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Hybrid Artificial Intelligence System for the Design of Highly-Automated Production Systems

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Abstract

The automated design of production systems is a young field of research which has not been widely explored by industry nor research in recent decades. Currently, the effort spent in production system design is increasing significantly in automotive industry due to the number of product variants and product complexity. Intelligent methods can support engineers in repetitive tasks and give them more opportunity to focus on work which requires their core competencies. This paper presents a novel artificial intelligence methodology that automatically generates initial production system configurations based on real industrial scenarios in the automotive field of body-in-white production. The hybrid methodology reacts flexibly against data sets of different content and has been implemented in a software prototype.

Keywords: Artificial Intelligence; Machine Learning; Automotive; Body-in-White; Production System Design; Data Analytics; Pattern Recognition; Process Automatization; Robotics, Industrial Data Quality

1. Introduction

The design of body-in-white (BIW) production systems (PS) is the interface between product development (PD) and serial production [1]. The virtual product model created by PD delivers a large amount of data and depicts the

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input for PS design. The PS designer needs to analyze this data and transfers the respective information to a virtual production system. The effort required for this process correlates highly with the number of product derivates/variants and the design complexity, both currently increasing significantly in the automotive industry. [2], [3]

Nowadays the production system design (PSD) is a highly manual process in which the data analysis takes a long time due to the high amount of product variants, where all variants must be analyzed and compared to each other. This analysis is an extremely repetitive process and indicates a high potential for automation. The actual PSD on the other hand represents a creative process and the design knowledge (DK) is hard to formalize [4]. Hence, the DK is usually not documented and is only well-known among the experts themselves.

In the initial phases of PSD the production planner has to create several design alternatives and needs to frequently react to product or project changes. Analyses have shown that due to this fact the planners spend about 80% of their capacity in non-value added processes such as the gathering, analysis and preparation of data. Only 20% of the time is spent on the actual PSD process. [4],[5] The high potential for process automation in these non-value adding activities and initial planning phases has been stated by different researchers [5],[6]. Hence, the automated data analysis and the generation of a first set of PS configurations can reduce the designers' workload significantly and can give them the opportunity to intensify their focus on value adding work.

The enhanced use of artificial intelligence (AI) is increasingly vital in the automotive industry to ensure high process efficiency [8]. Previous studies of Hagemann and Stark [5] have shown that different kinds of algorithms suit the PS design problem. However, the same study has shown that in industry the data basis for BIW PSD is rarely consistent, complete nor error-free [5],[9]. The novel AI methodology in this paper is addressing both the automated analysis of the data basis and the creation of initial PS configurations.

2. State of the Art

Manual design approaches have been improved over time; however, these approaches and even template-based PSD are reaching their limits in industrial practice due to the complex and dynamic environment of the automotive industry [1]. In addition, their potential has already been exhausted. Commercial software tools do provide the functionality to design PS and have already significantly improved the efficiency of PSD processes. However, these tools do not address the aforementioned challenges adequately and do not capitalize on the high potential for process automation [7].

The automated PSD is a young field of research which has not been widely explored by research nor industry in recent decades. Previous studies have identified the high potential of the automated PSD [5]. Existing approaches and prototypes target the automation of PSD sub-processes, but none of them satisfyingly and holistically solves the automated PSD problem for industrial use-cases. These algorithms have been rather designed to show the high potential of process automation or to solve single industrial scenarios [7],[10].

Michalos et. al. [7], for instance, have developed a prototype which reveals the great potential of automation in PSD with the focus on automotive BIW. The prototype exemplarily creates PS drafts based on a given and specific BIW assembly sequence. The application uses a rule-based and formula-driven algorithm. The authors show that for this specific industrial scenario the prototype delivers feasible results for sequential assembly lines. However, a generic use for the whole BIW is inconceivable. Lopes et. al. [10] focus on the optimal re-balancing and re-planning of existing assembly lines. The research project concentrates on interference constraints for multi-robot production cells and the accessibility of welding points. The prototype uses mixed integer programming techniques, but the creation of new, more complex production systems is not possible.

Hence, existing algorithms of knowledge-based engineering, artificial intelligence and mathematical optimization have been analyzed and evaluated as to their suitability for the PSD problem – which has been stated to be NP-hard [7],[10],[11]. Suitable algorithms have been divided into deductive algorithms, for instance rule-based algorithms and integer programming algorithms, and inductive algorithms, for instance machine learning algorithms. [5] In the context of automated PSD, deductive algorithms require manual adaptions depending on different use-cases. Inductive algorithms on the other hand differ from the latter through the generic applicability, independently from the use-case. Nevertheless, inductive algorithms are highly connected to the quality of the given data basis. [5]

3. Methodology

3.1. Problem description

In this publication, the term artificial intelligence refers to the definition of Stark et. al. [14] and relates to the merging of a large variety of methods to solve, inter alia, complex and creative problems in the field of engineering:

“[…] Artificial Intelligence depicts the replication of human intelligence through software“ [14]

In the same way, our methodology tries to replicate the human intelligence of the production planner and targets the automated generation of initial PS configurations. However, the development of this methodology does not intend to replace the production planners’ workplace and expertise, rather it aims at supporting by eliminating repetitive processes and by proposing initial PS configurations. The planners’ task in this new scenario is to improve the generated PS configuration and adapt it considering impact factors that have not been used by the algorithm. Thus, the planners can spend more time on topics which require their core competencies. As mentioned before, several algorithms have been already analyzed regarding the application in the PSD. The PSD problem can be further broken down into three sub problems. Firstly, the planner has to analyze the data basis and derive an initial PS structure. Secondly, the planner needs to assign specific resources from a resource library to the placeholders determined in the PS structure. The third and last step concerns the positioning of the resources. In this phase the planner has to determine the coordinates of stations and the assigned resources under consideration of the facility layout. This PS layout is not in the scope of this research project since its problem characteristics differ fundamentally from the other phases and thus requires different approaches.

The intention of this research project is to find a generic solution to PSD problems. Hence, the here presented methodology will be based on an inductive machine learning algorithm.

3.2. Hybrid Artificial Intelligence System

The proposed methodology is characterized as hybrid because it comprises statistical methods and neural networks as parts of the main algorithm. The statistical methods are applying clustering and regression algorithms for training and creation of production system configurations. Clustering enables a categorization of assembly processes and assembly stations based on their specific properties. The first step of the clustering procedure is the creation of vectors for each assembly process and station. The structure of the vectors are directly influenced by the selected properties. For instance, assembly processes are categorized based on the joining technique (welding vs. gluing), length of joining line and number of weld points. In a similar way, assembly stations are categorized based on properties, such as the number of joined components and number of robots (due to privacy only a fraction of all relevant properties are mentioned). The regression algorithm aims to detect relations between assembly processes and stations to determine suitable stations for given assembly processes.

The second approach in the main algorithm applies neural networks. Unlike the statistical methods we applied, neural networks use training data with explicit links between assembly processes and stations, so that the algorithm can replicate the technical and creative knowledge of production planners. The input and output layers in the neural network represent the processes and stations, which are connected via the intermediate hidden layers. Each training operation investigates to find the most suitable path between input and output layers. Based on training results, the AI system starts to “know” which components (i.e. manufacturing resources) are suitable for the assembly processes. This knowledge increases the flexibility in the created production system configurations. Algorithms form new stations by choosing suitable components for the given assembly processes instead of matching the processes with existing stations.

3.3. Necessity for a hybrid approach

Based on our initial analyses, we expect that neural networks based on linked data can lead to more versatile yet more precise production system configurations. Therefore, the software prototype examines first whether the existing training data provides sufficient links between assembly processes and stations (compare Figure 1). If that is the case, the neural networks approach is enabled and the user is asked to choose between statistical methods and neural networks.

The drawback of our neural network approach is the need for training data with explicit links, which requires significantly more effort to create (compare Figure 2 b). The limited availability of linked training data reduces the applicability of neural networks approach and therefore support the hybrid approach that contains statistical methods as an addition.

Despite the advantage of being independent from linked training data, the statistical methods have basic drawbacks too. They have to identify the logical coherences between assembly processes and stations based on the analysis of previous projects, since the links are not depicted explicitly in training data. The effectiveness of regression analysis, i.e. the learning capability in the AI methodology, depends strictly on the amount and quality of the learning data. The next section highlights the importance of a consistent data basis and discusses the existing challenges due to insufficient data quality.

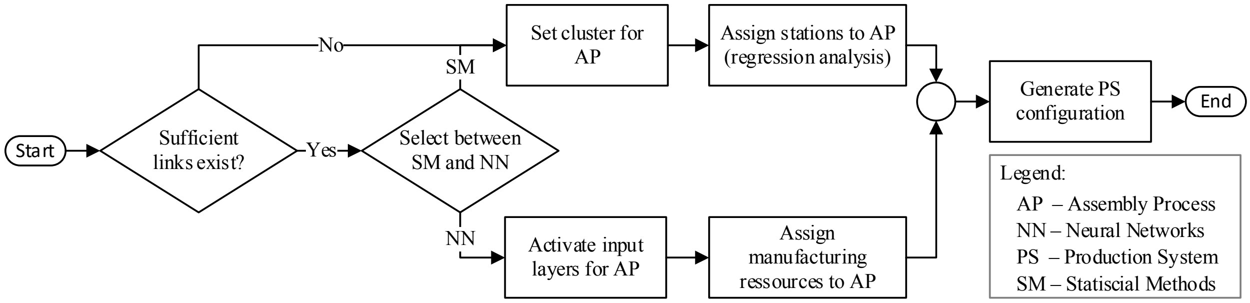

Fig. 1. Hybrid approach of the methodology

4. Data Basis

4.1. Product, process and resource information model

In theory a PS description is defined by the product, process and resource (PPR) information model [12],[13]. Hence, the description includes a detailed production process, the assigned and positioned PS resources including their hierarchy and the reference to the virtual product model. In addition, project related data (e.g. cycle time) have to be attached to the PS description. The data basis in the field of BIW has been deeply analyzed by Hagemann and Stark [5]. Figure 2 (a) provides a summarized overview of this data analysis. In this figure, you can see the PPR triangle as well as the data models (in smaller letters) which are used in BIW to describe the relevant information. As shown, these modules of the PPR are connected and references to each other to fulfill the requirements of the holistic information model. The data models can be described as the following:

- Product model: 3D product model and a large number of meta-data (i.e. attributes of joining elements).
- Assembly sequence: Tree structure describing the joining steps consisting of single parts and sub-assemblies.
- Process description: Description of all value adding and non-value adding processes conducted by each PS resource.
- PS structure and assigned resources: Tree structure describing the hierarchy of stations and their resources. The resources are linked to a resource library. In addition, each resource is described by its coordinates.

4.2. Data quality in industrial practice

Still, the biggest challenge regarding AI applications in industry is data quality [14]. Usually the PSD starts when the PD has not even finished the development of the first derivate of the product [1]. Therefore, at the beginning of PSD, the input data for production planning is incomplete. Inconsistent data originates from non-standardized PSD procedures and data structures. While, the high amount of involved employees and different suppliers lead to different kinds of random and systematic errors in industrial data sets and are usually based on human behavior.

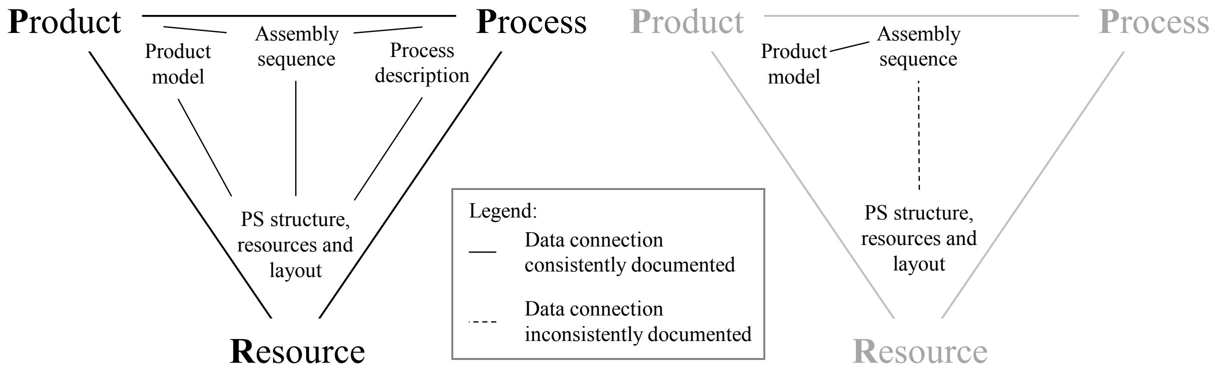

Fig. 2. (a) PPR Information Model; (b) PPR data in industry

Figure 2 (b) is an example of a large European automotive original equipment manufacturer (OEM) and illustrates the way in which data is documented in industrial practice in the early phases of PSD. The figure shows that the process description in particular is not well documented. Also the connections between the assembly sequence and PS structure is not consistently documented in industrial practice as indicated by the dotted line in the figure.

5. Prototype Development

In this section, the modular structure of the developed software prototype will be presented. As shown in Figure 3, the modules within the software have specific tasks and are connected to each other via data interfaces.

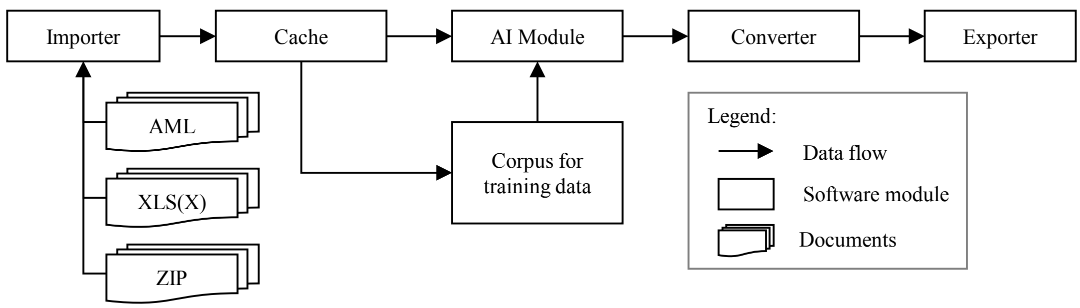

Fig. 3. Modular structure of the software prototype

The importer module converts the input files (i.e. Microsoft Excel and AML files which contain information about products and their production systems) via python scripts to files in comma-separated values (CSV) format. The main aim of the conversion to CSV is the better machine readability compared to XLS(X) and AML formats. Besides the conversion function, the importer module contains algorithms, which can eliminate the unnecessary parts of the input files. For instance, only information about stations and their resources is retrieved from the imported production system AMLs. Furthermore, the importer module can extract the contents of ZIP archives. The extraction of ZIP files comes in handy for training data, since each training dataset comprises multiple files. After the conversion is completed, all created CSV files are stored in a subfolder of the software to enable a faster access and utilization of data during operations.

The AI module consists of a learning corpus and three main functions: A configuration generator (CG), training system and monitoring of training (MoT). The configuration generator represents the core function of the software, i.e. the determination of suitable stations based on the input assembly processes. Within this function, the mentioned clustering algorithm categorizes the input assembly processes and stations. Subsequently, the regression algorithm determines the most suitable stations to create the PSD. The CG requires to convert all input information, e.g. assembly processes, joining points, manufacturing resources, stations and their components, since it can interpret existing data only in forms of scalars, vectors and matrices. Also the outputs of the CG are represented in the same format. Therefore, there are converter modules before and after the AI module. Similar to the CG function, the training system uses the same AI algorithms. The MoT function enables to track the progress of the AI capabilities with regard to the number of learning datasets. For this purpose, the average similarity of the automatically generated production system configurations to the existing production systems counts as a performance indicator for evaluating AI algorithms. The procedure of the MoT function comprises three main steps: (i) the serial generation of configurations, (ii) the creation of an Excel sheet with similarity indicators and (iii) visualization of the results with a line diagram.

As stated above, the AI module creates the production system configurations in a solely machine-readable form. The converter module interprets the configuration data and enhances the information regarding the components of stations with the corresponding IDs from the resource library. At this stage, the software still does not know about the necessary structure of the desired AML file with the production system configuration. The exporter, which is the last module in the general algorithm of the software, transforms the information about the production system configuration into the predefined AML structure. In the end, the configuration is written out as an AML file.

6. Conclusion

Today, the enhanced use of artificial intelligence techniques is to a large extent vital to ensure high process efficiency in the automotive industry. At the same time these techniques overcome prejudices and gain acceptance among the employees. In manufacturing science there is a long tradition regarding the use of artificial intelligence techniques. Nevertheless, in research and industry no holistic and sufficient solutions exist to support the production planner in production system design. It is exactly this research gap that is addressed in this paper. The proposed novel artificial intelligence methodology automatically generates PS configurations to support the production planner in the early phases of PSD. Current challenges, like for instance, missing data connections or error prone data sets have been overcome through the hybrid approach. Future research will focus on the evaluation of algorithm capabilities and on impact analysis of data sets with a different level of data quality. In addition, automated or at least supported data gathering from sources like the digital twin of PS shall be investigated, in order to increase the amount of available training data to a sufficient level for experiments and pilot applications with our research prototype.

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