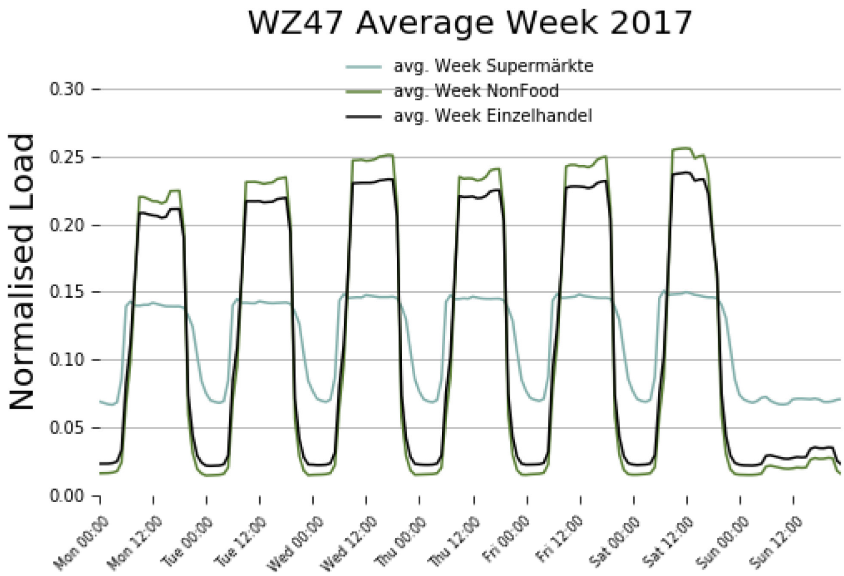

Figure 21: Illustration of an average week of the sector load profile WZ47 retail trade *including underlying sub-models retail non-food and retail food (supermarkets). Diagram taken from Gotzens et al. (2020, p. 100)*

The sector load profile of WZ52 *Warehousing and other transport services* was also divided into the following two sub-models:

- cold stores (25 %)
- multi-storey parking lots (75 %)

The weighting (percentages in brackets) was based on the power consumption values according to Geiger et al. (2019).

4.2.1.4 Evaluation of the Model Performance and Prediction Accuracy

For the (internal) evaluation of the model performance, the performance measures introduced in chapter 2.5.5 were used: R^2_{adj}, MAPE and nRMSE. Using the cross-validation introduced in chapter 2.5.6, the performance measures were calculated according to established scientific practice using unknown data. The following two separate cases must be distinguished:

1. the determination of the model performance of site-specific regression models
2. determination of the model performance of the subsector load profiles

The forecast quality of site-specific regression models (1.) serves to assess the basic performance of the multiple regression approach. In contrast, the forecast quality of the subsector load profiles (2.) contains information on the heterogeneity of a subsector. Thus, a high forecast quality of location-specific regression models of a subsector with a simultaneously low forecast quality of the associated subsector load profile indicates a pronounced heterogeneity of this subsector. In contrast, a small difference between the forecast quality of site-specific and cross-subsector forecasts indicates a homogeneous subsector in terms of the underlying load profile data. Both forecast quality assessments can also provide indications of structural outliers in the data, which are subsequently removed from the data set. Table 40 to Table 42 (appendix A.2.3) characterizes the heterogeneity per subsector using the difference of the MAPE between site-specific regression models and subsector load profiles.

Figure 22 illustrates the procedure of determining the model performance of the site-specific regression models (1.). When performing the cross validation for site-specific regression models, each individual site (C1, C2, ...) was considered separately. The load profile of each individual site was pseudo-randomly split into training and validation data in a ratio of 80:20 using the SciKit-based function ShuffleSplit.[19] Five different splits (Split 1-5) were performed for each site and then a regression analysis was performed for each split based on the respective training data. In total, five regression analyses (OLS model 1-5) were performed for each location, each with a different division of training and validation data. For each of the five regression analysis models (OLS-Model 1, OLS-Model 2, ...) the quality parameters (e.g. MAPE Split 1, MAPE Split 2, ...) were then determined by means of prediction (Prediction 1-5) and comparison using the retained validation data. The performance measures of five splits were averaged for each location (Avg. MAPE C1, Avg. MAPE C2, ...). The site-specific performance measures were again averaged within the subsector.

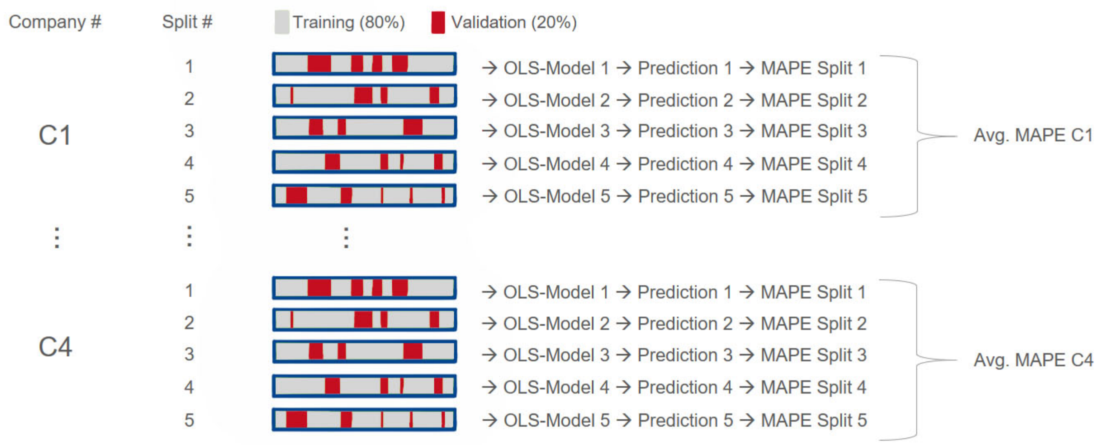

Figure 22: Illustration of the principle of cross-validation for robust determination of the forecast quality of site-specific regression models. Diagram by author, taken from Gotzens et al. (2020, p. 102)

According to the same principle, but more complex in the implementation, the determination of the forecast quality of the subsector load profiles (2.) was carried out. Appendix A.1.2 illustrates the corresponding procedure.

4.2.1.5 Comparison of Subsector Load Profiles with Existing Standard Load Profiles

In order to check plausibility of subsector load profiles, a comparison with literature-based load profiles was performed. Among potential candidates introduced in chapter 2.3.3, particularly VDEW SLP as well as De Monfort subsector load profiles generated by Dolman et al. (2012) appeared to be a suitable basis for comparison for newly generated subsector load profiles. This very comparison has been conducted by Rüdt (2020) as part of his bachelor's thesis. Rüdt not only i) checked the plausibility of TUB subsector load profiles but also ii) evaluated the performance of existing literature-based load profiles in the forecasting of metered load profile data (see chapter 4.1.1 for database). In addition, potential structural deviations of the load profiles were compared with the differential balancing group time series in order to find indications of similarities between the deviations.

To enable the assessment, metered load profile data had to be mapped to a subsector or consumer group within each type of load profile:

- TUB Subsector load profiles (TUB BLP, Module 1)
- VDEW SLP, and
- De Monfort load profiles.

[19] Normally, time series are split using a rolling forecasting horizon, so as to consider that the future is always predicted based on the past (Milanzi, 2020, p. 20; Tashman, 2000, p. 438). In the present case, however, the time series character of the load profiles was neglected in order to enable the consideration of data consisting of only one year. Using the shuffle split function, all annual load profiles could be considered, enabling a parametrization of all seasonal demand drivers.

The mapping was fairly trivial for TUB BLP and De Monfort load profiles, as subsectors were defined in a similar way. VDEW SLP, however, exhibit much more aggregated consumer groups. Appendix A.1.3 lists the mapping for the three load profile types. After mapping metered load data to respective consumer groups, all load profiles had to be normalized and parametrized according to regional calendar and weather data[20]. De Monfort profiles had to transformed from hourly to quarter-hourly values by linear interpolation. Eventually, the performance of all three load profile types to model real metered load was assessed using the 5-fold cross-validation approach, yielding the MAPE and R^2 in analogy to the previous chapter.

In addition to determining the profiles' performances, structural deviations were depicted and compared with differential balancing group time series of respective DSOs. In the case of office buildings, Energienetze Berlin was identified as the associated DSO. Structural deviations were analysed and depicted for seasonal average weeks and average days over all locations.

4.2.2. Quantile Regression

The Quantile Regression was conducted once per subsector using the *Quantreg* function from the *Statsmodels* package ("Statsmodels Quantreg," 2013). For each subsector, the model configuration of the Quantile Regression was identical to the multiple regression configuration (see previous chapter 4.2.1.1). The 5 % and the 95 % quantile were determined as prediction interval in order to represent the load patterns of 90 % of the underlying data. The reliability and plausibility of the predicted quantiles was qualitatively checked by visual inspection and quantitatively by checking the data points covered within the corridor.

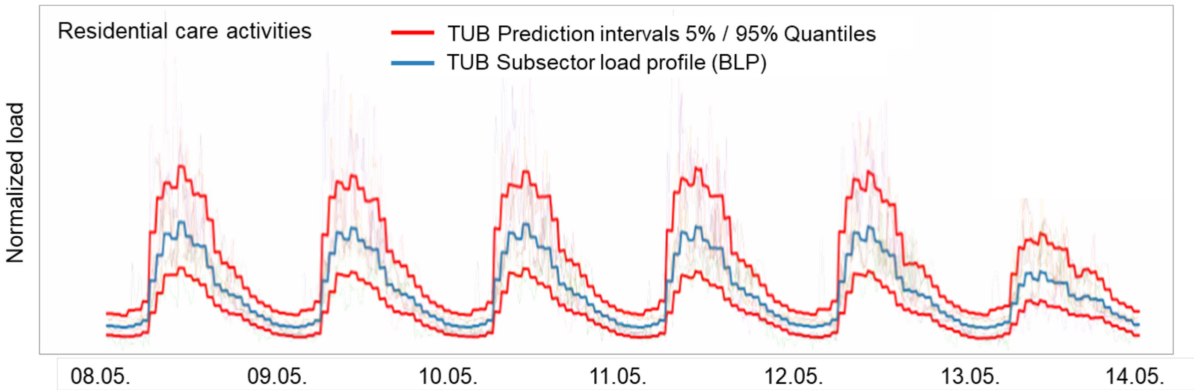

Figure 23: Illustration of the prediction intervals (95 % / 5 %, red lines) for WZ87 residential care activities*, generated by quantile regression. The blue line indicates the corresponding subsector load profile, developed using multiple regression. Diagram by author, adapted from Verwiebe and Seim (2019)*

Figure 23 illustrates these prediction intervals (red) for the example of WZ87 *residential care activities*, generated by quantile regression. The determined prediction intervals not only show the variance or the distribution of the load forecast, they also allow the estimation of upper and lower load levels in the sense of an extreme value observation. Especially for the estimation of upper and lower load levels, the question arises whether forecast intervals of different sector models or regions can be aggregated.

As described in Gotzens et al. (2020), no definitive statement can be made as to how the variance of two combined regression functions (i.e. prediction intervals of the subsector models) behaves in relation to the site-specific prediction intervals. The covariance of both regression functions can only be determined quantile- and case-specifically involving significant effort. Nevertheless, a partial

[20] As only TUB BLP consider temperature and solar radiation variables, weather data was neglected for both VDEW SLP as well as De Monfort profiles.

compensation of prediction intervals of sample subsectors could be found: the interquantile range decreases when several sectors are taken into account compared to the summation of individual prediction intervals, i.e. the 95 % prediction interval is lowered and the 5 % prediction interval is raised. The aggregated forecast intervals of the subsector load profiles thus form an extreme value observation (Gotzens et al., 2020, chapter 4.5.3.5).

4.2.3. Artificial Neural Network-based Regression Model

In order to carry out a comparison between the two techniques multiple regression and ANN, Milanzi (2020) developed subsector load profiles in her master thesis, using ANN for a selection of eight subsectors, four of which are identical to subsectors modelled using multiple regression. For these identical subsectors, the modelling results using ANN were compared with those of multiple regression, both for the modelling of individual consumers and the modelling of subsector load profiles. The following subsectors were analysed:

- retail – food (part of WZ 47)
- retail – non-food (part of WZ 47)
- offices (WZ 64-71)*
- public administration (WZ 84)*
- education – nurseries (part of WZ 85)
- education – schools (part of WZ 85)
- human health activities (WZ 86)*
- residential care activities (WZ 87)*

*indicates subsectors identical to the multiple regression approach

In her master thesis, Milanzi used a feed forward ANN with fully connected nodes that consider any possible relationship between input and output variables. The model was implemented in Python programming language and used Keras, a deep-learning framework for the modular development of neural networks. As a backend engine, TensorFlow was used for tensor manipulations and differentiation tasks (Chollet, 2018, p. 47; Milanzi, 2020).

The selection and pre-processing of metered load profile data and demand drivers was conducted in analogy to the multiple regression. Two subsets were created which allow to determine the forecast impact of the two weather variables temperature and solar radiation. Table 8 lists the two subsets used for the modelling.

Table 8: Demand drivers used in two ANN subsets A (excluding weather variables) and B (including weather variables temperature (tp) and solar radiation (sr)), based on Milanzi (2020, p. 49)

Set	Demand driver
A	Holiday, C(month), C(weekday), C(quart)
B	Holiday, C(month), C(weekday), C(quart), tp, sr

These two subsets of demand drivers were used separately in order to i) model the load of individual sites as well as ii) model the load profile of the entire subsector. In both cases, 5-fold cross validation was used to train, validate and test the models, making efficient use of available data and generating robust results. The cross-validation procedure was conducted similarly to the multiple regression approach (cf. chapter 4.2.1.4), in order to enable comparison. For individual sites (i), each consumer’s load profile was split into training/validation set and test set, using the above described methodology and ratio (80:20). For each subsector, all data of consumers within that particular subsector were used and split according to the same procedure.

After determining the network type (feed forward ANN with fully connected nodes) and the sets of demand drivers, hyperparameters have to be set. The hyperparameters were determined within an optimization procedure of the Python library *hyperopt* using the *Tree Parzen Estimator* (Chollet, 2018, p. 338). In iterative steps, different possible combinations of hyperparameters were examined, minimizing the mean squared error (MSE)-based loss function[21], similar to the OLS criterion and commonly used for regression-based problems (Chollet, 2018, p. 121). From the iterative procedure, the best possible hyperparameter combination for the aggregate of all subsectors was identified and used for further load modelling. In order to manage computation time, only the first split of the training and validation set has been used for hyperparameter optimization. Table 9 lists the optimised and literature-based hyperparameters for both sets of demand drivers (cf. Table 8: set A, B). These universal sets of hyperparameters were used for all subsectors and individual sites, assuming that it might not be the individual best, but a sufficiently good hyperparameter set. In her thesis, Milanzi (2020, pp. 63–64) was able to verify this assumption for individual selected subsectors. It could be demonstrated that a single set of hyperparameters can be used for all subsectors with only minor loss of performance.

Table 9: Optimized and literature-based hyperparameters for both ANN subsets A and B, adapted from Milanzi (2020, p. 64)

Hyperparameters | sets	A	B	
# hidden layers	2	2	Optimized by sequential model based optimization
# nodes 1/2	10	20	
# nodes 2/2	40	50	
Learning rate	0.00070	0.00038	
Batch size	32	64	
L2-penalty	0.00092	0.00107	
Loss function	MSE		Determined based on literature values
Activation function	ReLU		
Optimizer	Adam		
Early stopping patience	20		

The number of hidden nodes was set to two, which is a commonly used setup according to a literature review by Debnath and Mourshed (2018, p. 303): two hidden layers typically produced best results for multiple forecasting modules. For the number of nodes, Zhang et al. (1998, p. 44) insist that the choice usually depends on the underlying forecasting task. The chosen ReLU function (Rectified Linear Units) is the most commonly used activation function within machine learning and ensures that negative net input values are set to zero (Chollet, 2018, pp. 100, 102). The *Adam* algorithm is a variant of the SGD algorithm, applying momentum and individual adaptive learning rates to the weight updates (Kingma and Ba, 2017). The batch size of 32 or 64 lies in the typical range of SGD algorithms (Keskar et al., 2017). It depicts the number of observations being stochastically chosen form the data set in each training epoch in order to determine the gradient of the loss function with regards to the weight parameters of the neural network. The parameters are then being adjusted in the optimizer. The learning rate specifies how much these parameters are being adjusted. Very small learning rates have the risk of getting stuck in a local optimum (and missing the global optimum) (Chollet, 2018, p. 80). The early stopping hyperparameter ensures to stop the training as soon as one of the monitored performance indicators no longer improves during a certain number of epochs (here: 20 epochs). This avoids overfitting and saves time for training with unnecessary additional epochs. Overfitting is also reduced

[21] MSE – Mean Squared Error, similar to nRMSE introduced in chapter 2.5.5, without the normalisation and root operation.

by the L2 penalty function, which ensures that each weight of the layers gets increased by a predefined value of the loss function (Chollet, 2018, p. 148; Milanzi, 2020, pp. 54–55).

4.3. Application and Evaluation of Load Profiles

As introduced in chapter 4.1.2, regionalised subsector load profiles (TUB BLP) were applied in the *disaggregator* tool in order to model the annual regional load for each county. Using load profiles, this regionalized annual load could then be resolved into a temporal pattern. Depending on which load profile types were applied in the *disaggregator* tool, two approaches can be distinguished:

- **SLP only**: the temporal resolution of annual loads was carried out solely using VDEW SLP for CTS subsectors and generic shift load profiles for industrial subsectors (Gotzens et al. (2020, chapter 4.4.2)).
- **BLP application**: Where available, newly developed TUB BLP were used to replace VDEW SLP and generic shift load profiles

Figure 24 (p. 58) depicts the experimental setup of both approaches. In order to model the load patterns of residential consumers, both approaches used the ZVE profile (time of use survey-based, German: Zeitverwendungserhebung) developed in DemandRegio (Gotzens et al., 2020, chapter 3.4.2). For error analysis, the ZVE profile was replaced in a subsequent experiment by an average load profile of smart meter data (SM profile)[22]. Due to data restrictions, the application of the SM profile was conducted for all 11 DSOs only in the year 2019. All profiles except for the smart meter based average load profile (VDEW SLP, generic load profiles, TUB BLP, ZVE profile) can be generated using the *disaggregator* tool on GitHub (Verwiebe et al., 2020).

In her bachelor thesis, Held (2020) carried out the comparison of both approaches. Based on Held's preliminary work, some adjustments were made to the *disaggregator*'s configuration in this thesis. Table 10 (p. 59) depicts the mapping of economic subsector and load profile used for both the *SLP only* and the *BLP application* approaches. As for assumed similarities between subsectors, TUB BLP were in some cases used to replace SLP in *additional* subsectors:

- the TUB BLP for WZ 41 (*construction of buildings*) was also assigned to WZ 42 and 43
- the TUB BLP for WZ 64 – 71 (*offices*) was also assigned to WZ 58, 59, 73, 74, 75, 78, 95, 96, 99

Both approaches yield regional load profiles, which were compared separately and validated with the total load profile of selected DSOs and the ENTSO-E load for several years (cf. chapter 4.1.2). The validation's focus was not on the amount of electricity consumed, but on potential deviations in the profile shapes. Hence, total load profiles of DSOs and ENSTO-E as well as the *disaggregator* output were normalised to isolate profile deviations. However, deviations on the amount of electricity consumed in the regional disaggregation are presented in Gotzens et al. (2020, chapter 5.2) as well as Verwiebe and Seim (2019, pp. 11–22).

[22] The SM profile was developed by averaging 200 smart meter load profiles of the year 2019, the raw data of which was published in Beyertt et al. (2020). The H0-SLP (VDEW) has been found less accurate than the ZVE profile in the DemandRegio project (Gotzens et al., 2020, p. 129) and has thus not been applied anymore in this thesis.

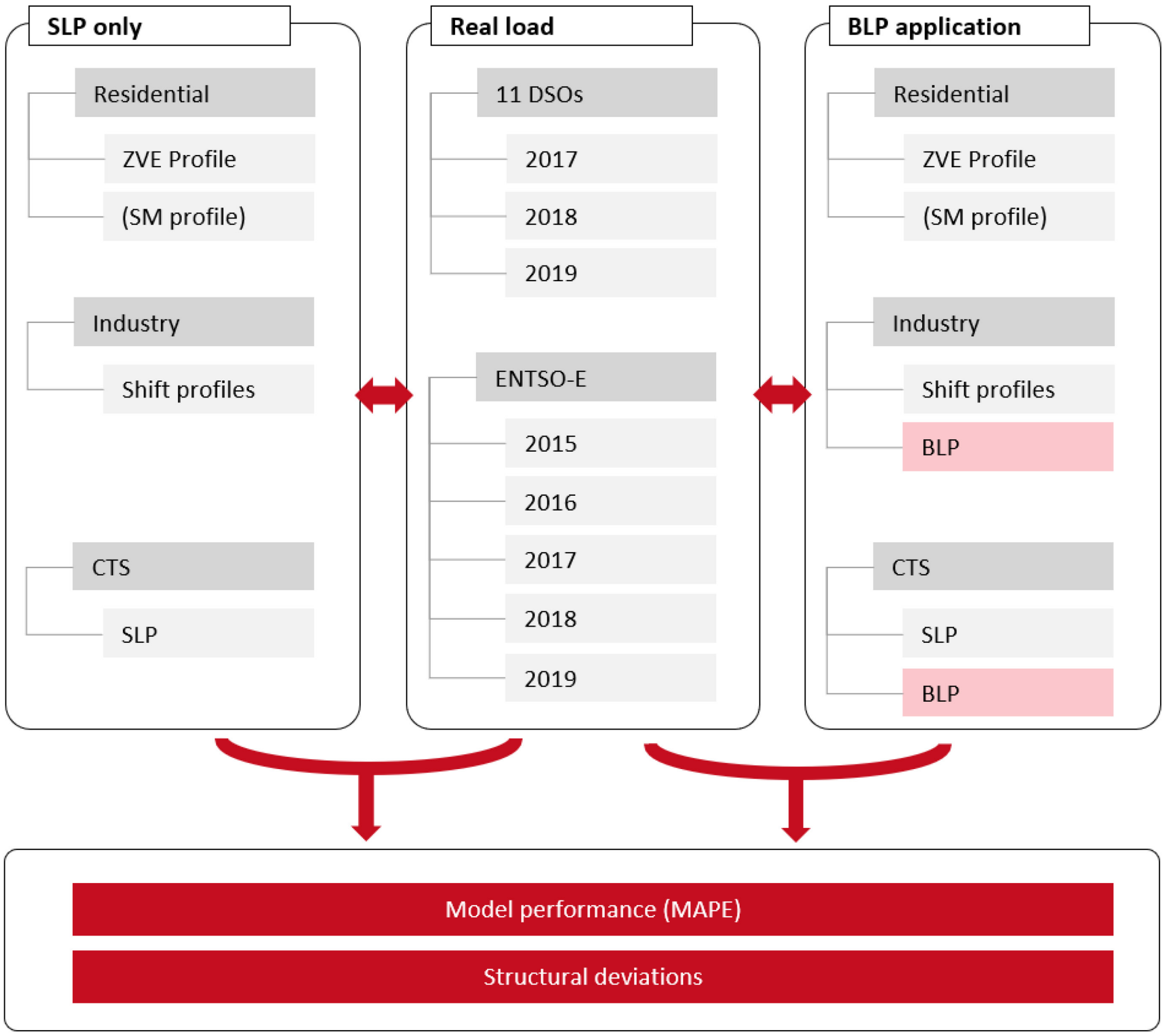

Figure 24: Experimental setup for the evaluation of the disaggregator *tool applying subsector load profiles (BLP), using real load data of selected DSOs and the total load of Germany as per ENTSO-E. Diagram by author.*

In both approaches, normalized load profiles of several years for 11 counties and the whole of Germany were created by the *disaggregator* tool. Similar to the approach in chapter 4.2.1.5, all load profiles had to be parametrized according to regional calendar and weather data[23]. The modelled load profiles were then compared with the DSOs' and ENTSO-E total load profiles to determine MAPE and R^2 performance measures and identify structural deviations with regards to the profile structures. As mentioned in chapter 4.1.2, this comparison of model output to real load data was only possible where (DSO/ENTSO-E) grid areas were (largely) identical to county areas. In the end, the model output could be validated using the data of 11 DSOs and ENTSO-E, both for multiple years (see Figure 24).

[23] As only TUB BLP consider temperature and solar radiation variables, weather data was neglected for both VDEW SLP as well as generic load profiles.

Table 10: Mapping of load profiles to economic subsectors (according to WZ 2008) in the SLP only *appraoch (SLP) and the* BLP application *approach (BLP app.), adapted from Held (2020) and adjusted. Mapping of VDEW SLP to subsectors is made according to VDEW (2000) and Gotzens et al. (2020, p. 72); mapping of generic load profiles in the industrial sector is made according to Gotzens et al. (2020, p. 73).*

Mapping of load profiles to WZ in the sector CTS						**Mapping of load profiles to WZ in the industrial sector**		
WZ	***SLP***	**BLP app.**	**WZ**	***SLP***	***BLP app.***	**WZ**	***SLP***	***BLP app.***
1	L0	L0	68	G1	BLP WZ 64-71	5	S3 WT SA	S3 WT SA
2	L0	L0	69	G1	BLP WZ 64-71	6	S3 WT SA SO	S3 WT SA SO
3	G3	G3	70	G1	BLP WZ 64-71	7	S3 WT SA	S3 WT SA
36	G3	G3	71	G1	BLP WZ 64-71	8	S3 WT SA	S3 WT SA
37	G3	BLP WZ 37	72	G1	BLP WZ 72	9	S3 WT SA	S3 WT SA
38	G3	BLP WZ 38	73	G1	BLP WZ 64-71	10	S3 WT	BLP WZ 10
39	G3	G3	74	G1	BLP WZ 64-71	11	S3 WT	BLP WZ 11
41	G1	BLP WZ 41	75	G1	BLP WZ 64-71	12	S3 WT SA	BLP WZ 12
42	G1	BLP WZ 41	77	G4	BLP WZ 77	13	S2 WT	S2 WT
43	G1	BLP WZ 41	78	G1	BLP WZ 64-71	14	S2 WT	S2 WT
45	G4	G4	79	G4	G4	15	S2 WT SA	S2 WT SA
46	G0	BLP WZ 46	80	G3	G3	16	S2 WT SA	S2 WT SA
47	G0	BLP WZ 47	81	L0	L0	17	S3 WT SA SO	BLP WZ 17
49	G3	G3	82	G0	BLP WZ 82	18	S3 WT SA SO	S3 WT SA SO
50	G3	G3	84	G1	BLP WZ 84	19	S3 WT SA SO	S3 WT SA SO
51	G3	G3	85	G1	BLP WZ 85	20	S3 WT SA SO	S3 WT SA SO
52	G3	BLP WZ 52	86	G3	BLP WZ 86	21	S3 WT SA SO	BLP WZ 21
53	G4	G4	87	G2	BLP WZ 87	22	S2 WT SA	BLP WZ 22
55	G2	BLP WZ 55	88	H0	BLP WZ 88	23	S3 WT SA SO	S3 WT SA SO
56	G2	G2	90	G0	BLP WZ 90	24	S3 WT SA SO	S3 WT SA SO
58	G1	BLP WZ 64-71	91	G0	BLP WZ 91	25	S3 WT	S3 WT
59	G0	BLP WZ 64-71	92	G2	G2	26	S2 WT	BLP WZ 26
60	G3	G3	93	G2	BLP WZ 93	27	S2 WT SA	S2 WT SA
61	G3	G3	94	G6	BLP WZ 94	28	S3 WT	BLP WZ 28
62	G3	BLP WZ 62	95	G4	BLP WZ 64-71	29	S3 WT	BLP WZ 29
63	G3	BLP WZ 63	96	G1	BLP WZ 64-71	30	S3 WT SA SO	S3 WT SA SO
64	G1	BLP WZ 64-71	97	H0	H0	31	S1 WT SA	S1 WT SA
65	G1	BLP WZ 64-71	98	H0	H0	32	S3 WT SA SO	BLP WZ 32
66	G1	BLP WZ 64-71	99	G1	BLP WZ 64-71	33	S2 WT SA	S2 WT SA

4.4. Bottom-up Modelling of Application Technologies

In the following chapter, the creation of engineering-based subsector load profiles using a bottom-up modelling approach is being briefly presented. For selected CTS subsectors in Germany, the model framework was developed in the master thesis of Böckmann (2021), further extended in collaboration and published. The description below corresponds to the publication in Böckmann et al. (2021). A more detailed description of the model framework can be found there. The model code has been published on GitHub (Böckmann and Seim, 2021).

The application technology-specific sub-load profiles were generated according to an engineering-based bottom-up approach for the year 2018 in quarter-hourly resolution. The selected white box approach allows to fully understand and manipulate the modelled interdependencies. In this way, structural changes with regards to technology shifts (e.g. from night storage heaters to heat pumps), changing consumption patterns or efficiency gains can be mapped within the framework of a long-term projection of electricity demands. Models solely relying on projecting historical load profiles, in contrast, might lead to inaccurate results as there is no way to consider changes in demand patterns (Boßmann et al., 2013, p. 1209).

Five of the six largest subsectors by electricity consumption were modelled using the engineering-based model framework: *offices* (WZ64-71), *trade* (WZ47)[24], *accommodation* (WZ55), *hospitals* (WZ86) and *education* (WZ85). However, the model framework is suitable for modelling all CTS or industrial subsectors. At the core, sub-load profiles of application technologies within the CTS sector were modelled. According to Rohde (2019, p. 9), these include in descending order of proportional electricity consumption: Lighting, mechanical energy, ICT, air conditioning, process cooling, jointly assessed space heat and hot water, as well as other process heat. As for the underlying database of application technology energy consumption, the subsector classification was based on the groups developed by Schlomann et al. (2015, p. 3). However, these groups can be mapped to the WZ 2008 classification (Destatis, 2008). This allowed a validation and fine-tuning of engineering-based load profiles with corresponding subsector load profiles developed in the first module of this thesis (Böckmann et al., 2021, p. 3).

As pointed out in chapter 4.1.3, the engineering-based load profiles were developed based on information on occupancy and usage, application technology data, calendar information, weather data, and annual energy demands for application technologies from national statistics. Figure 25 depicts the modelling procedure.

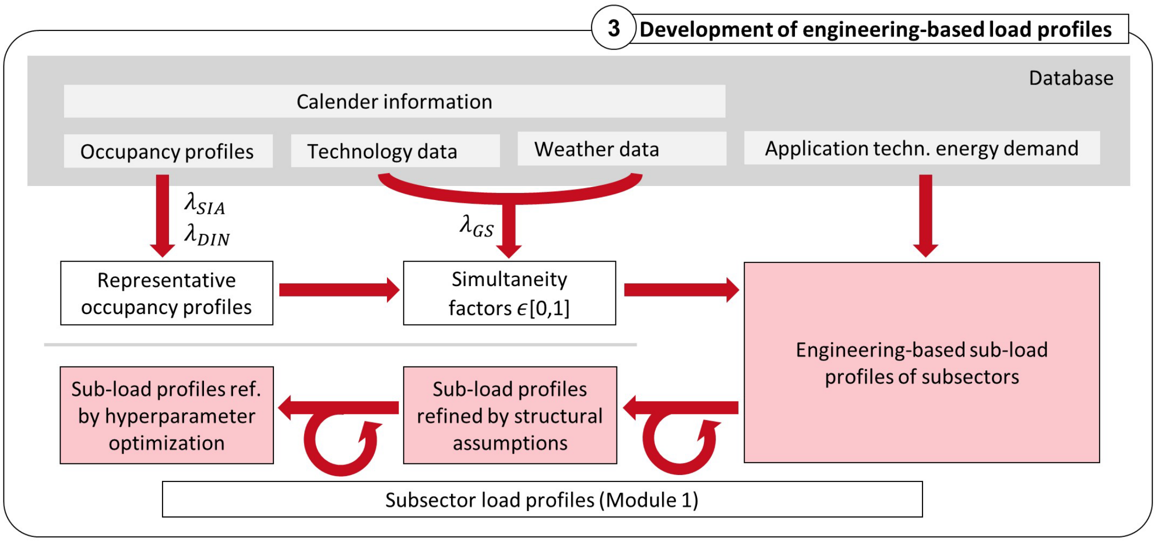

Figure 25: Illustration of the modelling procedure for engineering-based load profiles, figure adapted from Böckmann et al. (2021, p. 4)

First, the three standards (ISO 18523-1:2016(E) (2016), SIA 2024:2015 (2015), DIN V 18599-10:2018-09 (2018)) were combined into representative occupancy profiles per subsector and type day according to proportions determined by hyperparameters λ_{SIA} and λ_{DIN}. The influence of global radiation on lighting was described by the hyperparameter λ_{GS}, which was normalised to the interval [0,1]. Hyperparameters were introduced to make efficient use of scarcely available information. These hyperparameters enabled a fine-tuning of weights for demand drivers without violating functional plausibility (Böckmann et al., 2021, p. 5).

[24] For engineering-based models, the *retail trade* subsector (WZ47, German: Einzelhandel) is used as a proxy for the entire *trade* subsector including the *wholesale trade* sector (WZ46, German: Großhandel).

Then, using calendar data, technology data, weather data and representative occupancy profiles, simultaneity factors were created per time slice for the complete year 2018 per application technology and subsector. Simultaneity factors are utilisation rates, which are given per time slice of a day. Here, simultaneity factors were normalised on an interval [0, 1] and depict the ratio of electricity demand at a distinct time slice. This ratio can be scaled by an annual electricity demand (of application technologies) to yield a sub-load profile. The aggregation of sub-load profiles over all application technologies depicts the subsector load profile, which could be compared to the output of module 1 (Böckmann et al., 2021, p. 5).

These sub-load profiles were developed in three different modelling steps. In each step, modelled sub-load profiles were compared iteratively with existing subsector load profiles and refined gradually according to observed structural deviations. In analogy to the multiple regression and ANN approaches, structural deviations were identified using the performance measures MAPE and R^2. After each modelling step, the previous results were refined by structural assumptions and the hyperparameter optimization using a grid search process, maintaining the underlying functional validity of the model. As a result, engineering-based subsector load profiles have been derived which exhibit a transparent white-box modelling design and which can be validated against real data using subsector load profiles of module 1 (Böckmann et al., 2021, p. 5). The detailed procedure of the individual steps mentioned above is described in Böckmann et al. (2021, pp. 5–11).

4.5. Projecting Subsector Electricity Load Profiles into the Future

In the following, the projection of engineering-based load profiles will be described. The methodology was developed in collaboration (Böckmann, 2021) and published in Seim et al. (2021a, chapter 2.1).

Technology- and sector-specific development paths were quantified using literature-based scenarios, i.e. the baseline scenario and reference scenario (cf. chapter 4.1.4). These development paths were utilized to adjust engineering-based load profiles developed in Böckmann et al. (2021). According to Pfluger et al. (2017b, p. 63), the main drivers of the energy demand scenarios in the CTS sector are employees, electricity prices, energy reference areas, energy efficiency increases and implicit discounting rates for future company investments. In an opposite effect to efficiency gains, drivers like climate change or digitalization can also lead to an increased demand for some technologies, like air conditioning and ICT. All drivers determine the future electricity demand level of each application technology and sector. A changing composition of application technologies with individual sub-load profiles will affect the aggregated load profile of a subsector. In addition, changing temporal demand characteristics have an impact. The latter are difficult to model, as it is complex to anticipate future changes in building occupancy or a change in user behaviour (Seim et al., 2021a, p. 4).

In projecting engineering-based load profiles to the year 2035, occupancy profiles and technology data of Böckmann et al. (2021) were utilised with minor adjustments. Weather data of the year 2018 and calendar data of the year 2035 was used. To determine the technology-specific annual electricity consumption for 2018, the application energy demands of the CTS sector were disaggregated to individual subsectors according to Rohde (2019, p. 9) (see appendix A.1.4: Table 28). The necessary electricity consumption shares per application technology and subsector were taken from Repenning et al. (2015, p. 84). Using existing energy scenarios, future application technology energy demands had to be extrapolated to the year 2035 and transformed to the required granularity of subsectors (Pfluger et al., 2017b, pp. 68, 71). The distribution of these future electricity demands to individual sectors was based on subsector-specific shares of future energy reference areas. For this purpose, the values from Pfluger et al. (2017b, p. 64) could be used and extrapolated for the year 2035 (see appendix A.1.4: Table 29 and Table 30). Due to individual sector developments, the shares of application-specific electricity demands differ slightly between the years 2018 and 2035. While lighting still accounted for

24.1 % of total lighting consumption in the *trade* subsector in 2018, this share will increase by more than 2 percentage points to 26.7 % due to sector growth (Seim et al., 2021a, p. 5).

In Pfluger et al. (2017b, pp. 68, 71), the application technologies of air conditioning and ventilation are combined. For the present thesis, demand was divided in half, so that the growth rates are divided equally between the applications mechanical energy and air conditioning. According to Böckmann et al. (2021), 70 % of the electrical heat supply consists of hot water and 30 % of space heating. In the absence of literature data, these proportions were assumed constant for the target value in 2035. Information on the development of space heating was extracted from Pfluger et al. (2017b, p. 120). Here, a structural change due to the decline of night storage heaters and the increasing share of heat pumps was taken into account with the help of varying technology shares. As described in Böckmann et al. (2021), different load profiles were assumed for heat pumps and night storage heaters, so that the shift of technology ratio will result in load profile changes. All other technologies were assumed to have an identical and partly weather-dependent load profile. Thus, it is above all the increases in efficiency that influence the shares of application technologies in the total load profile (Seim et al., 2021a, p. 5).

4.6. Derivation of Technical Demand Side Flexibility Potential

After projecting subsector- and technology-specific load profiles into the year 2035, present and future DSF potentials were quantified. Only the engineering-based load profiles in high temporal resolution from Böckmann et al. (2021) allow a robust analysis of temporal availabilities and maximum capacities of flexible loads. In the following, the procedure for deriving technical DSF potential will be described. The procedure was applied in collaboration (Böckmann, 2021) and mainly follows the framework developed by Kleinhans (2014). The below description has been published already in German (Seim et al., 2021a, chapter 2.2).

To quantify the DSF potentials, a number of electric power, temporal and cost parameters at process and application level are used in the literature. The electric power parameters include the available switchable power, average, minimum and maximum load, installed power and the share of power that can be flexibilised. Temporal parameters include switching and shift durations as well as temporal availabilities. The cost parameters include capital expenditure, fixed costs and variable costs (Kochems, 2020, p. 3; Steurer, 2017, pp. 32–33). Following Kochem's definition, technical load shifting potentials are analysed, considering application-specific, time-dependent minimum and maximum loads as well as time-related availability restrictions. A technical control option may already be available or may be brought about by investments (Kochems, 2020, p. 1). According to Steurer (2017), many publications focus exclusively on the switchable power, which is insufficient for the consideration of the potential. When considering the technical potential, the temporal parameters are decisive. Technical restrictions, such as minimum and maximum loads of individual application technologies, are pivotal for quantifying the technical load flexibility potential. In this thesis, economic factors or other social and organizational factors were not taken into account (Seim et al., 2021a, pp. 5–6).

Kleinhans (2014) presents a framework for quantifying technical DSF potentials, which is used in the literature by Kies et al. (2016) and by Heitkoetter et al. (2020), among others. Here, load shifting is regarded as a process equivalent to energy storage. The maximum and minimum switchable loads $P_{min}^{q}(t)$ and $P_{max}^{q}(t)$ as well as the maximum and minimum shiftable energy quantities $E_{min}^{q}(t)$ and $E_{max}^{q}(t)$ of each application technology q at time t are calculated as characteristic quantities. The time availability of an application determines the scheduled (base) load profile of an application $L_q(t)$. The shift duration of an application in positive as well as negative direction is given as Δt_q and denotes the duration by which the start of a load increase (or a load reduction) can be shifted to earlier times or the end of the load increase (or reduction) can be shifted to later times. The maximum load of an application at time t is $\Lambda_q(t)$. $\mathrm{R}_q(t)$ is the realized load after load shifting (Kleinhans, 2014, pp. 3–4). All parameters and variables with units of the International System of Units (SI units) are shown in Table 11 (Seim et al., 2021a, p. 6).

Table 11: Parameters and variables for calculating the technical DSF potential according to Kleinhans (2014, p. 4)

Variable	Description	SI-Units
$\mathbf{Q}$	Number of application technologies	-
$\boldsymbol{\Delta t_q}$	Shift duration	s
$\boldsymbol{L_q(t)}$	Scheduled load for application q	W
$\boldsymbol{\Lambda_q(t)}$	Maximum load / capacity of application q	W
$\boldsymbol{\mathrm{R}_q(t)}$	Realized load (after shifting) for application q	W
$\boldsymbol{\mathrm{P}_q(t)}$	Switchable load of application q	W
$\boldsymbol{E_q(t)}$	Shiftable energy quantities of application q	Ws

Since in very few cases load profiles are available at the level of application technologies, many studies used SLP with assumptions on seasonal and time-of-day availabilities (Heitkoetter et al., 2020, p. 7; Klobasa, 2007, p. 26; Ladwig, 2018, p. 23; Steurer, 2017, p. 49). In contrast, this thesis used much more detailed technology- and subsector-specific load profiles from Böckmann et al. (2021). When considering load shifting as energy storage, $\mathrm{P}_q(t)$ in formula 15 describes the charging rate of the energy storage. $\mathrm{E}_q(t)$ in formula 16 characterises the amount of energy that can be shifted, which can be interpreted as the state of charge of an energy storage device in terms of a load flexibility measure (Kleinhans, 2014, p. 4). The storage is charged if $\mathrm{R}_q(t) > L_q(t)$ and discharged if $\mathrm{R}_q(t) < L_q(t)$. The storage level is then the integral of the charging rate (Kleinhans, 2014, p. 4; Seim et al., 2021a, p. 6).

$$P^q\big[R_q(t)\big](t) = R_q(t) - L_q(t) \tag{15}$$

$$E^q\big[\mathrm{R}_q(t)\big](t) = \int_0^t dt'\, P^q\big[\mathrm{R}_q(t)\big](t') \tag{16}$$

The square brackets designate that the expressions depend directly on the time series of realized loads for respective application technologies. Since any number of profiles are possible for the realised loads $\mathrm{R}_q(t)$ depending on the scheduled load profile $\mathrm{L}_q(t)$, the limits of the load shifting potentials can be characterised as respective minima and maxima of the charging rate and the storage level. These limits are also called envelope curves and are calculated according to formulae 17-20 (Kleinhans, 2014, p. 5).

$$E^q_{max}(t) := E^q\big[\mathrm{R}_q\big(t + \Delta t_q\big)\big](t) = \int_0^{t+\Delta t_q} dt'\, \mathrm{L}_q(t') \tag{17}$$

$$E^q_{min}(t) := E^q\big[\mathrm{R}_q\big(t + \Delta t_q\big)\big](t) = -\int_{t-\Delta t_q}^{t} dt'\, \mathrm{L}_q(t') \tag{18}$$

$$P^q_{max}(t) := \Lambda_q(t) - \mathrm{L}_q(t) \tag{19}$$

$$P^q_{min}(t) := -\mathrm{L}_q(t) \tag{20}$$

Figure 26 illustrates the relationships for an exemplary load profile. The red line represents the scheduled load $\mathrm{L}_q(t)$ of an application q, which can be varied – depending on the time – within the limits $\Lambda_q(t)$ (=maximum load) and 0 (=minimum load). In the present example, a scheduled load of

1 kW is shown from 14:00 to 16:00. This scheduled load can be shifted by $\Delta t = 4h$, i.e. either shifted to earlier or later times. In the most extreme case, the load can be shifted to 10:00 or shifted to 18:00, whereby any number of shifts by smaller time intervals is possible. These considerations result in the corresponding representations of the energy storage model as envelope curves with E_{max} (black line) and E_{min} (grey line). At an exemplary time t = 14:30, the area drawn below the scheduled load for the time interval $t + \Delta t_q$ results for E_{max}. This area can be read from the corresponding envelope curve at time t = 14:30 (see (1), Figure 26) with 1.5 kWh. The same results for E_{min} (Seim et al., 2021a, p. 7).

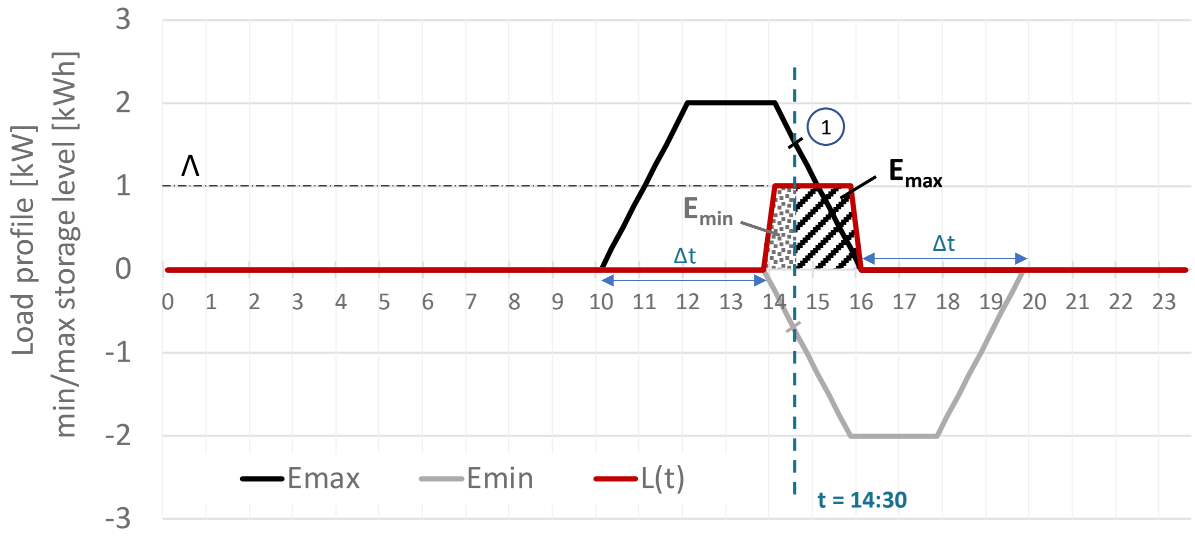

Figure 26: Schematic illustration of the shiftable energy quantities Emax, Emin as a function of the scheduled load L(t). Diagram by author, adapted from Seim et al. (2021a). The scheduled load L(t) rises abruptly from 0 to 1 kW at 14:00 and falls again at 16:00. Consequently, no ramps occur in the case of the load profile (red).

For each of the subsectors of *offices*, *trade*, *accommodation*, *hospitals* and *education*, DSF potentials were calculated for present (2018, chapter 4.4) and projected (2035, chapter 4.5) load profiles. Electric power parameters, temporal parameters and time availability were included in the quantification. Power parameters include the fundamental suitability for flexibilization of a technology as well as the switchable loads, while the time parameters describe switching and shift durations in particular (Kochems, 2020, p. 3; Seim et al., 2021a, p. 7).

Technologies suitable for load shifting include ventilation, air conditioning, process cooling, as well as space heating and hot water (Heitkoetter et al., 2020, p. 9; Klobasa, 2007, pp. 69–78; Ladwig, 2018, p. 23). The scheduled load of application q in subsector b, $L_q, b(t)$, corresponds to the modelled load profile of the application. Some published approaches used constant maximum loads $\Lambda_q(t)$ or installed capacities to estimate switchable loads (Gils, 2015, p. 14; Kleinhans, 2014, p. 11; Ladwig, 2018, p. 100). Others used simple assumptions regarding the seasonality of switchable loads (Klobasa, 2007, p. 26). Using installed capacities potentially overestimates the maximum charging rates and switchable loads (Kleinhans, 2014, p. 11). Using the high temporal resolution load profiles, the maximum switchable loads $\Lambda_{q,D}(t)$ of an application q at time t could be specified with formula 21 in this thesis. Here, D denotes the time frame in days in which the maximum load of the application is calculated. In the following, a time frame of $D = 1\ day$ (≙ 96 quarter hours) was assumed (Seim et al., 2021a, pp. 7–8).

$$\Lambda_{q,D}(t) = \max\{L_q(t)\}\ \forall t \in [1, 2, .., 96] + 96 \cdot k, k \in N\ \cap \{0\} \qquad (21)$$

The modelled shift durations for each application technology were taken from corresponding data in Ladwig (2018, p. 23) and Heitkoetter et al. (2020, p. 9). For ventilation, air conditioning and process cooling, $\Delta t = 1h$ applied; for space heating, the shift duration was $\Delta t = 12h$ (Seim et al., 2021a, p. 8).

4.7. Economic Assessment of Applying Newly Developed Subsector Load Profiles

In the next chapter, the experimental setup of economically assessing two use cases of subsector load profiles is presented. In the first chapter 4.7.1, the assessment of the influence of newly developed TUB BLP on electricity procurement and balancing group management is described. This assessment is intended to provide information on the extent to which the use of TUB BLP is beneficial from an economic point of view. In the second chapter 4.7.2 it is explained, how the economic value of identified DSF potentials in high spatial and temporal resolution can be determined. This assessment of concrete DSF potentials allows an indication as to which extent these potentials should be exploited from an economic standpoint. In the long term, the exploitation of economically viable potentials should be stimulated by an appropriate regulatory framework.

4.7.1. Procurement and Balancing Group Management

In the first use case, the application of newly developed TUB BLP is to be economically assessed. As mentioned in chapter 2.2.4, there are multiple fields of application for electricity load profiles spanning across all steps of the value chain. Among others, subsector load profiles are used for demand forecasting and energy system modelling, for the planning and design of power generation plants and for the procurement of energy (Schellong, 2016a, p. 375). In particular, the last use case, i.e. the procurement of electricity, is well suitable for economic evaluation, as electricity prices are available in high temporal resolution and topicality. Therefore, this thesis focuses on the assessment of the use of TUB BLP in the procurement and balancing group management of electricity.

Despite the suitability, economically assessing the application of newly developed subsector load profiles is not trivial since relevant forecasting models and procurement strategies used by traders, suppliers and DSOs are diverse and non-disclosed (Novello et al., 2021, p. 20). Moreover, market prices depend on (projected) demands, which further complicates the economic assessment of demand models. In spite of these challenges, the present thesis seeks to generate a rough estimation as to whether or not the application of newly developed subsector load profiles might have a positive impact on the procurement of electricity and the balancing group management. The estimation of potential economic impacts applying subsector load profiles was achieved using the *disaggregator* tool: both approaches (i.e. *SLP only* and *BLP application*) described in chapter 4.3 were used to simulate an i) electricity procurement and ii) balancing group management of the total German market (ENTSO-E data) as well as selected counties.

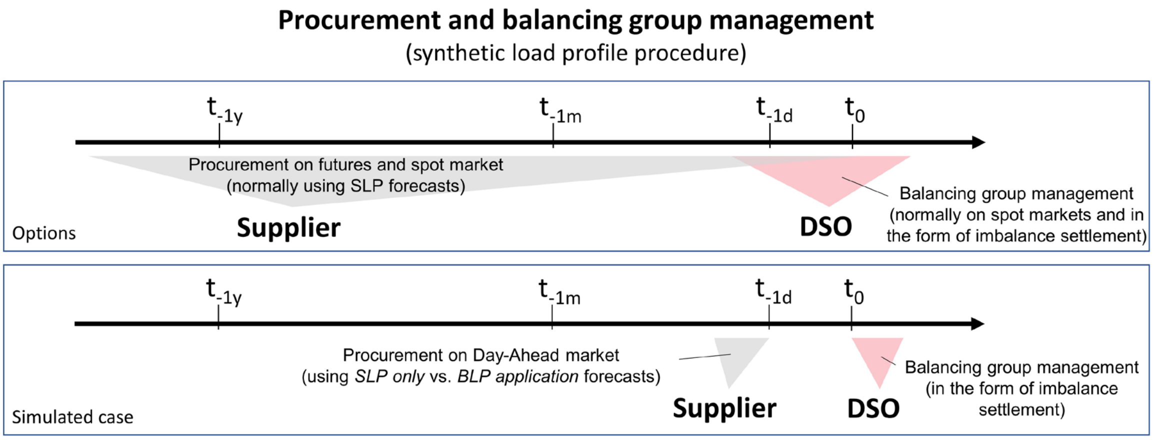

Figure 27: Depiction of simulated procurement and balancing group management case within the spectrum of options, considering the synthetic load profile procedure. Diagram by author.

Figure 27 illustrates the real spectrum of options for procurement and balancing group management as well as the simulated procurement and balancing group management case. The following paragraphs elaborate on why narrowing down the simulated case of i) procurement and ii) balancing group management strategies can be regarded plausible.

i) In the synthetic load profile procedure, suppliers usually procure electricity for their consumers on the futures and spot market, using load profiles provided by DSOs (usually SLP[25], cf. Figure 27). In this thesis, however, a procurement strategy was simulated solely procuring on the spot market. Yet this simplification seems to be plausible: the *disaggregator* model generates load profile shapes of the same overall level of electricity. As Novello et al. (2021, p. 20) found, the differences between load profile shapes do not have major price impacts on the long-term electricity procurement, because on the futures market there are only products available of low temporal resolution (baseload, peakload). While the *level* of electricity demand has important price implications for *long-term* procurement, the *profile shape* becomes more important in the *short-term* procurement, when products of higher temporal resolution are available. This thesis' focus on spot market electricity procurement is thus a plausible simplification.

ii) After suppliers procured the electricity, the DSOs are obliged to manage their balancing groups using the spot markets (cf. Figure 27). Remaining deviations will be levelled out using balancing energy and performing an imbalance settlement with BRPs. The extent to which balancing groups are actively managed remains uncertain, but there have been complaints in the past that balancing groups were managed insufficiently (BNetzA, 2013; Enkhardt, 2020). In this thesis, the balancing group management is represented in the marginal case where all imbalances are priced with the reBAP. While reBAP prices are more volatile than spot market prices, this simplification seems plausible: the prices of the intraday market, where some deviations are settled, correlate in direction with the imbalance settlement prices, because imbalances are already anticipated by market participants (Koch and Maskos, 2019, pp. 10, 13). The simplification made in the present analysis of limiting balancing group management to an imbalance settlement using the reBAP (and not taking intraday trading into account) thus might overestimate the assessed monetary values. However, the extent to which significant macroeconomic costs can be saved or not by using TUB BLP can very well be assessed.

[25] In his thesis, Beuker (2018) analysed the differential balancing group time series of DSOs for structural deviations. He randomly picked 100 DSOs, 46 of which published usable data. Of these 46 DSOs, only 6 (13 %) used their own residential load profiles. All remaining DSOs used the VDEW SLP for residential customers (H0).

Figure 28 illustrates the procedure of economic assessment for the total German load (ENTSO-E data). The experimental assumption was that the whole electricity demand of a balancing group, which has been modelled by the *disaggregator* tool (*SLP only* vs. *BLP application* approach), is being procured on the Day-Ahead market. The deviations between modelled and real load were assigned imbalance settlement and priced with the reBAP.[26] The assumption here was that there is no active management of the balancing group. Solely the procurement and balancing group management of two modelled demands (*SLP only* and *BLP application* approach) was economically compared. Any potential influence on the price by the changing demand structures of both approaches was neglected.

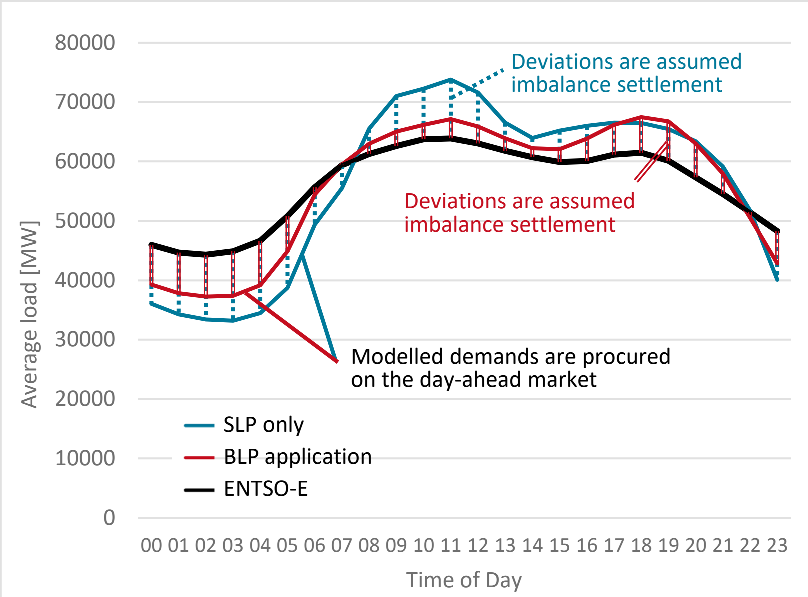

Figure 28: Principle of the economic assessment of newly developed subsector load profiles, comparing the SLP only *approach (blue) and the* BLP application *approach (red) in the* disaggregator *tool, procuring electricity on the Day-Ahead market and pricing deviations to the real ENTSO-E load (black) with the reBAP. Diagram by author.*

In analogy to chapter 4.1.2 and due to data availability, the economic assessment was conducted for the whole area of Germany (ENTSO-E data) in the years 2015 to 2019 as well as for 11 DSOs with varying years between 2017 and 2019. Since Day-Ahead spot market prices were only available in hourly resolution, quarter-hourly values for the economic assessment were transformed into hourly values. Imbalance settlement was priced using the reBAP (TransnetBW GmbH, 2021).

4.7.2. Economic Assessment of Demand Side Flexibility Potentials

As introduced in chapter 2.2.3, the residual load has to be balanced by means of flexible generation or storage technologies. DSF can play an important role in smoothing the residual load and reducing the need for peak load capacity, particularly gas turbine power plants (Boßmann, 2015, p. 212). This can be of relevance in times of high positive residual load, i.e. when high demand coincides with low electricity generation from wind and PV. In accordance with their cost structure and flexibility, gas turbine power plants are used to cover peak loads in a comparably low number of annual operating hours. Table 12 depicts the electricity generation costs of fossil power plants. As can be seen, gas turbine power plants are associated with high running costs (per MWh) and comparably moderate capacity costs (per installed output and year). While running costs are strongly dependent on the current gas price, capacity costs are more stable over time.

[26] Pricing deviations with the reBAP can result in extra costs or in revenues, depending on whether there is an electricity deficit or surplus in the system, and depending on whether deviations add onto that system imbalance or partially compensate it.

Table 12: Electricity generation costs of fossil power plants according to Konstantin (2017, p. 248); PP – power plant, CCPP – combined cycle power plant, TCE – tons of coal equivalent, UCV – upper calorific value

		Base load		Intermediate load		Peak load
Position	**Unit**	**Steam PP hard coal**	**CCPP Gas**	**Steam PP hard coal**	**CCPP Gas**	**Gas Turbine PP**
Power output	MW	700	400	700	400	150
Net efficiency	-	46%	56%	46%	56%	34%
Operating hours	h/a	7,500	7,500	5,000	5,000	1,250
Marginal fuel price	-	95 €/TCE	30 €/ MWh_{UCV}	95 €/TCE	30 €/ MWh_{UCV}	30 €/ MWh_{UCV}
Capacity costs	€/(kW·a)	202	80	202	80	56
Running costs (without CO_2 costs)	€/MWh	28.26	62.5	28,26	62.5	118.54
Total costs (without CO_2 costs)	€/MWh	55.2	73.17	68,66	78.5	163.34

In the following economic assessment, it will first be determined how much peak load capacity can be saved by shifting the load to later times applying the DSF potentials identified in module 5. For this purpose, the residual load for the year 2018 is determined in quarter-hourly resolution using the actual total load for Germany of the year 2018 and subtracting the actual electricity generation from intermittent renewables ("ENTSO-E," 2021), such as wind turbines (onshore and offshore) and PV plants. Figure 29 depicts the resulting residual load of 2018. As can be seen, the residual load of Germany peaked on several days, especially in January and February.[27]

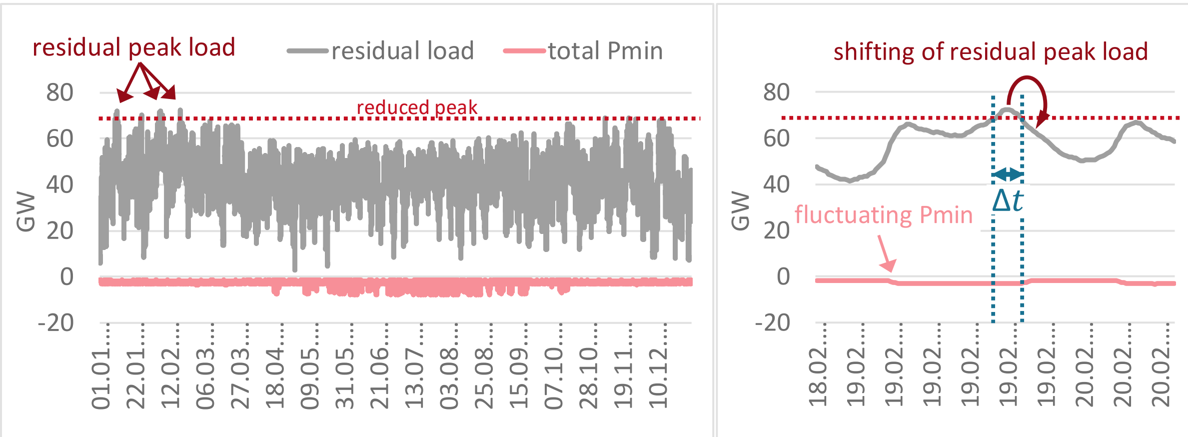

Figure 29: Left figure: German residual load and total load reduction potential (total Pmin) for the year 2018, indicating residual peak load times. Right figure: Zoomed illustration of residual peak load shifting to later times in the duration of shift Δt, indicating the required fluctuating total load reduction (DSF) potentials. Diagram by author.

The next step is to investigate to what extent DSF can support reducing the residual peak load through peak shifting. Since DSF potentials fluctuate largely during day and season, as will be shown in chapter 5.5, the use of DSF potentials in high temporal resolution is mandatory here. Hence, particularly the DSF potentials identified in module 5 of this thesis can be utilized for a robust estimation of the residual peak load reduction potential. As mentioned in chapter 2.3.5, alternative approaches (Gils, 2015; Heitkoetter et al., 2020; Ladwig, 2018; Steurer, 2017) differ from this thesis' approach in the use of

[27] The exact time of peak load was February, 19th at 18:30h. Similar loads could be observed on January, 11th, 26th, as well as February 06th to 8th.

(partly incorrect) standard load profiles (cf. chapter 2.3.2) or highly simplified profile assumptions in the determination of DSF potentials.

Utilizing the results of module 5, the residual load is matched by date and time with DSF potentials (as indicated in the above Figure 29) in order to identify the peak load reduction potential. Of particular importance are DSF potentials in respective peak load times. Both time series (residual load and DSF potentials) are placed next to each other to see whether the peak load can be shifted (i.e. reduced) and whether the shift is possible within the shift duration (energy quantities). More precisely, two restrictions must be respected for DSF to determine the feasible load capacity reduction:

- The peak load reduction cannot fall below the minimum switchable (i.e. maximum reducible) load $P_{min}^{q}(t)$ of all applications at time t.
- The energy quantities associated with the peak load reduction cannot fall below the minimum shiftable energy quantities $E_{min}^{q}(t)$ of all applications q throughout the duration of shift Δt_q.

Figure 30 outlines an exemplary peak load reduction potential, using the residual load duration curve. Subsequently, the feasible reduced peak load capacity is economically evaluated based on reduced annual capacity costs for gas turbine power plants, shown in Table 12. The monetary value determined corresponds to a maximum cost saving that can be achieved in the form of peak load reductions in the application of DSF.

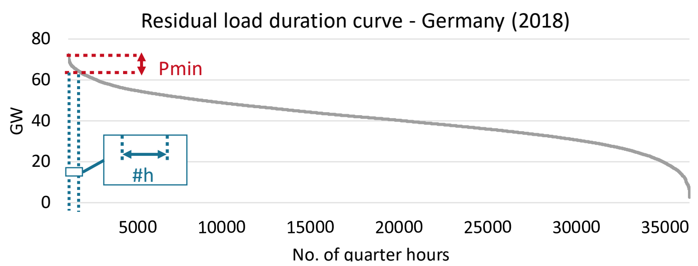

Figure 30: Illustration of peak load reduction potential Pmin in the accumulated duration of shifts #h using the residual load duration curve. Illustration by author.

In the next step, costs of accessing the DSF potentials have to be estimated. Table 13 lists cost parameters for the applications cooling, ventilation, AC and heat pumps.

Table 13: Cost parameters to access DSF potentials, according to Heitkoetter et al. (2020, p. 9) and Gils (2015).

Technology, c	c_{inv} **[€/MW]**	c_{fix} **[€/MW/a]**	c_{var} **[€/MWh]**
Cooling, ventilation, AC	10,000 €	300 €	5 €
Heat pumps	20,000 €	600 €	10 €

According to Gils (2015), cost parameters can be divided into specific investment costs, annual fixed costs and variable costs. The investment comprises costs for ICT components, including the installing and programming of devices. The annual fixed costs incur through maintenance works and the power consumption of ICT components (Steurer, 2017). The variable costs reflect the compensations for production and comfort losses (Gils, 2015, pp. 401–415; Heitkoetter et al., 2020, p. 8). Due to a lack of information, a conservative assumption of a lifetime of 10 years was made for the ICT components. In another context, Schellong (2016b, p. 275) estimates the lifetime of ICT components at 15 years, while smart meter gateways have to be replaced by law (calibration period, “Eichfrist”) after only 8 years (Gährs et al., 2021, p. 21). With an interest rate of 1%, annual costs are calculated using an average capital commitment (i.e. 6.4 million € for cooling, ventilation, AC and 16.5 million € for heat pumps).

Due to the different cost parameters of the application technologies in Table 13, the peak load reduction potentials identified above have to be split between cooling, ventilation and AC as well as heat pumps. As for its greater storage potential, the flexibilization of heat pumps was assumed preferable; the remaining technologies were used only to complement necessary energy shifts.

5. Results

In the next chapters, the results of all individual modules will be presented, starting with the newly developed TUB subsector load profiles and their benchmarking (chapter 5.1) as well as their application and evaluation within the *disaggregator* tool (chapter 5.2). Further, developed bottom-up engineering-based load profiles of five CTS subsectors will be presented (chapter 5.3) and will be projected to the year 2035 (chapter 5.4). These current and projected engineering-based load profiles are then used to determine technical DSF potential, which will be shown in chapter 5.5. Lastly, the results of the economic assessment of applying newly developed subsector load profiles in two different contexts will be presented in chapter 5.6.

5.1. Subsector Electricity Load Profiles (TUB BLP)

The profile of electricity demand in Germany is highly volatile. Electricity demand exhibits characteristic cycles on a daily, weekly and annual basis. On the one hand, this is due to seasonal differences in electricity demand for lighting and heating systems. On the other hand, economic cycles and weather conditions as well as the working and living habits of the population play an important role. In addition to seasonal cycles, this causes characteristic weekly and diurnal fluctuations in electricity demand. Towards the weekend, a substantial drop of load levels can be seen due to reduced economic activity (Schellong, 2016a, pp. 324–325). In order to depict these significant differences in the load profiles of individual subsectors, weekly average representations of different seasons are used in the following. In addition, correlation coefficients also allow indicative statements about the strength of a demand driver for individual subsectors (appendix A.2.2 and A.2.3). In total, the following 32 subsector load profiles have been created and made public (Seim et al., 2021b). A list with corresponding German names of modelled subsectors according to the classification WZ 2008 can be found in appendix A.2.1.

- WZ10: *Manufacture of food products*
- WZ11: *Manufacture of beverages*
- WZ12: *Manufacture of tobacco products*
- WZ17: *Manufacture of paper*
- WZ21: *Manufacture of pharmaceuticals*
- WZ22: *Manufacture of rubber and plastics*
- WZ26: *Manufacture of computer, electronic and optical products*
- WZ28: *Manufacture of machinery*
- WZ29: *Manufacture of motor vehicles*
- WZ32: *Other manufacturing*
- WZ37: *Sewerage*
- WZ38: *Waste collection, treatment and disposal*
- WZ41: *Construction of buildings*
- WZ46: *Wholesale trade*
- WZ47: *Retail trade*
- WZ52: *Warehousing and support activities for transportation*
- WZ55: *Accommodation*
- WZ62: *Computer programming, consultancy*
- WZ63: *Information service activities*
- WZ64-71: *Offices*
- WZ72: *Research and Development*
- WZ77: *Rental and leasing activities*
- WZ82: *Office administrative and support activities*
- WZ84: *Public administration*
- WZ85: *Education*
- WZ86: *Human health activities*
- WZ87: *Residential care activities*
- WZ88: *Social work activities*
- WZ90: *Creative, arts and entertainment activities*
- WZ91: *Libraries, museums and other cultural activities*
- WZ93: *Sports activities, amusement and recreation activities*
- WZ94: *Activities of membership organisations*

The below chapter 5.1.1 has partly been published in German in Gotzens et al. (2020, chapter 5.4). It presents three subsector load profiles in detail to illustrate the following different structural characteristics:

- pronounced diurnal and weekly structure (*Offices* (WZ64-71), chapter 5.1.1.1)
- pronounced weekly structure (*Manufacture of motor vehicles* (WZ29), chapter 5.1.1.2)
- without pronounced structure (*Paper manufacturing* (WZ17), chapter 5.1.1.3)

The validation of individual subsector load profiles can only take place where real metered data is available for modelling and testing. Using cross validation, each individual subsector load profile was validated with unknown data slices. All remaining subsector load profiles, their structural characteristics and performance measures are shown in appendix A.2.2 and A.2.3. The subsector load profiles are also published in digital form in Seim et al. (2021b).

Chapter 5.1.2 will benchmark subsector load profiles with a different model technique (ANN) and other literature-based load profiles. Chapter 5.1.2.1 will contrast the performance measures derived by applying multiple regression versus artificial neural networks for the regression task. Comparing the two approaches allows to evaluate the robustness of both techniques and their results. Chapter 5.1.2.2 will benchmark subsector load profiles with the VDEW SLP and the De Monfort Profiles. Also, structural deviations will be discussed.

5.1.1. Subsector Electricity Load Profiles Using Multiple Regression and Quantile Regression

5.1.1.1 Subsector Load Profiles with Pronounced Diurnal and Weekly Structure

The subsector load profile of *offices* is highly relevant due to its applicability in many subsectors and the associated high electricity demand. In the *BLP application* approach of the model, the subsector load profile for *offices* was used for the economic subsectors WZ 58, 59, 73-75, 78, 95, 96 and 99 in addition to the subsectors WZ 64-71 (cf. chapter 4.3). Offices show a distinct diurnal and weekly structure, similar to subsectors WZ 10, 26, 28, 32, 38, 46, 47, 63, 72, 82, 84 and 85. Figure 31 depicts the representation of an average week for *offices*. Electrical energy is mainly consumed on weekdays, with a slightly reduced level on Mondays and an earlier load drop on Fridays. The load increase in the morning and the load drop in the evening appears continuous without abrupt edges, which results from a distribution of the beginning and end of working time. A lunch break is hardly noticeable in the middle of the day, which is in line with findings by Brunner et al. (2009, p. 21), despite a distinct reduction of occupancy between 12:00h and 14:00h.

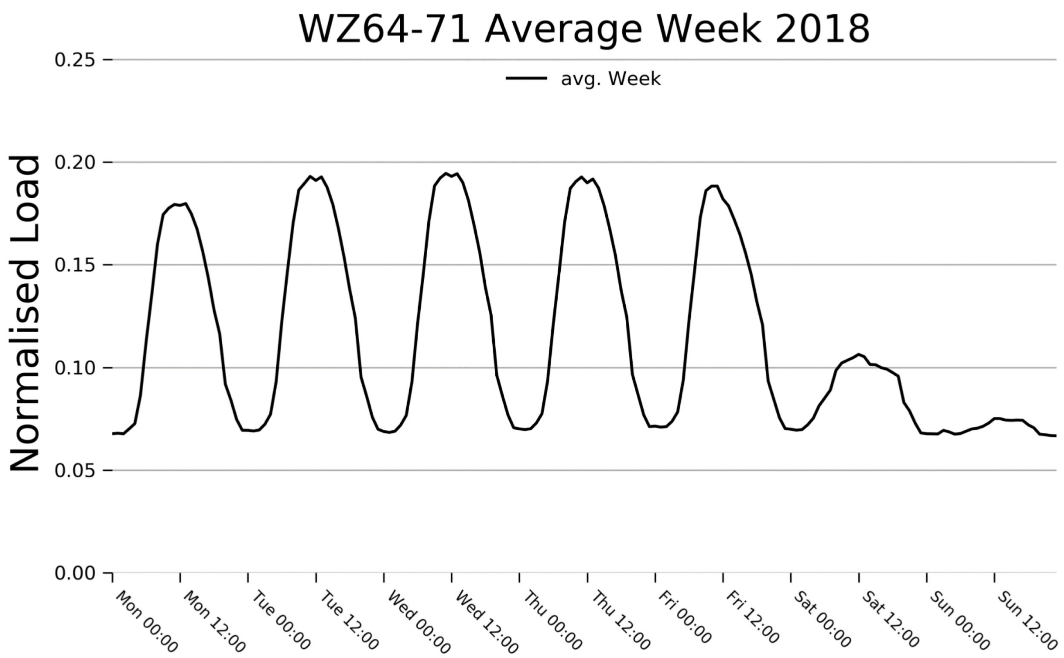

Figure 31: Average weekly subsector load profile for offices *(WZ64-71). Diagram by author, published in Gotzens et al. (2020, p. 113)*

Figure 32 shows seasonal differences (left) and the characteristic load profiles for type days (right). In the case of *offices*, seasonal fluctuations are pronounced modestly. The summer time, for example, exhibits a load peak that is about 10 % higher than winter time and transition period ("restofyear"). This indicates an increased electricity demand for building ventilation and air conditioning, which varies among office buildings. In office buildings that are equipped with air conditioning, these load differences can be up to 30 %. Looking at the type days (figure on the right), a load level reduced by more than 60 % can be seen for Saturdays, indicating an existing but lower activity level. In contrast, hardly any activity can be detected on Sundays, as the load level is barely above the base load level. The base load level, on the other hand, is clearly visible and indicates a pronounced stand-by demand.

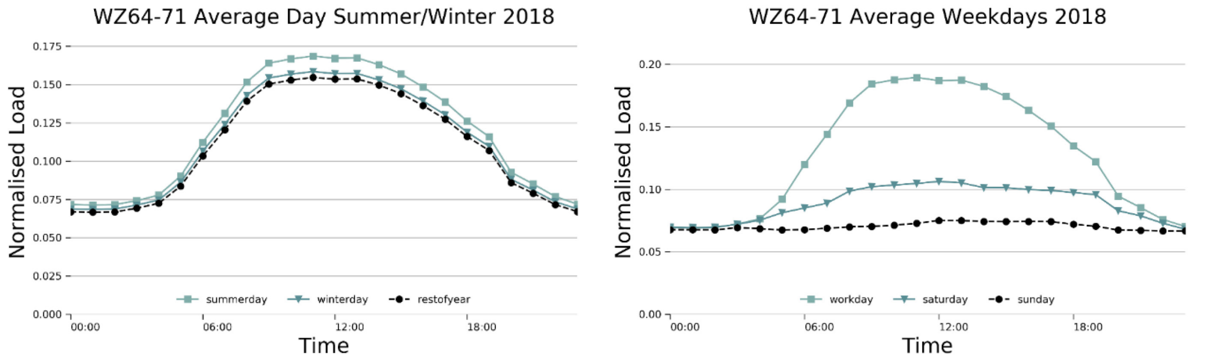

Figure 32: Average daily subsector load profiles for offices *(WZ64-71), on the left different seasonal periods (summer, winter, transition), on the right different type days (working day, Saturday, Sunday). Diagram by author, published in Gotzens et al. (2020, p. 114)*

Figure 33 shows the predicted subsector load profile (blue) including the 5 % and 95 % prediction intervals of the quantile regression. The interquantile range points to pronounced variances within the loads of individual locations (due to, for example, the above-mentioned differences in equipment). Since the interquantile range is largely constant over time, the load fluctuations hardly change their intensity. In particular, however, the interquantile ranges suggest larger load fluctuations for Saturdays, which indicates a varying work activity on Saturdays.

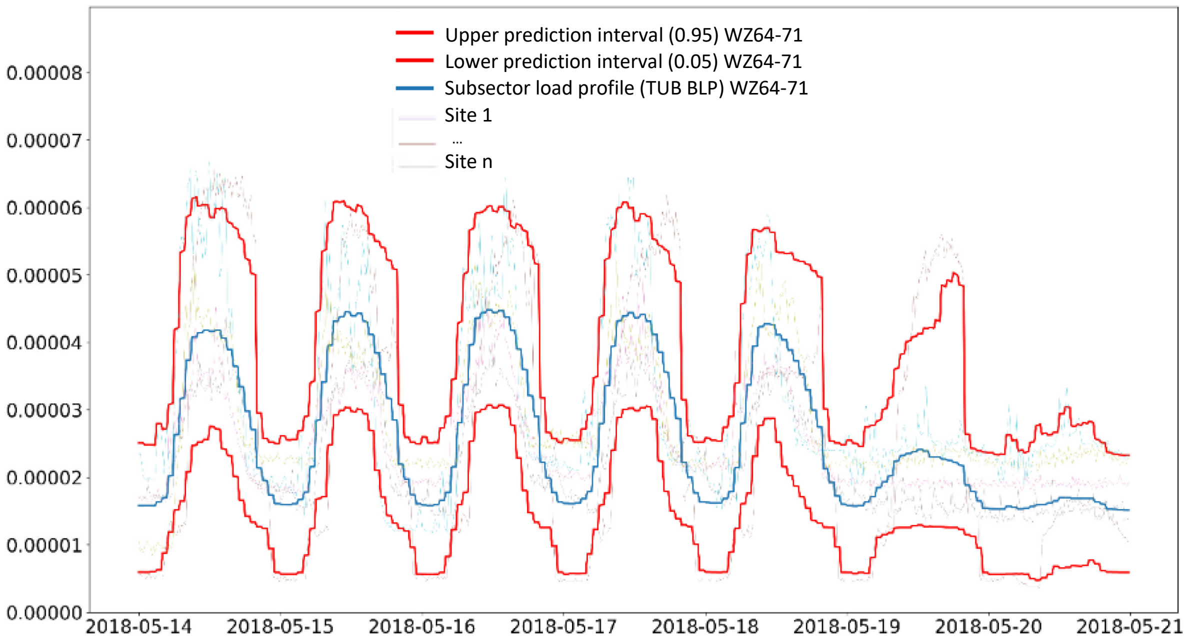

Figure 33: Predicted subsector load profile (blue) and corresponding prediction intervals of the quantile regression (red) for offices *(WZ64-71). Diagram by author, published in Gotzens et al. (2020, p. 114)*

Table 14: Performance measures for the offices *subsector load profile (WZ64-71) using cross validation*

WZ	**Subsector**	**Number of data sets**	**MAPE [%]**		**R^2_{adj}**		**nRMSE [%]**	
			indiv.	**subsector**	**Indiv.**	**subsector**	**Indiv.**	**subsector**
64-71	*Offices*	13	16.6	31.5	0.80	0.57	7.8	12.1

Table 14 summarizes the performance measures for the subsector load profile of offices. The individual values ("indiv.") denote the averaged regression performance measures for individual locations; the subsector values reflect the averaged regression performance of the whole subsector load profile compared to all individual locations. A total of 13 data sets were used to create the subsector load profile, which is associated with limited representativeness with regard to the relevance of offices. The overall model performance is reasonable, with an average MAPE of 31 % and an average R^2_{adj} of 57 %. In contrast, the forecast quality of individual locations is significantly better than that of the subsector, indicating a distinct heterogeneity of the subsector and data sets considered. The interquantile ranges in Figure 33 also reveal significant heterogeneity.

5.1.1.2 Subsector Load Profiles with Pronounced Weekly Structure

The subsector load profile for *manufacture of motor vehicles* (WZ29) is characterized by a typical weekly structure, similar to WZ 11, 22 and 28, for instance. Figure 34 illustrates patterns for an average week of *manufacture of motor vehicles*. Over the working days, the load periodically fluctuates at a high level, while a significant drop in load can be observed from Saturday afternoon. On Sunday evening, the late shift for the new week begins. A diurnal structure is only pronounced slightly during the week, which is an indicator for a three-shift operation. On weekdays, the night shift runs at a reduced level. During the day, recurring shift changes and breaks are also visible.

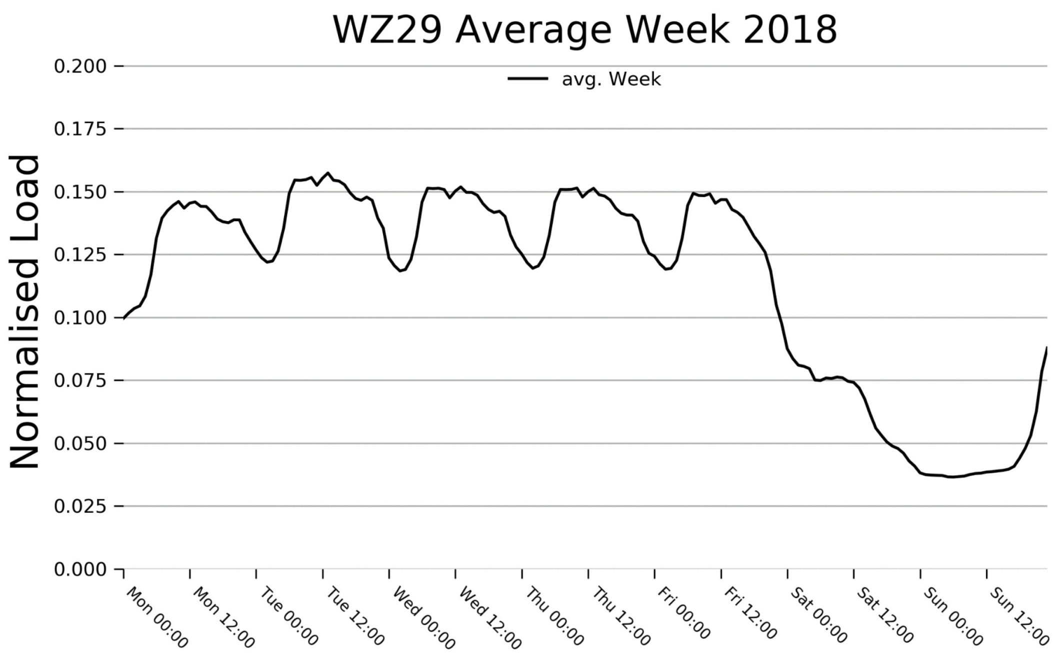

Figure 34: Average weekly subsector load profile for manufacture of motor vehicles *(WZ29). Diagram by author, published in Gotzens et al. (2020, p. 115)*

Seasonal differences in load structure are very small, as Figure 35 (left side) suggests. Summer time shows a higher power demand evenly distributed throughout the day, which could go back to ventilation and air conditioning loads. Looking at the working days (Figure 35, right), a reduced load level during the night shift (about 80 % of the daytime load level) can be observed. On Saturdays, the load drops continuously after the early shift from approx. 14h. The working week begins on Sunday evenings between 21h – 22h.

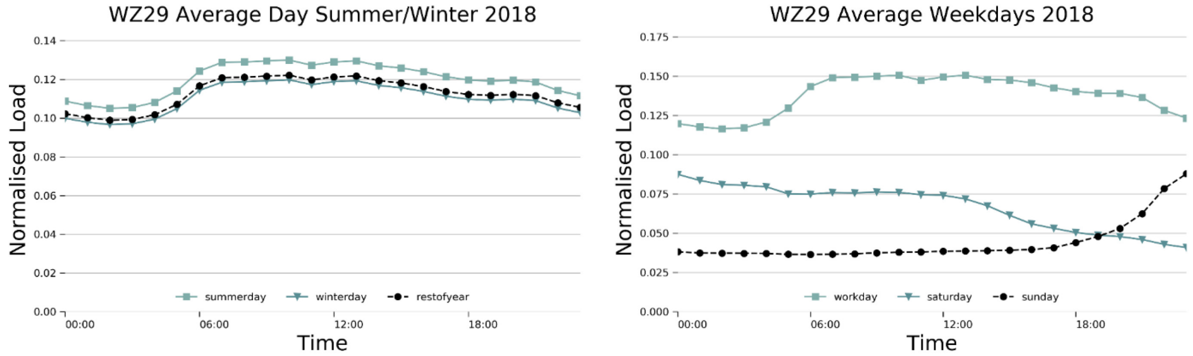

Figure 35: Average daily subsector load profiles for manufacture of motor vehicles *(WZ29), left different seasonal periods (summer, winter, transition), right different type days (working day, Saturday, Sunday). Diagram by author, published in Gotzens et al. (2020, p. 116)*

As shown in Figure 36, the interquantile range of the prediction intervals describes a relatively large variance of the occurring loads, which are more pronounced over the working days (day and night) than on weekends.

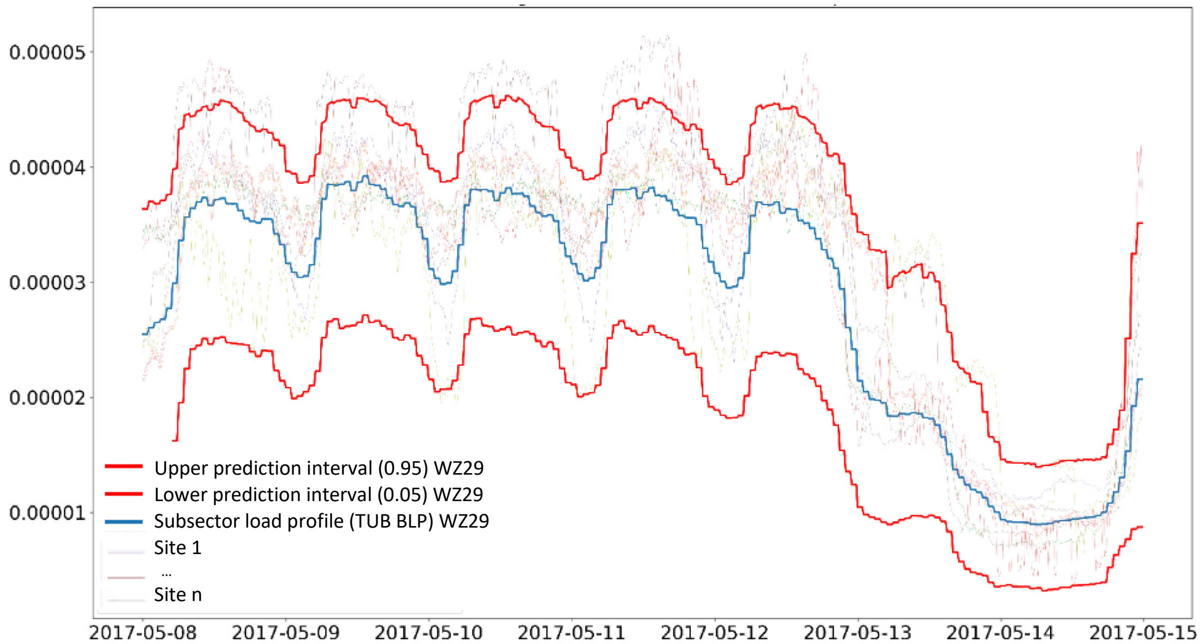

Figure 36: *Predicted subsector load profile (blue) and associated prediction intervals of the quantile regression (red) for* manufacture of motor vehicles *(WZ29). Diagram by author, published in Gotzens et al. (2020, p. 116)*

Table 15: Performance measures for the subsector load profile manufacture of motor vehicles *(WZ29) using cross validation*

WZ	Subsector	Number of data sets	MAPE [%]		R^2_{adj}		nRMSE [%]	
			indiv.	subsector	indiv.	subsector	indiv.	subsector
29	*Manufacture of motor vehicles*	21	34.8	52.3	0.76	0.69	11.9	13.9

Table 15 summarizes the performance measures for the subsector load profile of *manufacture of motor vehicles*. A total of 21 data sets were used to create the subsector load profile, which represents a comparably big database. The model performance of 69 % for R²adj. is regarded as good, particularly as for the distinct load variance that can be identified in interquantile ranges (Figure 36). In contrast, the MAPE values for individual sites as well as the whole subsector are only reasonable, which essentially goes back to load variance (and the associated difficulty in forecasting) and a certain heterogeneity of the subsector. The predictability of the subsector is therefore subject to limitations.

5.1.1.3 Subsector Load Profiles Without a Pronounced Structure

As Figure 37 illustrates, the subsector load profile for *manufacture of paper* (WZ 17) shows a very balanced and hardly fluctuating load behaviour over an average week, which essentially represents the continuous operation of an industrial paper production. Slight daily fluctuations can be seen in the load profile on weekdays, which goes back to the office-based share of electricity demand. The significant fluctuations and load dips that can be observed in measured load profile data for the subsector are hardly reflected in the representation of the average week, which underlines the stochastic nature of fluctuations. The regression analysis shows, however, that these fluctuations can very well have a significant influence in the direction of averaging (and thus reducing) the subsector load profile. In order to avoid this averaging of the load level due to fluctuations and to be able to map a representative load profile, the load fluctuations were considered in the model as endogenous variable for production schedules (cf. chapter 4.2.1.1). The subsector load profile created does not show any pronounced stochastic fluctuations; the company holidays (and associated production schedules) of the developed subsector load profile were set to the period from August, 2nd to August, 14th and from December´, 22nd to January, 2nd.

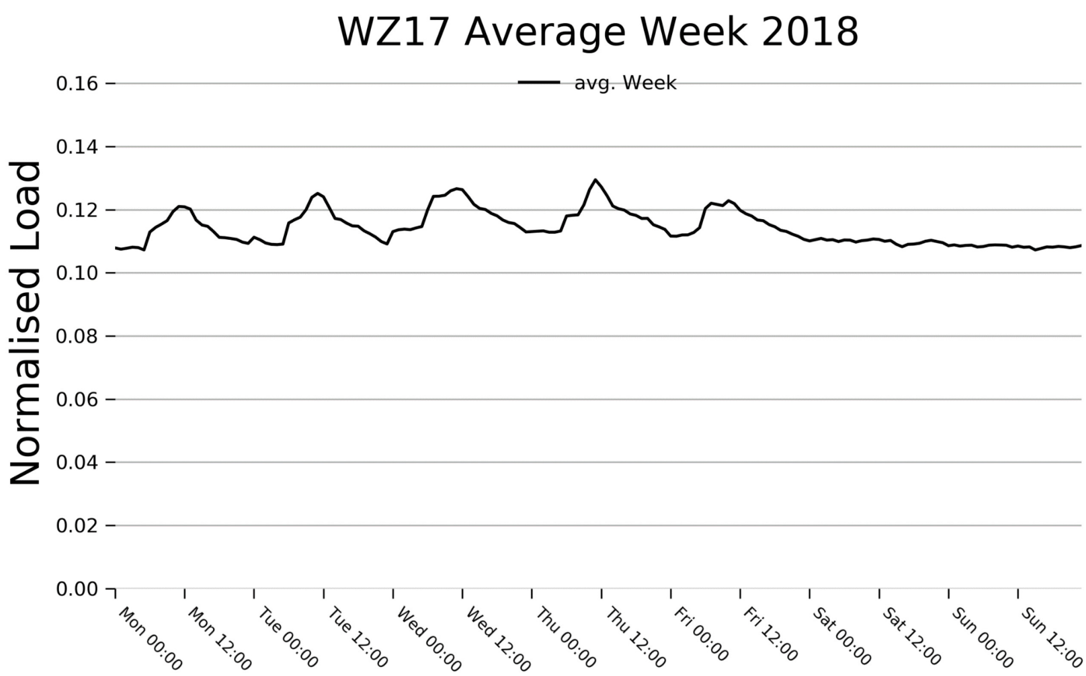

Figure 37: Average weekly subsector load profile for manufacture of paper *(WZ 17). Diagram by author, published in Gotzens et al. (2020, p. 118)*

As Figure 38 (left) suggests, seasonal load fluctuations in paper production are also very weak. The transition period is associated with slightly higher loads. The profile of the type days shows a balanced load profile over the course of the day. The load level on weekdays is slightly higher (10 %) than on weekend days (Figure 5.16 (right)), which might go back to administration and office-like electricity demands.

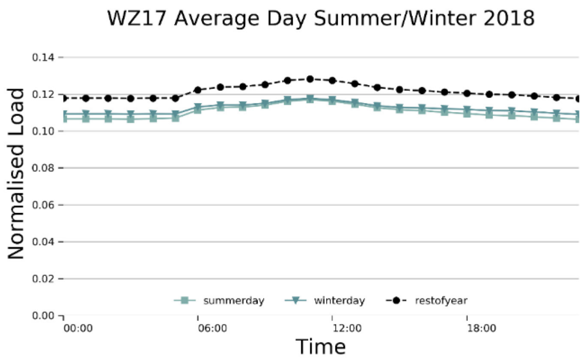

Figure 38: Average daily subsector load profiles for manufacture of paper *(WZ 17). On the left different seasons (summer, winter, transition), on the right different type days (working day, Saturday, Sunday). Diagram by author, published in Gotzens et al. (2020, p. 118)*

When looking at the quantiles (Figure 39), significant fluctuations can be seen. These fluctuations do not have a recurring structure and are therefore not reflected in the above average load profiles. The pronounced interquartile range stresses the wide fluctuation range of the loads in the *manufacture of paper*.

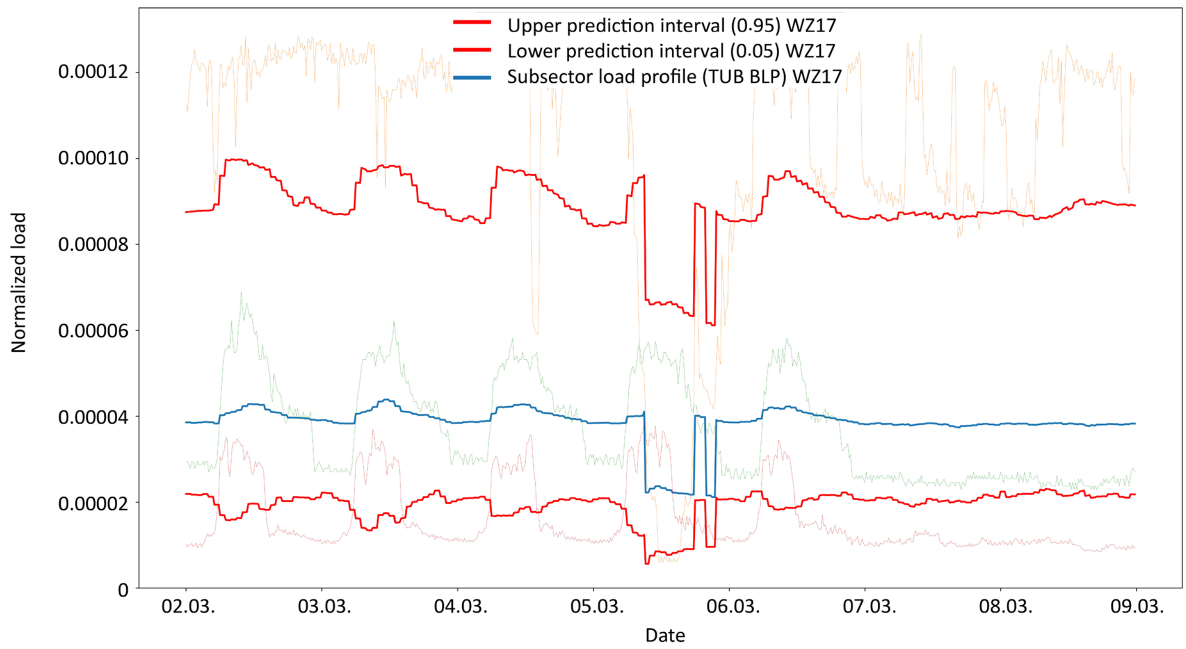

Figure 39: Predicted subsector load profile (blue) and associated prediction intervals of the quantile regression (red) for paper manufacturing *(WZ 17). Diagram by author, published in Gotzens et al. (2020, p. 119)*

Table 16: Performance measures of the subsector load profile of paper manufacturing *(WZ 17) using cross validation*

WZ	Subsector	Number of data sets	MAPE [%]		R^2_{adj}		nRMSE [%]	
			indiv.	subsector	indiv.	subsector	indiv.	subsector
17	*Paper manufacturing*	12	16.5	21.1	77.3	62.0	10.4	13.1

Table 16 summarises the performance measures of the subsector load profile for paper manufacturing. The good model performance observed despite the high fluctuation range is largely associated to utilizing the endogenous variable for production schedules (cf. chapter 4.2.1.1). In general, a largely evenly distributed load forecast seems to be a good approximation for the paper manufacturing industry.

5.1.2. Benchmarking of Model Performance Using Artificial Neural Networks-based Regression and VDEW Standard Load Profiles

In the following chapter, performance measures of the ANN model approaches will be introduced and compared to the above results using multiple regression. The comparison conducted by Milanzi (2020) allows to evaluate the robustness of both techniques as well as their performance. In addition, the performance of multiple regression -based subsector load profiles will be compared to VDEW SLP, as conducted by Rüdt (2020) and outlined in chapter 4.2.1.5.

5.1.2.1 Benchmarking of Model Performance Using Artificial Neural Networks-based Regression

As mentioned in chapter 4.2.3, the comparison of ANN to multiple regression is carried out for the following four subsectors:

- *offices* (WZ 64-71)
- *public administration* (WZ 84)
- *human health activities* (WZ 86)
- *residential care activities* (WZ 87)

For these four subsectors, Table 17 depicts the MAPE of the modelling of individual sites (indiv.) as well as the whole subsector for the ANN approach (chapter 4.2.3) and the multiple regression (chapter 4.2.1). Also, the performance of VDEW SLP are given with regards to underlying metered load profiles.

Table 17: Comparison of performance measures for selected subsectors using ANN, multiple regression and VDEW SLP. Adapted from Milanzi (2020, p. 72)

WZ	Subsector | MAPE [%]	ANN		Multiple Reg.		VDEW SLP
		indiv.	subsector	indiv.	subsector	
64-71	*Offices*	16.8	28.0	19.1	31.0	70.7
84	*Public administration*	12.4	20.0	14.8	19.7	63.6
86	*Human health activities*	5.3	6.3	6.4	7.0	13.6
87	*Residential care activities*	11.3	19.1	12.2	18.7	59.8

As can be seen, the ANN indeed exhibits a slightly better performance in the modelling of individual sites as compared to the multiple regression. The differences between both techniques range from a MAPE improvement from 0.7 % (Human health activities) up to 3.0 % (Public administration). These improvements are noticeable but modest and are in line with expectations from the literature (Debnath and Mourshed, 2018, p. 310): ANN are a capable and flexible forecasting technique. However, the performance differences between ANN and multiple regression in the modelling of subsector load profiles (Table 17) are even smaller and in the range of 0-3 %. For public administration and residential care activities, multiple regression is even slightly better performing (both around 0.2-0.4 %). According to the author, two implications can be drawn from this observation:

i. multiple regression as well as ANN appear to have captured most characteristic patterns within the subsectors analysed as they perform very similarly.
ii. the differences between modelling individual sites and the subsector represent inherent heterogeneity within subsectors which can only be captured to a limited extent. As an average model, the subsector load profile is naturally subject to deviations driven by a heterogenic database. The prediction can only be as good as the structure is predictable and not random.

The second implication was already partly verified by Milanzi, who looked at the standard deviation of underlying metered load profiles per subsector (cf. Table 18). It was found that a higher standard deviation of underlying metered load profiles goes along with lower model performances. In a separate analysis, Milanzi could also confirm the model configuration chosen in chapter 4.2.1.1 of this thesis. Applying two subsets for the modelling, the influence of weather variables, i.e. temperature and solar radiation, was analysed in Table 18.

Table 18: Performance measures of the ANN model sub-sets for selected subsectors. Set B includes weather variables. The variance of all metered load profiles within a subsector is used as an indication its heterogeneity. Table adapted from Milanzi (2020, p. 65)

WZ	Subsector	MAPE [%]		Number of data sets	Variance (σ^2)
		Set A	Set B		
47	Retail – food	14.8	14.2	33	100
47	Retail – non-food	56.5	55.9	14	664
64-71	Offices	34.0	33.0	9	704
84	Public administration	20.7	20.0	10	304
85	Education – nurseries	64.0	62.1	5	1502
85	Education – schools	36.3	33.4	14	660
86	Human health activities	7.5	6.3	2	23
87	Residential care activities	19.9	19.1	6	559

According to Milanzi (2020, p. 65), set B (including weather variables) outperforms set A (excluding weather variables) for 84 out of 93 individual consumers. On average, the MAPE is 5.3 % better for set B, but weather dependency varies significantly among subsectors. These findings underline the conclusion of chapter 4.2.1.1: weather variables provide explanatory value to the models. It was also found that the residuals of the ANN model prediction ($y_i - \hat{y}_i$, formula 2, page 27) are unbiased and exhibit an approximated normal distribution for the majority of subsectors considered. Structural errors of the model are thus unlikely. Further, a strong relation between forecast errors and exceptional values for temperatures or solar radiation has not been identified. In general, however, the load is overestimated on holidays, while it is slightly underestimated on average for working days. According to Milanzi (2020, p. 67), this might go back to holidays with special opening hours increasing on average the expected demand for all holidays.

5.1.2.2 Benchmarking of Model Performance Using VDEW Standard Load Profiles

As depicted by Table 17 (p. 77) in the previous chapter, the SLP for all four subsectors show large deviations in the modelling of underlying metered load profiles. This is a strong indication in favour of the initial hypothesis that SLP are inaccurate to model selected subsectoral load patterns. Rüdt (2020) did a structured comparison with literature-based load profiles, which is outlined in chapter 4.2.1.5. In the following, only the subsector of *offices* (WZ64-71) will be presented in detail due to its comparably high electricity demand and relevance (appendix A.1.3: Table 27). Figure 40 (left) shows the average residual profile ($y_i - \hat{y}_i$, formula 2, page 27) of the G1 SLP in the modelling of metered office sites. Positive residuals represent the SLP's underestimation and negative residuals the SLP's overestimation of the real load. As can be seen, the G1 SLP exhibits a strong overestimation of electrical load during the day between 8:00 and 12:00, and a significant overestimation in the afternoon hours. In contrast, the G1 SLP exhibits a slight underestimation of electricity demand in the night and early morning hours. Notably, the structure of these deviations is similar to deviations identified in differential balancing group time series (cf. chapter 2.3.2). Furthermore, it can be observed that the variance of the forecast deviations (i.e. length of the boxes and antennas) seems to increase with the level of the forecast load, which is a hint for heteroscedastic data.

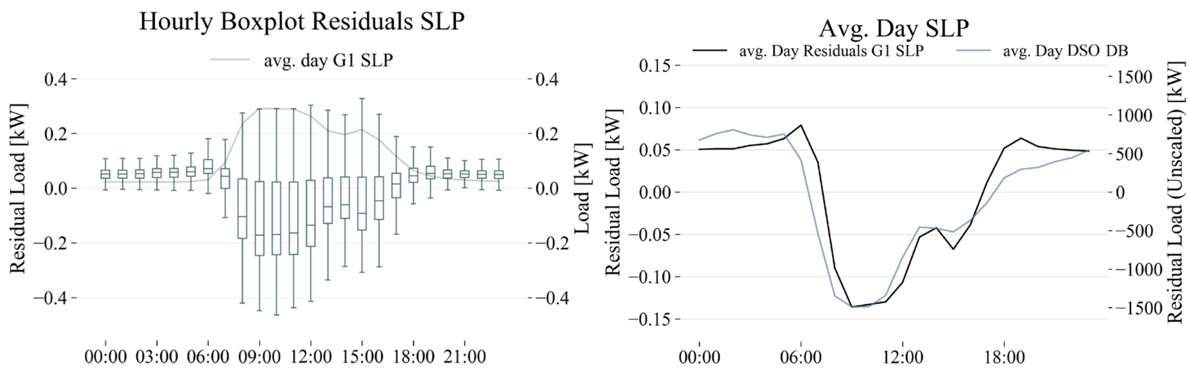

Figure 40: Left: boxplot diagram representing hourly residuals (deviations) using the G1 SLP to model metered load profiles. Right: Comparison of these hourly average residuals (deviations) compared with the average differential balancing group time series (DSO DB) of Energienetze Berlin. Figures generated by Rüdt (2020, p. 23).

If the average daily residuals of the G1 SLP are plotted against the average daily deviations of a differential balancing group time series of the associated DSO (Figure 40, right), the structural similarities between the two residual profiles are clearly noticeable. Considering the relevance of the G1 profile in the modelling of smaller consumers, the above identified G1 deviation is likely to significantly propagate to DSO model deviations, as depicted in Figure 40 (right).

Figure 41 captures the comparison of multiple profiles: it illustrates an average week of real metered load data (light grey), the subsector load profiles (TUB BLP, red), the De Monfort Profile (blue) as well as the G1 SLP (green). When compared with the De Monfort Profile from the UK, the TUB BLP exhibits very similar structures. The most significant difference between the two profiles seems to be on Saturdays, where the TUB BLP indicates a higher activity level. In contrast, the G1 SLP is associated with large deviations: the electricity demand is significantly overestimated during the day, while significantly underestimated during night time – similar to what has been discussed for the above Figure 40 (right) as well as in the literature (chapter 2.3.2, Figure 5). As will be discussed in the next chapter, however, the G1 SLP is not the only cause for deviations: depicting residential consumers, the H0 SLP (VDEW) has a similar structure to the G1 SLP but is far more relevant. It is thus likely, that the above deviations in the differential balancing group time series (Figure 40) do not solely result from G1 inaccuracies. In both cases, structural deviations most likely stem from two developments in particular:

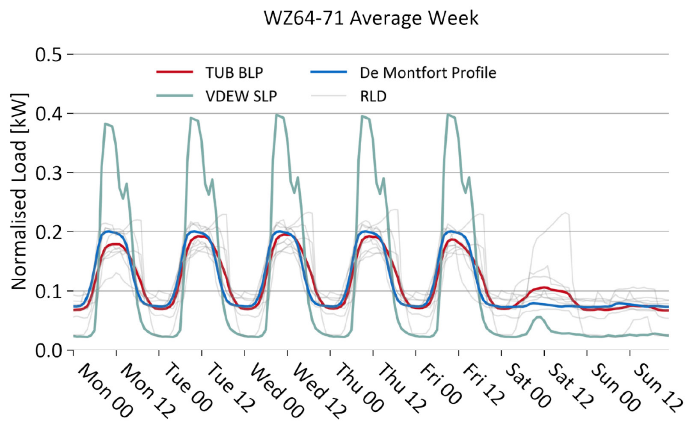

Figure 41: Comparison of 13 real office load profiles (RLD, grey) with the VDEW G1-SLP, the corresponding subsector load profiles (BLP) and the De Montfort Profile. Illustration of an average week. Figure published in Seim et al. (2021).

- an increased base load, driven by a higher number of applications (e.g. ICT, air conditioning) in offices and households (BDEW, 2012, p. 1; co2online, 2021, p. 2). This might particularly explain the increased load levels at night time.
- a reduced peak load due to a higher efficiency of used applications (Umweltbundesamt, 2020).

A quantitative assessment by Rykala (2018) concludes that in a selected DSO grid area the influence of the H0 profile on the DSO differential balancing group can be estimated at about 44 %, whereas the

G1 profile is estimated to have the second largest influence, with a share of 19 %. Reducing these SLP deviations by applying more accurate load profiles will improve the overall DSO model forecast.

In his further comparison, Rüdt clustered remaining subsectors according to how accurate they can be modelled using VDEW SLP. Cluster 1 presents subsectors which are associated with large deviations when modelled using VDEW SLP. Even worse, cluster 2 captures those subsectors, to which VDEW SLP seem to be falsely allocated to. Cluster 3 is associated with decent modelling results for both VDEW SLP as well as TUB BLP, and on the other hand, cluster 4 is associated with mediocre results for both VDEW SLP as well as TUB BLP. Table 19 presents identified clusters. The exact performance measures of VDEW SLP to model real metered load data of selected subsectors is summarised in appendix A.2.4: Table 43.

Table 19: Clustering of subsectors according to the performance of VDEW SLP. Adapted from Rüdt (2020, p. 33).

Cluster	Description	Subsector
1	Strong over- and underestimation by VDEW SLP	WZ64-71, WZ72, WZ84, WZ85, WZ93
2	False allocation of VDEW SLP	WZ37, WZ87, WZ88, WZ94
3	VDEW SLP and TUB BLP exhibit similar good modelling results	WZ52, WZ86
4	VDEW SLP and TUB BLP exhibit similar poor modelling results	WZ38

In his bachelor thesis, Rüdt (2020) concluded that indeed, TUB BLP are a suitable tool for the electricity demand modelling. Compared to VDEW SLP, they hardly show any significant forecast deviations and enable a more detailed (and thus accurate) depiction of small consumers' load profiles.

In the next chapter, the application of all load profiles (VDEW SLP, TUB BLP) in the DemandRegio *disaggregator* tool will be validated in the *SLP only* as well as the *BLP application* approach (cf. chapter 4.3). Comparing both approaches allows to assess the overall improvement potential of TUB BLP to replace seemingly inaccurate VDEW SLP.

5.2. Evaluation of Applied Subsector Load Profiles

The evaluation of the temporal distribution of the model results is not trivial due to the limited data availability. In addition to the validation of individual profiles sketched in chapters 5.1.1 (cross validation) and 5.1.2 (benchmarking), created subsector load profiles can be evaluated as a whole in the mapping of aggregated regional units. Using the *disaggregator* tool, the smallest regional units are counties. However, real metered load profiles on the county level only exist in exceptional cases, as described in chapter 4.1.2. The essential database for such a validation are the DSO load profiles, which are partially available due to the publication obligations according to § 17 StromNZV. In the few cases, where county areas coincide with DSO grid areas and the DSO load profiles are accessible, the *disaggregator* model output can be validated. This validation was performed for the available data sets of 11 DSOs over several years. In addition, the validation was carried out for the territory of the whole of Germany, using ENTSO-E cumulative loads.

A comparison between subsector load profiles and VDEW SLP enables to assess the added value of newly generated subsector load profiles which are not only up-to-date but also use a finer subsector granularity. As described in chapter 4.3, the *disaggregator* model results will be presented in a *SLP only* (using SLP and generic load profiles) as well as in a *BLP application* approach (using TUB BLP, where available) and compared with selected DSO and ENTSO-E load profiles.

In the following chapter, only the *profile* of both model approaches is compared with real load data. The electricity demand *level* is not considered. Therefore, model results and real data are shown in normalized form. The comparison with the ENTSO-E cumulative load is discussed in detail; the evaluation with DSO loads is only shown in condensed form.

5.2.1. Model Evaluation Using DSO Loads

The model results of the *SLP only* approach and the *BLP application* approach were validated using 22 datasets of 11 DSO. The *disaggregator*'s performance of both approaches to model respective DSO loads are shown in Table 20.

Table 20: Performance measures of both model approaches compared to the total load of selected DSOs, adjusted from Seim et al. (2021b).

Validation basis	County (AGS)	Year	*SLP only*		*BLP application*	
			R^2	MAPE [%]	R^2	MAPE [%]
SÜC Energie u. H2O GmbH Coburg	09463	2017	*0.64*	*22.2*	*0.73*	*13.8*
Stadtwerke Straubing	09263	2017	*0.58*	*18.9*	*0.61*	*15.5*
		2018	*0.74*	*15.0*	*0.81*	*10.8*
Netz Lübeck GmbH	01003	2017	*0.87*	*14.3*	*0.88*	*10.1*
		2019	*0.83*	*15.2*	*0.88*	*10.2*
SWB Bielefeld	05711	2017	*0.77*	*14.0*	*0.81*	*11.4*
		2018	*0.76*	*14.5*	*0.80*	*11.5*
Stadtwerke Bochum	05911	2018	*0.78*	*13.1*	*0.79*	*9.7*
		2019	*0.79*	*13.2*	*0.81*	*9.3*
DO-Netze Dortmund	05913	2017	*0.76*	*16.2*	*0.78*	*10.7*
		2019	*0.77*	*16.2*	*0.79*	*10.4*
EVB Eisenach	16056	2017	*0.83*	*14.2*	*0.86*	*10.8*
		2019	*0.82*	*13.8*	*0.85*	*10.5*
SWE Netz Erfurt	16051	2017	*0.38*	*27.3*	*0.35*	*20.6*
		2019	*0.32*	*28.2*	*0.30*	*21.9*
KNS/TWL Ludwigshafen am Rhein	07314	2017	*0.83*	*21.6*	*0.83*	*22.6*
		2019	*0.84*	*19.7*	*0.86*	*20.7*
WSW Wuppertal	05124	2017	*0.74*	*14.3*	*0.75*	*11.7*
		2019	*0.76*	*14.1*	*0.76*	*11.4*
SWK Stadtwerke Kaiserslautern	07312	2017	0.76	13.3	0.79	9.3
		2018	0.74	13.6	0.76	9.8
		2019	0.73	14.3	0.75	10.1
	Average value		***0.73***	***16.7 %***	***0.75***	***12.8 %***

It can be seen that the *disaggregator* model results already show a good approximation of the load profile for different counties or DSO grid areas. Already in the *SLP only* approach, the average coefficient of determination is R^2 = 72.8 % with an average MAPE of 16.7 %. This already good result is further improved by replacing individual profiles (standard load profiles, operating shift profiles) with newly developed TUB BLP in the *BLP application* approach, improving the coefficient of determination by more than 2 % (to 75.1 %) and reducing the MAPE by nearly 4 %. Only for SWE Netz Erfurt and KNS/TWL Ludwigshafen, the model exhibits a slightly higher performance using SLP, indicating structural specifics in these two DSO grid areas. In any case, SWE Netz Erfurt performs rather poorly in both approaches. In the majority of cases, however, the use of the TUB BLP yields significant improvements.

In order to further analyse the structural differences between model results and real loads, the following chapter will discuss in more detail the comparison with the ENTSO-E cumulative loads.

5.2.2. Analysis of Structural Model Deviations and Evaluation Using ENTSO-E Loads

In analogy to the previous comparison with selected DSO loads, Table 21 presents the performance measures of modelling ENTSO-E loads. Afterwards, the structural deviations in Figure 25 to Figure 31 are analysed in more detail to identify possible reasons for these deviations and future research needs. The following chapter has been published in a similar fashion in the DemandRegio final report (Gotzens et al., 2020, chapter 5.6.3.2); however, the profiles and validation base used have been updated and improved, hence slightly deviating results.

Table 21: Performance measures of both model approaches compared to the total load of ENTSO-E

Validation basis	**Year**	***SLP only***		***BLP application***	
		R^2 [%]	**MAPE [%]**	**R^2 [%]**	**MAPE [%]**
ENTSO-E load	2015	*0.80*	*14.0*	*0.83*	*8.9*
	2016	*0.79*	*14.1*	*0.82*	*8.8*
	2017	*0.77*	*14.0*	*0.81*	*9.2*
	2018	*0.79*	*14.1*	*0.82*	*9.2*
	2019	*0.77*	*14.4*	*0.80*	*9.5*
	Average value	***0.79***	***14.1 %***	***0.82***	***9.1 %***

A comparison with the ENTSO-E cumulative load also demonstrates the high performance of the *disaggregator* tool, both in the *SLP only* and the *BLP application* approach. The use of newly developed TUB BLP improves the forecast more distinctly as compared to the DSO analysis of the previous chapter: replacing SLP and generic profiles by TUB BLP, where possible, the coefficient of performance (R^2) improves by about 3 % and average errors (MAPE) show an improvement of 5 %. With an overall model performance of MAPE 9.1 %, the model can be regarded as 'highly accurate' according to Lewis's benchmark (chapter 2.5.5).

In the following, the question arises as to what the structural deviations between model and real data look like and whether the structural deviations of the VDEW SLP could be reduced. Figure 42 first compares the average daily profile of the model output (both approaches) with the real data from ENTSO-E. As shown in Figure 42, the structural deviations identified in chapter 2.3.2 continue to exist even after a large number of VDEW SLP have been replaced by newly developed TUB BLP. The *disaggregator* model result shows an underestimation of demand during night-time and an overestimation during the day, even in the *BLP application* approach (red). However, these structural deviations have been noticeably reduced compared to the *SLP only* approach (blue, using only SLP), which is also reflected in the improved performance of the above described Table 20 and Table 21.

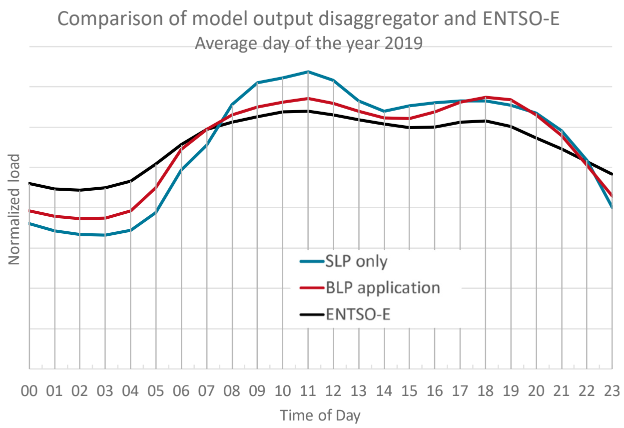

Figure 42: Validation of the model output of the SLP only *approach (blue) and the* BLP application *approach (red) using the ENTSO-E cumulative load (black), display of the normalized load of an average day in 2018, illustration by author.*

Figure 43 shows the comparison of the model results with the real data grouped by type days. It can be seen that the above-mentioned structural deviations during the middle of the day are mainly due to deviations on working days (MAPE 9.2 %) and Saturdays (MAPE 10.6 %), whereas the structural underestimation of night hours can be seen across all type days. When using the BLP, the *BLP application* approach improves the representation of working days in particular. Saturdays are improved over the night time and morning hours, while slightly worsened during the daytime. Sundays, on the other hand, are represented very similarly to the *SLP only* approach.

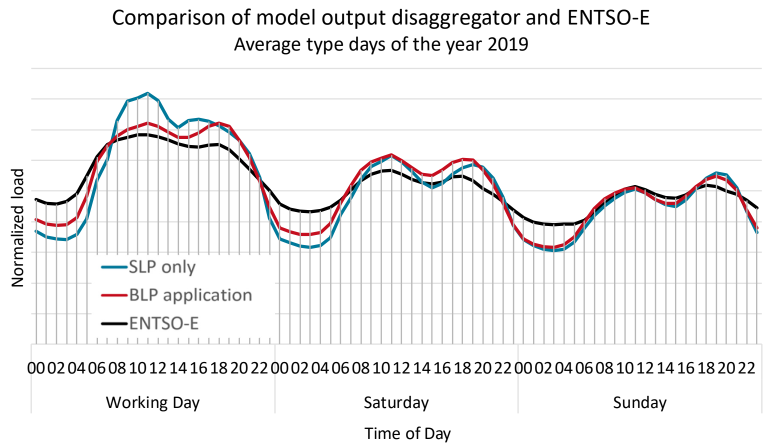

Figure 43: Validation of the model output of the SLP only *approach (blue) and the* BLP application *approach (red) using the ENTSO-E cumulative load (black), representation of the normalized load of an average type day (working day, Saturday, Sunday) in 2018, illustration by author.*

Figure 44 shows seasonal differences for the forecast quality of both approaches. The *BLP application* approach represents an improvement for all seasons. The forecast quality within the seasons does not differ significantly, with MAPE values of 9.2 % (summer), 9.6 % (transition) and 9.7 % (winter). In winter time, particularly the base-load appears under-estimated. Seasonal fluctuations appear slightly underestimated in both model approaches, as the ENTSO-E load appears to be slightly more variant across all seasons. At the same time, however, the ENTSO-E load seems more balanced in daily fluctuations which get overestimated by both approaches.

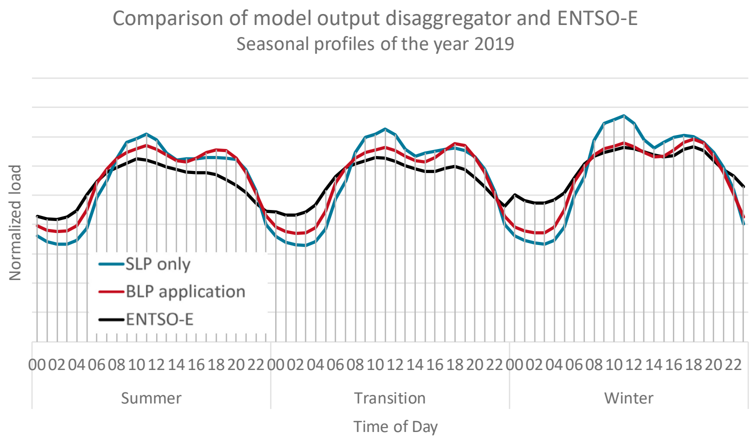

Figure 44: Validation of the model output of the SLP only *approach (blue) and the* BLP application *approach (red) using the ENTSO-E cumulative load (black), representation of the normalized load of an average day of the seasons summer, transition and winter of 2018, illustration by author.*

In analogy to the heatmap shown in chapter 2.3.2, Figure 45 shows the residuals of the *SLP only* approach (left) and the *BLP application* model approach (right) to the ENSTO-E cumulative load for 2018. Using a so-called heatmap, further structural deviations can be identified in the course of the day and year. In both approaches, the heatmaps underline the model's tendency to overestimate daytime demands and underestimate night-time demands. The *SLP only* approach exhibits a particular overestimation from morning to midday on working days, which was reduced significantly in the *BLP application* approach. Moreover, the comparatively low deviations in summer time are shown, especially in the *BLP application* approach. As a remarkable feature, clear vertical lines can be seen between 6 and 8 a.m. and 11 p.m. These lines presumably go back to abrupt transitions of generic load profiles, which were used to model industrial subsectors if no TUB BLP were available.

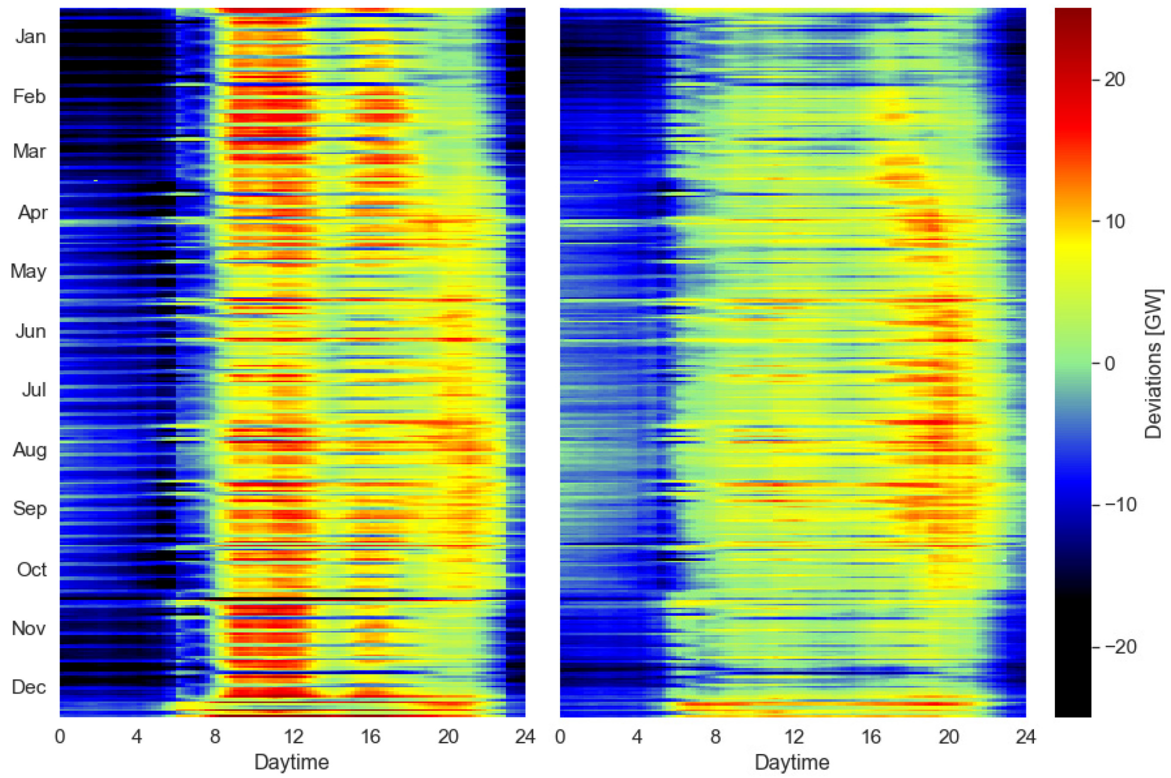

Figure 45: Residuals of the DemandRegio disaggregator *tool forecasting the ENSTO-E load of 2019, using the* SLP only *approach (left) and the* BLP application *approach (right).*

Finally, the model results were compared with the ENTSO-E cumulative load for validation in the form of their annual load duration curve. Figure 46 illustrates the comparison and underlines the upward and downward deviations identified above. The *disaggregator* model results show a slightly higher load in almost half of the annual hours compared to the real data. In the other half of the year, the model results show a slightly lower load than the real data. Again, the ENTSO-E load appears more balanced over the year as a whole.

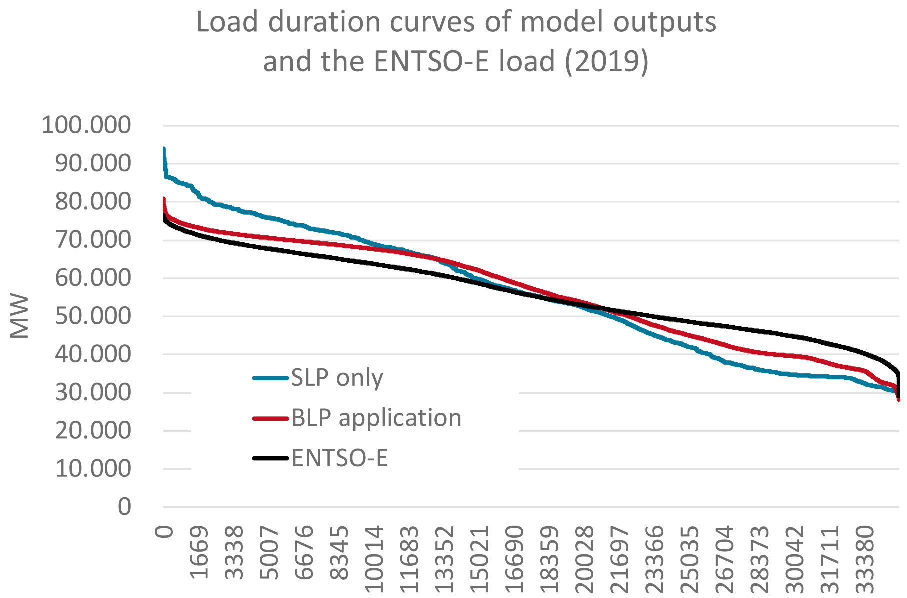

Figure 46: Load duration curves of the model results of the SLP only *approach (blue) and the* BLP application *approach (red) compared with the load duration curve of the ENTSO-E cumulative load (black) of 2018. Diagram by author.*

5.2.3. Comparison of Structural Model Deviations with the ZVE Residential Load Profile

In the following chapter, a potential reason for the structural deviations of the *disaggregator* model (*BLP application* approach) shall be identified. For this purpose, a look at the ZVE load profile for residential consumers is useful; on the one hand, because this profile alone makes up on average 25 % of the total electricity demand; on the other hand, because the validation basis of the ZVE load profile was very limited due to data availability. Therefore, the structural deviations of the model results identified in the previous chapter are compared to the ZVE load profile. The following chapter was published in a similar fashion in Gotzens et al. (2020, chapter 5.6.3.3); figures have been updated.

In this in-depth analysis, the residential load profile for the ENTSO-E region is mapped and compared to the hourly Mean Percentage Error (MPE) of the *disaggregator* model output (*BLP application* approach). The Mean Percentage Error is calculated in the same way as the MAPE (see formula 4-20), but without the dashes, according to the following formula 22:

$$MPE = \sum_{i=1}^{n} \frac{y_i - \widehat{y_i}}{y_i} \qquad (22)$$

In analogy to the previous chapter 5.2.2, the ZVE residential load profile is compared with the MPE in the following two ways:

- illustration of average days in the seasons summer, transition and winter (Figure 47)
- illustration of average type days (weekday, Saturday, Sunday) (Figure 48)

As can be seen from the seasonal analysis in Figure 47, the structural deviations of the model results of the *BLP application* approach show strong similarities with the shape of the ZVE load profile. The zero-line of the error value (MPE) serves almost as a mirror plane, in that particular scaling. Throughout all seasons, the positive MPE indicates that the *disaggregator* model underestimates the real power consumption, especially at night - at a time of day when the ZVE load profile inversely shows a very low load. Similarly, the error structure during the day has a similar shape as the characteristics of the ZVE load profile. The similarity between the ZVE load profile and structural *disaggregator* model deviations seems to be particularly pronounced for the summer and transition periods. This similarity of shape is only an *indication* that observed model deviations in the *disaggregator* actually stem from structural deviations in the ZVE load profile, it is not a proof. An isolated validation of individual profiles is only possible on the basis of a larger amount of real data, as happened in the case of individual subsector load profiles in the context of cross-validation (see chapter 4.2.1.4). However, Rykala (2018) also found indications in his master's thesis, using the example of a selected DSO, that the VDEW residential load profile (H0 SLP) is responsible for strong deviations in the grid operator's differential balance.

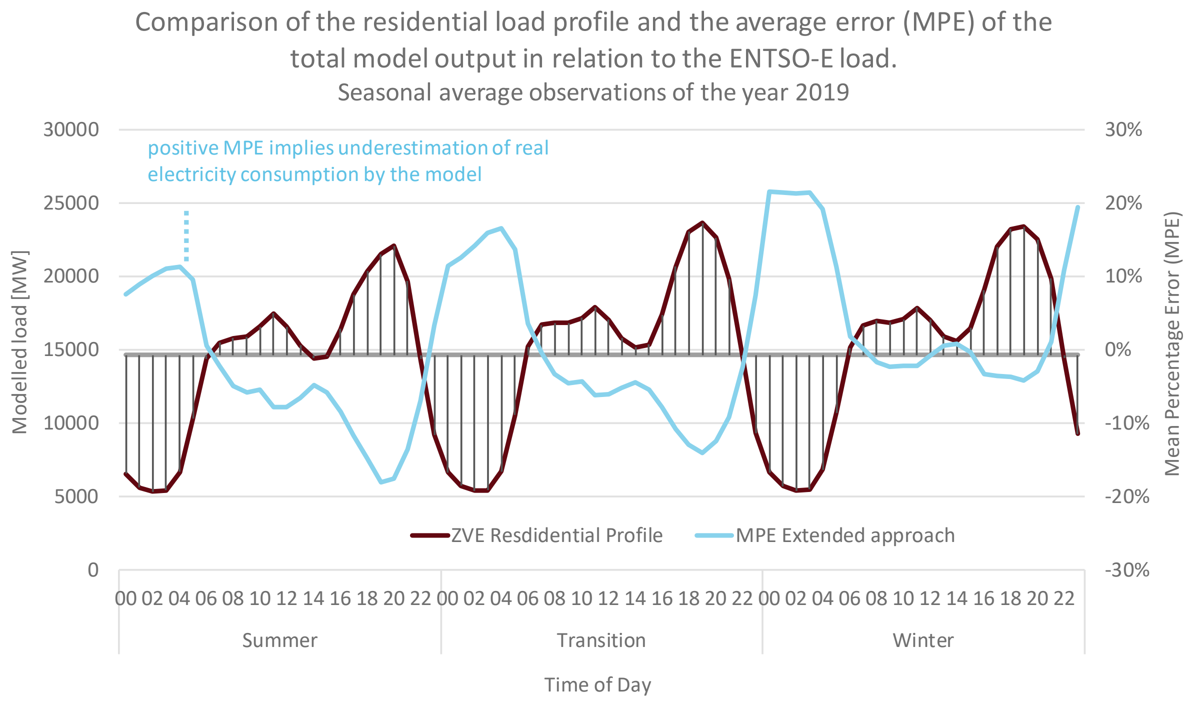

Figure 47: Comparison of the ZVE residential load profile (red) to structural deviations (Mean Percentage Error, MPE) of the BLP application *approach (blue) modelling the ENTSO-E total load. Illustration of seasonal averages for the year 2019. Diagram by author.*

Figure 48 also shows clear similarities between structural model deviations and the ZVE load profile across all type days. However, especially the night time across all type days exhibits distinct similarities as well as the day times of working days and Saturdays. Only on Sundays during the day the similarities are pronounced less strongly.

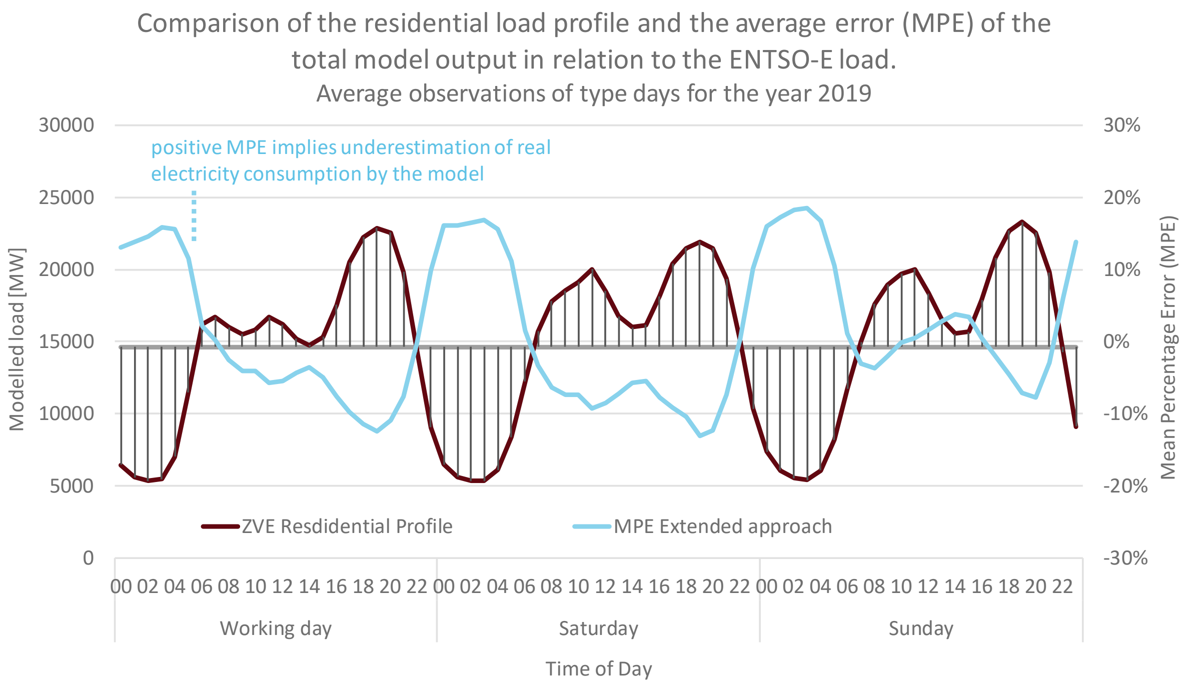

Figure 48: Comparison of the ZVE residential load profile (red) to structural deviations (Mean Percentage Error, MPE) of the BLP application *approach (blue) modelling the ENTSO-E total load. Display of average type days in 2019. Diagram by author.*

In a different error analysis for selected DSOs, the ZVE load profile was replaced by the SM load profile - an average load profile of 200 smart meter load profiles (cf. chapter 4.3). Despite its simplicity, the SM load profile significantly improved the model results by 1.6 % or 1.2 % MAPE (*SLP only* or *BLP application* approach) and by 0.4 % or 1.7 % R^2. This is another indication that the ZVE load profile is still associated with structural deviations, which should be improved in the future.

5.3. Bottom-Up Application-specific Electricity Demand Model for Selected Subsectors

In the following chapter, the engineering-based profiles of five CTS subsectors are being introduced. The five depicted subsectors, *offices* (WZ64-71), *trade* (WZ47), *accommodation* (WZ55), *hospitals* (WZ86) and *education* (WZ85), represent about 62 % of the total electricity consumption of the CTS sector (Schlomann et al., 2015, p. 84). In the following, only the final engineering-based profiles of the four most relevant subsectors (excluding *education*) are presented, including structural assumptions and hyperparameter optimisation. Intermediate results, school profiles and a more detailed discussion can be found in Böckmann et al. (2021). All load profiles are publicly accessible in csv format; the model code can be accessed and used on GitHub (Böckmann and Seim, 2021).

The procedure described in chapter 4.4 yields electricity sub-load profiles for individual subsectors and at the level of application technologies. Figure 49 depicts final engineering-based load profiles for four of the five subsectors for an average day in the year 2019. The aggregation of all application technology sub-loads yields the total subsector load which are compared to subsector load profiles (module 1). Deviations are discussed below.

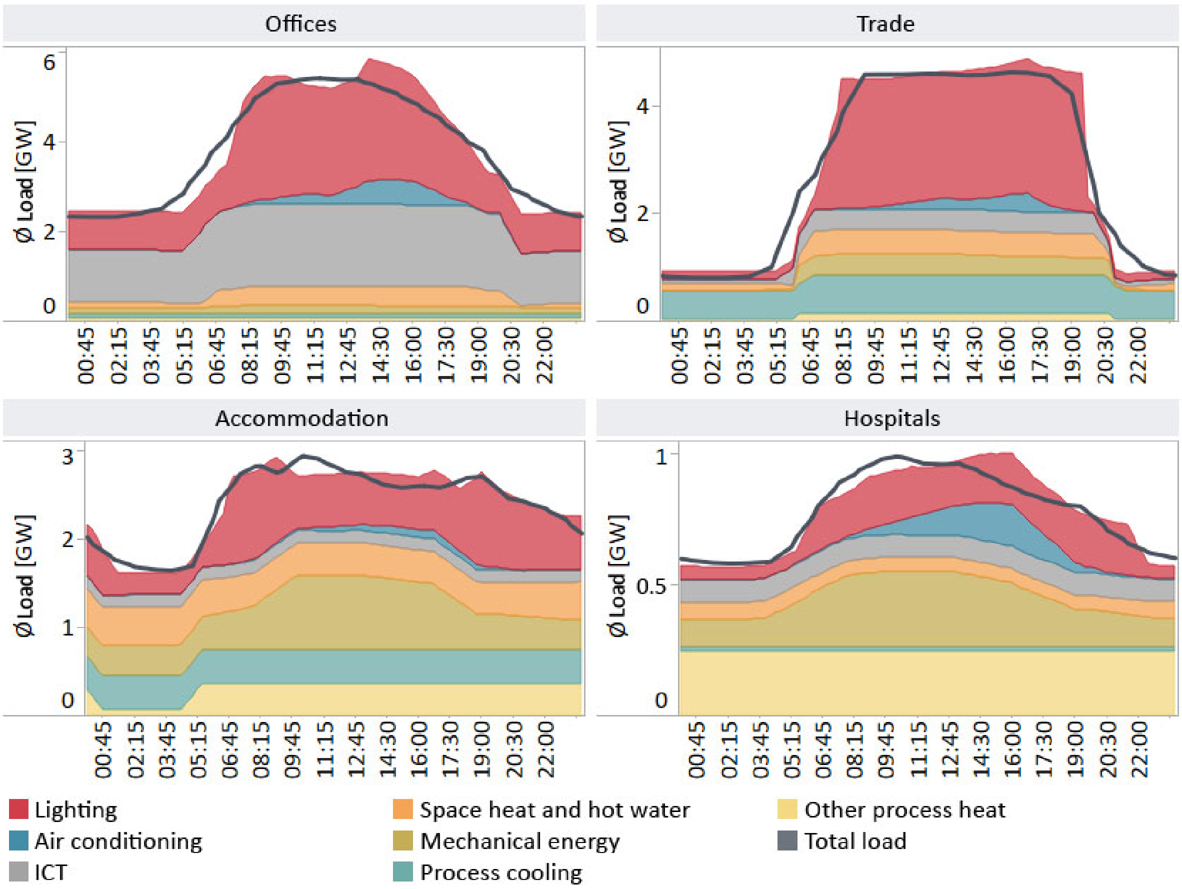

Figure 49: Final result of the load profiles after hyperparameter optimisation per subsector and application technology in comparison with the sector load profiles (black line) of the year 2018, adapted from Böckmann et al. (2021, p. 13).

In addition to characteristic daily structures shown above, application technology sub-loads also exhibit seasonal variations: due to a lower level of solar radiation in winter time, lighting exhibits an increased electricity demand in that season. While hot water demand is considered constant over the year, space heating does exhibit a significant increase in electricity demand over the winter period due to cold temperatures. In contrast, the electricity demand for process cold and air conditioning increases with warmer temperatures, showing higher demands in summer time. A more detailed analysis of seasonal fluctuations can be found in Böckmann et al. (2021) or looking at the published profiles.

The engineering-based profiles rely largely on occupancy profiles (chapter 4.4). Using the three standards of ISO 18523-1:2016(E) (2016), SIA 2024:2015 (2015) and DIN V 18599-10:2018-09 (2018), representative occupancy profiles per subsector and type day were derived. The process of fine-tuning these occupancy profiles (and resulting engineering-based models by model comparison with subsector load profiles (module 1)) can be illustrated in Figure 50. As can be seen in the below figure, occupancy profiles only changed slightly in the optimization process for *offices* and *hospitals*: for these two subsectors, the combination of the three standards already included sufficient information to accurately describe these subsectors. For remaining subsectors *trade* and *accommodation*, the comparison to subsector load profiles (module 1, chapter 5.1) has shown significant potential for improvement by finetuning the occupancy profiles. This is illustrated by the difference between the first level bottom-up model (grey line, without structural assumptions and hyperparameter optimization) and the fine-tuned bottom-up model (red line). For the final engineering-based models shown above, the fine-tuned occupancy profile was used (Böckmann et al., 2021, pp. 14–15).

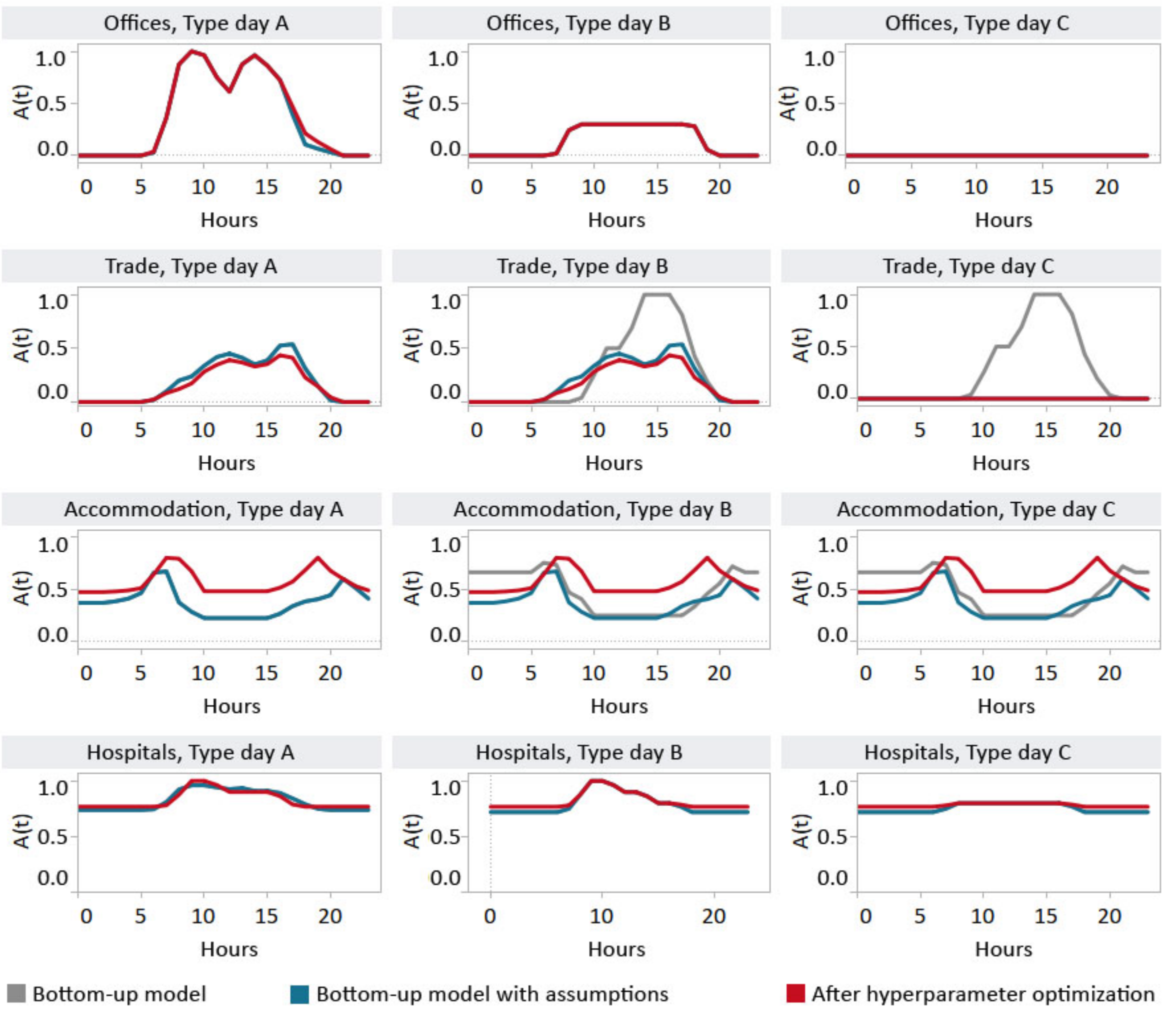

Figure 50: The occupancy A(t) of the modelled subsectors and type days in the course of the model development, adapted from Böckmann et al. (2021, p. 15)

As indicated above, deviations between the engineering-based models and the subsector load profiles remain – despite the optimization process. Table 22 depicts the model performance in the course of finetuning. Similar to the occupancy profiles, only *trade* and *accommodation* showed significant improvements by the finetuning steps. According to Lewis's benchmark (1982), the final engineering-based models can be considered 'highly accurate' (*accommodation* and *hospitals*), 'good' (*offices* and *trade*) or 'reasonable' (*education*).

Table 22: The development of performance measures during the three modelling steps, adapted from Böckmann et al. (2021, p. 16)

WZ	Subsector	Bottom-up		+ Assumptions		+ Optimization	
		MAPE [%]	R^2	MAPE [%]	R^2	MAPE [%]	R^2
64-71	*Offices*	10.9	0.84	10.3	0.87	10.0	0.88
47	*Trade*	48.7	0.64	14.5	0.93	14.0	0.94
55	*Accommodation*	16.4	0.10	13.6	0.32	8.2	0.76
86	*Hospitals*	8.3	0.59	8.3	0.59	8.4	0.61
85	*Education*	24.4	0.62	22.7	0.66	21.9	0.68

The structure of these deviations between the engineering-based profile and the subsector load profiles (module 1) can be drawn back to several aspects for offices: naturally, the depiction of holidays is a difficult undertaking in the load forecasting literature (Ziel, 2018, p. 191), which appears to be the case here, too. Besides, working times in offices seem to be a source for deviations: observed working times within subsector loads profiles (module 1) and reported working times in the standards do not completely match. Moreover, the load profile used for air conditioning in offices might be distorted. Due to a lack of data, a Californian profile for air conditioning was used (Ladwig, 2018, p. 61), which might not be representative for Germany. Deviations might also stem from modelling seasonal differences of lighting, which are pronounced more strongly in engineering-based models (Böckmann, 2021, p. 70).

Some of these deviations represent interesting starting points for further research, while others go partially back to limitations of a bottom-up model to capture the heterogeneity of a subsector. For all other subsectors, deviations between the engineering-based profile and the subsector load profile are elaborated in Böckmann et al. (2021).

5.4. Future Projections of Selected Subsectors

In the following, the subsector- and technology-specific load profiles for the year 2035 are presented, which were projected using the baseline scenario and reference scenario described in chapter 4.1.4. Chapter 5.4.1 first describes the development of annual electricity demand per subsector and scenario. Chapter 5.4.2 then presents the projected electricity load profiles.

5.4.1. Comparison of the Technology Shares of Electricity Demand per Scenario

The annual electricity demand will develop differently per application technology (and thus per subsector) and scenario. Figure 51 illustrates this development aggregated at the level of the considered subsectors.

As shown in Figure 51, the annual electricity demand in the reference scenario increases in all subsectors except for *education*. In the baseline scenario, on the other hand, an increase in electricity demand is only shown for *hospitals*; the annual electricity demand of all other sectors decreases until 2035. Since the reference and baseline scenarios make the same framework assumptions regarding employees and energy reference area (Pfluger et al., 2017b, p. 63), this difference in total demand stems from different energy efficiency improvement pathways. These efficiency improvements are different for each application technology and – according to their share of electricity demand – for individual subsectors (Seim et al., 2021a, p. 8). In both scenarios, an average increase in the number of employees of 12 % (2010 to 2050) and an average increase in the energy reference area of 33 % (2010 to 2050) is assumed for the *offices* and *trade* subsectors (Pfluger et al., 2017b, p. 64).

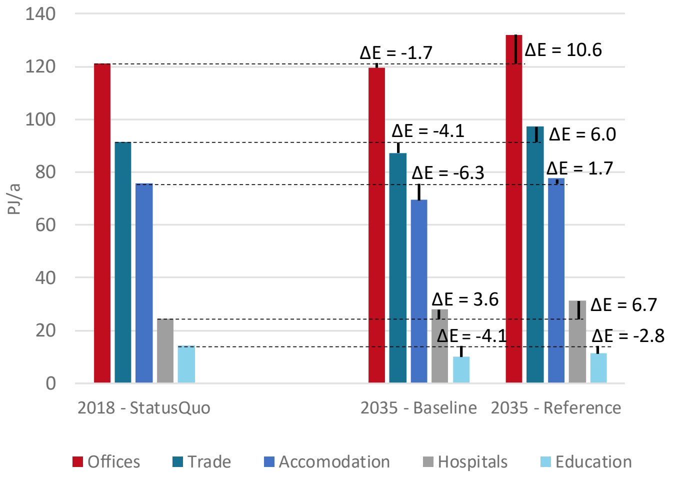

Figure 51: Annual electricity demand per scenario and subsector, adapted from Seim et al. (2021a)

Combining subsector-specific framework assumptions and efficiency improvements per application technology will yield a projected annual electricity demand per subsector. The projected profile of this electricity demand, however, is exclusively determined by the changing demand shares of application technologies due to efficiency improvements as well as a technological shift from night storage heaters to heat pumps. Figure 52 shows these changes in demand shares in relation to the year 2018.

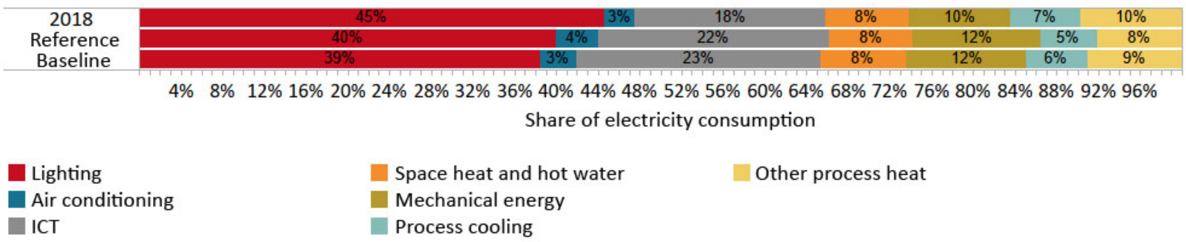

Figure 52: Share of application technologies in electricity demand per modelled scenario, adapted from Seim et al. (2021a, p. 9)

Differences can be observed in particular for lighting and ICT. In both future scenarios, the share of lighting in electricity demand decreases. On the contrary, the electricity demand share of ICT increases in both the reference and baseline scenarios. For ICT, any efficiency gains are overcompensated by increased utilization. The shares of air conditioning and mechanical energy, such as electric drives, also increase slightly (Seim et al., 2021a, p. 9).

5.4.2. Comparison of Projected Load Profiles

By summing up individual sub-load profiles per application technology and subsector, the projected cumulated load profiles of the whole subsectors can be derived. As indicated above, differences between the scenarios and subsectors result from different demand shares of application technologies as well as from the technology shift in the area of space heating (i.e. from night storage heaters to heat pumps). Figure 53 shows the cumulative load profile of the five subsectors per scenario for the year 2018 and 2035.

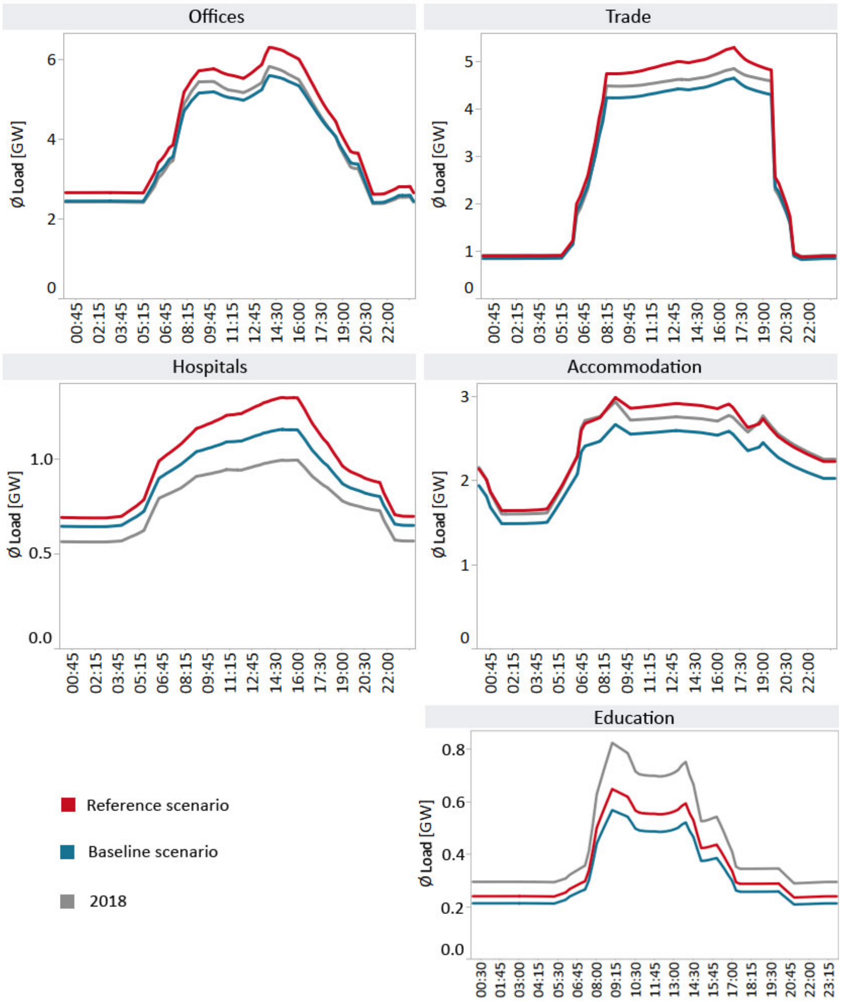

Figure 53: Electric load profile in 2035 per subsector and scenario compared with the modelled total load profile of 2018, representation of an average week, adapted from Seim et al. (2021a, p. 9).

The main difference between scenarios lies in the general demand level of the load profiles. Yet, differences can also be observed in the load profile shape. For *offices*, the afternoon peak in the reference scenario is on average 9 % higher than the morning peak, whereas in the baseline scenario the difference is only about 8 %. This largely goes back to the use of air conditioning, which reaches its peak load in the afternoon (cf. Böckmann et al. (2021, p. 16)). The load profile of the baseline scenario lies slightly below the level of 2018 during the day, but less so in the afternoon. This difference can also be observed in the *trade* subsector, relying on the increase of air conditioning compared to 2018. Particularly for the *trade* subsector, more pronounced load peaks are to be expected in the future, which is reflected in an increasing ratio of peak load to base load in both scenarios (Seim et al., 2021a, p. 25). In *hospitals*, demand increases are to be expected in both scenarios, but these are only slightly accompanied by an increasing ratio of peak load to base load. In all other subsectors, the ratios of peak load to base load show only minor variations within the scenarios. The profile changes particularly go back to demand reductions in lighting and demand increases in ICT, which span across both scenarios (cf. Figure 52) (Seim et al., 2021a, pp. 8–9).

5.5. Current and Future DSM Potential of Selected Subsectors

Using the electric power parameters and shift durations presented in chapter 4.6 and the projected load profiles from the previous chapter 5.4, it is possible to quantify technical load shifting potentials with high temporal resolution for each subsector, application technology and scenario. In the following sections, the aggregated potentials per subsector are compared (chapter 5.5.1) and then presented in high spatial as well as temporal resolution (chapters 5.5.2 and 5.5.3). Finally, the identified flexibility potentials are put into the context of existing literature and the German energy sector (chapter 5.5.4). Details can be found in the related German publication (Seim et al., 2021a).

5.5.1. Comparison of Demand Side Flexibility Potentials per Scenario

For each quarter-hourly period t of the years 2018 and 2035, the maximum switchable load $P_{max}^{q}(t)$, the minimum switchable load $P_{min}^{q}(t)$ and the maximum and minimum potentials of shiftable energy quantities $E_{max}^{q}(t)$ and $E_{min}^{q}(t)$ per technology q are identified according to the framework presented in chapter 4.6. The frequencies of occurring values per subsector and scenario are shown as a density distribution in Figure 54 (p. 93).

Based on the boxplot parameters in Figure 54, it can be seen that especially in *trade* and *accommodation*, high load reduction potentials can be accessed more frequently than high load increase potentials. For *hospitals*, it is exactly the opposite, whereas *offices* appear balanced. The reason for this is the increased utilisation rate of all flexible technologies except air conditioning. The technologies process cooling, ventilation, space heating and hot water are consistently modelled in all subsectors with a distinct base load (cf. Böckmann et al. (2021, chapter 2.3)), which potentially can be reduced at any time. In *offices*, particularly large load increase potentials of air conditioning at warm outdoor temperatures ensure that the mean potentials for load increases are higher than for load reduction. However, these load increase potentials of air conditioning are only available on a few days per year. It is also noticeable that the load reduction potential is never zero. This is due to the fact that the aggregated electricity demand of all potentially flexible technologies is greater than zero at all times, and there are no restrictions with regard to a technology switch-off. In all subsectors except education, the reference scenario offers a higher potential of load increase or reduction. This is directly related to the projected level of load profiles from Figure 53, page 91: a higher electricity demand of an application leads to a higher maximum load (and thus the switchable load $P_{max}^{q}(t)$) of that same application (Seim et al., 2021a, p. 10).

The shiftable energy quantities $E_{max}^{q}(t)$ and $E_{min}^{q}(t)$ from Figure 54 are more evenly distributed in their frequency than the switchable loads. While the greatest extremes of load increase and reduction potentials can be found in *offices*, the *trade* subsector offers the greatest potential of shiftable energy quantities. Space heating and hot water contribute significantly to this. In particular, the shift duration of space heating of Δt = 12h compared to Δt = 1h for ventilation, air conditioning and process cooling (cf. chapter 4.6) ensures high energy shift potentials for space heating and hot water (Seim et al., 2021a, pp. 10–11).

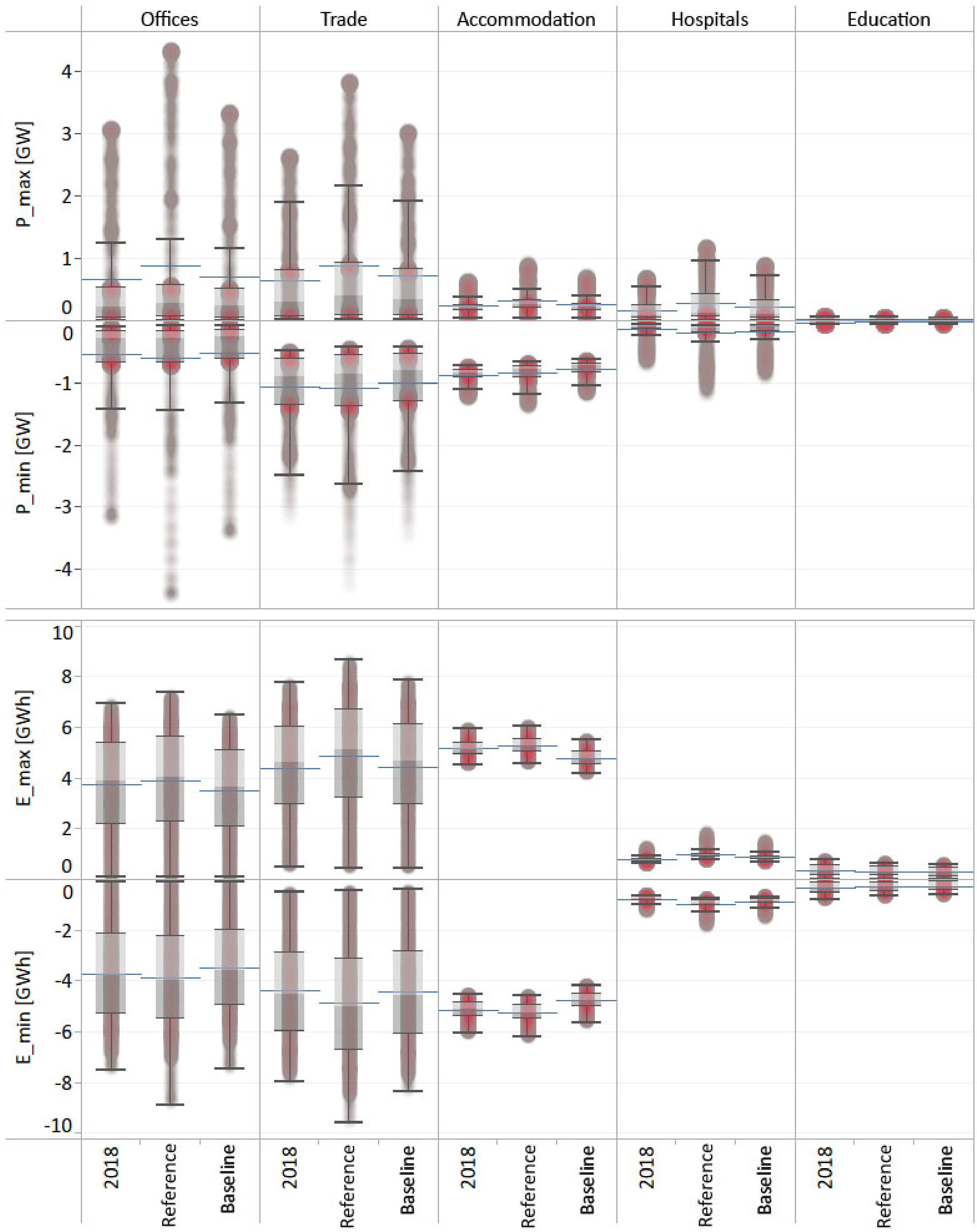

Figure 54: Boxplot representation of the load increase and load reduction potentials as well as the potentials of shiftable energy quantities (quarter-hourly values) in different scenarios. Density: red - high density; light grey - low density. Mean value: blue line. Whiskers at 1.5 times the interquartile range. Adapted from Seim et al. (2021a, p. 11).

Figure 55 summarises the technology shares of the load increase and reduction potential per subsector and scenario. For relevance and illustration purposes, the subsector of education has not been displayed. Notably, air conditioning offers high shares in the load increase potential, especially in spring, autumn and summer. Counterintuitively, electricity-based space heating and hot water show only minor seasonal fluctuations due to the high share of hot water (70 %), which varies only little over seasons. Process cooling, which is particularly evident in *trade* and *accommodation*, provides more load reduction potential than load increase potential, as it runs on a significant base load level. In *offices*, most of the flexibility comes from air conditioning and space heating. In *trade*, a large part of the flexibility potential also comes from process cooling, whereas in *hospitals* ventilation as part of mechanical energy contributes to DSF potentials. For the average amount of shiftable energy potentials, space heating takes by far the greatest share again due to long shift durations (Seim et al., 2021a, p. 12).

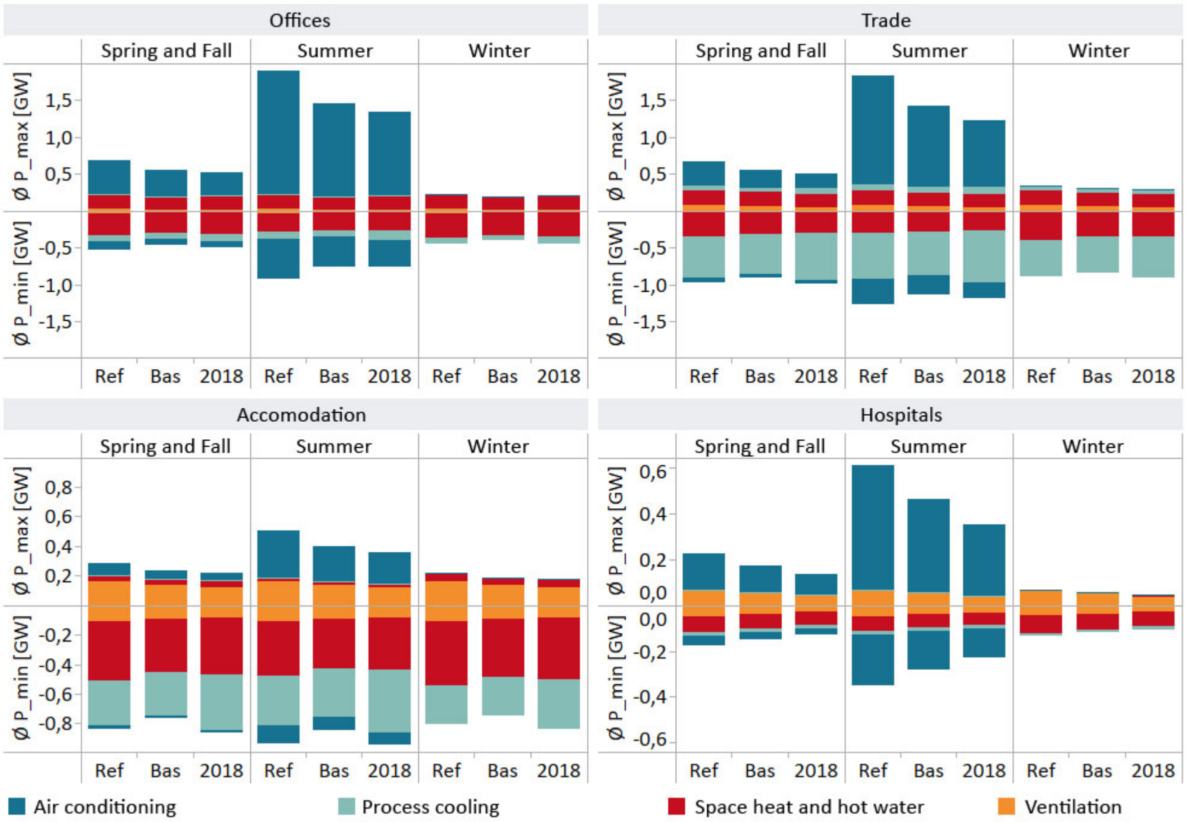

Figure 55: Average load increase and load reduction potentials by application technologies, subsectors, seasons and scenarios. Adapted from Seim et al. (2021a).

The load shifting potentials can be summarised over the entire year and all five modelled sectors with regard to the extreme and average values in Table 23.

Table 23: Extreme and mean values of the cumulated load shifting potentials over the five subsectors offices, trade, accommodation, hospitals *and* education *(Seim et al. (2021a))*

		P_{max} [GW]	P_{min} [GW]	E_{max} [GWh]	E_{min} [GWh]
2018	Max/Min	7.12	-7.79	21.62	-22.04
	Average	1.72	-2.66	14.39	-14.38
Baseline scenario	Max/Min	8.04	-8.33	20.86	-22.12
	Average	1.90	-2.50	13.87	-13.85
Reference scenario	Max/Min	10.34	-10.38	22.98	-25.56
	Average	2.38	-2.78	15.31	-15.30

5.5.2. Spatially Resolved Demand Side Flexibility in the Baseline Scenario

The spatial resolution of DSF potentials can represent a relevant information basis for matters of local congestion management. For example, local DSF potentials could help to avoid grid bottlenecks and to reduce the often associated curtailment of renewable energies (Hirth et al., 2018a, p. 34), (Heitkoetter et al., 2020, p. 11). For this purpose, Figure 56 shows the average load shifting potentials per county for the baseline scenario. Here, the average DSF potentials from Table 22 (1.90 GW) were disaggregated according to the proportion of employed persons per subsector and district. Additional figures of the average load shifting potentials as well as the shiftable energy quantities per county can be found in Seim et al. (2021a, appendix E).

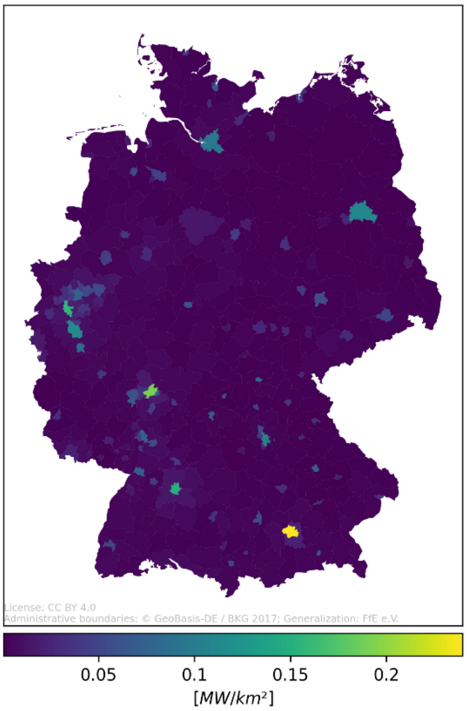

Figure 56: *Average area-specific load increase potential (P_{max}) per county of the baseline scenario, adapted from Seim et al. (2021a, p. 13)*

Expectedly, the DSF potentials of considered CTS subsectors predominantly exist in regions of high population density. It is therefore not surprising that Berlin, Hamburg, Munich, Frankfurt a.M., Cologne, Stuttgart and Düsseldorf are urban centres which stand out in Figure 56 with high average load shifting potentials. The Hannover Region also stands out noticeably from its surroundings. Due to the area-specific illustration of potential, smaller urban centres can also be identified very well. A list of identified county-specific potentials of the baseline scenario P_{max}, P_{min}, E_{max} and E_{min} can be found in the digital appendix of Seim et al. (2021a).

In future, the spatial DSF potentials can be combined with information on grid bottlenecks and grid expansion paths, for example from the electricity network development plan (*Netzentwicklungsplan Strom 2035*, 2021, pp. 117–128), as well as on the spatial generation of fluctuating RES and electricity price information, in order to determine economic load shifting potentials. From an economic perspective, possible utilization for DSF potentials exist in short-term spot markets, the balancing power markets and the regulation for interruptible loads. Further possible economic applications result from optimizing electricity procurement costs, for example with regard to the power-related components of the grid fees, as well as with an increasing spread and anticipation of dynamic tariffs in the electricity end customer segment (Bertsch et al., 2019; Steurer, 2017, pp. 23–27).

5.5.3. Temporally Resolved Demand Side Flexibility Potentials in the Baseline Scenario

The DSF potentials presented in the previous sections are subject to temporal fluctuations. Information on the temporal availability for switchable loads and shiftable energy quantities allow a precise analysis of the temperature-, type-day- and time-of-day-dependent potentials. The scenarios used to characterize the potentials influence the amount, but not the temporal distribution of the potentials. In the following, only the baseline scenario is considered. Figure 57 shows the potential for increasing and reducing the load. For reasons of relevance and simplified illustration, the subsector *education* is not displayed. The high potential of switchable loads for air conditioning (particularly load increases) can be clearly seen in all subsectors, although these can only be used at times of high outdoor temperatures, hence predominantly in the summer season (Seim et al., 2021a, p. 14).

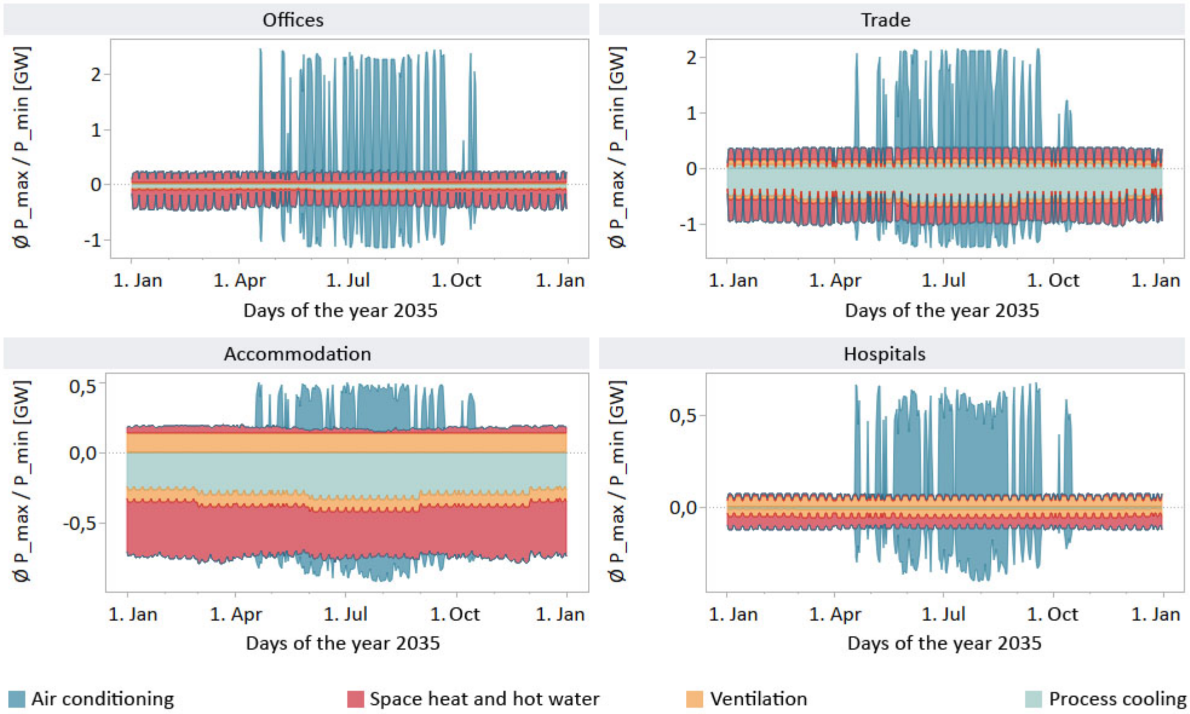

Figure 57*: Average daily load increase and load reduction potential per subsector and technology of the year 2035 in the baseline scenario. Figure adapted from Seim et al. (2021a, p. 14).*

The switchable loads of process cooling and space heating, especially the potentials of load reduction, are also subject to slight seasonal fluctuations. Fluctuations with regard to the type day can also be observed. The subsectors of *accommodation* and *hospitals* provide the most temporally stable potential of switchable loads. The process cooling of the *trade* subsector is also only subject to slight weekly fluctuations and could be switched in a stable manner over time (Seim et al., 2021a, p. 14).

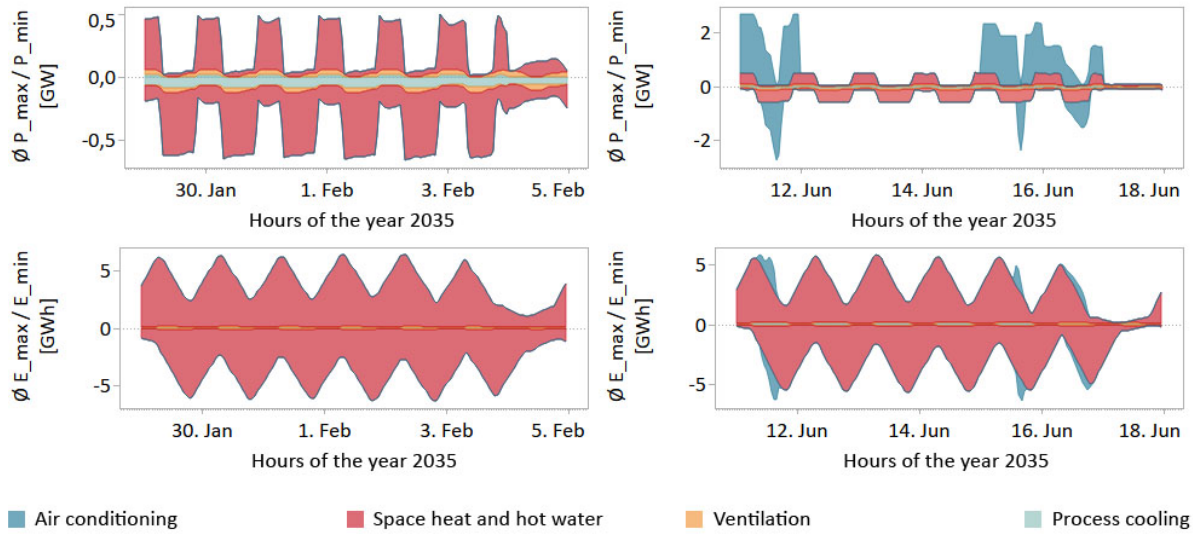

Figure 58*: Hourly average switchable loads and shiftable energy quantities of* offices *in a winter and summer week (Monday-Sunday) in the baseline scenario. Figure adapted from Seim et al. (2021a, p. 15).*

Figure 58 shows the exemplary diurnal fluctuations in the subsector of *offices* (note that axes are not synchronised). It can be seen that the potentials of air conditioning, space heating and hot water are not only subject to fluctuations depending on the type of day, but also on the time of day. Within a weekday, peaks of E_{max} at 07:00 and peaks of E_{min} at 19:00 can be seen. This means that in *offices*, the majority of the day's energy demand can be shifted into the morning or the evening. In comparison, the *accommodation* subsector exhibits DSF potentials which are much less volatile (Seim et al., 2021a, pp. 15–16). The related figure for *accommodation* can be found in appendix A.2.5: Figure 64.

5.5.4. Contextualization of Demand Side Flexibility Potentials

In the following chapter, the results of the technical DSF potentials are compared and contextualised with the literature to ensure their validity. Since there is only little information at a disaggregated subsector- and technology-specific level, particularly the aggregated potential can be compared with literature (Seim et al., 2021a, p. 16). However, a comparison by subsector and technology can be carried out to a limited extent with Klobasa (2007, p. 79). Table 24 describes the differences between the modelled load increase and reduction potentials. It should be noted that both articles use different reference years, 2004 and 2018.

Table 24: Comparison of subsector- and technology-specific DSF potentials of the present approach with Klobasa (2007) (Klobasa, 2007, p. 79). Adapted from Seim et al. (2021a)

		Extreme values P_{max} / P_{min} [MW]	
		Klobasa (2007)	Seim et al. (2021a)
Process cooling	*Trade*	±200-685	+255 / -428
Air conditioning	*Offices*	±1,750	±2,541
	Trade	±2,800	±1,785
	Accommodation	±420	±437

As can be seen, the modelled potentials of both approaches are in the same order of magnitude. While process cooling in *trade* and air conditioning in *accommodation* are very similar, the load flexibility potentials of air conditioning in *offices* are estimated higher in the present approach, which could stem from an increased air conditioning demand. In *trade*, on the other hand, these potentials are estimated lower in the present approach compared to Klobasa. For the sum of considered technologies, the present approach estimates a DSF potential which is 7 % lower than Klobasa, which could go back to a more conservative assumption of seasonal maximum loads in parameter D (cf. chapter 4.6). If, as in the existing literature, switchable loads are calculated with seasonal assumptions or installed capacities with regard to the maximum load, these tend to be overestimated (Kleinhans, 2014, p. 11; Seim et al., 2021a, p. 16).

While the five considered subsectors are responsible for about 62 % of the total CTS electricity demand, they even account for 74 % of technical DSF potentials in the entire CTS sector (baseline scenario). The latter can be approximated by the share of the flexible technologies within these five subsectors as compared to the entire CTS sector (cf. appendix A.1.4: Table 31). According to a recent literature review, the average values for P_{max} and P_{min} for the entire CTS sector are well below 1,000 MW per application technology (Kochems, 2020, p. 9). In comparison, in the present approach, the values of the five modelled subsectors per application category in 2018 range on average between approx. 80 - 970 MW for P_{max}. According to the same review, the maximum switchable loads reach up to 3,000 MW (Kochems, 2020, p. 8). In contrast, the present analysis of the five modelled subsectors across all application technologies shows a total of between 1.7 - 2.4 GW per scenario (cf. Table 23, page 94), which - considering the share of the five subsectors in the total flexible load share of the CTS sector of approx. 74 % (see above) - fits well with the literature values (Seim et al., 2021a, pp. 16–17).

The transformation of the energy system will lead to a considerable need for grid expansion, especially in the distribution grid (Hirth et al., 2018a, p. 72). DSF is discussed as an option to reduce the need for grid expansion and to eliminate local supply bottlenecks (Hirth et al., 2018a, pp. 34, 72). According to Fürstenwerth and Waldmann (2014, pp. 66–67), in order to minimise grid expansion costs at the distribution grid level, a short-term storage requirement of 700 MW or 2,100 MWh will arise in 2033, which can be provided cost-effectively, for example, through DSF measures due to higher efficiencies and lower capital costs (Fürstenwerth and Waldmann, 2014, p. 3; Misconel et al., 2021, p. 3). In addition, around 3-16 GW of short-term storage is needed at transmission grid level to integrate renewable energies and reduce system costs (Fürstenwerth and Waldmann, 2014, p. 79). The technical DSF potentials identified in the present approach are in the order of magnitude of this short-term storage demand. In the overall system, the identified shiftability of 13-14 GWh (cf. Table 23, 2018 and baseline scenario values) represents about one third of the storage capacity of all German pumped storage power plants, which can be regarded a relevant size (Samweber et al., 2016, p. 460). At least from a technical perspective, the five CTS subsectors considered could cover the demand at distribution grid level completely and the demand at transmission grid level partially. DSF measures compete with short-term storage, whereby the latter is currently considered more expensive than demand side management (Fürstenwerth and Waldmann, 2014, pp. 3, 91). The high potentials of the *offices* and *trade* subsectors as well as the temporally stable shiftable energy quantities of *hospitals* and *accommodation* can thus contribute to reducing the amount of residual load, to the integration of renewable energies, to cost minimisation and system stability of the energy system (Seim et al., 2021a, p. 17).

5.6. Economic Value of Applying Newly Developed Load Profiles

In the following chapter, developed subsector load profiles and derived DSF potentials are assessed economically in two use cases. In the first use case (chapter 5.6.1), a rough estimation is made of the influence that newly developed TUB BLP can have on electricity procurement and balancing group management. In the second use case (chapter 5.6.2), the DSF potentials identified in the engineering-based modelling approach are economically assessed utilizing data on feed-in management in high temporal and spatial resolution.

5.6.1. Procurement and Balancing Group Management

In the following chapter, the application of both the *SLP only* and *BLP application* approaches in the *disaggregator* tool are economically assessed and compared, building on and utilizing the results of module 2. First, the focus will be on the hypothetical electricity procurement for Germany, using ENTSO-E load as real data reference (Figure 28). Secondly, identified county loads will assessed in analogy.

For the years 2015 to 2019, Figure 59 (p. 99) illustrates the average costs of the initial procurement of electricity quantities on the Day-Ahead market and the costs and revenues incurring for the utilisation of imbalance settlement for the Federal Republic of Germany. As can be seen, the *BLP application* approach reduces the total costs on average by about 24 Mio €, ranging from savings of 106 Mio € in 2015 up to additional costs of 16 Mio € in 2018. As can be seen in the annual analysis (appendix A.2.6, Table 44), the costs are reduced significantly by applying the *BLP application* approach in all years except 2018. This mainly goes back to reduced average initial procurement costs of 196 Mio € associated with the *BLP application* approach. For imbalance settlement, however, the *SLP only* approach is associated with significantly higher average revenues of 172 Mio €, which is driven by arbitrage, i.e. the sale of surplus electricity quantities during the day (at higher prices) and the purchase of deficit electricity quantities during the night and morning hours (at lower prices). The exact annual cost figures can be found in appendix A.2.6, Table 44.

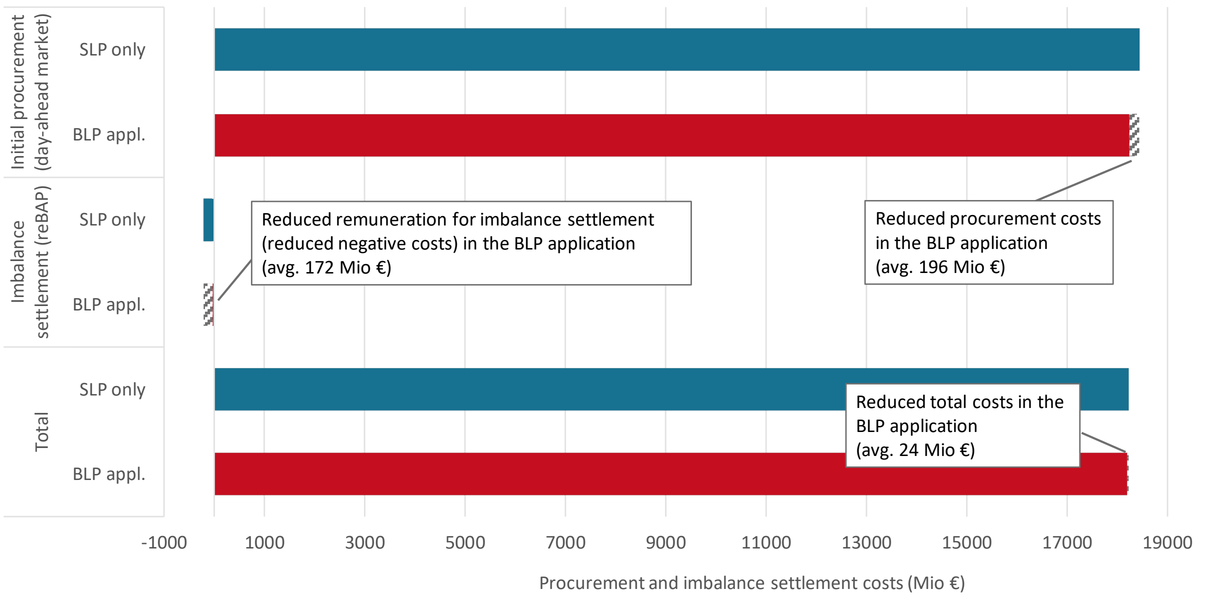

Figure 59: Approximation and comparison of procurement and imbalance settlement costs and revenues for the German electricity demand in Mio €, using ENTSO-E data and the SLP only *as well as the* BLP application *demand modelling approaches. Average figures of the years 2015 to 2019. The hatched line indicates the delta between both approaches. Diagram by author.*

In the analogous implementation of the cost analysis using county loads of the years 2017 to 2019, more differentiated results can be obtained. The exact results are presented in appendix A.2.6, Table 45 to Table 47. Observed counties vary over the years due to data availability. While in the year 2017, the *BLP application* approach proves preferable in total costs for 8 out of 11 selected counties, it is only preferable in total costs for 1 out of 5 counties in the year 2018, and only in 3 out of 9 counties in the year 2019. In monetary terms, using the *BLP application* approach amounts to average total cost savings of 12,564 € in the year 2017, whereas additional costs incur in the years 2018 and 2019 of 54,348 € and 47,787 €, on average. The above observations indicate two findings:

i. the economic profitability of a specific procurement strategy significantly depends on the interrelation of the price structure and demand structure in a particular year, including model deviations. Hence, different results for different years and counties.[28]
ii. while the *BLP application* approach is economically preferable in 4 out of 5 years for the total German load, it is mostly not preferable for selected county loads. This indicates the limited representativeness of county loads, which exclusively represent city loads (cf. chapter 4.1.2).

In almost all counties and years, applying the *BLP application* approach is associated with a significant cost reduction in the initial electricity procurement. This is in line with observations using the ENTSO-E data. The *SLP only* approach, however, is associated with higher revenues for the utilization of imbalance settlement for selected counties, overcompensating the initial cost savings. This might be an indication of why many DSOs still require suppliers to use VDEW SLP in their network area[29] (cf. chapter 2.2.2). In the synthetic load profile procedure, the DSO provides load profiles for smaller consumers, the electricity demand of which has to be initially procured by suppliers. Using SLP in the *SLP only* approach, suppliers bear higher initial procurement costs, while DSOs can realize higher revenues utilizing imbalance settlement (or managing their differential balancing group). Despite obvious SLP deviations, the DSO would profit from the provision of SLP according to the above analysis.

[28] The implications of market price structures in the short-term and long-term electricity procurement have recently been analysed and described in Novello et al. (2021, p. 20): the monetary impact of forecast deviations depends significantly on the development of market prices and differs depending on the forecast horizon.
[29] In an analysis conducted by Beuker (2018), 87 % of DSOs used residential VDEW SLP (cf. footnote 25, p. 66)

As a conclusion, not only is the use of inaccurate SLP potentially associated with extra costs, but also the distribution of costs between suppliers and DSOs is affected. From a consumer perspective, this might barely be noticeable: all costs borne by suppliers and DSOs will be passed on to consumers as either electricity sales prices or grid fees. However, a cost shift from the competitive supplier market to the regulated DSO sphere might affect DSO efficiency scores in the benchmarking process of incentive-based regulation (BNetzA, 2015, chapter 1.1.1.4), required by § 12 ARegV (2019). If only some DSOs can profit from that cost shift, efficiency scores might be distorted.

It is important to notice that due to a lack of data the above procedure is only a rough estimation of real procurement processes: in contrast to the above analysis, some electricity quantities are already procured long-term by the supplier on the futures market in order to manage price risks.[30] In addition, the DSO is obliged to actively manage its differential balancing group and avoid predictable deviations, e.g. through intraday trading using the remaining load (cf. chapter 2.2.2). Also, price effects of changing procurement strategies in the system (due to improved forecasts) are complex to anticipate. Nevertheless, the above analysis reveals a tendency that the use of newly developed and more accurate load profiles could be attractive from a macroeconomic perspective, whereas DSOs might have incentives, not to switch and keep old SLP. This was also confirmed by Rykala (2018), who examined closely the load projection a specific DSO and found that improved projections should be beneficial for the system, while they might not be beneficial for the unbundled DSO.[31] In line with that, the think tank Agora Energiewende (2020) recently demanded that DSOs should be given incentives to update SLP annually in order to better take into account changing consumption patterns. According to the same press release, DSOs should be obliged to manage the differential balancing groups transparently and more actively.

As a conclusion, the switch to more precise BLP can ensure an improved, long-term predictability and profitability of load forecasts from a system perspective. Also, deviations and associated unnecessarily procured electricity quantities can be avoided. These considerations are in line with findings from Agora Energiewende (2020) as well as from Gobmaier and von Roon (2010), who discuss the effects of changing residential load profile structures due to an increased penetration of EVs and rooftop PV.

5.6.2. Economic Value of Demand Side Flexibility Potentials

Utilizing DSF potentials of application technologies, which have been identified in module 5, can significantly reduce the annual peak load of Germany. For the year 2018, a specific peak load reduction potential of about 2.9 GW can be found, representing a 4 % reduction of the former peak load. Figure 60 (p. 101) indicates this peak load reduction potential and the associated accumulated shift duration $\#\mathrm{h}$ of less than 15 hours (i.e. 57 quarter hours). The accumulated shift duration specifies in how many hours (or quarter hours) the load had to be shifted in the present analysis, reflecting the effort of interventions.

[30] In the long-term procurement of electricity, however, deviations in the amount of electricity have a greater impact than structural deviations. Hence, the simplification in the present analysis to only consider the Day-Ahead market for electricity procurement should not significantly distort the result. In the short-term electricity procurement, structural deviations do depict an important factor to influence overall costs, driven by both spot market and imbalance settlement effects (Novello et al., 2021, p. 20).

[31] The exact analysis and result cannot be published due to a non-disclosure agreement.

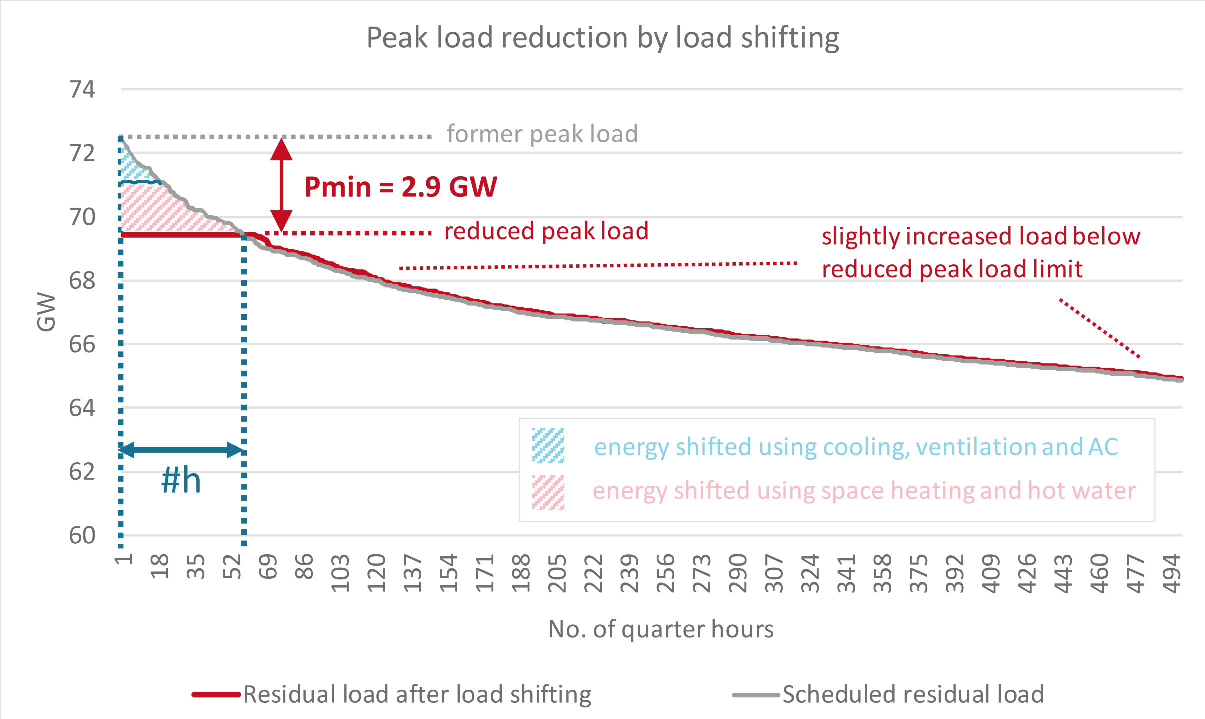

Figure 60: Illustration of the peak load reduction potential by load shifting, comparing a residual load duration curve of scheduled load (grey) with the adjusted residual load after load shedding (red). Figure by author.

In the load shift modelled, all restrictions mentioned in chapter 4.7.2 have been respected: all technical restrictions of the minimum and maximum switchable loads as well as the minimum shiftable energy quantities of all applications throughout the load shifting processes were met. The above peak load reduction requires a flexible capacity of 1,275 MW of cooling, ventilation and AC technologies as well as 1,648 MW of flexible heat pump capacity (in total: 2,923 MW). Due to the assumed priority of thermal storage (cf. chapter 4.7.2), the shifted energy quantities of cooling, ventilation and AC amounted to only 2,700 MWh, while the energy shifted using heat pumps amounted to 14,838 MWh. The DSF capacity of 2,923 MW required for peak load reduction is only part of the total DSF potential identified in Chapter 5.5, which can be up to 7.8 GW depending on the time of year and day (see Table 23, p. 94).

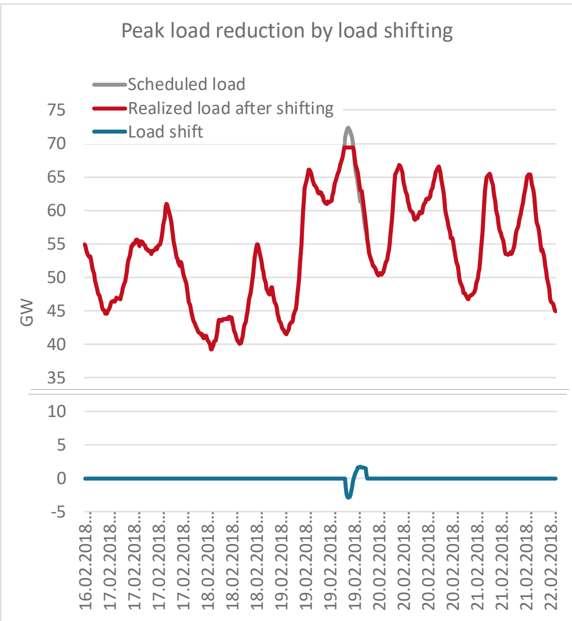

Figure 61: Illustration of the peak load reduction by load shifting. Figure by author.

Figure 61 illustrates the load shift at the peaking time in 2018 as an example. Similar load shifts can be observed on January, 11th, 26th, as well as February 06th to 8th. As can be seen, the scheduled load was shifted at the peaking time (i.e. reduced for 2.5 hours), resulting in a realized load that peaked on a considerably lower level. Respecting technical restrictions, the load increase lasted for 3.5 hours.

For the subsequent economic assessment, Table 25 lists the individual entries for annual costs to access these DSF potentials.

Table 25: Technical and annual cost parameters for the flexibilization of application technologies, utilized for peak load reduction.

	Cooling, ventilation, AC	Heat pumps
Technical parameters		
Flexible capacity [MW]	1,275	1,648
Shifted energy [MWh]	2,700	14,838
Annual Costs		
Investment costs[32]	1,416,443 €	3,662,551 €
Fixed costs	382,460 €	988,942 €
Variable costs	13,501 €	148,375 €
Total annual costs per technology	1,812,404 €	4,799,868 €
Total annual costs	6,612,273 €	

As can be seen from Table 25, the exploitation of the utilized DSF potentials is associated with annual costs of about 6.6 million €. In the next step, these costs can be compared to potential cost savings associated with the peak load reduction. Table 26 brings together costs and cost savings to determine the economic value of the peak load reduction using identified DSF potentials.

As can be read from Table 26, the total savings through peak load reduction (and associated reduction of gas turbine PP capacity) significantly exceed the costs associated with exploiting the required DSF potentials. In total, cost savings of about 157 million € could be realized annually replacing gas turbine capacity by DSF potentials. As a very recent study by Gierkink et al. (2021, p. 11) shows, the early coal phase-out by 2030 requires, among other things, a significant expansion of new hydrogen-capable gas-fired power plants of 23 GW. Part of this expansion of peak load capacity could be avoided by DSF as described.

Table 26: Annual costs and cost savings of peak load reduction measures using flexible application technologies.

Item	Value
Reduced peak load capacity	2,923 MW
thereof cooling, ventilation, AC	1,275 MW
thereof heat pumps	1,648 MW
Annual costs and savings	
Capacity costs of gas turbine PP (cf. Table 12)	56,000 € / MW·a
Total annual savings through reduced peak load	163,693,765 €
Total annual costs (cf. Table 25)	6,612,273 €
Total annual cost savings	157,081,493 €

The economically attractive application of DSF potentials for peak load reduction or saving of corresponding peak load technologies is also confirmed by Misconel et al. (2021, pp. 3, 12). In addition to these cost savings, DSF ensures that remaining capacities are better utilised. Moreover, the above

[32] As mentioned in chapter 4.7.2, investment costs have been allocated dynamically among an assumed lifetime of equipment of 10 years. The investment sums of 12.7 million € (flexibilization of cooling, ventilation, AC) and 33.0 million € (flexibilization of heat pumps) were converted to annual costs at an interest rate of 1% and an average capital commitment of 6.4 million € (flexibilization of cooling, ventilation, AC) and 16.5 million € (flexibilization of heat pumps).

case of peak load reduction would only require utilization of DSF potentials for 15 hours in the whole year of 2018 (or 40 hours, including the load increase). In the remaining time, the potentials could also be used, for example, to reduce curtailed electricity in the context of EinsMan measures (cf. chapter 2.2.3). According to BNetzA (2021b, pp. 149–153), the curtailed electricity in the context of EinsMan measures steadily increased in the last decade, amounting to 5,403 GWh in 2018. The largest part of this amount is associated to the curtailment of onshore and offshore wind turbines (72% and 25% in 2018), equalling compensation costs of 719 million € in 2018 (1,058 million € in 2019).[33]

As already mentioned in chapter 5.5.2, DSF potentials can also be utilized to optimize the electricity procurement on short-term spot markets, balancing power markets and the regulation for interruptible loads (Bertsch et al., 2019; Steurer, 2017, pp. 23–27). In principle, using DSF potentials becomes all the more relevant as the share of fluctuating renewable energies increases (Misconel et al., 2021, p. 2). Due to their smaller scales, application technologies like cooling, ventilation, AC and heat pumps are associated with higher investment costs as compared with DSF potentials of industrial processes or power-to-gas technologies. However, they exhibit the lowest variable costs as for their least user and production process interference (Heitkoetter et al., 2020, p. 15). In spite of the various fields of application and the above described potential system benefits of DSF potentials, however, there are still obstacles for the individual economic application. In the CTS sector, obstacles include uncertainties and missing incentives on the part of companies as well as the high transaction costs for aggregators, due to a large number of consumers with moderate DSF potentials (WindNODE, 2020, p. 45). Moreover, according to Beucker et al. (2020a, p. 7), the fixed and inflexible system of levies and charges needs to be revised in order to be able to effectively exploit the flexibility potential. An important measure, for example, is seen in the dynamization of grid fees, taking into account market and grid signals (Fritz et al., 2021, p. 2).

[33] A precise determination of reduction potentials of curtailed energy through the use of DSF is difficult due to incomplete data of temporally highly resolved EinsMan instances (Ostermann et al., 2019, pp. 2–3). However, reproducing a method developed by Ostermann et al. (2019), Henkel (2021) was able to generate EinsMan instances in high temporal and spatial resolution for 154 affected counties in 2018. Matching these EinsMan instances with DSF potentials identified in module 5, Henkel estimated an energy saving potential for reduced EinsMan instances of about 143 GWh (i.e. about 3 % of total curtailed energy). Assuming an average value for compensation of 118 €/MWh (BNetzA, 2021b, pp. 150–154), this would amount to cost savings of about 16.9 million € per year. These cost savings are opposed to estimated annual exploitation costs of about 2.1 million €, considering annual investment and fixed costs for 491 MW of flexible capacity as well as variable costs for 143 GWh of shifted energy (cf. Table 13, p. 69).

6. Discussion

In order to contextualise the main results of this thesis, uncertainties in the analysis and result generation of the six consecutive modules should be addressed in this chapter.

In the first module, 32 subsector load profiles (TUB BLP) were developed and published, based on 1,104 datasets. In comparison, 607 commercial load profiles have been used to generate VDEW SLP more than twenty years ago. While the database for TUB BLP appears larger, VDEW SLP exhibit a higher aggregation level of only seven individual SLP in the CTS sector; for industrial electricity demand, no VDEW SLP exist. The representativeness of TUB BLP depends on data availability, the limitations of which have been thoroughly investigated and described in chapter 2.1. The underlying database of TUB BLP can be regarded as good in some subsectors, but not necessarily as representative in others. In future research, the database should be enlarged for some subsectors. Also, there is a number of especially industrial subsectors which have not been modelled at all, due to data limitations. While these subsectors are currently approximated with generic load profiles, there is the possibility to expand the database in future research and to model remaining industrial subsectors. Particularly in industrial subsectors, however, stochastic effects and the lack of knowledge of production schedules poses a considerable challenge to the modelling of subsector electricity demand, as has been described for WZ 17 *manufacture of paper* in chapter 4.2.1.1. While the performance measures for all subsectors appear to be a neutral basis for comparison of the TUB BLP's reliability, performance measures are significantly distorted by subsectoral heterogeneity. A heterogeneous subsector will inevitably be associated with poorer performance measures. Also, the modelling of holidays is a known challenge in the energy demand modelling research. The improvement of modelling holiday load patterns in TUB BLP depicts an opportunity for future research. Besides, in the present approach all individual load profiles were normalized before the modelling procedure in order to equally consider all different load patterns. Another reasonable option would be to assign a weighting to individual models based on their electricity consumption level, considering the higher relevance of larger energy consumers. In the benchmarking of TUB BLP, the comparison with VDEW SLP only yields an indication for the SLP's inaccuracy as for different aggregation levels.

In the application and evaluation of TUB BLP, the representativeness of selected DSOs can be questioned since all of them are independent cities, only. This goes back to the fact that these independent cities depict a separate county and are simultaneously supplied by their own DSO – both preconditions in order to compare *disaggregator* model results (county level) with published real metered regional loads (DSO). Notwithstanding, the limited representativeness of selected DSOs was compensated evaluating model results with total loads of the Federal Republic of Germany, using ENTSO-E data. In the depiction of county loads, TUB BLP are regionalized using county specific weather and calendar data. Beyond that, TUB BLP do not offer any regional specification. In that way the *disaggregator* model is limited to depict very specific economic structures in counties, as it maps average load patterns of each subsector. Using TUB BLP significantly reduced model deviations for most datasets evaluated (DSOs, ENTSO-E), but some deviations remained. In general, with the existing database it is not possible to attribute the deviations to individual profiles. However, a considerable part of these deviations might be associated with the residential ZVE profile, which has only been analysed roughly in the present thesis. The development of a residential profile based on smart meter data already improved the model performance significantly. As for its relevance, there are multiple approaches to model or simulate residential load profiles (Fraunhofer ISE, 2020; Pflugrath, 2020; Ziegler et al., 2020), which could help to further improve model results in the future. For future projections, especially the expansion of electric vehicles, PV systems and heat pumps will have significant impacts on the load profiles of residential but also commercial consumers (Agora Energiewende, 2020; Gobmaier and von Roon, 2010; Hinterstocker et al., 2014, pp. 1–2; Spiegel, 2018, pp. 796–797). In addition, the trends of increasing stand-by loads and simultaneous efficiency increases will likely affect load profiles.

In the development of engineering-based sub-load profiles, five of the six largest CTS subsectors by electricity consumption have been modelled with good consistency and plausibility. Nevertheless, deviations to subsector load profiles still remain, which could be considered in future research. According to Böckmann et al. (2021, p. 19), opportunities for improvement exist in the adjustment of heating and cooling limits, a greater consideration of real sub-load profiles (which could not be found) and particularly the consideration of a representative German load profile for air conditioning. Also, the database of AGEB's application balance (Rohde, 2019) is incomplete with regards to technology shares and could be improved. Besides, the subsector load profiles are themselves only models, the reliability of which relies on their database. In addition to improving developed engineering-based load profiles, the same methodology could be applied to additional subsectors from industry or CTS.

The projection of energy demand in general and electricity load profiles in particular are naturally associated with uncertainties. The uncertainties of the present approach are particularly associated with the energy scenarios utilized. Since energy scenarios are a very important basis for decision-making, they are repeatedly put to the test and updated. In this respect, the existing database for projected load profiles in the present thesis should also be updated if possible. Moreover, single assumptions are particularly uncertain and can be varied in future research, such as future shares of hot water vs. space heating generation of heat pumps. Also, the mapping of electric vehicle charging will likely have significant effects on future load profiles in both residential and CTS subsectors, which is not depicted as of now (Seim et al., 2021a, p. 18).

For the identification of technical DSF potentials in high temporal and spatial resolution, the present approach relied on generic literature-based assumptions for the shift duration of individual application technologies. In contrast to existing literature, newly developed engineering-based load profiles were used to get a more robust picture of the temporal availabilities of individual application technologies. The existence of a technical control option may be available or may be brought about by investments (Kochems, 2020, p. 1). Naturally, the economic DSF potential is a subset of the technical DSF potential. Consequently, economic factors or other social and organizational factors must be considered in future research in order to determine the economic usability of the technical potential. In the present thesis, social and organizational factors have not been considered (Seim et al., 2021a, pp. 5–6). There are barriers to tapping into the DSF potentials, however. With a low energy intensity of about 1 %, companies in the CTS sector often lack incentives to tap into the savings potential through efficiency measures and load flexibilization (Pfluger et al., 2017b, p. 70). Consequently, there is a need for research into the technological, regulatory and economic exploitation of these potentials.

In the economic assessment of applying newly developed subsector load profiles, two use cases were presented. In the first use case, a hypothetical procurement strategy was presented which is supposed to shed light on trends and potentials as opposed to the exact monetary value. Hourly load and price values were used due to data availability, whereas quarter-hourly values would be exact. Actual procurement strategies, demand models and data of suppliers, traders and DSOs are all undisclosed and not usable for analysis. Also, the extent to which model deviations are actually addressed by balancing group management cannot be concluded from the data. According to Beucker et al. (2020b, p. 10), an increased use of the intraday market for balancing has been observed in the last few years. In any case, replacing SLP reduces the necessary amount of short-term balancing group management and shifts it to the suppliers, who procure electricity for their customers. In this way, the management requirement of the deviations can be reduced, which generates an advantage with regard to the planning of the necessary generation capacities, the volatility of the imbalance settlement price and the price risk on the electricity market.

In the second use case of economic validation, the peak load reduction potential by load shifting through the utilization of DSF potentials has been assessed. Here, solely load shifts to later times have been assessed, while load shifts to earlier times are just as well feasible. With shiftable energy quantities (i.e. virtual storage capacity) of DSF potentials being the bottleneck, the additional peak load reduction through simultaneous load shifts to earlier and later times is likely to be marginal. The underlying cost parameters for exploiting the DSF potentials are estimates from the literature that will deviate in the real application case based on the scale of the applications. As for a lack of information, the life time of ICT components was assumed to be around 10 years, while they could probably live longer. Since power generation capacities have very long lifetimes, the savings potentials of reduced peak load capacity are of a long-term nature. However, the generation side of the German energy sector is undergoing profound change due to the phase-out of nuclear power as well as the medium-term phase-out of coal power. With the simultaneous expansion of renewable energies, there is thus a need for additional peak load power plant capacity at an earlier stage, which could be reduced by DSF potentials.

7. Conclusion

The ongoing decarbonisation of the energy system requires far-reaching interventions as well as their sound planning to ensure an efficient, safe and sustainable system transformation. As it is a decisive building block, the assessment of different transformation pathways requires the application of energy demand models in high temporal and spatial resolution. While there were several research projects investigating changes of the generation side, the demand side was less considered. Distinct data gaps for demand data in high temporal and spatial resolution were identified. Addressing some of the above gaps, only recently an openly accessible demand modelling toolset (*disaggregator*) has been published within the research project DemandRegio, from which this thesis emerged. In the electricity sector, the use of SLP is still common practice in various contexts, such as the balancing group system, the procurement and the load modelling. However, SLP rely on 20- to 40-year-old load data and are associated to structural deviations. To address future flexibility needs of the system, technical demand side flexibility potentials were assessed using these generic and oftentimes imprecise load profiles. Based on the research project DemandRegio, this thesis addressed many of the above research and data gaps. Divided into six individual modules, the four central research questions were answered.

In the first module, 32 subsector load profiles (TUB BLP) of the sectors CTS and industry were developed in quarter-hourly resolution using a multiple regression approach. These TUB BLP were made publicly accessible and usable, and include a thorough description of the load characteristics and demand drivers of each covered subsector. TUB BLP were made available for 10 weather years (2009 – 2018). In order to evaluate performance and reliability of each subsector load profile, the forecast performance measures (MAPE and R^2) were determined using a cross validation approach, and prediction intervals were identified using quantile regression. The performance of subsector load profiles varies greatly between subsectors, which can be traced back to their predictability and varying heterogeneity. The modelling of these subsector load profiles required the development of a comprehensive database of 1,104 individual real metered load profiles. Potentially sensitive real metered load profiles were transformed into usable average characteristic demand patterns. Assessing the applied methodology, the multiple regression approach was benchmarked against a feedforward ANN, finding that both exhibit similar results for the subsector load profiles while the ANN performs slightly better for individual sites. Further, the performance of newly developed TUB BLP was benchmarked against existing load profiles such as the VDEW SLP as well as the De Monfort profiles, confirming a significant improvement of TUB BLP against SLP, whilst revealing similar structures compared to the De Monfort profiles. As the most relevant SLP, the G1 reveals a significant overestimation of electricity demand during the day, and a significant underestimation during night time. This was traced back to an increased base load level driven by a higher number of applications in office buildings and households, as well as a reduced peak load due to a higher energy efficiency of used applications. VDEW SLP are still widely used to model the load behaviour of small consumers.

In module 2, all 32 TUB BLP were applied and evaluated within the DemandRegio toolset *disaggregator*, creating electricity demand forecasts for each county in Germany in high temporal resolution. These electricity demand forecasts were evaluated using 11 DSO loads of several years, that were suitable for the comparison and published corresponding regional load data. In addition, these electricity demand forecasts were evaluated using ENTSO-E loads of five years, representing the entire load of Germany. In nearly all cases, the application of TUB BLP once again revealed a significant improvement of model performance measures in comparison to the use of VDEW SLP. Remaining structural deviations still exhibit an overestimation of electricity demand during the day, and an underestimation during night time. These remaining deviations can stem from subsectors that have not yet been covered due to data limitations. However, due to its high relevance, the residential load profile (ZVE profile) in particular is suspected of showing deviations that are visible in the overall picture. Applying TUB BLP in the *disaggregator*, the error profile of remaining deviations looks similar to the ZVE profile shape. Replacing the ZVE profile with the H0 SLP further deteriorates the forecast, whereas replacing the ZVE profile with a newly generated smart meter-based profile yielded significant improvements for selected DSOs.

In module 3, a novel bottom-up approach of developing engineering-based sub-load profiles for five selected CTS subsectors *offices*, *trade*, *accommodation*, *hospitals* and *education* was introduced. These five subsectors represent about 62 % of the total CTS electricity consumption. The approach was made publicly accessible in data and code. The methodology can be further developed with regards to future technology shifts or applied to additional CTS or industrial subsectors. The alignment with previously developed TUB BLP ensured that the engineering-based load profiles can be regarded as consistent and valid. Deviations to TUB BLP can be mainly traced back to times of changing occupancy, uncertainties for temperatures of heating and air conditioning thresholds as well as a lack of characteristic application sub-loads in literature. Engineering-based load profiles enable the projection of load profiles and the identification of DSF potentials in high temporal resolution (Böckmann et al., 2021, p. 19).

In module 4, developed engineering-based sub-load profiles were projected into the year 2035, using two recognized energy scenarios from literature: a baseline scenario (normative) and a reference scenario (explorative). Depending on the scenario, the developments of individual application technologies was derived and allocated to respective subsectors. While the baseline scenario indicates a reduction of electricity demand for four of the five subsectors (except for *hospitals*) due to efficiency gains, the reference scenario projects an increase of electricity demand in each but the education subsector. In both scenarios, electricity-based space heating will be partially shifted from night storage heaters to heat pumps. Also, the share of electricity demand for lighting decreases in both scenarios, whereas the share of both ICT and mechanical energy increases. Resulting projected load profiles exhibit similar shapes as compared to the year 2018, whilst revealing a different level of electricity demand. Particularly for the *trade* subsector, more pronounced load peaks are to be expected in the future. In *hospitals*, demand increases are to be expected in both scenarios. In all other subsectors, the ratios of peak load to base load show only minor variations within the scenarios (Seim et al., 2021a, pp. 17–18).

In module 5, developed and projected engineering-based sub-load profiles were utilized to derive demand side flexibility potentials in high temporal and spatial resolution for the years 2018 and 2035. Based on an approach developed by Kleinhans (2014), both switchable loads and shiftable energy quantities of five CTS subsectors were quantified and published, covering 74 % of technical DSF potentials in the entire CTS sector. In contrast to previous studies, the present analysis used robust technology-specific load profiles of high temporal resolution, which have been validated against subsector load profiles. Moreover, the spatial resolution of technical DSF potentials can help to reduce local grid bottlenecks in future, and thus potentially offer an economic alternative for grid expansion projects or short-term storage. Across all scenarios, air conditioning as well as space heating and hot water offer high load shifting potentials. Air conditioning, however, is subject to strong diurnal and seasonal fluctuations. Space heating and hot water also have immense potential for shiftable energy quantities due to high shift durations. Notwithstanding, space heating and hot water fluctuate in most subsectors according to the time of day and slightly according to the season. In contrast, *hospitals* provide very constant flexibility potential over time for all technologies except air conditioning due to stable occupancy profiles. The potential of process cooling in *retail* as well as space heating, hot water, process cooling and ventilation in *accommodation* also show temporal stability. A comparison of the identified potentials with literature values underlines the plausibility of the present approach. By analysing the five subsectors, it was possible to identify large technical load flexibility potentials in the tertiary sector with high temporal and spatial resolution (Seim et al., 2021a, p. 18).

In module 6, newly developed subsector load profiles were evaluated economically in two use cases. In the first use case, the influence of newly developed TUB BLP on electricity procurement and balancing group management was assessed. As part of a hypothetical procurement strategy, the *disaggregator* model outputs (module 2) were priced with the Day-Ahead market prices. Any model deviations were priced by the imbalance settlement price (reBAP). The assessment indicated that the total costs from procurement and imbalance settlement can be significantly reduced for the whole system by applying TUB BLP. In contrast, it was also shown that potential arbitrage gains in short-term trading or imbalance settlement calls are smaller using TUB BLP. Smaller arbitrage gains depict a potential disincentive to use novel and improved subsector load profiles, especially for DSOs in the synthetic load profile procedure. In the second use case, a potential economic value was derived for DSF potentials identified in module 5. While there are multiple ways how DSF potentials can generate system value, in the present thesis the peak load reduction potential was assessed. In order to determine the peak load reduction potential, the residual load curve of the Federal Republic of Germany of the year 2018 was matched by time and date with identified DSF potentials of cooling, ventilation, AC and space heating. Technical restrictions of the load reduction potentials and shiftable energy quantities were taken into account. Utilizing DSF potentials, a total peak load reduction of 2.9 GW could be realized. Assuming that this reduction would result in a reduction of physical gas turbine PP capacity, annual cost savings of around 157 million € can be realized. These cost savings are opposed to estimated exploitation costs of only 6 million €, indicating an economically attractive application of DSF potentials. Further options to utilize DSF potentials seem also promising from a system perspective, however, obstacles for the individual economic application remain: Among others, the fixed and inflexible system of levies and charges for electricity needs to be revised to incentivize efficient flexibilization of demands.

8. Outlook

The present thesis focused on the development and application of subsector load profiles for the long-term load forecasting. There are opportunities to expand the present approaches in future research.

Utilizing the *disaggregator* model output in future research, the electricity demand in high spatial and temporal resolution can be mapped with regional electricity generation by fluctuating RES, in order to determine regional residual loads. These residual loads can be used to determine electricity flows in the network and gain insights regarding network utilization as well as storage or DSF requirements. Moreover, further research could utilize identified regional DSF potentials and match them with grid bottlenecks and expansion paths from the electricity network development plan (*Netzentwicklungsplan Strom 2035*, 2021, pp. 117–128), as well as on the spatial RES generation and electricity price information, in order to identify specific economic load shifting potentials.

Despite the data limitations discussed, the database for subsector load profiles as well as engineering-based sub-load profiles can be expanded, both enhancing the database for already existing subsector load profiles and increasing their representativeness; as well as broadening the database for (particularly industrial) subsectors which have not been modelled yet. A greater coverage of electricity demand models could yield better forecasts and reduce remaining deviations. In this regard, especially the residential sector is of great relevance and should thus be modelled more precisely. Existing approaches, such as so-called load profile generators, could be further developed and integrated into the *disaggregator* tool (Fraunhofer ISE, 2020; Pflugrath, 2020; Wörner et al., 2020; Ziegler et al., 2020). Especially future trends like PV generation, the charging of electric vehicles and the technology shift towards heat pumps should be reflected in these simulation tools.

With regards to newly developed subsector load profiles, the normalisation procedure can be changed so that loads are weighted according to their electricity demand level in the final subsector load profile. Also, holidays might be mapped more accurately in future model designs, by connecting the holiday variable with the hours of the day, in analogy to weekdays. Another option to improve the overall *disaggregator* modelling result is a top-down adjustment of load profiles. Based on the model deviations against the ENTSO-E total load, remaining SLP and generic load profiles could be adjusted by a correction factor which minimizes deviations. This top-down (retrofit) procedure would distort respective load profiles, but would improve overall model results, which could be tested and quantified against the DSO loads. This adjustment procedure would also account for electricity demand patterns which have not yet been explicitly taken into account, for example (but not limited to) street lighting loads. Moreover, In the *disaggregator* tool, generic load profiles could be developed further and smoothed as to avoid sharp load increases or drops, which were visible in the heatmap illustration in chapter 5.2.2. On a more general note, the update cycles of subsector load profiles should not be as long as 20 years (or longer), as prevailing trends will have an effect on future load patterns: the expansion of electric vehicles, heat pumps and PV systems, as well as enhancing energy efficiency and a trend towards more digitalization and associated base-loads. Also, the flexibilization of demand, as investigated in module 5, will have a significant effect on the shape of subsector load profiles. However, developed subsector load profiles can still be used as scheduled load (as done in this thesis), a part of which can be shifted according to price signals. Hence, the applicability of subsector load profiles remains even considering enhanced demand side flexibilization.

Data availability will likely improve in the future due to the advancing smart meter roll-out and further open source / open data research projects. The additional load data can be used to expand the database and enhance subsector load modelling. An enhanced database might also encompass application technology-specific sub-load profiles which could be used to improve the engineering-based load modelling approach. In any case, as for the different fields of application of subsector load profiles, the need for cumulative subsector load profiles will likely prevail even if the smart meter penetration reaches high levels (Gerblinger et al., 2014, p. 3). According to Lopion et al. (2018), the demand for models and data with high temporal and spatial resolution is increasing, also associated with the expansion of energy system models across the sectors of electricity, transport and buildings (Bai et al., 2016; Verwiebe et al., 2021b, p. 7859). From a policy perspective, it is recommendable to improve accessibility of demand data by establishing an orchestrated data platform, similar to their transparency efforts in the SMARD database. Moreover, the need to enhance funding for open source- / open data research projects was emphasized (Seim et al., 2019, p. 18) (cf. chapter 2.1).

In the engineering-based model approach, future research could focus on using the same methodology to model further subsectors. As for their relevance, particularly industrial subsectors could be modelled this way. Existing sub-load profiles could be further improved by a top-down adjustment to exactly match subsector load profiles of module 1 (TUB BLP). This would increase consistency between both approaches, but potentially impair the plausibility of sub-loads. Another opportunity to further develop engineering-based load profiles is to incorporate a charging module for electric vehicles which will likely have a significant impact on load patterns in the mid-term future. In this regard, the projection of engineering-based load profiles can also be updated in future research with novel energy scenarios. Also, load profiles could be projected to further years in the future in order to analyse shifts in load patterns or determine future DSF potentials in the far future. Existing or future engineering-based load profiles could also be integrated into the *disaggregator* tool, to enable scaling the load characteristics to different regional entities.

For DSF potentials, future research could particularly focus on further narrowing down the technical towards economic DSF potentials in high spatial and temporal resolution. This includes future research to overcome organizational, regulatory and economic barriers in order to maximize exploitation of technical DSF potentials. Barriers encompass, for example, the low priority of energy costs in CTS subsectors, impairment of the comfort level or data protection concerns regarding the technological implementation of load management. Regulatory incentives are missing or lacking in attractiveness. From an economic point of view, the consideration of DSF potentials in the grid congestion management process is particularly interesting if it can substitute more expensive flexibility options or increase the use of renewable electricity. Methodologically, additional subsectors could be analysed with regards to their technical DSF potentials, especially those that have a high power consumption. The inclusion of an electric vehicle module in the engineering-based approach will also lead to the identification of further future DSF potential.

In the economic assessment, two use cases can be differentiated: In the first use case, the economic assessment of a specific procurement strategy could be complemented with other procurement strategies, including the utilization of the futures and the intraday market. The resulting economic assessment will depict sensitivities and thus be more robust than the indicative procurement case analysed in this thesis. Also, quarter-hourly prices could be used to get a more exact estimation. For the second use case, further research could assess the economic value of other fields of application for DSF potentials, e.g. optimising procurement strategies on the spot market and balancing power market, the regulation for interruptible loads as well as the reduction of curtailed electricity due to network congestion; the rough estimation of the latter mentioned in this thesis should be refined in future research. In particular, the interplay of these various fields of application for DSF potentials could be analysed in future research. The identified economic potential of DSF appears very promising from a system perspective. Hence, further research could focus on the exploitation of these potentials by creating incentives and reducing obstacles for electricity consumers.

9. Literature

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10. Appendix

A.1. Appendix to chapter 4

A.1.1. Energy Consumption for each Subsector (WZ 2008) and Data Availability

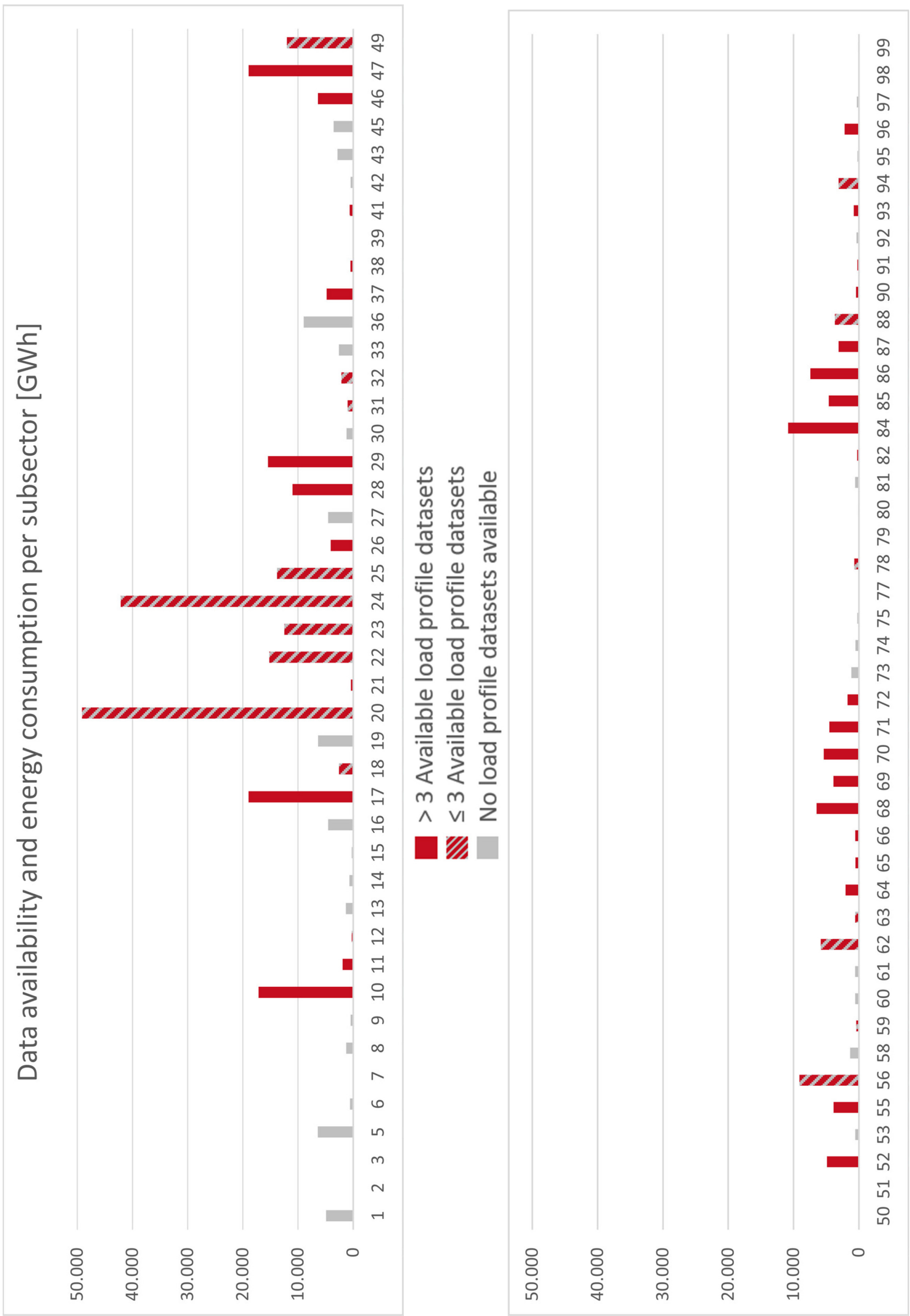


Figure 62: Illustration of the data availability and energy consumption per subsector. Diagram by author, adapted from Verwiebe and Seim (2019)

A.1.2. Cross Validation Procedure for Subsector Load Profiles

The determination of the forecast quality of the subsector load profiles (2.) was carried out in analogy to the site-specific regression models (see chapter 4.2.1.4), but required a more complex implementation described below in Figure 63.

For each subsector, five separate subsector models (Avg. 1 - Avg. 5) were created based on the training data of site-specific regression models (OLS model C1, OLS model C2, ...). In a subsector with four locations, this yields 20 regression models, whose regression coefficients are averaged to five separate subsector models for each split (Avg. Coefficients Split 1, Avg. Coefficients Split 2 ...). For each of the five separate subsector models (Avg. 1, Avg. 2, ...) the performance measures are then determined based on retained validation data of the individual locations (C1, C2, ...). As a result, the site-specific performance measures (e.g. MAPE 1, MAPE 2, ...) of each individual subsector model are averaged (Avg. MAPE C1, Avg. MAPE C2, ...).

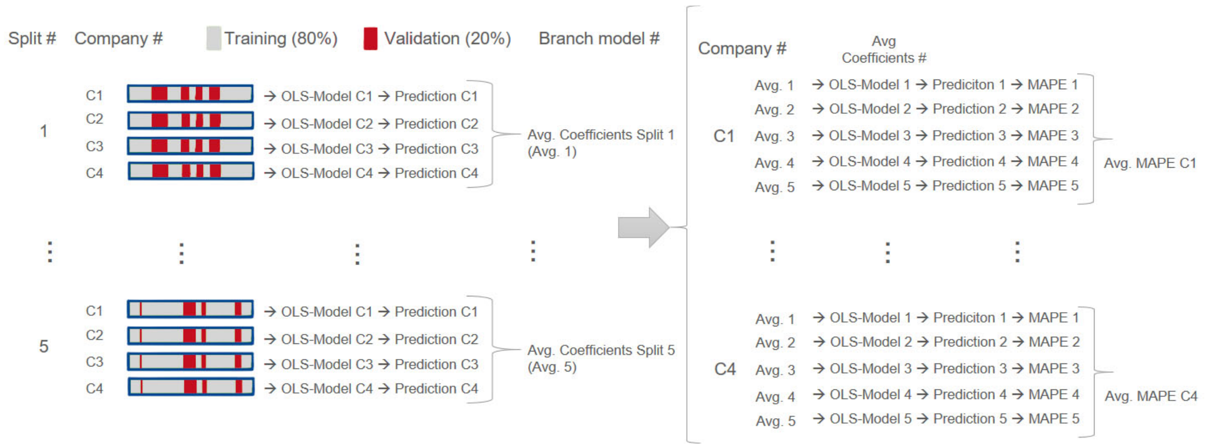


Figure 63: Illustration of the principle of cross-validation for the robust determination of the forecast quality of the subsector load profiles compared to the underlying real data. Diagram by author, adapted from Gotzens et al. (2020, p. 103)

A.1.3. Mapping of Load Profile Types for Model Comparison

*Table 27: Mapping of three load profile types, based on works by Rüdt (2020, p. 18). * According to Gotzens et al. (2020)*

<table>
<tr><th>TUB BLP (WZ)</th><th>Electricity consumption of WZ [GWh]*</th><th>Database (metered load profiles)</th><th>De Monfort profiles</th><th>VDEW SLP</th></tr>
<tr><td>Offices (WZ 64-71)</td><td>68332.5</td><td>13</td><td>Commercial Offices</td><td rowspan="4">G1</td></tr>
<tr><td>Research and Development (WZ 72)</td><td>17489.4</td><td>11</td><td>Commercial Offices</td></tr>
<tr><td>Public administration (WZ 84)</td><td>10834.0</td><td>38</td><td>Government</td></tr>
<tr><td>Education (WZ 85)</td><td>4615.9</td><td>154</td><td>Education</td></tr>
<tr><td>Residential care activities (WZ 87)</td><td>14229.0</td><td>24</td><td>Health</td><td rowspan="2">G2</td></tr>
<tr><td>Sports activities, amusement and recreation activities (WZ 93)</td><td>7832.6</td><td>8</td><td>Sports & Leisure</td></tr>
<tr><td>Sewerage (WZ 37)</td><td>4825.0</td><td>8</td><td>Other</td><td rowspan="4">G3</td></tr>
<tr><td>Waste collection, treatment and disposal (WZ 38)</td><td>519.2</td><td>11</td><td>Other</td></tr>
<tr><td>Warehousing and support activities for transportation (WZ 52)</td><td>4887.4</td><td>25</td><td>Warehouses</td></tr>
<tr><td>Human health activities (WZ 86)</td><td>14229.0</td><td>8</td><td>Health</td></tr>
<tr><td>Retail trade (WZ 47)</td><td>18957.5</td><td>123</td><td>Retail</td><td>G4</td></tr>
<tr><td>Manufacture of food products – Bakeries (WZ 10)</td><td>19380.0</td><td>219</td><td>Retail</td><td>G5</td></tr>
<tr><td>Activities of membership organisations (WZ 94)</td><td>7832.6</td><td>3</td><td>Other</td><td>G6</td></tr>
</table>

A.1.4. Scenario-based annual Electricity Demand per Sector and Application Technology

Table 28: Application balance of the year 2018 in PJ/a. Calculation by Böckmann (2021), with values from (Schlomann et al., 2015, p. 84) and (Rohde, 2019, p. 9).

Subsector | Applications [PJ/a]	Light.	Mech. En.	ICT	AC	Proc. cool.	Proc. heat	Sp. Heat & Hot w.	Total
Construction industry	6.66	2.50	1.35	0.47	0.00	0.45	3.63	**15.1**
Offices	49.19	4.64	49.08	4.19	3.35	1.82	9.09	**121.3**
Manufacturing	5.55	5.71	1.80	0.00	0.00	0.00	1.82	**14.9**
Trade	40.69	7.49	8.55	2.33	20.10	2.72	9.54	**91.4**
Hospitals	4.44	6.06	2.70	1.40	0.48	7.72	1.82	**24.6**
Schools	10.73	0.36	1.80	0.00	0.00	0.45	0.91	**14.2**
Pools	0.74	3.92	0.00	0.00	0.00	0.00	0.00	**4.7**
Accommodation	19.60	17.12	4.50	0.93	11.96	9.53	12.27	**75.9**
Bakeries	0.00	0.00	0.00	0.00	0.00	1.36	0.00	**1.4**
Butchers	0.37	0.00	0.00	0.00	0.48	0.45	0.00	**1.3**
Rest of food trades	0.37	0.36	0.00	0.00	0.00	0.00	0.00	**0.7**
Laundries	0.37	0.00	0.00	0.00	0.00	0.91	0.00	**1.3**
Agriculture	4.07	6.42	0.90	1.86	0.48	0.00	3.18	**16.9**
Horticulture	0.74	0.00	0.00	0.00	0.00	0.00	0.45	**1.2**
Airports	1.85	1.43	0.45	0.47	0.00	0.45	0.91	**5.6**
Textile, freight transport	2.22	0.36	0.90	0.00	0.00	0.00	0.91	**4.4**
Not covered by questionnaire	4.07	28.18	18.46	0.00	13.88	1.82	1.36	**67.8**
Others	21.45	30.67	4.50	0.47	0.48	0.91	0.91	**59.4**
Total	**173.1**	**115.2**	**95.0**	**12.1**	**51.2**	**28.6**	**46.8**	**522.0**

Table 29: Application balance of the baseline scenario (2035) in PJ/a. Calculation by Böckmann (2021), with values from (Schlomann et al., 2015, p. 84), (Rohde, 2019, p. 9) and (Pfluger et al., 2017b, pp. 69, 123)

Subsector | Applications [PJ/a]	Light.	Mech. En.	ICT	AC	Proc. cool.	Proc. heat	Sp. Heat & Hot w.	Total
Construction industry	5.13	2.76	1.62	0.52	0.00	0.40	3.36	**13.79**
Offices	38.04	5.15	59.08	4.66	2.61	1.61	8.43	**119.59**
Manufacturing	4.27	6.32	2.16	0.00	0.00	0.00	1.68	**14.43**
Trade	34.46	9.11	11.28	2.84	17.16	2.64	9.69	**87.19**
Hospitals	4.05	7.95	3.84	1.83	0.44	8.07	1.99	**28.18**
Schools	6.95	0.33	1.82	0.00	0.00	0.34	0.71	**10.14**
Pools	0.57	4.34	0.00	0.00	0.00	0.00	0.00	**4.91**
Accommodation	15.10	18.95	5.40	1.03	9.29	8.42	11.34	**69.53**
Bakeries	0.00	0.00	0.00	0.00	0.00	1.20	0.00	**1.20**
Butchers	0.28	0.00	0.00	0.00	0.37	0.40	0.00	**1.06**
Rest of food trades	0.28	0.39	0.00	0.00	0.00	0.00	0.00	**0.68**
Laundries	0.28	0.00	0.00	0.00	0.00	0.80	0.00	**1.09**
Agriculture	3.13	7.11	1.08	2.07	0.37	0.00	2.94	**16.70**
Horticulture	0.57	0.00	0.00	0.00	0.00	0.00	0.42	**0.99**
Airports	1.42	1.58	0.54	0.52	0.00	0.40	0.84	**5.30**
Textile, freight transport	1.71	0.39	1.08	0.00	0.00	0.00	0.84	**4.02**
Not covered by questionnaire								**0.00**
Others	21.45	30.67	4.50	0.47	0.48	0.91	0.91	**59.39**
Total	**129.01**	**90.54**	**92.05**	**13.86**	**30.53**	**24.91**	**42.87**	**423.79**

Table 30: Application balance of the reference scenario (2035) in PJ/a. Calculation by Böckmann (2021), with values from (Schlomann et al., 2015, p. 84), (Rohde, 2019, p. 9) and (Pfluger et al., 2017b, pp. 64–68)

Subsector | Applications [PJ/a]	Light.	Mech. En.	ICT	AC	Proc. cool.	Proc. heat	Sp. Heat & Hot w.	Total
Construction industry	5.95	3.27	1.70	0.69	0.00	0.40	3.75	**15.76**
Offices	44.13	6.09	61.84	6.22	2.68	1.61	9.41	**131.98**
Manufacturing	4.96	7.47	2.26	0.00	0.00	0.00	1.88	**16.57**
Trade	39.97	10.78	11.81	3.79	17.59	2.64	10.83	**97.41**
Hospitals	4.70	9.41	4.02	2.45	0.45	8.07	2.22	**31.32**
Schools	8.06	0.39	1.90	0.00	0.00	0.34	0.79	**11.48**
Pools	0.66	5.14	0.00	0.00	0.00	0.00	0.00	**5.80**
Accommodation	17.52	22.42	5.65	1.38	9.53	8.42	12.66	**77.57**
Bakeries	0.00	0.00	0.00	0.00	0.00	1.20	0.00	**1.20**
Butchers	0.33	0.00	0.00	0.00	0.38	0.40	0.00	**1.11**
Rest of food trades	0.33	0.47	0.00	0.00	0.00	0.00	0.00	**0.80**
Laundries	0.33	0.00	0.00	0.00	0.00	0.80	0.00	**1.13**
Agriculture	3.64	8.41	1.13	2.76	0.38	0.00	3.28	**19.59**
Horticulture	0.66	0.00	0.00	0.00	0.00	0.00	0.47	**1.13**
Airports	1.65	1.87	0.57	0.69	0.00	0.40	0.94	**6.11**
Textile, freight transport	1.98	0.47	1.13	0.00	0.00	0.00	0.94	**4.52**
Not covered by questionnaire								**0.00**
Others	21.45	30.95	4.50	0.47	0.48	0.91	0.91	**59.67**
Total	**149.63**	**107.14**	**96.34**	**18.50**	**31.30**	**24.91**	**47.89**	**475.73**

Table 31: Shares of flexible electricity demand per subsector in the baseline scenario (2035) in PJ/a. Calculation by Böckmann (2021), with values from (Schlomann et al., 2015, p. 84), (Rohde, 2019, p. 9) and (Pfluger et al., 2017b, pp. 69, 123). Sectors considered in this article are highlighted in light red.

Subsector | Applications [PJ/a]	Ventila-tion	AC	Proc. Cool.	Sp. Heat & Hot w.	Total	Share [%]
Construction industry	0.66	0.52	0.00	3.36	4.54	**4.1**
Offices	1.24	4.66	2.61	8.43	16.94	**15.3**
Manufacturing	1.52	0.00	0.00	1.68	3.20	**2.9**
Trade	2.19	2.84	17.16	9.69	31.88	**28.8**
Hospitals	1.91	1.83	0.44	1.99	6.17	**5.6**
Schools	0.08	0.00	0.00	0.71	0.79	**0.7**
Pools	1.04	0.00	0.00	0.00	1.04	**0.9**
Accommodation	4.55	1.03	9.29	11.34	26.21	**23.7**
Bakeries	0.00	0.00	0.00	0.00	0.00	**0.0**
Butchers	0.00	0.00	0.37	0.00	0.37	**0.3**
Rest of food trades	0.09	0.00	0.00	0.00	0.09	**0.1**
Laundries	0.00	0.00	0.00	0.00	0.00	**0.0**
Agriculture	1.71	2.07	0.37	2.94	7.08	**6.4**
Horticulture	0.00	0.00	0.00	0.42	0.42	**0.4**
Airports	0.38	0.52	0.00	0.84	1.73	**1.6**
Textile, freight transport	0.09	0.00	0.00	0.84	0.93	**0.8**
Others	0.00				0.00	**8.3**
Total	**7.36**	**0.47**	**0.48**	**0.91**	**9.21**	**100.0**

A.2. Appendix to Chapter 5

A.2.1. German names of modelled subsectors according to the classification WZ 2008

- WZ10: Nahrungsmittelherstellung
- WZ11: Getränkeherstellung
- WZ12: Tabakverarbeitung
- WZ17: Papierherstellung
- WZ21: Pharmazeutische Erzeugnisse
- WZ22: Gummi- und Kunststoffwaren
- WZ26: Datenverarbeitungsgeräte
- WZ28: Maschinenbau
- WZ29: Kraftwagen und Kraftwagenteile
- WZ32: Herstellung sonstiger Waren
- WZ37: Abwasserentsorgung
- WZ38: Abfallentsorgung
- WZ41: Hochbau
- WZ46: Großhandel
- WZ47: Einzelhandel
- WZ52: Lagerei u. sonstige Verkehrsdienstleistungen
- WZ55: Beherbergung
- WZ62: IT-Dienstleistungen
- WZ63: Informationsdienstleistungen
- WZ64-71: Büroähnliche Betriebe
- WZ72: Forschung und Entwicklung
- WZ77: Vermietung beweglicher Sachen
- WZ82: Dienstleistungen für Unternehmen und Privatpersonen
- WZ84: Öffentliche Verwaltung
- WZ85: Erziehung und Unterricht
- WZ86: Gesundheitswesen
- WZ87: Heime
- WZ88: Sozialwesen
- WZ90: Kreative, künstlerische und unterhaltende Tätigkeiten
- WZ91: Bibliotheken, Museen und zoologische Gärten
- WZ93: Sport, Unterhaltung und Erholung
- WZ94: Interessenvertretungen, Vereine

A.2.2. Overview of Developed Subsector Load Profiles

Table 32: Exemplary illustrations of created subsector load profiles WZ10 – WZ17.

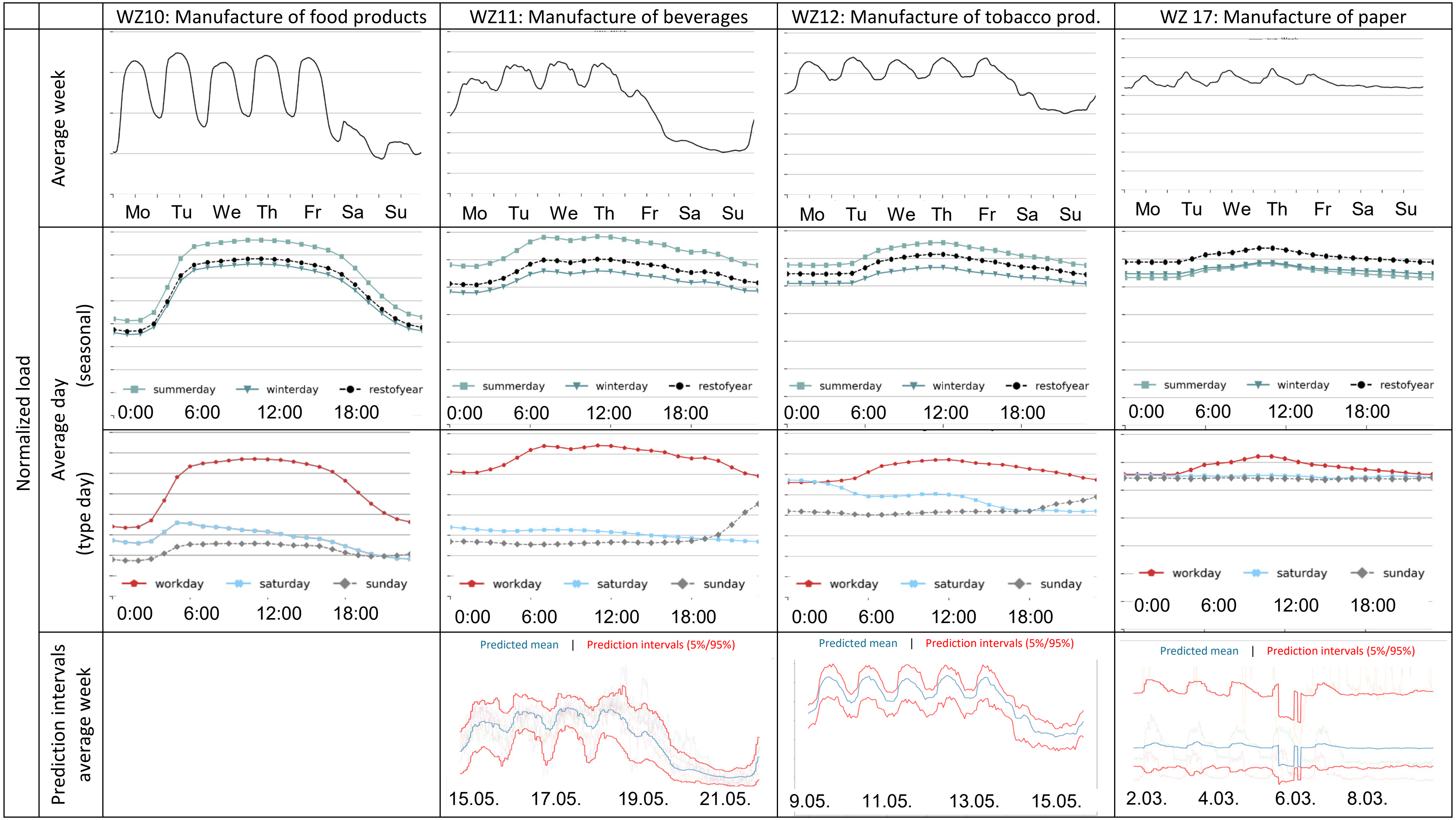


Table 33: Exemplary illustrations of created subsector load profiles WZ21 – WZ28.

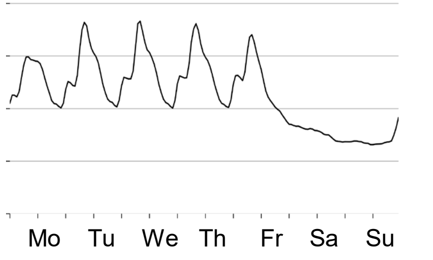
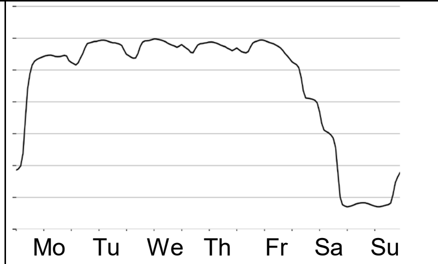
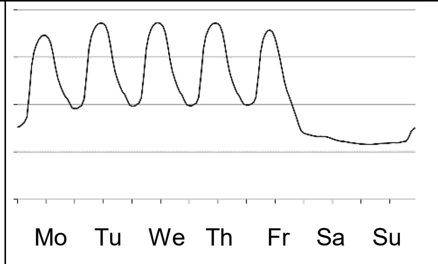
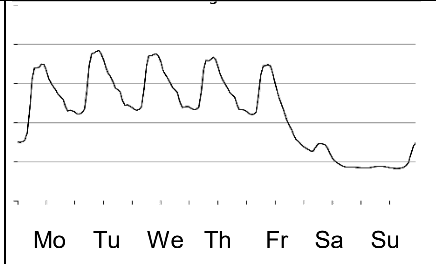
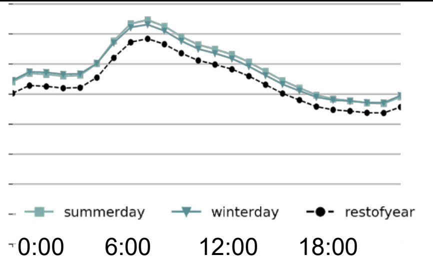
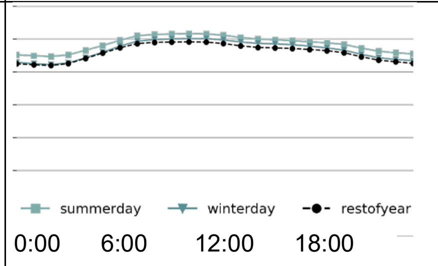
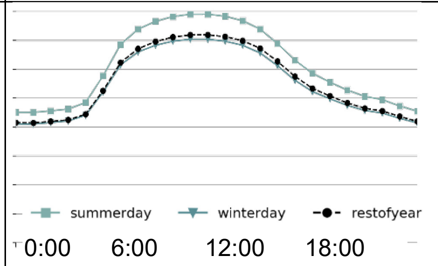
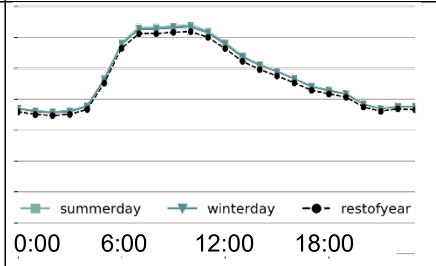
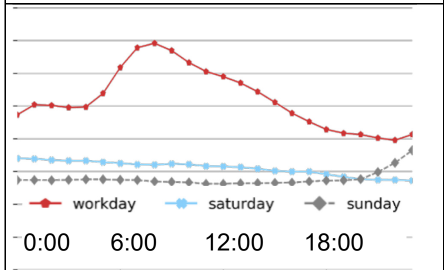
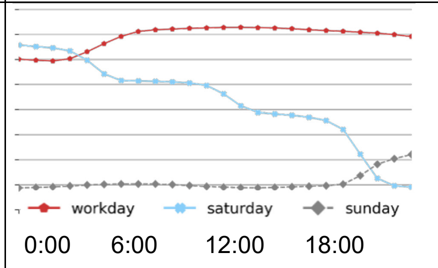
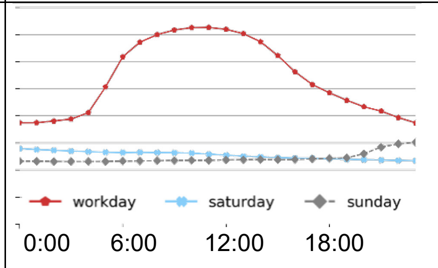
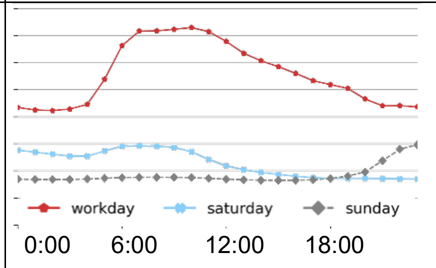
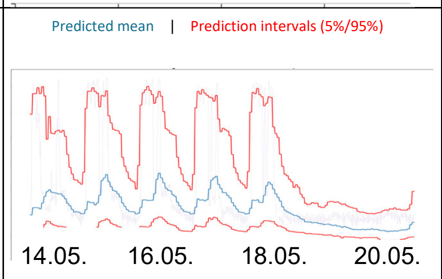
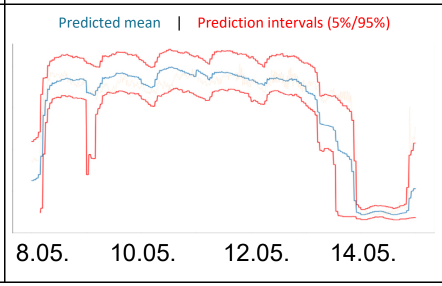
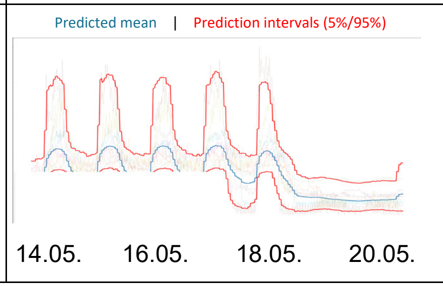
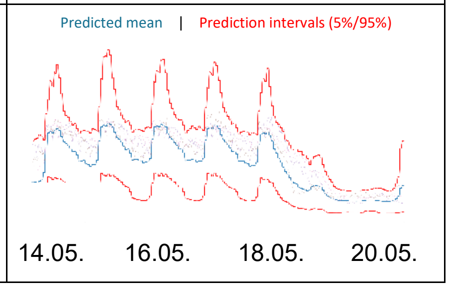
		WZ21: Manufacture of pharmaceuticals	WZ22: Manufacture of rubber and plastics	WZ26: Manufacture of computer, electronic and optical products	WZ28: Manufacture of machinery
Normalized load	Average week				
	Average day (seasonal)				
	Average day (type day)				
	Prediction intervals average week				

Table 34: Exemplary illustrations of created subsector load profiles WZ29 – WZ38.

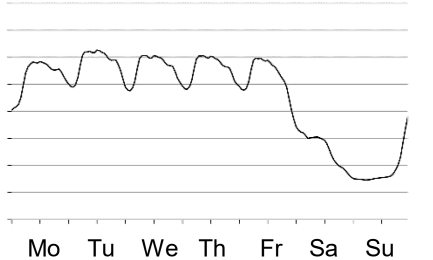
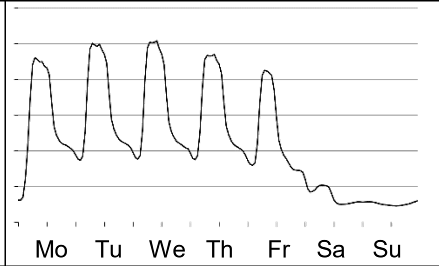
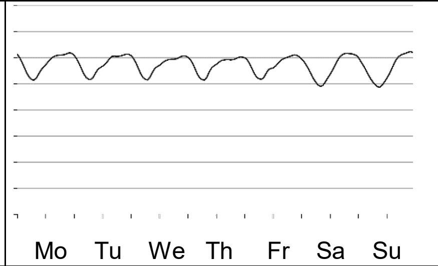
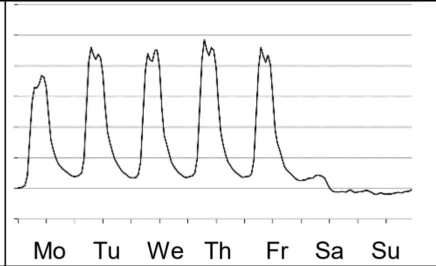
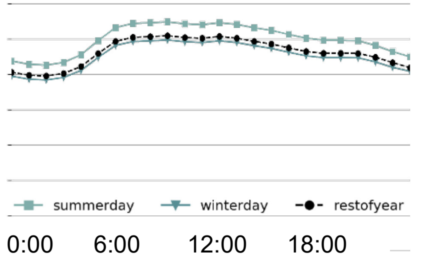
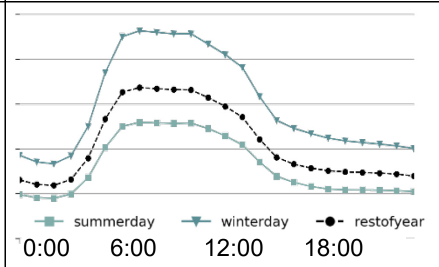
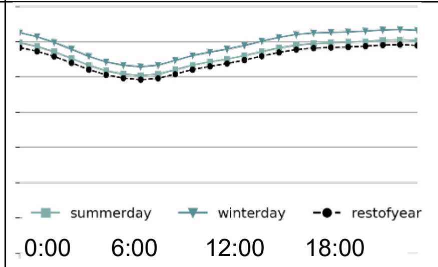
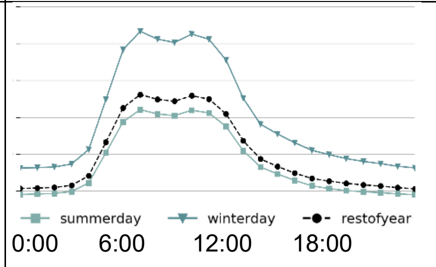
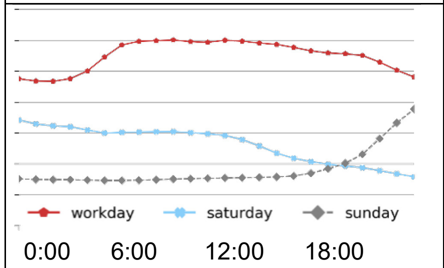
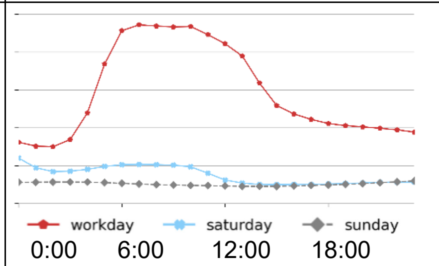
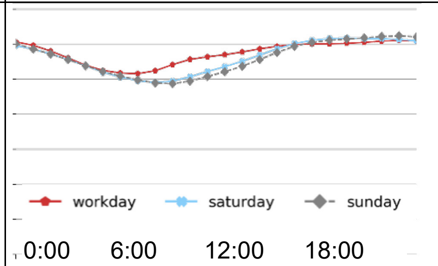
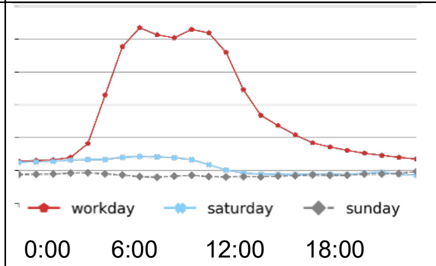
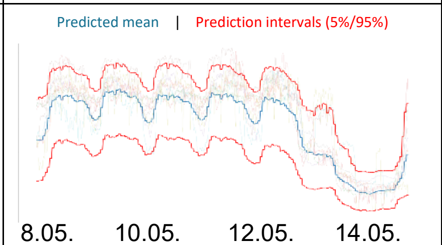
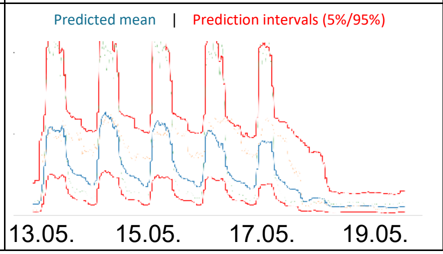
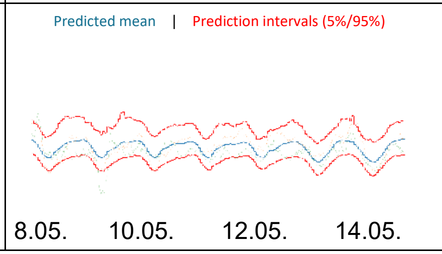
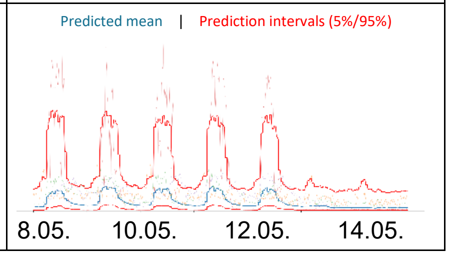
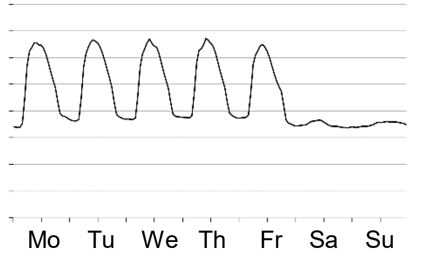
		WZ29: Manufacture of motor vehicles	WZ32: Other manufacturing	WZ37: Sewerage	WZ38: Waste collection, treatment and disposal
Normalized load	Average week				
	Average day (seasonal)				
	Average day (type day)				
	Prediction intervals average week				

Table 35: Exemplary illustrations of created subsector load profiles WZ41 – WZ52.

<table>
<tr><th></th><th></th><th>WZ41: Construction of buildings</th><th>WZ46: Wholesale trade</th><th>WZ47: Retail trade</th><th>WZ52: Warehousing and support activities for transportation</th></tr>
<tr><td rowspan="4">Normalized load</td><td>Average week</td>
<td>
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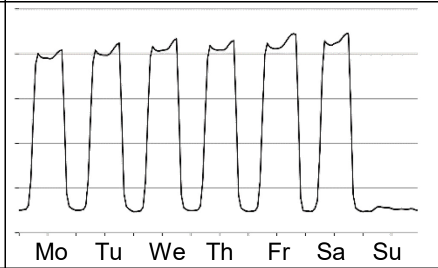
<td>
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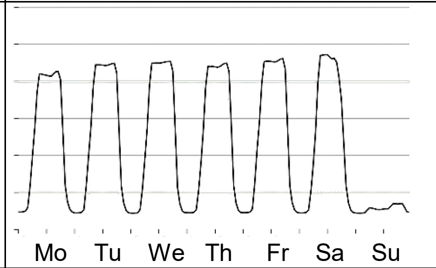
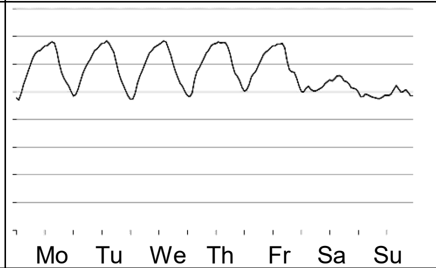
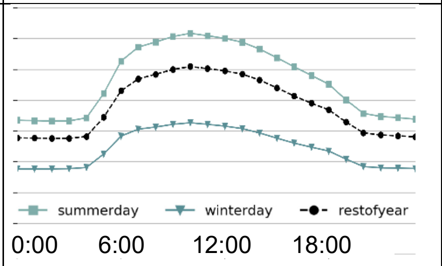
<td>
</td>
<td>
</td></tr>
<tr><td>Average day (seasonal)</td>
<td>
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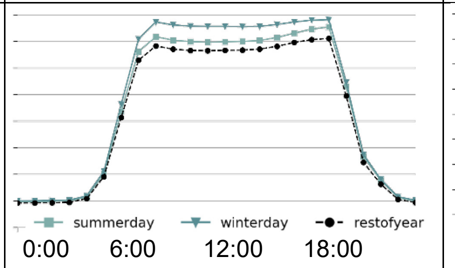
<td>
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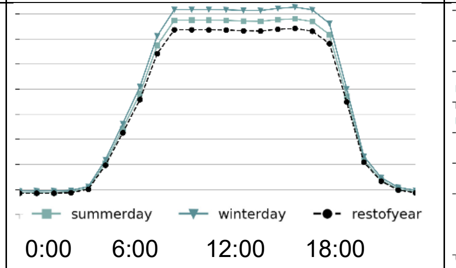
<td>
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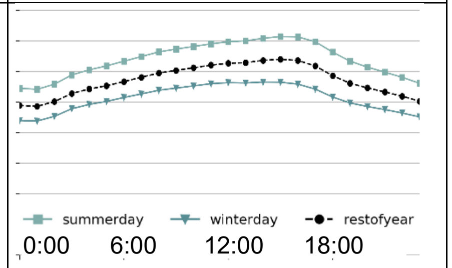
<td>
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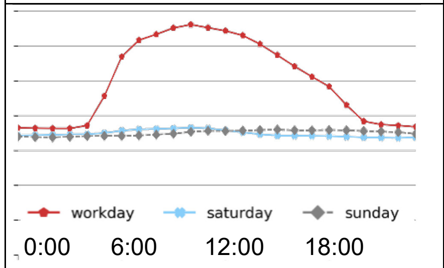
<tr><td>Average day (type day)</td>
<td>
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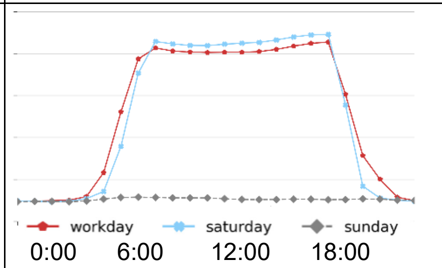
<td>
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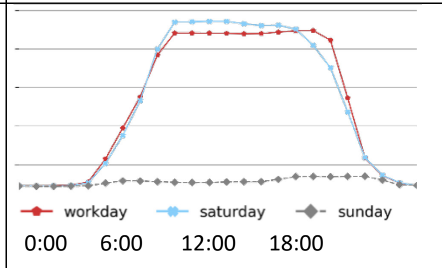
<td>
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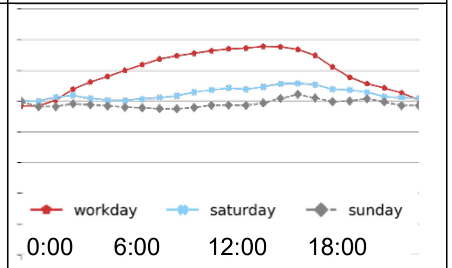
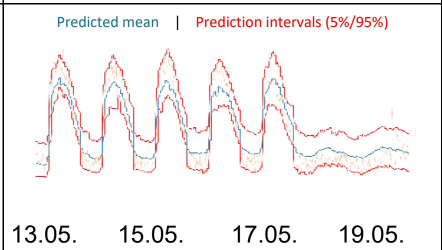
<td>
</td></tr>
<tr><td>Prediction intervals average week</td>
<td>
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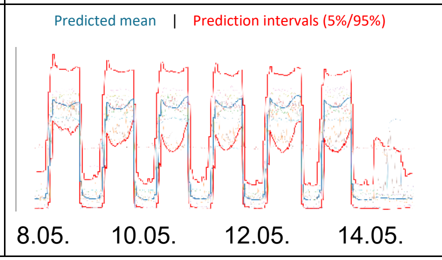
<td>
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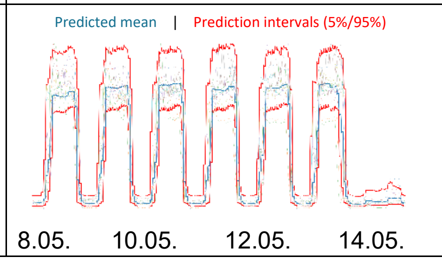
<td>
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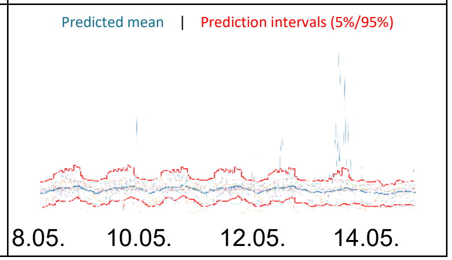
<td>
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Table 36: Exemplary illustrations of created subsector load profiles WZ55 – WZ71.

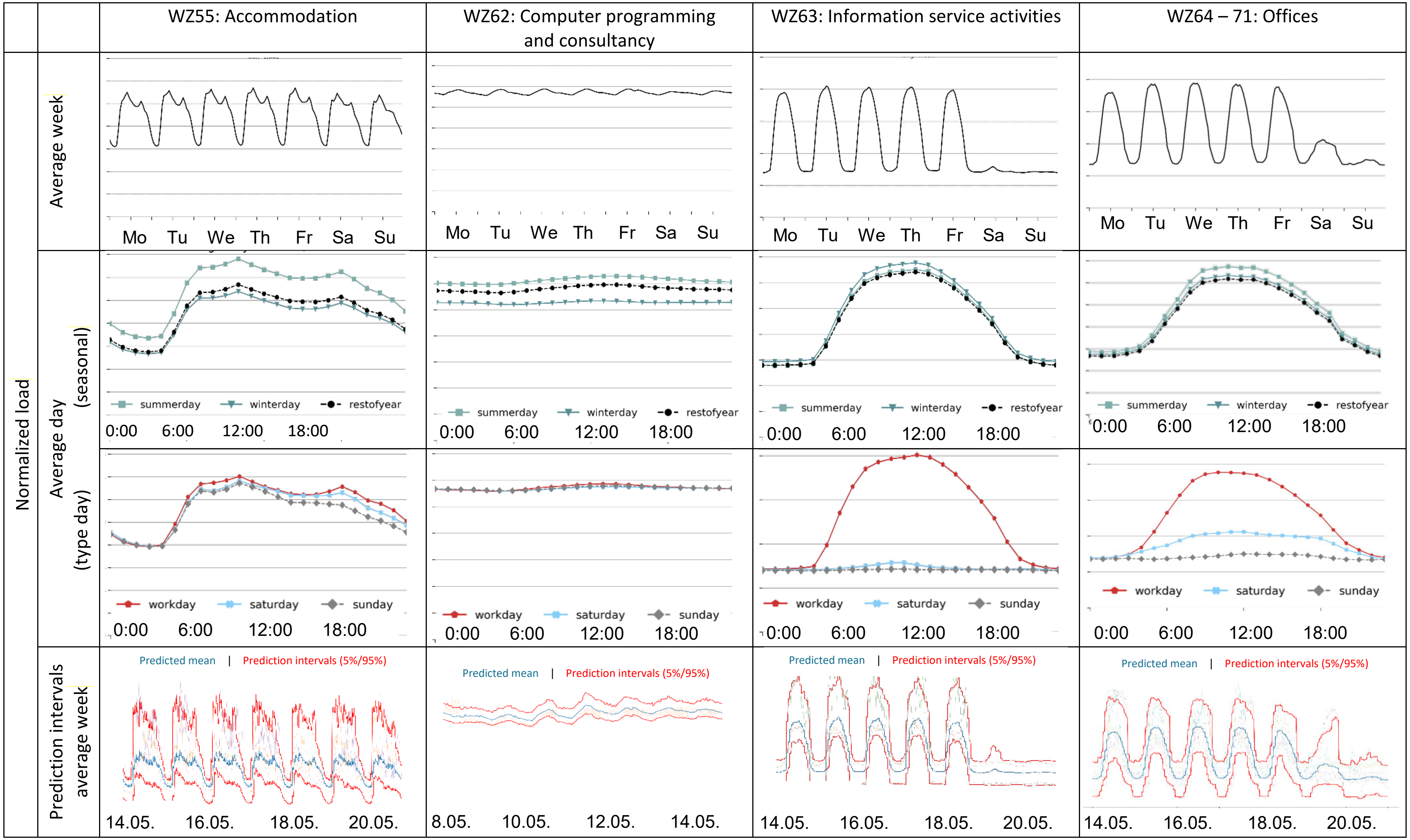


Table 37: Exemplary illustrations of created subsector load profiles WZ72 – WZ85.

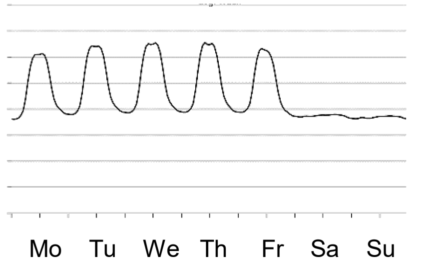
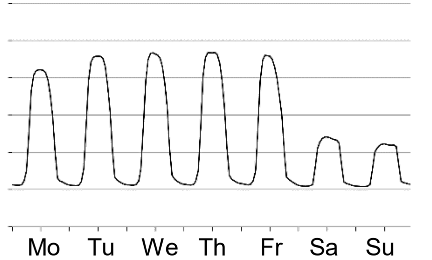
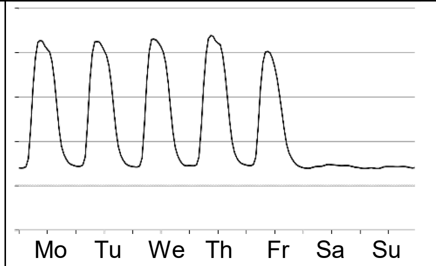
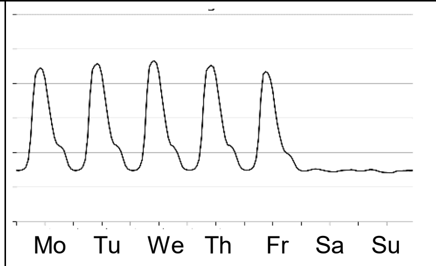
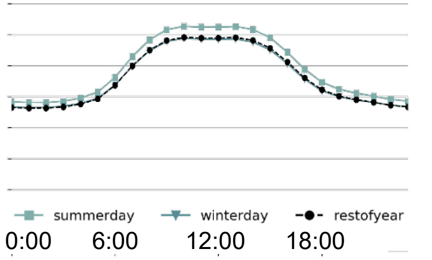
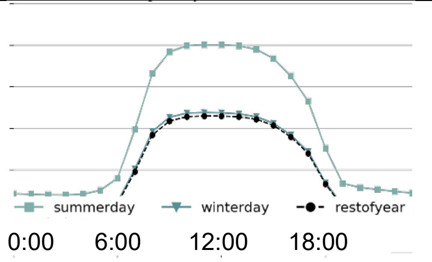
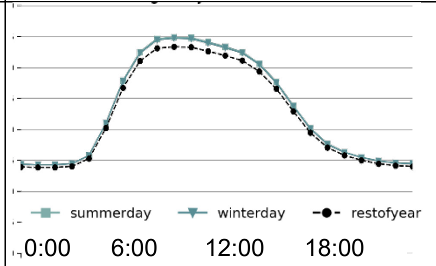
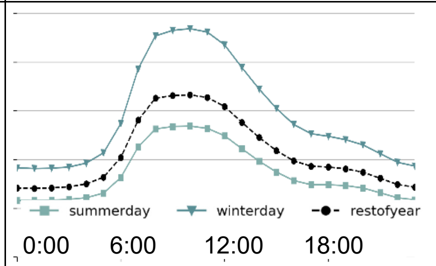
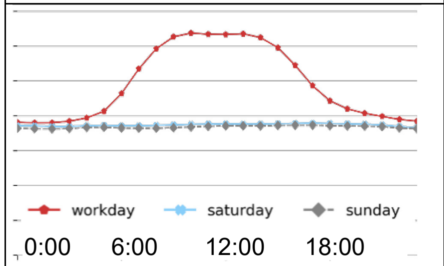
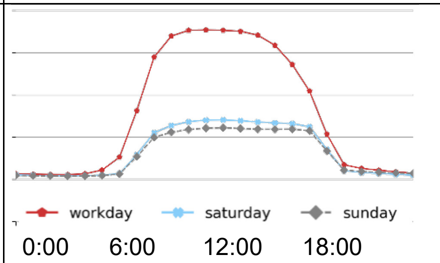
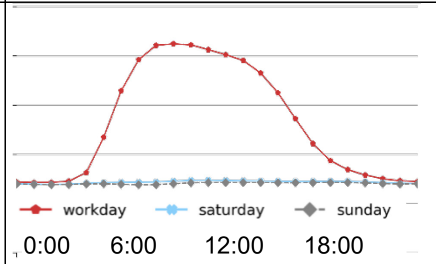
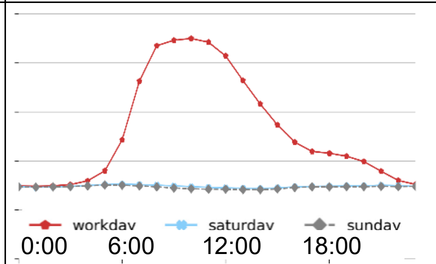
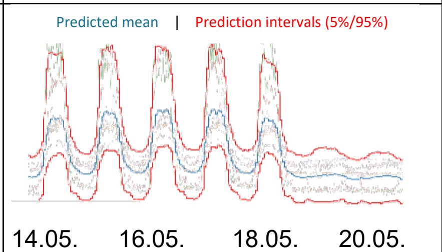
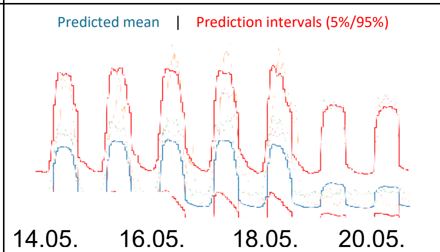
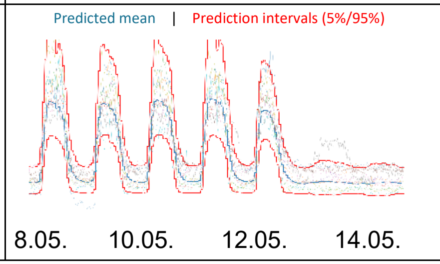
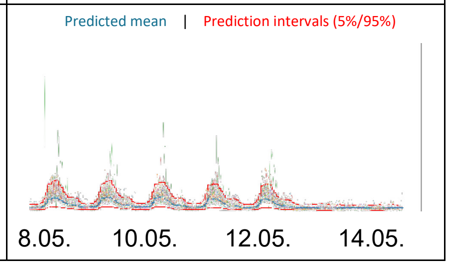
<table>
<tr><th></th><th></th><th>WZ72: Research and development</th><th>WZ82: Office administrative and support activities</th><th>W84: Public administration</th><th>WZ85: Education</th></tr>
<tr><td rowspan="4">Normalized load</td><td>Average week</td>
<td></td>
<td></td>
<td></td>
<td></td></tr>
<tr><td>Average day (seasonal)</td>
<td></td>
<td></td>
<td></td>
<td></td></tr>
<tr><td>Average day (type day)</td>
<td></td>
<td></td>
<td></td>
<td></td></tr>
<tr><td>Prediction intervals average week</td>
<td></td>
<td></td>
<td></td>
<td></td></tr>
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Table 38: Exemplary illustrations of created subsector load profiles WZ86 – WZ90.

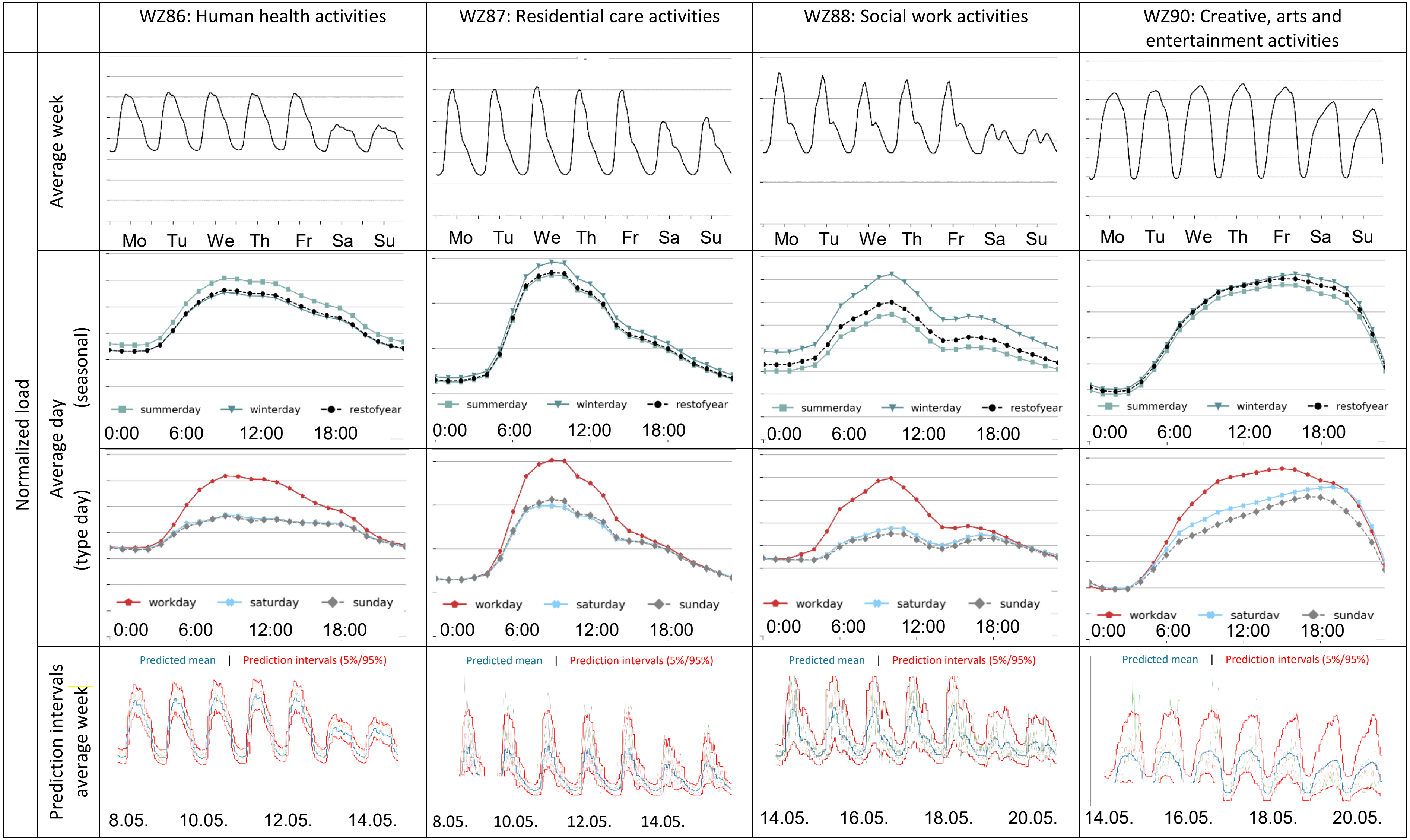
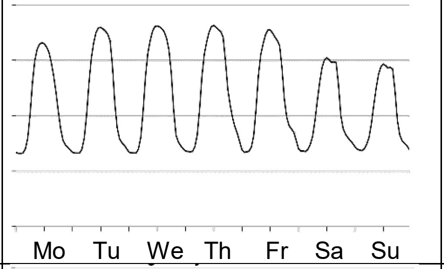
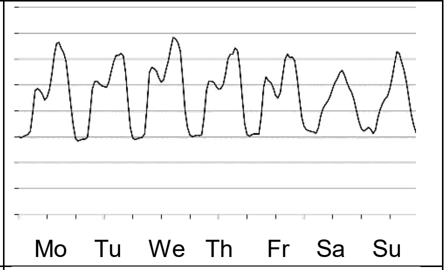
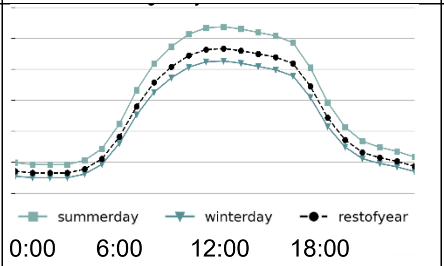
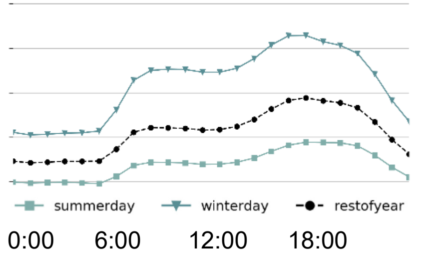


Table 39: Exemplary illustrations of created subsector load profiles WZ91 and WZ93.

<table>
<tr><th></th><th></th><th>WZ91: Libraries, museums and other cultural activities</th><th>WZ93: Sports activities, amusement and recreation activities</th></tr>
<tr><td rowspan="4">Normalized load</td><td>Average week</td><td>
</td><td>
</td></tr>
<tr><td>Average day (seasonal)</td><td>
</td><td>
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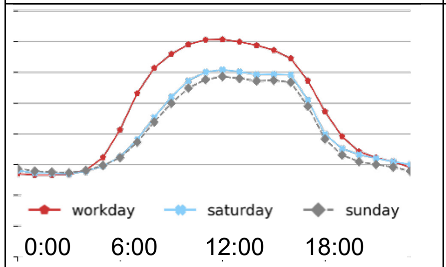
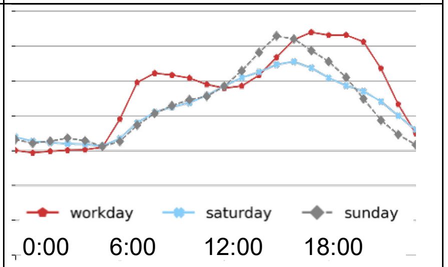
<tr><td>Average day (type day)</td><td>
</td><td>
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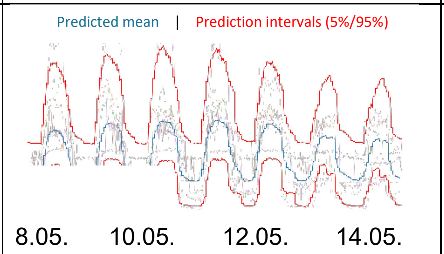
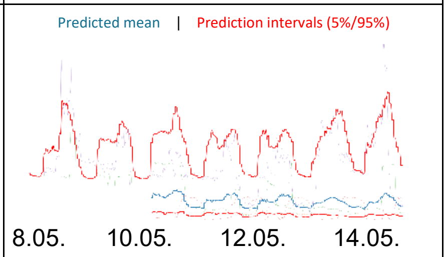
<tr><td>Prediction intervals average week</td><td>
</td><td>
</td></tr>
</table>

A.2.3. Demand drivers and performance measures of subsector load profiles (TUB BLP)

Table 40: Demand drivers and performance measures of subsector load profiles (TUB BLP) for subsectors WZ 10 – WZ32

	Demand driver | Subsector	10 Manufacture of food products	11 Manufacture of beverages	12 Manufacture of tobacco products	17 Manufacture of paper	21 Manufacture of pharma-ceuticals	22 Manufacture of rubber and plastics	26 Manufacture of electronic and optical products	28 Manufacture of machinery	29 Manufacture of motor vehicles	32 Other manu-facturing
	Holiday	-0.01	-0.17	-0.17	-0.12	-0.11	-0.24	-0.16	-0.18	-0.25	-0.2
	Temperature	0.04	0.21	0.28	0.03	0.01	0.05	0.18	0.056	0.09	-0.2
	Solar radiation	0.1	0.16	0.27	0.01	0.17	0.06	0.26	0.2	0.13	0.17
	Workday	0.03	0.73	0.56	-0.01	0.46	0.68	0.63	0.66	0.72	0.54
	Early	0.12	0.1	0.12	-0.004	0.24	0.06	0.29	0.27	0.12	0.38
	Late	0.003	0.01	0.04	0.01	-0.12	0.024	0.01	-0.07	0.02	-0.1
	Night	-0.12	-0.11	-0.16	-0.005	-0.12	-0.08	-0.3	-0.2	-0.14	-0.3
	Office	0.1	0.09	0.17	-0.001	0.16	0.07	0.31	0.19	0.11	0.22
	Summer	0.02	0.18	0.2	0.05	-0.02	0.03	0.1	-0.001	0.05	-0.2
	Winter	-0.01	-0.16	-0.22	-0.05	0.08	-0.03	-0.06	-0.003	-0.04	0.2
	Company Holiday / Vacation / Phase			-0.45	0.89			-0.11	-0.12		-0.1
	Model performance	10	11	12	17	21	22	26	28	29	32
Data	Number of data sets	241	7	< 4	12	6	< 4	17	15	21	< 4
Data	Heterogeneity of subsector	+	o		o	o		+	o	+	+
Performance measures	R^2_{adj} individual site models	0.63	0.83		0.77	0.72		0.87	0.78	0.76	0.85
Performance measures	R^2_{adj} subsector model	0.53	0.76	0.79	0.62	0.31	0.91	0.44	0.68	0.69	0.67
Performance measures	MAPE subsector model	0.46	0.17	0.08	0.21	0.33	0.17	0.30	0.30	0.52	0.52
Performance measures	nRMSE subsector model	0.13	0.11	0.07	0.13	0.17	0.09	0.14	0.11	0.14	0.16

For Δ MAPE individual vs. subsector model > 0.3, subsectors were marked as very heterogeneous by "++"; for Δ MAPE individual vs. subsector model > 0.15, subsectors were marked as heterogeneous by "+". All remaining subsectors were marked with low to medium heterogeneity by "o" where more than 3 records were available. For economic sectors with less than 4 data sets, the R^2adj of the individual models was not listed for data protection reasons. The values of WZ 10 are to be understood as mean values of the sub-models (see chapter 4.2.1.3).

Table 41: Demand drivers and performance measures of subsector load profiles (TUB BLP) for subsectors WZ 37 – WZ 64-71

Demand driver | Subsector		37 Sewerage	38 Waste collection, treatment & disposal	41 Construction of buildings	46 Wholesale trade	47 Retail trade	52 Warehousing and support activities for transport.	55 Accommodation	62 Computer programming, consultancy	63 Information service activities	64-71 Offices
Holiday		-0.06	-0.04	-0.08	-0.15	-0.06	-0.009	-0.04	-0.06	-0.02	-0.11
Temperature		-0.13	-0.05	0.58	0.1	0.08	-0.55	-0.07	0.12	0.81	0.13
Solar radiation		-0.21	0.07	0.46	0.37	0.15	-0.076	-0.02	0.19	0.3	0.23
Workday		0.07	0.1	0.33	0.25	0.09	0.07	0.06	0.17	0.021	0.41
Early		-0.31	0.15	0.35	0.38	0.13	0.12	-0.03	0.16	0.004	0.41
Late		0.22	-0.06	-0.005	0.28	0.11	0.15	0.13	0.09	0.07	0.06
Night		0.09	-0.09	-0.34	-0.66	-0.24	-0.27	-0.1	-0.25	-0.08	-0.47
Office		-0.09	0.08	0.33	0.47	0.18	0.19	0.02	0.33	0.1	0.49
Summer		-0.04	-0.05	0.38	-0.02	0.03	-0.55	-0.07	0.02	0.62	-0.006
Winter		0.18	0.07	-0.46	0.06	-0.008	0.67	0.06	-0.05	-0.65	0.028
Company Holiday / Vacation / Phase									-0.04		
Model performance		37	38	41	46	47	52	55	62	63	64-71
Data	Number of data sets	8	11	< 4	10	125	25	7	< 4	< 4	13
Data	Heterogeneity of subsector	o	++		+		o	o			+
Performance measures	R^2_{adj} individual site models	0.30	0.34		0.89	0.88	0.51	0.71		0.85	0.80
Performance measures	R^2_{adj} subsector model	0.26	-0.04	0.82	0.83	0.78	0.27	0.33	0.76	0.73	0.57
Performance measures	MAPE subsector model	0.12	1.78	0.15	0.44	0.30	0.21	0.18	0.03	0.27	0.31
Performance measures	nRMSE subsector model	0.07	0.17	0.07	0.12	0.11	0.10	0.14	0.05	0.12	0.12

For Δ MAPE individual vs. subsector model > 0.3, subsectors were marked as very heterogeneous by "++"; for Δ MAPE individual vs. subsector model > 0.15, subsectors were marked as heterogeneous by "+". All remaining subsectors were marked with low to medium heterogeneity by "o" where more than 3 records were available. For economic sectors with less than 4 data sets, the R^2adj of the individual models was not listed for data protection reasons. The values of WZ 47 are to be understood as mean values of the sub-models (see chapter 4.2.1.3).

Table 42: Demand drivers and performance measures of subsector load profiles (TUB BLP) for subsectors WZ 72 – WZ 94

Demand driver | Subsector		72 Research and Develop-ment	82 Office administra-tive activities	84 Public administra-tion	85 Education	86 Human health activities	87 Residential care activities	88 Social work activities	90 Creative, arts and entertain. activities	91 Libraries, museums and other cultural activities	93 Sports activities, amusem. and recreation	94 Activities of member-ship organisat.
Holiday		-0.13	-0.08	-0.1	-0.07	-0.08	-0.02	-0.06	-0.05	-0.06	-0.05	-0.07
Temperature		0.24	0.34	0.11	-0.19	0.35	0.09	-0.24	0.14	0.26	-0.23	0.21
Solar radiation		0.32	0.41	0.31	0.16	0.44	0.38	0.22	0.24	0.42	-0.07	0.27
Workday		0.39	0.22	0.43	0.3	0.29	0.11	0.23	0.09	0.13	-0.001	0.31
Early		0.3	0.31	0.51	0.37	0.58	0.69	0.5	0.14	0.3	0.01	0.27
Late		0.08	0.12	-0.05	-0.06	0.13	-0.08	-0.03	0.43	0.18	0.28	0.08
Night		-0.38	-0.43	-0.46	-0.31	-0.71	-0.61	-0.47	-0.57	-0.48	-0.29	-0.35
Office		0.46	0.56	0.5	0.34	0.63	0.57	0.39	0.36	0.51	0.17	0.4
Summer		0.11	0.22	-0.00	-0.23	0.16	-0.06	-0.28	-0.02	0.11	-0.29	0.07
Winter		-0.07	-0.1	0.03	0.27	-0.09	0.07	0.33	0.03	-0.08	0.33	0.002
Company Holiday / Vacation / Phase		-0.13			-0.09							
Model performance		72	82	84	85	86	87	88	90	91	93	94
Data	Number of data sets	11	5	38	156	8	24	< 4	8	13	8	< 4
Data	Heterogeneity of subsector	o	++	o	+	o	o	o	o	+	++	o
Performance measures	R^2_{adj} individual site models	0.70	0.85	0.85	0.65	0.91	0.80	0.70	0.60	0.70	0.45	0.59
Performance measures	R^2_{adj} subsector model	0.37	0.49	0.76	0.51	0.89	0.64	0.56	0.50	-1.62	0.15	0.14
Performance measures	MAPE subsector model	0.17	0.66	0.20	0.50	0.07	0.19	0.15	0.33	0.40	1.24	0.30
Performance measures	nRMSE subsector model	0.10	0.14	0.09	0.10	0.05	0.11	0.09	0.11	0.17	0.17	0.12

For Δ MAPE individual vs. subsector model > 0.3, subsectors were marked as very heterogeneous by "++"; for Δ MAPE individual vs. subsector model > 0.15, subsectors were marked as heterogeneous by "+". All remaining subsectors were marked with low to medium heterogeneity by "o" where more than 3 records were available. For economic sectors with less than 4 data sets, the R^2adj of the individual models was not listed for data protection reasons.

A.2.4. Performance Measures of VDEW SLP for Selected Subsectors

Table 43: Performance measures of VDEW SLP to model real metered load data of selected subsectors. Adapted from Rüdt (2020, pp. 35, 37, 38, 41).

WZ	MAPE [%]		
	VDEW SLP	TUB BLP	De Monfort Profile
10	122.1	74.2	148.6
64-71	70.3	31.5	36.4
86	13.6	6.9	9.8
87	60.0	19.8	29.8

A.2.5. Demand Side Flexibility Potentials

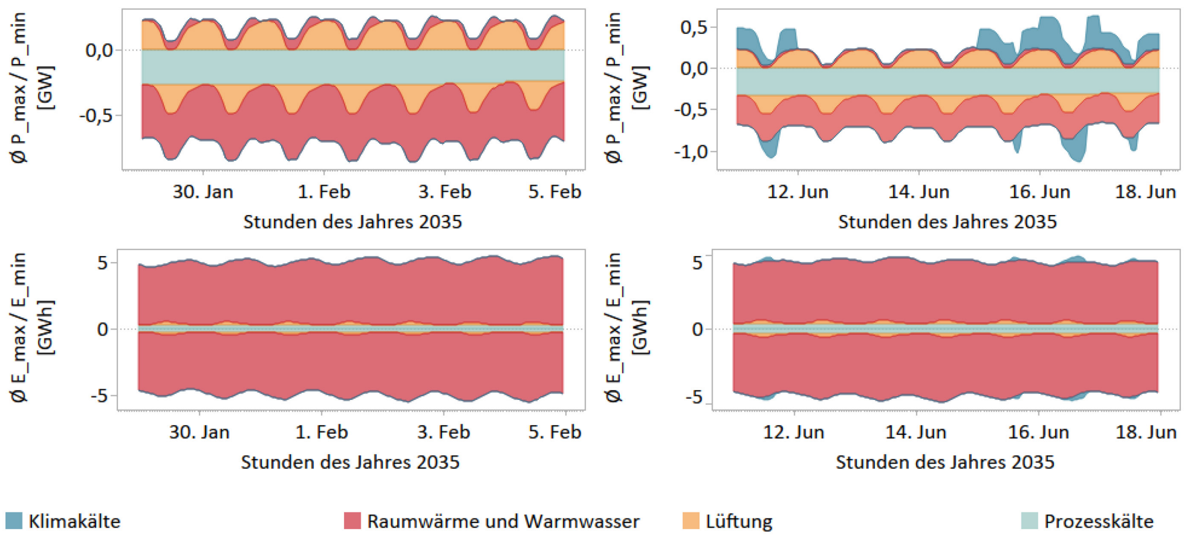


Figure 64: Hourly average switchable loads and shiftable energy quantities of the accommodation subsector in a winter and summer week (Monday-Sunday) of the baseline scenario. Adapted from Seim et al. (2021a, p. 26)

A.2.6. Economic Assessment

Table 44: Approximation and comparison of procurement and imbalance settlement costs and revenues for the German electricity demand in Mio €, using ENTSO-E data

ENTSO-E (Mio €)		2015	2016	2017	2018	2019	MEAN
SLP only	Initial procurement	16,224.9	14,988.4	18,087.4	23,351.6	19,535.1	
	Imbalance settlement	-152.7	-154.2	-209.2	-363.0	-170.1	
	Total	**16,072.3**	**14,834.2**	**17,878.3**	**22,988.6**	**19,365.1**	
BLP app.	Initial procurement	16,048.9	14,793.8	17,842.1	23,167.6	19,355.4	
	Imbalance settlement	-83.2	28.7	16.7	-162.6	9.0	
	Total	**15,965.6**	**14,822.4**	**17,858.8**	**23,005.0**	**19,364.3**	
Δ (SLP only – BLP app.)	Initial procurement	176.1	194.6	245.3	184.0	179.7	196.0
	Imbalance settlement	-69.4	-182.9	-225.9	-200.4	-179.0	-171.5
	Total	**106.6**	**11.8**	**19.4**	**-16.4**	**0.7**	**24.4**

Table 45: Approximation and comparison of procurement and imbalance settlement costs and revenues for the selected county electricity demands of the year 2017, in Thousand €.

Counties (2017) | Thousand €		DE223	DE243	DEA1A	DEA18	DEA41	DEA52	DEB32	DEB34	DEF03	DEG0N	DEG01
SLP only	Initial procurement	11,689	22,459	74,973	40	60,935	83,522	23,726	18,707	32,705	7,534	40,973
	Imbalance settlement	-392	-57	1,051	1	1,399	-957	33	1,280	-233	-126	-1,969
	Total	**11,297**	**22,403**	**76,023**	**41**	**62,334**	**82,565**	**23,759**	**19,988**	**32,472**	**7,408**	**39,004**
BLP app.	Initial procurement	11,566	21,994	73,899	39	60,049	81,926	23,347	18,643	32,274	7,475	39,931
	Imbalance settlement	-307	354	2,123	2	2,219	682	407	1,348	149	-91	-876
	Total	**11,260**	**22,349**	**76,022**	**41**	**62,268**	**82,608**	**23,755**	**19,991**	**32,423**	**7,384**	**39,055**
Δ (SLP only – BLP app.)	Initial procurement	123	465	1,074	0	886	1,595	379	64	432	59	1,042
	Imbalance settlement	-86	-411	-1,073	-0	-820	-1,639	-375	-68	-382	-35	-1,093
	Total	**37**	**54**	**2**	**0**	**66**	**-43**	**4**	**-4**	**49**	**24**	**-51**

Table 46: Approximation and comparison of procurement and imbalance settlement costs and revenues for the selected county electricity demands of the year 2018, in Thousand €.

Counties (2018) | Thousand €		DE223	DEA18	DEA41	DEA51	DEB32
SLP only	Initial procurement	13,718	51	77,325	59,683	30,074
	Imbalance settlement	-62	1	156	-787	-328
	Total	**13,656**	**51**	**77,480**	**58,897**	**29,746**
BLP app.	Initial procurement	13,616	50	76,643	59,121	29,775
	Imbalance settlement	33	1	902	-74	29
	Total	**13,649**	**51**	**77,545**	**59,047**	**29,805**
Δ (SLP only – BLP app.)	Initial procurement	102	0	681	563	299
	Imbalance settlement	-95	-0	-746	-713	-357
	Total	**7**	**-0**	**-65**	**-150**	**-58**

Table 47: Approximation and comparison of procurement and imbalance settlement costs and revenues for the selected county electricity demands of the year 2019, in Thousand €.

Counties (2019) | Thousand €		DEA1A	DEA18	DEA51	DEA52	DEB32	DEB34	DEF03	DEG0N	DEG01
SLP only	Initial procurement	77,337	21	50,358	89,620	24,932	20,373	34,851	7,733	41,930
	Imbalance settlement	861	1	-70	-1,237	-34	989	-134	-91	-1,493
	Total	**78,199**	**22**	**50,288**	**88,382**	**24,898**	**21,362**	**34,717**	**7,642**	**40,437**
BLP app.	Initial procurement	76,607	21	49,784	88,540	24,661	20,324	34,546	7,696	41,220
	Imbalance settlement	1,673	1	617	4	279	1,041	143	-68	-710
	Total	**78,280**	**21**	**50,401**	**88,544**	**24,940**	**21,365**	**34,688**	**7,628**	**40,510**
Δ (SLP only – BLP app.)	Initial procurement	731	0	574	1,080	271	49	305	37	709
	Imbalance settlement	-812	-0	-687	-1,241	-312	-52	-276	-22	-783
	Total	**-81**	**0**	**-113**	**-161**	**-41**	**-3**	**28**	**15**	**-73**