COORDINATION ALGORITHMS FOR SUPPLY AND DEMAND MATCHING IN FUTURE POWER NETWORKS

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To the soul of my father

ABSTRACT

It is envisioned that Smart power Grid will depend on a large number of renewable energy resources connected directly to the low and medium voltage power network(s). The dependence on the intermittent renewable energy resources for feeding consumption in real time leads to stability and reliability problems. Controllable loads or an active consumer network are one way to tackle these problems. Loads should be controlled to respond to the time of low generation to maintain the system stability and reliability. To control and coordinate the operation of the network with these new characteristics efficiently and with a certain degree of reliability, intelligent coordination approaches are required.

The thesis work aims to propose and develop algorithms to control and coordinate the operation among different entities within the Smart Grid. Matching between supply and demand aims to maximize the dependability on the renewable energy resources and to minimize the stability problems within power networks that depend on the renewable and distributed resources. Variations between supply and demand affect the general system stability as well as the generation and the consumption units.

For controlling demand and supply, information and communication technology (ICT) play a central role in this case. Our work belongs to the research efforts that are directed to developing optimization and coordination technique for the future smart grid. Because of the distributed nature of the problem the multi-agent systems are proposed as computing paradigm for developing and testing the performance of the proposed control and optimization algorithms. Depending on using agent technology, we can satisfy the local constraints of different entities (consumption and generation units) while simultaneously satisfying global goals by using intelligent approaches for coordinating and adapting the agents' actions (resources production or consumption). For controlling and coordinating the multi-agent actions, intelligent coordination and optimization techniques are required. In this work, two quantum-inspired algorithms for developing coordination and optimization algorithms for the future Smart Grid are presented. The proposed coordination algorithms depend on integrating a quantum-inspired evolutionary algorithms and multi-agent system, which in turn controls the power resources for matching supply and demand within the future power network(s).

Zusammenfassung

Es wird erwartet, dass intelligente Stromnetze, auch Smart-Grids, von einer großen Anzahl Erneuerbarer-Energieressourcen, welche direkt an die Mittel- und Niederspannungsnetze angeschlossen sind, abhängen werden. Die Abhängigkeit von fluktuierenden erneuerbaren Energieressourcen bei Echtzeitdeckung der Nachfrage führt zu potenziellen Stabilitäts- und Zuverlässigkeitsproblemen. Steuerbare Lasten bzw. ein aktives Konsumnetz sind ein möglicher Weg, diese Probleme anzugehen. Lasten sollten gesteuert werden, um auf Zeiten geringerer Einspeisung zu Reagieren und damit die Systemstabilität und –zuverlässigkeit aufrechtzuerhalten. Um die Betreibung eines Netzes mit diesen neuen Anforderungen effizient und zuverlässig regeln und koordinieren zu können, sind intelligente Koordinierungsansätze notwendig.

Im Rahmen dieser Dissertation werden verschiedene Steuer- und Koordinierungsalgorithmen für den Betrieb zwischen verschiedenen Einheiten des Smart-Grids vorgeschlagen und entwickelt. Die Abstimmung zwischen Angebot und Nachfrage zielt darauf ab, die Verlässlichkeit erneuerbarer Energien zu maximieren und dabei die Stabilitätsprobleme im verteilten, auf Erneuerbaren beruhenden Stromnetz zu minimieren. Unterschiede zwischen Angebot und Nachfrage beeinflussen sowohl die allgemeine Systemstabilität als auch die Angebots- und Verbrauchseinheiten.

Informations- und Kommunikationstechnlogien spielen eine zentrale Rolle für die Steuerung von Angebot und Nachfrage. Die vorliegende Arbeit leistet einen Beitrag zu dem Forschungsvorhaben bzgl. der Entwicklung von Optimierungs- und Koordinierungstechniken für das Smart-Grid der Zukunft. Aufgrund der verteilten Struktur des Problems gelten Multiagentensysteme als IT-Paradigma für die Entwicklung und Überprüfung der Leistung von Steuer- und Optimierungsalgorithmen. Durch die Nutzung von Agententechnologien können die lokalen Beschränkungen der verschiedenen Einheiten (Nachfrage und Generierung) eingehalten werden bei paralleler Erfüllung globaler Ziele durch die Nutzung intelligenter Ansätze für die Koordinierung und Anpassung der Aktionen von Agenten (Ressourcenproduktion oder -konsum). Zur Steuerung und Koordinierung der Multiagentenaktionen werden intelligente Koordinierungs- und Optimierungstechniken benötigt. In dieser

Dissertation werden zwei quanteninspirierte Algorithmen präsentiert für die Entwicklung der Koordinierungs- und Optimierungsalgorithmen des Smart-Grids der Zukunft. Die vorgeschlagenen Algorithmen beruhen auf der Integration eines quanteninspirierten evolutionären Algorithmus und eines Multiagentensystems, welches wiederum die die Elektrizitätsressourcen steuert zur Ausgleichung von Angebot und Nachfrage im zukünftigen Stromnetz.

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Erklärung der Urheberschaft

This Ich erkläre hiermit an Eides statt, dass ich die vorliegende Arbeit ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe; die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht. Die Arbeit wurde bisher in gleicher oder ähnlicher Form in keiner anderen Prüfungsbehörde vorgelegt.

Berlin, den 5.2.2016 Rashad L. I. M. Badawy

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1 INTRODUCTION

1.1 Introduction

On the verge of a global call to address climate change, many communities around the world are under pressure to change the manner in which they generate and consume energy. Smart Grids have become the future choice by many utility departments to attain bottom line goals of energy management. The future Smart Grid is predicted to depend on a large number of renewable energy resources that is directly connected to the low and medium voltage power network [1]. While such energy resources are climate friendly, stability and reliability are major concerns when feeding energy consumers in real time due to the intermittent nature of renewable energy [2]. For example, the generation from solar photovoltaic panels and wind turbines depends on volatile weather conditions. To maintain the stability and reliability of the Smart Grid, an effective load controlling mechanism is needed. As the number of energy devices and their operation constraints increase, effective demand side management becomes a challenging prospect. In reality, control and coordination mechanisms (e.g. load shaping, valley filling, load clipping) for energy management depend on the type of device unit under control [3] and other factors such as time of the day, weather situation, and users' preferences that must be taken into consideration.

Currently, there are great efforts directed toward realizing the power network of the future, namely the smart grid [4]. The current electrical power network depends mainly on producing power in large central generation plants, what is costly and not eco-friendly. The future smart grid will be operated depending on significantly large numbers of small-scale highly dispersed renewable energy resources connected directly to the low and medium voltage power network(s). The new architecture of the electrical power network reduces power losses during transmission, hence reducing the electrical power price and carbon dioxide emissions. However, many issues need to be addressed to realize the full scale of the future smart grid architecture. For example, to operate the future power systems securely and efficiently, it is necessary to monitor and control output levels and power schedules when connecting a diverse number of units to the power system since it is typically embedded at the distribution level. Another challenge is related to the dynamic nature of the electrical power consumption that needs continuous monitoring and controlling systems to manipulate the different issues and to make an efficient use of the electrical power energy. Transforming future power loads to be active loads instead of the current passive loads is clearly an important element for realizing smart grids, which requires novel and intelligent power control mechanisms. Furthermore, the future smart grid is expected to integrate renewable energy resources, which are known for its intermittency and variability nature. While adding storage elements to stabilize and optimize the future grid is helpful, these elements require new mechanics to control and coordinate their integration in the future smart grid.

The aforementioned issues raise the following question: How to control and coordinate the operation in an efficient, reliable and distributed manner, given the new characteristics of the system? Information and communication technology is the key to answer this question. In this direction, intelligent coordination and control approaches are required to solve the control and coordination problems for effective realizing of the future power grid. Agent-based systems as a distributed computing approach are proposed and implemented to control and coordinate the operation of different entities within the future power network. Agent-based systems play a vital role in building the smart grid that depends on renewable distributed energy resources and is operated by multiple actors. Through using agent technology as computing paradigm, the local constraints of different entities can be satisfied while simultaneously satisfying global goals, using approaches for coordinating and adapting the agents' actions (e.g. resources production or consumption).

On the other hand, utilizing and exploring quantum computing principles to improve the performance of intelligent systems is one of the active research areas nowadays.

This research area is concerned with studying quantum computing, which is characterized by certain principles of quantum mechanics, combined with computational intelligence or soft computing approaches [5]. Similarly, quantum-inspired evolution algorithms combine evolution theory and the quantum information theory. The quantum-inspired evolutionary algorithms follow the main scheme of the classical evolutionary algorithms [6]. However, the population space is represented using quantum bits (qubits) and the evolution operators are designed using some features inspired by the principles of quantum mechanics, such as quantum bit evolution (quantum bit rotation), interference, and superposition.

In this thesis, control and coordination approaches that integrate quantum-inspired algorithms with a multi-agent to coordinate supply and demand within future smart power networks are presented. Matching between supply and demand aims to minimize the variability and the voltage flicker within power networks that depend on renewable and distributed resources, which affect the general system stability as well as the generation and consumption units. We belief that quantum soft computing and quantum inspired computing are promising lunge for introducing intelligent optimization, coordination, and control approaches for future smart grids.

The rest of this chapter is organized as follows: The next section describes the new characteristics of the future power network. Section 3 presents the coordination and optimization techniques for the future smart grid. In Section 4, the quantum and the quantum-inspired computing are presented. Finally, Section 6 introduces an abstract for the thesis chapters.

1.2 New characteristics of the future power network

The current electric power networks depends on generating power in large central generation plants, transmitting the power to the consumption areas, and then distributing the power inside these areas. The architecture of such power networks can lead to blackouts resulting in economic losses. Furthermore, this architecture results in inefficient power losses: About 20% of the generated power is lost the during transmission and distribution process. Additionally, most current power plants depend on classical high-emissions fuels (e.g. coal power plants) or on unsafe fuels, such as nuclear power plants.

The smart power grid is envisioned as the paradigm for introducing solutions to all current power networks drawbacks. The smart grid will depend on small-scale distributed energy resources (DER) located near the low voltage consumption areas. Distributing power resources minimizes power losses during transmission and minimizes dependability on the central generating plant, what in turn minimizes the risk for blackouts. The combined heat and power units (CHP), the renewable energy resources, and the demand response resources (DRR) are examples of such small-scale power resources. Recently, the United States government decided to add about 40 gigawatts of power from combined heat and power (CHP) units by 2020 [28].

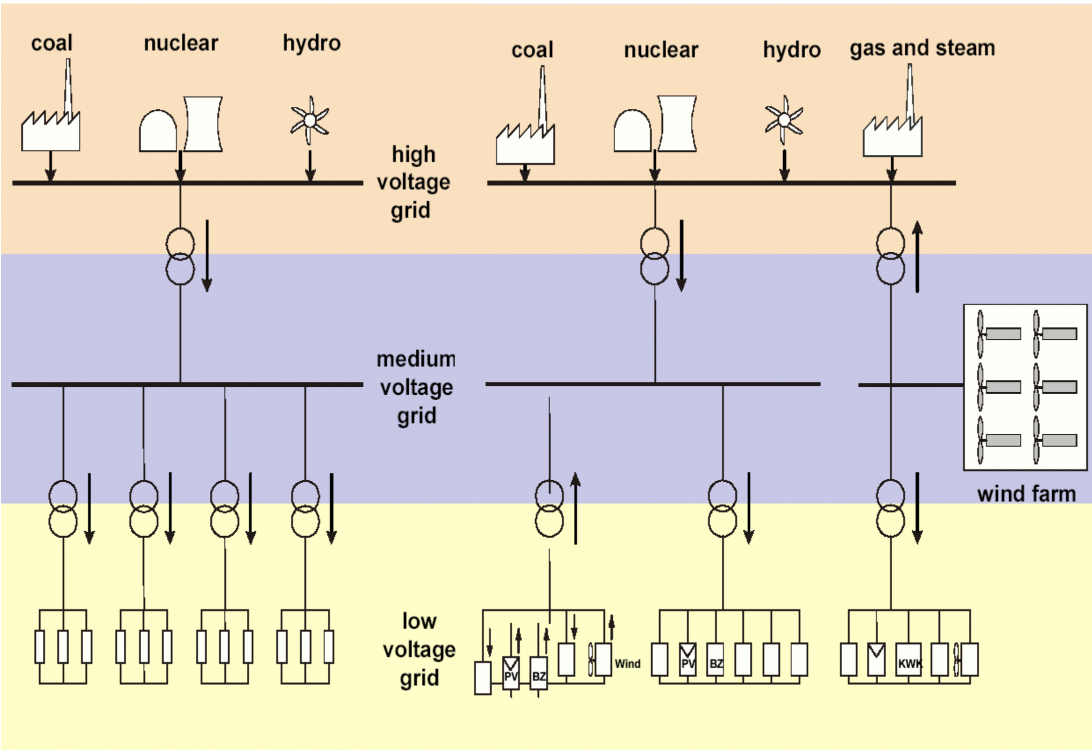


Figure 1.1: Current (left) and smart (right) power grid architecture

The contribution of distributed generation resources in the total electricity generation is above 30% in a number of European countries [7]. At the same time, depending on renewable energy resources help to reduce carbon dioxide emissions. Figure 1.1 compares the architectures of the current and the future energy network. Using DERs changes the way of controlling the electricity networks [8].

1.2 New characteristics of the future power network

The dynamic nature of the electrical power consumption needs continuous monitoring and controlling systems to manipulate the different issues and to make an efficient use of the electrical power energy. Controlling power loads to be active loads instead of the current passive loads is clearly an important element for realizing smart grids. The future power consumption is expected to exhibit new and different consumption patterns. For example, consumers give permission to the energy service providers for direct control for some household appliances. This enables energy service providers to minimize or to shift the power consumption during peaks times. Power loads will have different priorities, which enable the energy service providers to use the low priority loads as dynamic loads that can be shed during the peaks time. There are number of demand controlling programs, e.g. interruptible load, direct load control, real-time pricing and time-of-use programs [9] [10] [11]. In addition, the increased use of electric vehicles creates opportunities to integrate the vehicles' batteries to play an important role within the demand response program [12]. Also, there are consumer/producer users that are called hybrid users (prosumer). Those users have their own resources that may be partially sufficient for their consumption sometimes and exceed their consumption during other times.

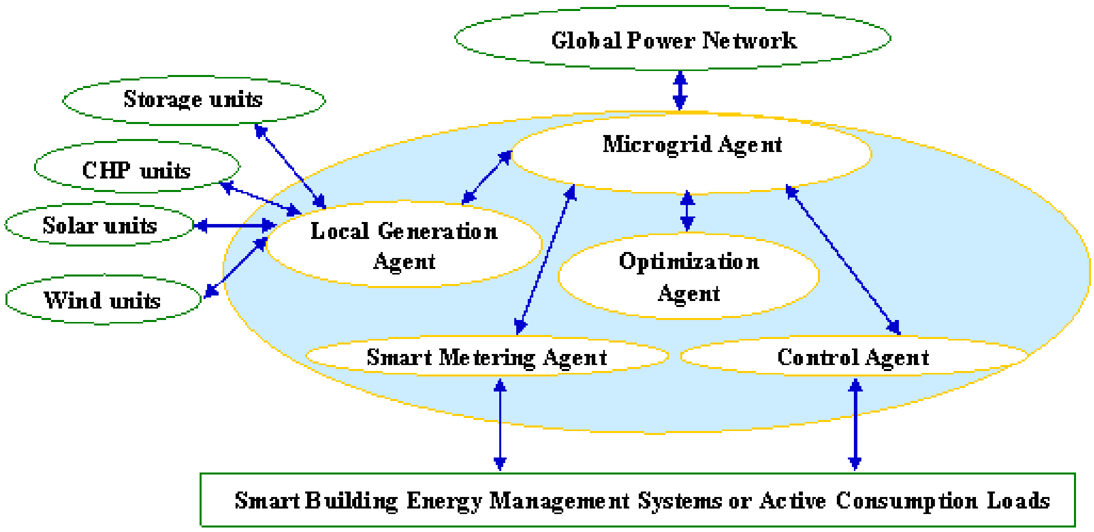


Figure 1.2: Main components of the coordination and optimization system within the smart power Network

The previous new consumption patterns entail monitoring consumer consumption continuously for defining their participation and for the billing processes. For this purpose, there are efforts for realizing smart metering systems [13] [14] [15]. Constructing smart metering systems leads to a feedback indication from the consumption section to the generation section and allows to link generation with consumption. The integration of advanced metering technology and load control technologies are used to achieve positive changes in energy-using behavior [16] [17] [18] [19]. The main components of the system are shown in Figure 1.2. The question is how the smart meters' output can be manipulated to match between supply and demand within the smart grid? The answer to this question is effective coordination and optimization algorithms.

Microgrids, virtual power plants (VPP), thermal storages, and electrical storages are used for realizing the future smart grid. In the following section, short descriptions of the different building blocks for realizing the future smart grid are presented.

1.2.1 Power Microgrids

Because of the new characteristics within electric power networks, the expected future architecture of the power network relies on microgrid and local low-volt power networks. These microgrids depend mainly on local renewable and distributed energy resources for feeding the local consumption of the network. Microgrids depend on control, optimization, and monitoring to coordinate the local network's consumption, generation and storage units. The microgrid depends on control and optimization units for coordinating the local power network generation and consumption [20] [21] [22] [23] [24] [25]. The master control unit is responsible for the operation of the microgrid in isolation mode or connected mode with the main power network depending on the local and the global supply and demand, where local refers to the onsite supply and demand of the microgrid. Global refers to the supply and demand of the main network. In isolation mode, the microgrid depends on the onsite power generation without connection to the main power network. The master control unit has early predictions about the critical time depending on the expected local consumption and generation curves and the load of the general power network. The master controller unit depends on a number of local controller units (agent) for the different power resources (consumption, generation, and storage units).

1.2.2 Virtual power plants (VPP)

Despite depending on smart metering systems, the time of use pricing, demand response programs, and distributed generation introduces many benefits. However, there are challenges for controlling, optimizing and insuring reliability of the new power network. How to manage the power network with these new characteristics? Virtual power plants (VPPs) are one of the concepts for managing the new power network. VPPs are an aggregation of a number of power units (consumption and/or generation) interconnected by an ICT-system and operated similar to a normal electrical power plant. Depending on advanced ICT infrastructure, the VPP represents a feasible solution to be implemented [26]. VPP models can be classified into commercial virtual power plants and technical virtual power plants. While the first one is directed to market activities such as maximizing the profit of generation, the latter is directed to provide power system quality, reliability and security.

1.2.3 Vehicle to grid (V2G)

Electric vehicles (EVs) are growing in popularity as more efficient, low-emission alternatives to the conventional fuel-based automobile. Depleting of the classical energy resources, attempts to stop the nuclear power stations, and increasing the governmental regulations to adopt more sustainable technologies have driven the development of electric vehicles. A number of famous automobile manufacturing companies have already begun to roll out EVs from their production lines [27] [28] [29]. The high penetration of EVs supports developing the greenest energy system of the future by maximizing the renewable energy resources using through storing surplus power during generation peaks [30]. At the same time, EVs can be utilized to improve the smart grid's reliability and stability. EV batteries can be used in frequency regulation [31] [32] [33] [34], minimizing the power losses in the distribution network [35] [36], improving the system load profile, and reducing peak demand [37] [38].

The high penetration of electric vehicles is a challenge for the future smart grid operation. For example, the uncontrolled charging of EVs undesirably reshapes the demand power cure within the future smart grid. EVs owners go home from work most probably at the same period and plug-in their vehicles to charge during an already peak demand time. This uncoordinated and random charging of EVs could significantly affect the distribution system. The random and unpredictable nature of EVs activity in a domestic household situation entails developing a fast and adaptable real-time coordination strategy. Thus, intelligent coordination and optimization algorithms are required for avoiding or mitigating the aforementioned affects for the future smart grid operation.

1.3 Smart power grid coordination and control algorithms

The distributed nature of consumption and the generation units dictates a decentralized system to accomplish the coordination and the optimization task. Furthermore, services that are expected to be provided by the smart grid and the supporting computer networks are also distributed either logically or physically. Recently, several approaches on coordination and optimization have been proposed in an effort to optimally manage the diversified energy resources of the future smart grid. These are classified [39] into market-based and non-market-based approaches. In this section, we examine a sample of such studies that we believe to be representative and specifically related to our topic. Although far from being exhaustive, this section gives a comprehensive idea of the current state of the art.

The author in [40] follows a microeconomic principle and proposed a multi-agent coordination system based on market oriented algorithms, which provides a framework for distributed decision making. In [41], Guo et al. proposed a coordination algorithm, which depends on a genetic algorithm for supply and demand matching. This algorithm depends on a fully distributed architecture of the resources agents (consumption/generation), where a stigmergic memory space [42] is used for indirect communication among the agents. Such features make the system scalable, adaptable and robust. The main disadvantage of this approach is the resulting solution's sub-optimality.

Powermatcher [3] is another market-based algorithm with several applications. Powermatcher is a coordination approach that combines microeconomic with control theory principles. The system depends on tree architecture of distributed agents to match supply and demand within the controlled area. The powermatcher concept depends on the COTREE algorithm described in [40] to distribute the aggregation of the demand function to the intermediate agent in a binary tree. A demand function defines the amount of power the agent wishes to consume or produce at a certain price. Depending on using the COTREE algorithm, the computational complexity of the market approach becomes $O(lg\ p)$, where p is the number of participants in the market. The powermatcher concept was used in simulation and real life field tests such as those described in [43] [44] [45].

The work presented in [20] focuses on auction-based algorithms to define the state of supply and demand for the upcoming time periods. The solution is formulated as a symmetrical assignment problem. The main advantage of this algorithm is that it allows the operator to determine if the supply is going to meet the local demand or not. While helpful, the approach does not intend to alter the demand to match the supply and hence requires other mechanisms to optimize the consumption level.

In [46], the developed system depends on intelligent local controllers (ILCs) to maximize the use of local renewable energy units and to minimize the use of local fuel generation units within the microgrid. Since renewable energy resources are intermittent by nature, the system depends on storage units and ILCs for different loads to reshape the consumption curve when the consumption exceeds the local renewable energy generation. If the renewable resources and the storage elements are not sufficient to feed the local loads, ILCs discard lower priority loads. If the demand still exceeds the production, fuel generation units are used. ILCs have communication and negotiation abilities to communicate together and with different household devices to determine the loads that need to be shifted.

In [47], the authors demonstrate the shortcomings using price mechanisms to reduce consumption level during peak demand. Using a price based cap to minimize energy consumption for specified time intervals synchronizes the device consumption and leads to instant consumption peaks when the price cap is released, which then can affect the system stability. On the other hand, forcing devices to operate at minimal consumption levels for long periods of time decrease their lifetime. The authors suggest the use of multi-objective functions to evaluate the effectiveness of the coordination system to match supply and demand. The coordination approach they proposed depends on a modified Q-learning algorithm for reinforcement learning [48]. The main disadvantage of this approach is the dependency on the initial information about the controlled consumption area to perform the learning process. Additionally, depending on the estimation model of the system behavior, the expected performance of this approach could be unpredictable, and, hence, it is not practical for large-scale deployment.

In [49], the developed algorithm is implemented using the homeotaxis principle. The homeotaxis principle is inspired by the biology of organisms. Specifically, the principle is related to the organisms' innate behavioral response to a specific directional stimulus. This stimulus may be temperature (thermotaxis), light (phototaxis) or electric current (galvanotaxis) [50]. This model, although interesting and ingenious, does not suit the expected large-scale deployment due to the complexity of estimating the controlled system behavior.

1.4 The quantum and quantum-inspired computing

Quantum Computing is a branch of theoretical computer science dealing with the application of quantum mechanical features for solving computational problems. It is a new computing paradigm for solving untractable computational problems by using the classical computing paradigm. Quantum computing brings together ideas from classical information theory, computer science, and quantum physics to manipulate the complex computational problems. Quantum computing mimics behavior of atoms in processing information, where controlled evolution of quantum particles is used as a new efficient computation technique for solving the complex classical computational problem. The main principle is that since everything in this world is composed of quantum particles, any kind of process might be reduced to a quantum process (at least in principle) [51]. Quantum computing is characterized by certain principles of quantum mechanics such as standing waves, interference, quantum bits, coherence, and superposition of states. Additionally, the mathematical apparatus of quantum mechanics could be applied to introduce solutions of various problems outside physics, although it was developed to describe phenomena in the micro-world [51]. Quantum computation can provide dramatic advantages over classical computation for some computational problems [52] [53].

Currently, exploiting and exploring quantum computing principles to improve the performance of intelligent systems is one of the active research areas. This research area focuses on studying computing algorithms that are characterized by certain principles of quantum mechanics combined with computational intelligence or soft computing approaches [7]. Similarly, quantum-inspired evolution algorithms combine the evolution theory and the quantum information theory. Quantum-inspired evolutionary algorithms follow the main scheme of classical evolutionary algorithms [54]. However, the population space is represented using quantum bits (qubits) and evolution operators are designed by using some features inspired from the quantum mechanics principles such as quantum bit evolution (quantum bit rotation), interference, and superposition. Quantum-inspired algorithms do not require a functional quantum computer. In this thesis, we exploit the extra ability of the quantum-insipid evolutionary algorithm to explore global optima for the multi-objective optimization problem using the classical computer.

1.5 Research aims

Optimizing and stabilizing the consumption of energy inside the local power networks (microgrids) is a very important step for energy networks that depend on high penetration of renewable energy resources. The main aim of the thesis is to develop optimization and control algorithms that are responsive to different situations in the consumption area. We aim to introduce, develop, and test coordination and optimization approaches, which integrate multi-agent and quantum-inspired algorithms to control and coordinate different building entities for smart energy networks (e.g. microgrids, VPP, V2G). Quantum soft computing and quantum-inspired computing are promising lunge for introducing intelligent optimization, coordination, and control approaches for the future smart power grid. The proposed algorithms aim to define how the optimization and the coordination algorithms can lead power utilization within buildings or local power networks that depend on renewable energy resources. The proposed control and coordination algorithms contribute to the research effort for building control algorithms for microgrids and to allow cooperation and coordination within the future Smart Grid. The steps of this work can be summarized into the following points:

- Reviewing the previously developed algorithms for coordinating supply and demand of the smart grid
- Modeling different power (consumption/generation) units that are used for testing the developed algorithm
- Developing coordination and optimization algorithms for supply and demand matching within the smart grid
- Evaluating the developed algorithm for different operation constraints

1.6 Structure of the thesis

The contents of the thesis can be summarized as follows: The introduction chapter presents an overview about the characteristics of smart grids that entail using intelligent optimization and coordination algorithms. The review of the related work is presented in Chapter 2. An introduction to quantum and quantum-inspired algorithms is presented in Chapter 3. The fourth chapter presents the modeling and the simulation environment of the smart building energy management (SBEM). Chapter 5 illustrates the quantum inspired evolutionary algorithm that is developed for supply and demand matching. Chapter 7 presents the proposed algorithm for matching supply and demand within the smart building environment. The proposed algorithm for controlling and coordinating virtual power plant (or microgrid) is presented in Chapter 8. Conclusion and future work are presented in Chapter 9. In the following section, the abstracts of the thesis chapters are presented:

- Chapter 2: In this chapter, the review for the related work is presented. The developed algorithms can be classified into market and non-market-based algorithms. Three non-market-based algorithms (learning, bio-inspired and genetic algorithms) are presented. Market-based coordination algorithms are classified into without-altering-demand algorithms and altering-demand algorithms. In order to compare the features of the different algorithms, a comparison among them according to number of factors is presented at the end of the chapter.

- Chapter 3: This chapter introduces quantum and quantum-inspired computing. Quantum computing is a branch of theoretical computer science dealing with applications of quantum mechanical principles for solving computational problems. Taxonomy of the research efforts for quantum and quantum-inspired computing is presented. Furthermore, the principles of quantum computing and the quantum-inspired computing are presented. The quantum-inspired evolutionary algorithm is presented in details.

- Chapter 4: In this chapter, the modelling of different consumption and generation units that are used in this work is presented. As a part of that, models of cooling/heating appliances, dryer machines, ventilation appliances, and heater water coils are presented. An electric vehicle battery model is presented as a storage unit within the smart home energy management system.

- Chapter 5: description about the evolutionary optimization algorithm that is used for supply and demand matching within the smart power grid is presented. In addition, the evaluation of the multi-objective functions is presented.

- Chapter 6: The simulation environment of the smart building energy management system is described. The different agent's roles within the smart environment are presented. Monitoring and control functions used within the simulation environment are presented.

- Chapter 7: In this chapter, we introduce a non-market-based approach that integrates the quantum-inspired evolutionary algorithm (QIEA) with multi-agent systems to coordinate supply and demand within the smart home energy management environment. The mathematical formulation of the optimization problem is presented. A number of objective functions are formulated for optimizing the different consumption devices' performance and the smart building energy management system performance. The effectiveness of the proposed algorithm is tested at the end of the chapter.

- Chapter 8: In this chapter, a non-market-based approach that integrates the quantum-inspired evolutionary algorithm (QIEA) with multi-agent systems to coordinate supply and demand within the virtual power plant (VPP) or microgird is presented. The mathematical formulation of the optimization problem is presented. The objective functions for satisfying the system's optimal performance requirements are formulated. The system performance is tested under different operation conditions.

- Chapter 9: This chapter introduces the conclusion and the future work of the thesis.

1.7 Publications

In the following, we mention the journal, and conference papers which resulted as the outcome of this thesis. The contents of the published contributions are modified to construct the thesis chapters.

Published papers

1. Introduction

i. Rashad Badawy, Benjamin Hirsch, and Sahin Albayrak. Agent-based coordination techniques for matching supply and demand in energy networks. Integrated Computer-Aided Engineering Journal, 17:373-382, 2010.

ii. Rashad Badawy, Axel Hessler, Benjamin Hirsch, and Sahin Albayrak. Integrating Multi-agent and Quantum-Inspired Evolution for Supply and Demand Matching in the Future Power Energy Networks. Power and Energy Systems and Applications (PESA-2011), Pittsburgh-USA, 2011.

iii. Rashad Badawy, Abdulsalam Yassine, Axel Heßler, Benjamin Hirsch, and Sahin Albayrak. A Novel Multi-Agent System Utilizing Quantum-Inspired Evolution for Demand Side Management in the Future Smart Grid, Integrated Computer-Aided Engineering Journal, 2013.

iv. Rashad Badawy, Abdulsalam Yassine, Axel Heßler, Benjamin Hirsch, and Sahin Albayrak, Quantum-inspired Algorithm for Smart Building Energy Management System, The 4th International Conference on Engineering Optimization, Lisbon , span, 9-2014.

2 Coordination Approaches for Power Supply and Demand Matching

2.1 Introduction

The future power network is predicted to depend on a large number of renewable energy resources that are directly connected to the low and medium voltage power network [1] . However, when depending on the intermittent renewable energy resources for directly feeding consumption, stability and reliability problems arise [2] [34]. Controllable loads or an active consumer network (one of the demand side management aims [55]) are one way to tackle these problems [1]. Loads should be controlled to respond to the time of low generation to maintain the system stability and reliability. There is large number of consumers with a variety of devices with different operation constraints. The challenge is to control and coordinate the response of these large numbers of entities without affecting the local constraints of different entities and maintain the global goals of the system. Agent-based systems are proposed and being implemented to control and coordinate the operation of different entities inside the future power network [21] [56] [57] [58] [59] [60] [61]. Agents as autonomous entities can satisfy the local operation constraint for the controlled entities (consumption or production). Additionally, agents as reactive entities can respond to the changes in their environment to satisfy global goals [20] [62] [63] [64] [65].

The developed agent-based coordination approaches generally rely on hierarchal systems that comprise three levels of control [24] [47] [66]. The first level is the coordination agent that coordinates the consumption of a number of local controller (LC) agents (like home energy-management units). The second level consists of the local controller agents for controlling sub-groups of devices, while the third level comprises the controller agents of different devices. Device controller agents in some applications are replaced by on/off switches controlled by an intelligent local controller (ILC) agent [46]. The ability of the coordination agent is restricted by the abilities of the local controller agents to plan and alter the expected consumption or generation of the devices under their control for a certain period. The device controller agent's task is to control the device in an economical manner. Under the flexible operation of the generation units and consumption loads, coordination approaches can be used to match supply and demand. For controlling consumption loads participating in the coordination task, two main types of control have been identified in the developed coordination approaches [47] [67], price-based control (indirect control) and direct-load control. While the first type depends on the manual response of the consumers according to price signals from the energy service provider or the network operator, the second type ignores the consumers' response and directly changes the setting of the devices under prior permission from the consumers. Some directed load control approaches (market-based) use price as control signal to the devices to alter their consumption according to the predicted market price. The approaches mentioned in this chapter depend on the second control type.

2.2 Supply and demand matching algorithm

The capabilities of the agents which represent consumers and energy production units in the system and the data available to these agents about the inter-operation of the system components distinguish the different approaches that have been developed to match supply and demand. Such approaches can be classified in the following two groups:

- Building coordination approaches based on market-based algorithms as described in [23] [3] [68], depend on modeling consumer and production units as bidding entities (amount of power and price). The coordination agent collects bids from the local controller agents, and sets the equilibrium market price for selling and buying power to match between supply and demand as shown in Figure 2.1. The local controller agents adjust the actual consumption or generation according to the new market price signal.

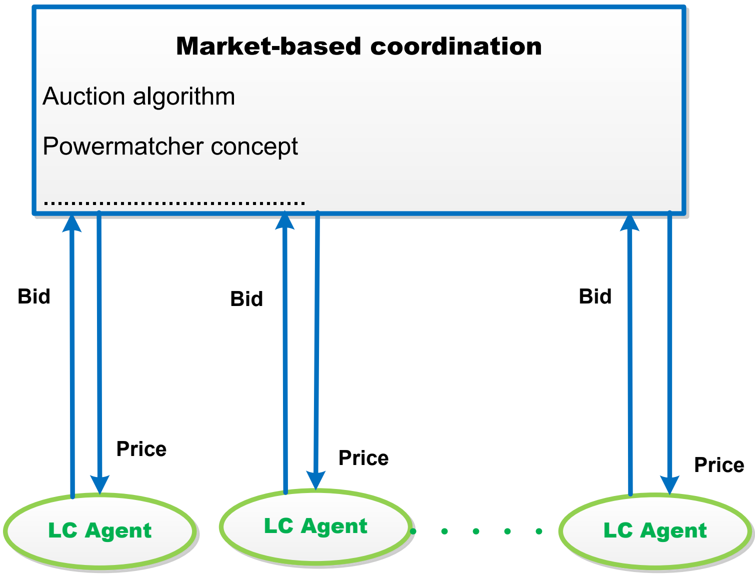


Figure 2.1: Market based algorithm

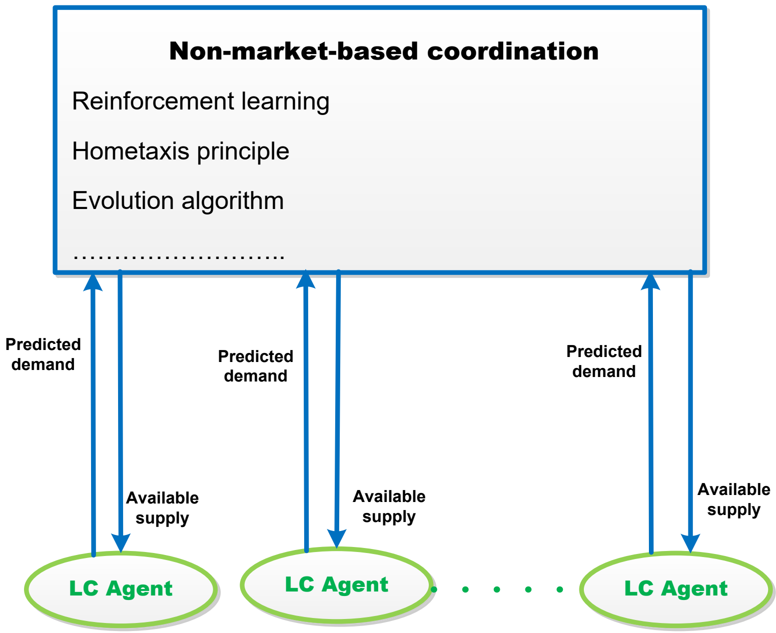


Figure 2.2: Non-market based algorithm

- Building non-market-based coordination approaches that depend on learning, bio-inspired and genetic algorithms as described in [47] [66] [41], depend on modeling consumer and production units as entities that have planning and modification abilities and can calculate the predicted levels of local consumption and generation. The coordination agent collects consumption levels (or plans), and sets the permitted consumption levels according to the available supply cap as shown in Figure 2.2.

2.3 The non-market based approaches

The non-market based coordination algorithms depend on the ability of the local load controllers to maintain the operation of a group of devices within an area where power is consumed. This area is defined according to the user preference and the constraints related to the different devices' operation limits. In [47], the authors demonstrate the shortcomings of using a price-following mechanism and a minimal consumption level mechanism for reducing devices consumption during peak demand. Using a price-based cap to minimize energy consumption for specified time intervals synchronizes the device consumption and leads to instant consumption peaks when the price cap is released, which then can affect the system stability. On the other hand, forcing devices to operate at minimal consumption levels for long periods of time decrease their lifetime. So, they developed non-market based approaches that depend on a multi-objective function to evaluate the effectiveness of the coordination system to match supply and demand. This multi-objective function combines the consumption cost with system stability measures (in contrast to market-based approaches which depend only on the price) to assess the control strategy.

Depending on the flexible operation of the local controllers, a central coordinator for a group of local controllers is implemented. The task of the central coordinator is to allocate the dynamically available power among the different local controllers, without violating the constraints for the different local controllers.

The coordinator depends on a number of local controller agents to control and coordinate the consumption in an active consumer area. The task of the local controller agents is to define the minimal energy necessary for the operation of devices under their control taking into account the possibilities offered by device control agents (such as load shifting and load reduction). This minimal level is defined by the constraints related to the device operation within the limits that are defined by the manufacturer or by the consumer. Also, local controller agents define the unconstrained consumption level of the devices under their control. The unconstrained consumption level is the consumption of appliances without any intervention during their operation. These two levels, in addition to the actual consumption level, are sent to the local coordinator to optimize the operation of a number of local controller agents. In this system, there is no negotiation between agents at the same level; the coordination is accomplished centrally on the higher level. The task of the coordinator is to define consumption levels for every local controller agent (between minimal and unconstrained level), without violating the available supply cap. The coordination systems objective is to achieve a balance between different parameters in the system, resource consumption, stability and the stress within the system. These parameters are interdependent, which means that changing one affects the others so the coordinator must compromise between these parameters. The local coordinator is implemented using different approaches; descriptions about number of the developed approaches are presented in the following sections.

2.3.1 Reinforcement learning

The reinforcement learning coordination algorithm depends on a modification of the Q-learning algorithm as an approach for reinforcement learning [47] [48]. The learning data comes from the market (price, supply cap) and from the local controller agents (the minimum consumption level, the unconstrained consumption level and the actual consumption during the previous period). The reward function for the coordinator depends on a linear weighted combination of the cost of consumption and the stability of the system. The coordinator has two matrices: decision matrix Q and reward matrix R. During the learning process the system updates the two matrices (the action and its reward). After the learning process the coordinator depends on the Q-matrix for the decision making (setting the future energy quota for the local controllers agents). The disadvantage of this approach is the need for initial information about the controlled consumption area, like the overall consumption in order to set the threshold between the consumption levels. At the same time, the quality of the learning process depends on the model that estimates the system behavior, so this approach is not practical for large scale problems. Figure 2.3 shows the input and output signals for the coordination agent.

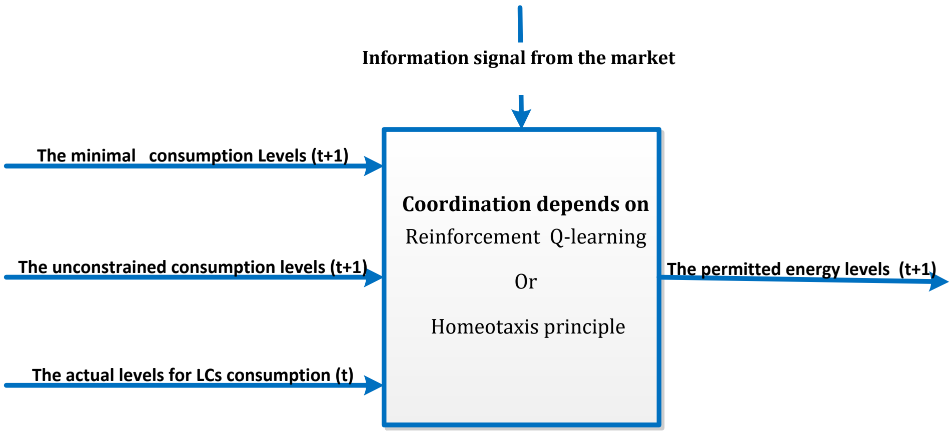


Figure 2.3: Input and output signal of two non-market based coordination techniques

2.3.2 Coordination approach depending on self-organization principles

The self-organization principles algorithm is implemented using the homeotaxis principle [49]. The homeotaxis principle is based on a principle inspired by biology, where some organisms have an innate behavioral response to a specific directional stimulus. This stimulus may be temperature (thermotaxis), light (phototaxis) or electrical current (galvanotaxis) [50]. The homeotaxis approach is a domain invariant self-organizing control mechanism for multi-agent systems, where agents depend on a internal-model for predicting the environmental conditions and compare predicted values with the actual values of the sensors to modify their behavior. The coordination agent uses the signals from the local controller agents and the market signal as the sensor inputs of the environment. Through comparing the signals to the predicted values from the internal system model, it can decide on the required changes in the energy consumption within the system to match the demand and the available supply cap. The output of the coordinator represents the actuation signals to local controller agents that alter the devices' consumption under their control during the next operation cycle. As with the previous approach, the success of the coordination task depends on the model that estimates the controlled system behavior.

2.3.3 Evolutionary algorithm

Evolutionary algorithms (EAs) are popular metaheuristic methods to solve optimization problem. Coordinators depending on evolutionary algorithm are described in a number of papers [69] [70] [41]. In [41] a genetic algorithm was used to centrally calculate the predicted consumption and generation plans (sequence of switching state (on/off) for different resources) for a group of resources for a future cycle. The objective of the genetic optimization algorithm is to minimize demand (that is, minimizing number of concurrently turned on resources) for this group of resources when demand exceeds generation without affecting the local constraint for the individual resources.

The authors point out that by using genetic optimization algorithms the overall demand of the controlled resources can be minimized without affecting the local constraints of individual recourses. However, the lack of required scalability and adaptability to sudden changes are disadvantages for this coordination approach. In [69] the authors tried to avoid the disadvantage of the previous central planning coordination approach by distributing the planning task to different resource agents (every resource agent prepares its own plan depending on a model for its controlled recourse) and sending it to an indirect communication space between agents (stigmergic memory space [42]). The proposed coordination system consists of four components as shown in Figure 2.4: a group of resource agents (RA), broker agents (BA), a memory space for indirect communication and a summarizing agent (SA). The resource agents represent consumers' loads and generation units. Each resource agent is the decision maker and controller for the respective resource and tries to satisfy local constraints given the global goal (minimizing overall demand). The broker agent (market operator) uses information about the predicted market and network usage and the demand and supply of the controlled resources to construct global goals (supply cap or power price). The memory space is used for indirect information exchange between the different agents. The summarizing agent relies on plans that are sent by resource agents to calculate the predicted total of the resource agents' demand over time. The predicted supply and demand status can be checked by resource agents and the broker agent. Resource agents can respond to supply cap violations by revising their plans for consumption by using the so-called cordcap algorithm described in [69] [66], without affecting the local constraints (temperature range). Using this feature, resources agents become reactive to the overall changes of supply and demand.

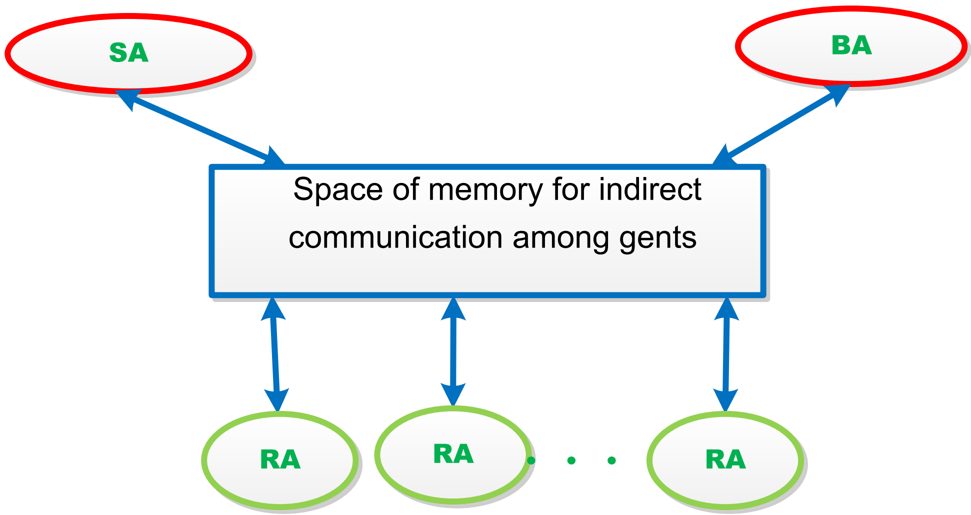


Figure 2.4: Coordination system architecture for the evolutionary algorithm

In [20], the authors combined the previous two coordination approaches by using a genetic algorithm with the architecture of the second approach to optimize the response of number of consumer agents, according to the supply cap dictated from the broker agent. This approach depends on indirect communication between the resource agents and the broker agents, and no synchronization is required for modifying and sending consumption plans from different resources. Resource agents respond to supply cap violations in an unsupervised manner (by revising the consumption plan). These features make the system intrinsically scalable, adaptable and robust as reported in [70] [66]. Disadvantages of this approach are that the resulting solution is unknown or sub-optimal [66].

2.4 The market based approaches

Multi-agent coordination based on market-oriented algorithms provides a framework for distributed decision making based on a microeconomic theory [40]. In market-based power supply and demand matching, resource agents send their predicted generation/consumption to a central coordination agent. The coordination agent aggregates the total supply and demand and determines the equilibrium price that balances between total supply and demand in the system. The equilibrium price represents the control signal to the resource agents to alter their generation/consumption according to their local constraints and the predicted market price. The market-based algorithms represent the half way between fully centralized and fully distributed algorithms, where communications between agents are limited to the bids and the price signals [71].

There are a number of agent-based market approaches that were developed to control and coordinate the consumption and generation of electrical energy for different aims. These approaches are different depending on the goal of the coordination as well as the abilities of the agents to control and coordinate the operation of different entities within the system. One of these algorithms [20] is used to match supply and demand in a microgrid (small electrical power network that can be operated in either islanded mode or connected to the main network) during time periods in the future to decide if the amount of energy from local generation units (e.g. renewable energy resources) will be more or less than the local demand. This approach does not try to alter the actual demand in order to match supply and demand.

On the other hand, there are agent-based market approaches that aim to alter the operation of generation and consumption devices in order to match supply and demand during the peak time periods or when demand exceeds the supply [3] [46]. In the following section, different approaches in these two directions are described.

2.4.1 Coordination without altering demand

The developed system in [22] depends on a hierarchal structure of the control system, where the control system consists of three control levels, namely distribution network operator (DNO) and market operator (MO) that represent the technical and market operation of the main electrical power network, a microgrid central controller (MGCC) for active low voltage areas, and local controllers (LC) for energy resources or loads. The information flow between different entities of the system is shown in Figure 2.5. The coordination system depends on multiple agents and a market-based algorithm to coordinate the operation inside the power microgrid between the local generation and consumption units, as well the exchange of power with the main grid to optimize the operation of the microgrid. If the local generation resources are not sufficient for the local demand, the microgrid can buy power from the main grid. The microgrid central controller uses an algorithm to optimize the local resource allocation without altering the demand of the local loads. The problem is formulated as a symmetrical assignment problem and solved by an auction algorithm as described in [20]. The auction algorithm is accomplished by creating a number of virtual market agents to represent the production and consumption units in the negotiation process among supply and demand units as shown in Figure 2.6. Each market agent represents a block (certain amount of energy) of local energy supply or a block of local energy demand, not an individual production or consumption unit. The auction is and ascending multiple items auction (English auction), where the agents that represent the blocks of local supply bid to the agents that represent the demand blocks. This process continues for a number of iterations until the auction assigns only one supply block for each demand block. From the trial test reported in [20], the number of iterations increases nearly linear with the number of agents (range: 10 to 40 agents) that participate in the auction algorithm.

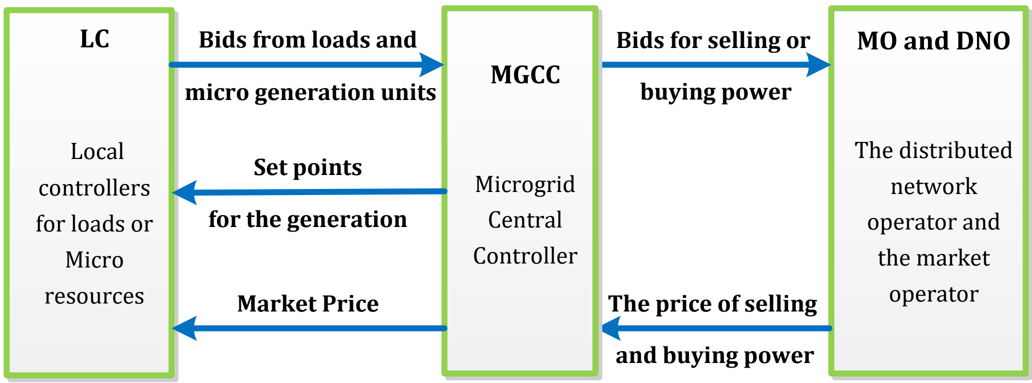


Figure 2.5 Information flow between different entities

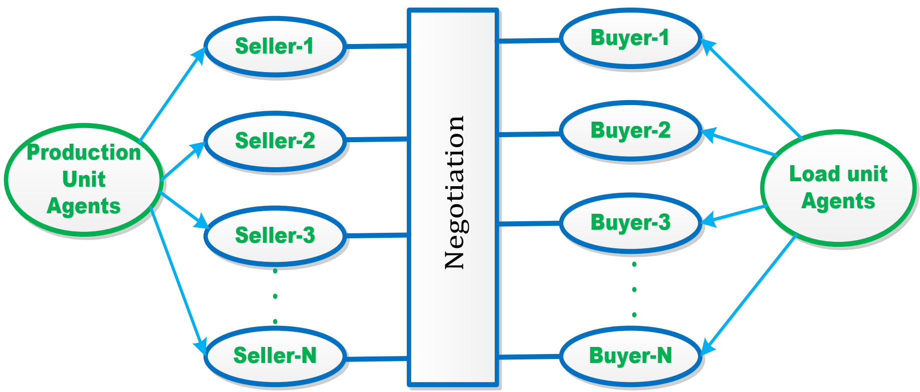


Figure 2.6: Virtual market-agents for define the supply and demand status for period into future

The authors reported that the maximum number of iterations for accomplishing the auction algorithm should not exceed 100 iterations because otherwise, the negotiation time last several minutes or hours. They concluded that the total number of agents that can be implemented to represent production and consumption units is no more than 30 agents.

The aim of this auction algorithm for the MGCC is to make the assignment of the local supply to the local demand in order to determine whether the local generation is sufficient for the next period of local market operation or if the microgrid has to buy power from the main grid. At the same time, the microgrid can sell power to the main grid when the local generation exceeds the demand. After the auction algorithm finishes, the MGCC sends the computed points to the local micro generation units for the next operation cycle. The distributed energy resources (DER) inside the microgrid adjust their operation point dependent on the negotiation with the other units, their operational cost and the local load demands.

2.4.2 Coordination depends on altering demand

Two coordination algorithms depend on modifying demand for matching supply and demand are introduced in the following section. The first coordination algorithm depends on intelligent load controllers for shedding the unimportant loads during the peak consumption periods. The second coordination algorithm depends on the powermatcher concept.

2.4.2.1 Coordination depending on intelligent load controller (ILC) abilities

This coordination approach depends on the same control architecture as the previous system (2.4.1). The developed control system in [46] aims to maximize the use of local renewable energy units and to minimize the use of local fuel generation units within the microgrid. Due to the intermittent nature of the renewable energy resources, the microgrid coordinator depends on storage units and intelligent local controllers for different loads to reshape the consumption curve when the consumption exceeds the local renewable energy generation. The microgrid local controller monitors the local renewable energy resources, storage elements and the local load consumption. If the renewable resources and storage elements are not sufficient to feed the local loads, a so-called shed signal is sent to the intelligent local controllers (ILCs) to shed unimportant loads. If the demand still exceeds the production even after the unimportant load shedding, the fuel generation unit is used. On the other hand, when the renewable energy resources generation exceeds the demand, a charge signal is sent to the control agents of the storage elements. ILCs use PLC (power line communication) switches to turn devices in the home on or off when they receive a signal from the local microgrid controller for load shedding. This means that the local controllers' decisions depend on the current status of demand and supply for the microgrid only, and the effects of these decisions to the comfort of consumers are ignored. However, the system tries to minimize the effects of load shedding by dividing loads into important and unimportant ones.

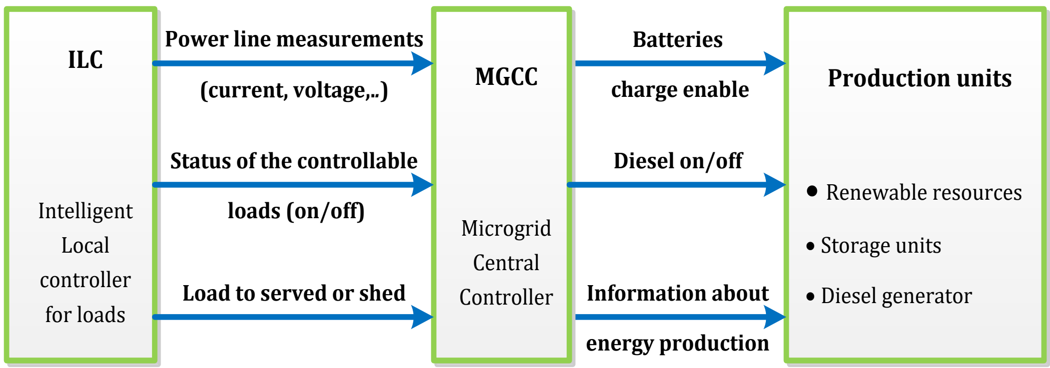


Figure 2.7: Information flow between microgrid coordinator and its controlled entities

At the same time, if the user wants to use a device considered unimportant, the system uses a negotiation algorithm between ILCs to divide the time of shedding for unimportant loads among different consumers inside the controlled area. The information flow between the microgrid central controller and its controlled entities is shown in Figure 2.7.

The intelligent local controller (ILC) as described in [46] has communication and negotiation abilities to communicate with different household devices and with other local controllers to accomplish negotiation when needed. Additionally, ILCs measure different signals like frequency, current and voltage, continuously monitor the status of the controllable loads (on/off) and inform the local coordinator. The developed system was tested under real life condition in the Kythnos Microgrid in Greece [46].

2.4.2.2 Powermatcher concept

Powermatcher is a coordination approach that combines microeconomic with control theory principles, depending on agents to match supply and demand [3] [72] [73] [74].

2.4 The market based approaches

The coordination system depends on tree architecture of distributed agents (powermatchers) to match supply and demand within the controlled area as shown in Figure 2.8. A powermatcher agent represents a node for consumers and producers in the power network, and uses a local optimization algorithm to minimize the required communication within the system [75]. The powermatcher concept depends on the COTREE algorithm developed by [40] to distribute the aggregation of the demand function to the intermediate agent (powermatcher) in a binary tree, where the demand function defines the amount of power the agent wishes to consume or produce at a certain price. Through using the COTREE algorithm, the computational complexity of the market approach becomes $O(\lg p)$,where p is the number of participants in the market [3].

The system operation cycle starts from the root agent in the tree, by broadcasting a request signal through the branches to communicate their predicated demand functions during a given period in the future. The predicted demand functions (representing the consumption curve for the device with respect to the price changes) are aggregated by intermediate powermatcher agents in a bottom up manner. Supply units are considered negative demand functions. The root powermatcher computes the compound supply and demand function, sets the equilibrium price for the next period and broadcasts this price signal back to the system. The equilibrium price represents the root of the compound demand function (when supply equals demand) [72]. The consumption and production units adjust the actual consumption and generation according to the new price signal (altering their operation according to the broadcast future market price). The leaves of the tree are resource agents which are responsible for the economic operation of different consumption and production units; they send power bids to the direct powermatcher and adjust the operation of their respective units after receiving updates of the general market price. The powermatcher concept was used in number of simulation and real life field tests [43] [44] [45]. In [44], a powermatcher approach is described that coordinates the operation of a virtual power plant that comprising 10 micro-CHP (combined heat and power) units, in order to achieve significant peak load reduction in the low voltage power network.

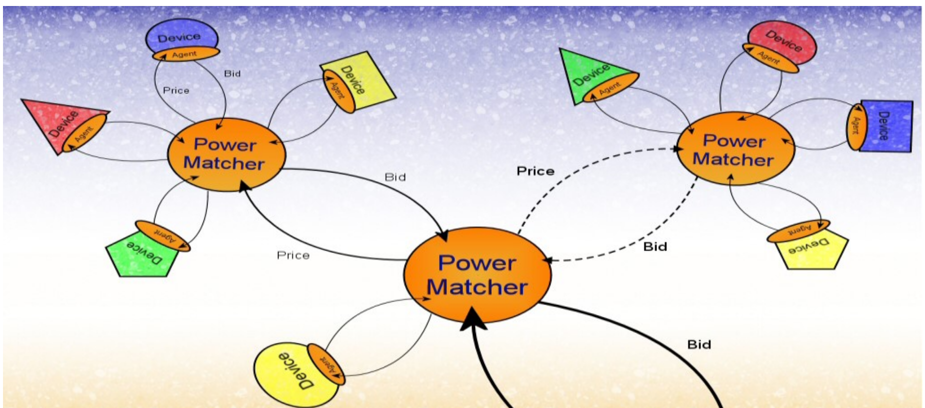


Figure 2.8: Powermatcher architecture

With respect to the coordination of the future power networks, there are two coordination goals, the coordination of network technical operations and the coordination of business operations. With respect to a dual coordination model for the technical and business goals, the powermatcher concept is used to implement multi-goal coordination model by using multi-layered powermatcher networks [76]. Flexibility, high scalability, standard communication inside the system and local autonomy of each consumer are reported advantages of the powermatcher concept [75] [74].

2.5 Comparison of supply and demand matching algorithms

Supply and demand matching is an essential task for the operation of the future power network that relies on distributed renewable energy resources. Multi-agent systems were proposed and are being developed to coordinate the supply and demand for the future power network. The developed coordination algorithms can be classified into two approaches: market-based and non-market-based. The distribution of consumption and generation units and the local constraints of these units entail using a decentralized system for accomplishing the coordination task. All developed systems presented here depend on multi-agent systems for the system implementation as a distribution approach. There is a distinction between the decentralization of design and implementation, and the decentralization of the computation [40].

In order to compare the features of the developed market-based and non-market based systems, a comparison of the developed systems according to a number of factors is presented now. Table 1 shows a summary of the comparison of the developed systems. The coordination approach that depends on reinforcement learning is the only one required Pre-information about the system to define the state space for the system before the learning process.

The distribution of computation among agents within the developed systems is different from one to the other. A number of the reported systems in this article depend on a central computation agent (coordinator) to lead the coordination task within the system, which limits the system's ability to manipulate large-scale applications. More details about the advantages and disadvantages of the central coordination approaches for multi-agent system are reported in [71]. On the other hand, the third non-market based algorithm (see Table 1) represents a fully decentralized computation approach, where there is no central coordination agent and the communication between agents is indirect. So, the system is scalable for large scale applications. The powermatcher approach represents the half way between the fully centralized and the fully decentralized approaches, where part of the demand function aggregation is delegated to the intermediate powermacher agents. Additionally, the communication is standard and limited to the bids and the price signals among different agents within the system.

There are differences among the developed systems with respect to the information requirements and the quality of the resulted solution. Approaches that use a central coordinator rely on complete information about the system to coordinate the system operation and gravitate to the point of equilibrium.

The advantage of those approaches is that the resulting solution is most probably optimal. On the other hand, the third non-market based algorithm depends on partial information about the system, but the resulting solution is sup-optimal. Information requirement is limited to bids and price signals in the powermatcher approach and the resulting solution is pareto optimal. The required computation cost with increasing numbers of resource agents is an important indicator for system performance. We compared the developed systems according to the reported available data of experimental tests for the computation cost with increasing numbers of resource agents. While the reported data reveals that the required computation cost increased nearly linear in the approaches that depend on central coordinator (non-altering demand, reinforcement learning and self-organization), the computation cost is nearly constant in the fully decentralized approach (evolutionary algorithm). The computation cost for the powermatcher is proportional to O(lg p), where p is the number of resources agent. Two of the developed systems are already used in field tests (ILCs and powermatcher), the others are laboratory tested.

	Market based			Non-market based		
System	Non-Altering demand	Based on ILCs abilities	Powermatcher	Reinforcement learning	Self-organization principles	Evolutionary algorithm
Required pre-information	X	X	X	√	X	X
Computation type	centralized	centralized	partially decentralized	centralized	centralized	decentralized
Information requirements	complete	complete	partial	complete	complete	partial
Solution quality	optimal	not defined	pareto optimal	optimal	optimal	sub-optimal
Computation cost	Linear	?	O (lg p)	Linear	Linear	almost constant
System test	Laboratory test	Field test	Field test	Laboratory test	Laboratory test	Laboratory test

Table 1: Comparison of the developed coordination systems

While market-based algorithms suffer from a number of drawbacks as reported in [19], some of the non-market-based algorithms lack the required scalability due to their dependence on central optimization techniques, while the fully decentralized non-market-based algorithms lack the required solution optimality. The most current developed approaches rely on the transfer of information (partial or complete) to a central coordination agent to coordinate their consumption and gravitate to the point of equilibrium. While these coordination algorithms might solve the supply and demand matching problem, the obvious question is the communication cost between the system entities and the scalability of these approaches for large scale applications.

2.5 Comparison of supply and demand matching algorithms

The current coordination approaches rely on the restricted abilities of the local controller agents of energy resources and loads. Whenever improving local controllers' abilities for computation and communication, more information and control abilities for the home devices can be obtained and more intelligent coordination approaches can be developed. At the same time, whenever improving the local controllers' abilities, optimization tasks can be assigned to the local controllers to mitigate the communication burden and the required processing for the system coordination can be flattened (instead of the current hierarchal processing).

3 QUANTUM AND QUANTUM-INSPIRED COMPUTING

3.1 Introduction

Quantum Computing is a branch of theoretical computer science dealing with applications of quantum mechanical principles for solving computational problems. It is a new computing paradigm for solving un-tractable computational problems by using the classical computing paradigm. Quantum computing brings together ideas from classical information theory, computer science, and quantum physics to manipulate the complex computational problems. Quantum computing mimics behavior of atoms in processing information, where controlled evolution of quantum particles is used as a new efficient computation technique for solving the complex classical computational problem. The main principle is that: since everything in this world is composed of quantum particles, any kind of process might be (at least in principle) reduced to quantum processes [51] [77]. Quantum computing is characterized by certain principles of quantum mechanics such as standing waves, interference, quantum bits, coherence and superposition of states. Additionally, mathematical apparatus of quantum mechanics could be applied to introduce solutions of various problems outside physics, although it was developed to describe phenomena in the micro-world [51] [78]. It is proved that Quantum computation can provide dramatic advantages over classical computation for some computational problems [52] [53].

There are number of reasons push the research for realizing quantum computers. One of these reasons is the Moore's law, which states that computer power is doubled for constant cost roughly once every two years. As electronic devices are going to be smaller and smaller, quantum effects are beginning to interfere their functioning. One of the solutions for this problem is developing the quantum computing paradigm, which based on the idea of using quantum mechanics to perform computation instead of classical physics. Another reason for quantum computers realization is that they will solve certain types of problems faster than any classical computers. Prominent examples for hard problems are the traveling salesman problem, and the graph isomorphism problem, and the problem of factoring a number into primes [79].

Quantum computing is a new and different paradigm compared with the classical computing. For example, there are differences between composing state in classical and quantum system. Assume a classical and a quantum systems consist of number of subsystems which define the overall state of the two systems. To define the overall state of the classical system, the different states of subsystems are just permuted to define the individual states of the state space of system. In quantum system, the overall system state is defined depending on mixing the states instead of just permuting them. There are two parameters define the result of the mixing process, the state amplitudes and the state phases. State amplitudes can be amplified to enforce the desired states in the mixing. State phases can be used to control the constructive and destructive interference in the mixing process.

There are number of features that give the quantum computation superiority higher than the classical computation. Quantum computation exploits the inherent parallelism that is provided by the superposition of the quantum state. A quantum register with n binary cells is able to store 2^n sequences simultaneously, in contrast to a classical register, which can store only 1 of the 2^n sequences at a time. Depending on exploiting the parallel process for those states, quantum algorithms can provide substantial exponential speedup over classical methods [80]. Thereby quantum information turned out to be extremely useful for speeding up or securing a number of important information processing and communication tasks [79]. It was proved that a quantum computer can factorize an integer number in polynomial time (Peter Shor's algorithm) [52], or search for an element within an unstructured list of "n" elements, in time square root of "n" (Grover's search algorithm) [53]. Additionally, using quantum computer as a computing tool it could solve problems almost instantly by using qubits without using any transistors or chips, and in theory computer could run without energy consumption while being a billion times faster than the current computers [79].

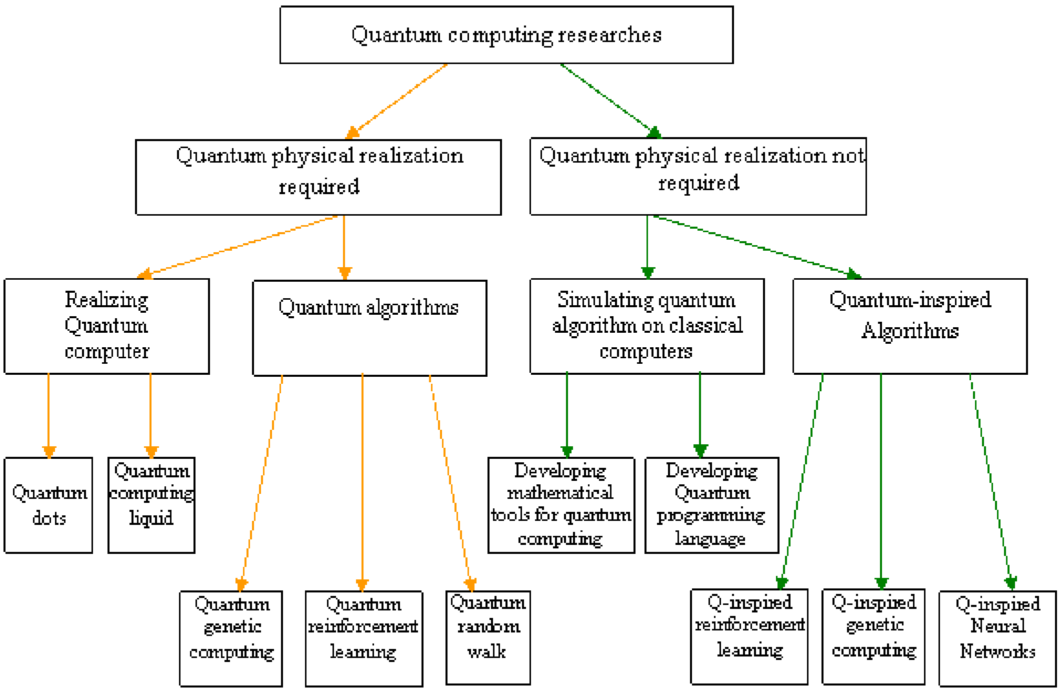


Figure 3.1: Research directions for quantum computing

The research for exploiting quantum principle for enhancing the computing ability to solve the complex computational problem takes several aspects. Figure 3.1 shows the research directions for the quantum computing. The first research effort is directed to realize the quantum computer. With the rapid development of quantum computation technology, some quantum computer models can be constructed [81]. Recent advances in nanofabrication have made it possible to create nanostructures such as quantum dots and quantum wells that behave like artificial atoms or molecules and exhibit complex quantum behavior [82]. Some physical realization methods of the qubit are being experimented with varying degrees of success. Quantum dot basically is a single electron trapped inside a cage of atoms. The electron has two energy levels, the ground state and the exited state. The existence of the electron in the two energy levels is controlled by using laser light. One laser pulse moves the electron from ground state represented by "0" to the existed state represented by "1". Using another laser pulse the electron return to the ground state. Another method for realizing qubits depends on a sea of molecules (quantum liquids) to store the information instead of using a tiny and isolated medium for representing qubits. This quantum liquid when it held in a magnetic field, each nucleus within a molecule spins in a certain direction, which can be used to describe its state. Spinning upwards can represent a "1" state and spinning down can represent a "0". Nuclear Magnetic Resonance (NMR) techniques can be used to detect these spin states and bursts of specific radio waves can flip the nuclei from spinning up "1" state to spinning down "0" state and vice-versa. Unfortunately, there are number of practical problems face the realization of the two methods.

Although the discovery of efficient quantum algorithm by Shor and Grover has interest in the field of quantum computing, it is still hard to find new quantum algorithm [83]. The low level of the quantum program is one of the reasons for this problem. So, there are research effort directed toward simulate quantum algorithms on the classical computer for testing and developing new quantum algorithms which called quantum soft computing [84]. Simulating quantum algorithms on a classical computer entails developing quantum programming languages [85] [86] [87]. This simulation aims to test and develop new quantum algorithms. Without efficient quantum algorithms, the power of quantum computer cannot be exploited. The third research direction directed toward combines the quantum mechanics principles with computational intelligence approaches for improving the performance of the computational intelligence approaches which called quantum-inspired computing [5]. Quantum-inspired evolutionary algorithm [88] [89] [90] [91] [92], quantum-inspired reinforcement learning [93] [94] [95], quantum-inspired immune clonal algorithm [96], multi-agent reinforcement learning based on quantum theory [97] [98] and quantum-inspired neural networks [99] [100] [101] are examples for the quantum-inspired algorithms.

3.2 Quantum postulates and quantum computing

Quantum computation is based on several principles of quantum mechanics which is a mathematical model that describes the evolution of physical elementary particles. Quantum unitary evolution, quantum interference, quantum parallelism and quantum entanglement are features that are used for constructing the quantum computational algorithms. In the following section, the interaction between quantum mechanics and quantum computation are presented.

3.2.1 Quantum system state

Quantum mechanics is a mathematical framework for the development of the physical theory. Quantum mechanics stands on number of postulates, these postulates provide a connection between physical world and mathematical world [5]. In quantum mechanics the system is described by using wave function (state function) which is a function of all coordinates of the particles and of the time.

$\Psi = \Psi(x, y, z, t)$

By using this function the quantum system state can be expected. Wave function contains all the dynamic information about the system it describes. The wave function itself has no physical interpretation since it can be a complex function. However the square modulus of the wave function at state x is proportional to the probability of finding the system at state x.

In quantum computing a quantum system is represented by state vector in complex state space called Hilbert space. Qubit is the basic quantum unit in the quantum computing. System with single qubit can be mathematically represented by the Dirac notation as follows:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

Where α and β are complex numbers, $|\alpha|^2$ and $|\beta|^2$ are the probability of finding the system in state "0" or "1" respectively when it is measured. Under the condition that $|\alpha|^2 + |\beta|^2 = 1$. $|0\rangle = [1\ 0]^T$ and $|1\rangle = [0\ 1]^T$ are orthogonal vectors called the basis vector of the state space. For describing a composite quantum system consists of number of subsystems (qubits) for example three qubits. The composite system is described by using the tensor product of the three systems as follows:

$$|\psi\rangle = (\alpha_1|0\rangle + \beta_1|1\rangle) \otimes (\alpha_2|0\rangle + \beta_2|1\rangle) \otimes (\alpha_3|0\rangle + \beta_3|1\rangle)$$

$$= \alpha_1\alpha_2\alpha_3|000\rangle + \alpha_1\alpha_2\beta_3|001\rangle + \ldots\ldots\ldots\ \ldots\ldots + \beta_1\beta_2\beta_3|111\rangle$$

$$= \gamma_1|000\rangle + \gamma_2|001\rangle + \ldots\ldots\ldots\ \ldots\ldots + \gamma_8|111\rangle$$

The composite system is represented by superposition of all its basis state. The square of the coefficients of the basis states γ_i that called amplitude, represent the probability of the basis state to be the system state when the system is measured.

3.2.2 Quantum gate representation

In quantum computation, most quantum algorithms are described through a quantum circuit that is represented as a finite sequence of quantum gates. The quantum gate operates on fixed number of qubits. Figure 3.2 describes the single and the double quantum gate. The first is called the phase gate that rotates the state of the qubit by ϕ angle. The second is called the control NOT gate that simulates the XOR operation. When $|\phi>$ is $|0>$ the output corresponding to the quantum qubit $|\psi>$ and when $|\phi>$ is $|1>$ the output is the inversion of $|\psi>$. There are a lot of fundamental quantum gates used for constructing quantum algorithms like Hadmard gate, Pauli(X,Y,Z) gates, Toffoli gate and Fredkin gate[8].

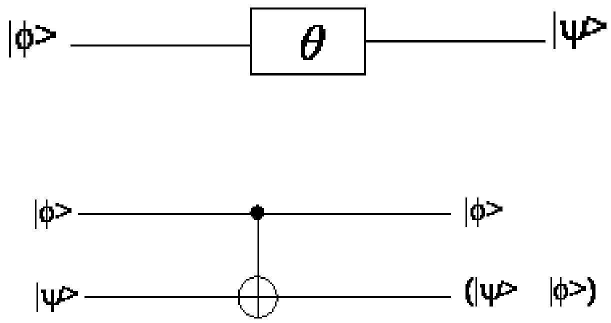


Figure 3.2: One and Two bit quantum gate

3.2.3 Quantum system evolution

The quantum mechanical system evolution with time is described by the following Schrödinger equation:

$$i\hbar \frac{d\,|\psi>}{dt} = H\,|\psi>$$

Where $\hbar$ is the plank's constant depends on the system. H is a Hermitian operator known as the Hamiltonian of the system. If we know $\hbar$ and H, the system dynamics can be understood completely. Through solving this equation, everything about the system can be known. The solution of the Schrödinger equation is as follows:

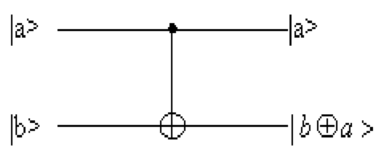
$$\psi(t) = \exp(-iHt/\hbar)\psi(0)$$

In quantum computing the quantum system evolution is described by unitary transformation. This transformation is described by the following equation:

$$|\Psi(t)> = U\,|\Psi(0)>$$

Where U is unitary operator which changes the system state from $|\Psi(0)>$ to $|\Psi(t)>$. There are a lot of unitary operators that can be used to change the quantum system state, depends on the required evolution of the system. There are universal unitary operators like the two qubits CNOT (controlled-NOT gate) U_{CNOT}. This gate inverts the second qubits if the first qubit is "1", and does nothing if the first qubits is "0". Figure 3.3-a and Figure 3.3-b show the symbol and the matrix representation for the CNOT gate.

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$



|a>	|b>	The output	
		|a>	$\|b \oplus a>$
0	0	0	0
0	1	0	1
1	0	1	1
1	1	1	0

(a) (b) (c)

Figure 3.3: Representation of the Controlled-NOT gate

Where (a) The matrix representation Controlled-NOT gate (b) The symbol of Controlled-NOT gate and (c) The input and the output of the Controlled-NOT gate

3.2.4 Quantum system observation (measurements)

The quantum system observing requires some type of interaction with the quantum system called measurements. Measurements in the quantum world are accomplished by using collection of operators called measurements operators. The quantum wave function assigns probabilities for the system basis states. These probabilities define the different basis states probability to be the system state when the system is measured. When the system is measured, the wave function collapses into only one of the basis states. Because of basis states represent all possible outputs of a measurement, the sum of the state probabilities must be one. Similarly, in quantum computation, measuring quantum system is accomplished by using collection of unitary operators acting on the state space of the system that is measured. Each operator represents by a Hermitian matrix constitutes the spectrum of the operators.

3.3 Quantum algorithm

Quantum computational algorithm depends on number of operators to control quantum states (qubits) evolution from the initial state to the final state that by measuring it we could find answer for the problem. There are two parameters used to control quantum states evolution for the most quantum algorithms [5], the state amplitudes and the state phases. State amplitudes can be used to amplify desired states during the evolution process. State phases can be used to control the constructive and destructive interference for the states during the interference process. Quantum algorithm input is a function to investigate its qualitative property. The output of the algorithm is a quantitative form according to the qualitative properties of the function [84]. The quantum algorithm can be described by quantum circuit that is a language for describing the sequence of the algorithm operations to direct the system evolution [102]. Quantum circuit consists of sequence of unitary quantum operators (quantum gates) which specify the procedure of computation during the states evolution from the initial state to final state Figure 3.4 shows the general structure of the quantum circuits. Quantum operators that are used in the quantum algorithm can be divided into four groups: superposition, entanglement, interference and measurement operators. Each operator is embedded in quantum gate that represents certain evolution for the quantum states. Quantum computation exploits the inherent parallelism that is provided by the superposition of the quantum state. Superposition operator acts on the quantum register initial pure state to convert it into a superposition mixed state.

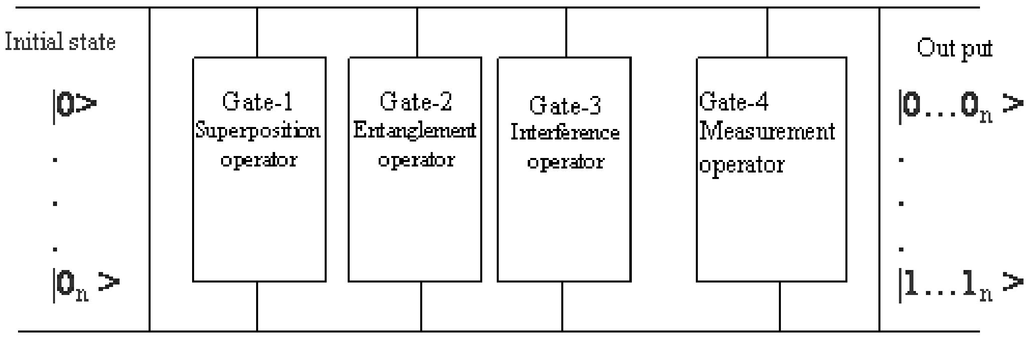


Figure 3.4: General structure of the quantum circuits

A quantum register with n binary cells is able to store 2^n sequences simultaneously, in contrast to a classical register, which can store only 1 of the 2^n sequences at a time. After that, entanglement operator is used. Entanglement is the potential for quantum systems to exhibit non-local correlations among subsystems that cannot be accomplished by classical computation. In quantum computation an entanglement is carried by an entanglement operator, where CNOT (controlled-not) operator can create the entanglement operator from superposition of quantum states. Interference is a familiar wave phenomenon. Wave peaks that are in phase constructively add, while those that are out of phase interfere destructively. Similarly, interference operators arrange interaction among the parallel computational paths to cancel undesired states and enforce expected desired state. While interference is a quantum operator with a classical counterpart, entanglement is a completely quantum phenomenon for which there is no direct classical analog.

3.3.1 Simulating quantum algorithm on classical computers

Design Large scale quantum computer until now is leading step [81]. For testing and developing quantum algorithm, simulating quantum algorithm on the classical computer is required. There is research effort for developing schema for simulating quantum algorithm on the quantum computers [83]. These efforts aim to develop a systematic way for design quantum algorithms and to minimize the computational complexity of simulating quantum algorithm on classical computers. It is proved that any classical function computation can be converted to quantum computation with certain computational complexity [103] [85]. The problem of simulating quantum algorithms on classical computer is the computational complexity of the algorithm and the memory required. There, the matrix dimension of the unitary operator increases exponentially with the number of input qubits.

The direct representation of the quantum operators is stable and precise, but the required memory growth exponentially with increasing the number of qubits. So, this method is useful for representing quantum algorithm with small number of qubits (for 11 qubits the memory required is about 1G bytes). The algorithm simulation for the quantum operator aims to avoid the total storing for the quantum operators. Thereby, the maximum number of qubits that can be represented on classical computer is affected by the number of operation that is required to calculate the operator elements and the required memory for storing the state vector (by this method up to 19 qubits or more can be represented). Compute on demand approach can lead to approach-oriented problems related to storing infinitesimal number ($1/2^{n/2}$) when the number of qubits is high.

3.3.2 Tools for quantum soft computing

Quantum computation depends on number of specific transformations of an n qubits system. The computation cost of performing qubits transformation is important factor for implementing and simulating different quantum algorithms. The question is how to implement the efficient qubits transformation? Efficient means the implementation takes a number of steps that is polynomial in n [104]. Exploiting quantum computing features for creating new computing algorithms for complex computational problems require developing new building blocks that exploit the quantum parallel processing [104] [105] [106] [107]. Tools for quantum computing have been developed and used in the developed quantum algorithms. There are two sorts of tools are reported. First, the mixing amplitudes tools, such as the Fourier and Walsh transform. Second, the Selective phase change tools. Therein, the phases of certain states are changed to promote amplitude cancellation or amplification when states are mixed during states evolution. The computational cost for implementing those tools is investigated [104]. The computational cost is reported in terms of time, calls to the oracle function for the algorithm and the number of additional qubits that are required for implementation.

3.4 Quantum-inspired computing

Exploiting and exploring quantum computing principles to improve the performance of intelligent systems is one of the active research areas nowadays. This research area concerned with studying quantum computing that is characterized by certain principles of quantum mechanics combined with computational intelligence or soft computing approaches [5]. Research on applying principles of quantum computing to improve engineering of intelligent systems has been launched since late 1990s. There are number of quantum-inspired computing systems have been developed for solving the complex computational problems. Quantum-inspired evolutionary algorithm [108] [109], quantum- inspired reinforcement learning [93], quantum-inspired swarm intelligence [110] [111], quantum-inspired immune system and quantum-inspired neural networks [100] [112] [99] are examples for the quantum-inspired approaches. Through exploiting advantages of quantum computation, the inspired integrated algorithms by quantum principles enhance the performance of existing algorithms on traditional computers. Additionally, encouraging the development of related research areas such as quantum computer and machine learning. In the following section, the quantum-inspired evolutionary algorithms are shortly presented.

The quantum-inspired evolutionary algorithm

Evolutionary algorithms (EAs) are one of the popular metaheuristic to solve optimization problem [55] [113] [114] [115]. The major problem of EAs is that they may be trapped in the local optima of the objective function. Therefore, various new methods have been proposed and developed. Exploiting quantum mechanics features for enhancing evolutionary algorithms abilities for exploring the population space to reach to the optimal solution is one the recent research directions. Quantum-inspired evolution algorithm inspired from the biological evolution (the evolution theory) and the unitary evolution of the quantum system (the quantum information theory). Where, the population space representation depends on the quantum bits (qubits) and the evolution operators are designed by using some features inspired from the quantum mechanics principles like the quantum bit evolution (quantum bit rotation), interference and superposition. The quantum evolutionary algorithm follows the main scheme of the classical evolutionary algorithm. However, the main stages of the algorithm are implemented upon principles of quantum computing. There are two types of quantum-inspired evolutionary algorithms according to the population space representation [108] [6]. Algorithms of the first type rely on the quantum binary representation for the population space [6]. The second type algorithms depend on real-valued representation for the population space [108]. There are several reported applications of the two types for combinatorial and numerical optimization problems [88] [116] [117]. Quantum aspects that are employed to modify and enhance the main stages of classical evolutionary algorithms are briefly presented in the following area.

- **The quantum population space representation**

Quantum-inspired evolution algorithm employs binary quantum coding and real-coding for population space representation. In binary quantum coding the qubits are used to represent the evolutionary genes instead of the classical binary bits [6]. Qubits is the basic unit in the quantum information theory. Qubits mathematically is represented by using the Dirac notation (there is also Heisenberg notation) as follows:

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle$$

Where α and β are complex numbers, $|0\rangle = [1\ 0]^T$, $|1\rangle = [0\ 1]^T$ and $|\alpha|^2 + |\beta|^2 = 1$

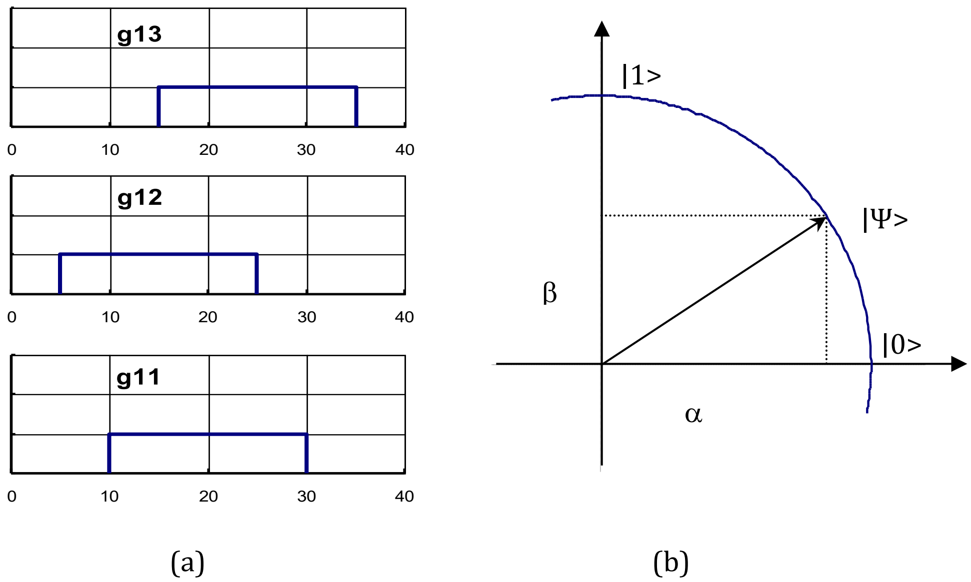


Figure 3.5: The real and binary coding of the population space individuals

Where (a) Three instances of the real-coded gene and (b) The binary qubits representation

Figure 3.5-b shows the graphical representation of the binary qubit state. The vector position defines the probability of the quantum state to be "0" ($|\alpha|^2$) or to be "1" ($|\beta|^2$) when it is measured or observed. The quantum population space is represented by using quantum chromosome (or quantum register) that contains number of qubits

(quantum genes) equal to the number of the solution variable. The quantum chromosome is as follows:

$$q_j = (g_1, g_2, \ldots\ldots\ldots, g_N)$$

$$q_j = \begin{matrix} \alpha_{g1} & \alpha_{g2} & . & . & . & . & . & . & . & \alpha_{gN} \\ \beta_{g1} & \beta_{g2} & . & . & . & . & . & . & . & \beta_{gN} \end{matrix}$$

$q_j \in Q$, Q is the quantum solution space, and N is the number of solution variables

While in real-coded population space, the evolutionary genes are represented by real pulses. Each pulse width covers the variable solution domain that it represent and its height is defined depends on the population space size [108] [118]. For example, if the real coded quantum gene represents variable x in the population space where $10<x<30$ and the population space size is M. The gene width will be 20 and the height of the gene will be $1/(20*M)$. Through this representation, the summation of the areas of all genes of quantum individuals that represent the same variable is one. Figure 3.5-a shows three instance for the real-coded gene. More details and description about the quantum-inspired real-coded algorithm can be found in [108] [118].

- **Evolution of the quantum individual**

Quantum operators are used to acting to the quantum population space for creating the new generation. Quantum operators are represented by using rotation gates, which a unitary operator is acting on the qubit basis states. The general quantum operator for single bit is as follows:

$$U(\theta = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$$

Where θ is the rotation angle for the quantum bit

The quantum bit after update by angle θ is as follows:

$$\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix}$$

There are two ways for selecting the quantum individual for reproduction according to their fineness. The first way evaluates the quantum individuals in the quantum population space. There are various stochastic and deterministic measures of quality for quantum individuals are possible. The second way, quantum individuals is mapped into the classical population space first and then evaluated. After that the best classical individuals are selected to update the quantum population space.

4 THE POWER RESOURCES MODELLING FOR SMART BUILDING SIMULATION ENVIRONMENT

4.1 Introduction

Smart building energy management (SBEM) systems are expected to be one of the basic building units for Smart Grid and it is expected to play a crucial role in energy efficiency. Innovative SBEM systems for effective control of the energy-using are needed. At the same time, research efforts toward more efficient use of energy dictates that collecting specific information about the household appliances energy consumption leads to maximizing the ability of using more energy conservation approaches [119] [120] [121] [122]. SBEM systems will be the effective controller for energy-using in the building and the source of information for constructing coordination and optimization algorithm within the local power network or microgrid. For simulating the SBEM system in this work, a multi-agent computing paradigm is used to represent the performance of the different appliances and resources in the simulation environments. A SBEM system relies on number of agents for controlling and optimizing the devices operation. Consumption appliances and energy resources agents rely on device model for each device under their control. Agents use these models for define the operation periods (start/stop) for the appliances, which define the appliances power consumption. In this simulation, models are built depending on physical and operational characteristics of the appliances [123]. The operational control of energy power resources and residential devices are presented in [3]. The energy power resources can be classified to stochastic generation resources, controllable resources and storage units. The stochastic generation resources (e.g. solar and wind generation units) operation depend on unpredictable parameters such as weather conditions. Controllable resources (e.g. diesel generators) can be turned "on" or "off" as required. The power storage units allow usage control based on market prices. The residential consumption devices can be classified to shift operation devices (e.g. washing and drying machines), thermal buffer devices (e.g. heating and cooling devices) and user action devices (e.g. audio and lighting loads). In [124] the loads are classified into two categories: controllable and critical. Controllable loads are defined as the loads that can be controlled without noticeable effects to the consumers' comfort. The critical load category contains loads that are either very important or noticeable when being controlled.

Thus, for simulating the participation of the consumer/prosumer in the smart power networks and for developing coordination and control algorithms, number of models for the power resources, storage units and residential load models are required. These models can facilitate the study of changes in electricity demand in response to customer behavior and/or signals from the energy service provider. At the same time, load models are used to evaluate the proposed control and coordination algorithms effects to consumers' preferences, to the general performance of the power network (e.g. stability and reliability) and at the distribution circuit level (e.g. the power flow). For appropriate modeling of loads that is used for the demand response simulation, some characteristics are required [123]. For example, the availability of external intervention to alter their default operation without affecting the constraints related to the device operation within the limits that are defined by the manufacturer or by the consumer. The variety of controllable loads should be modeled and the models should reflect the semi-real behaviors for the tested appliances. So, these models should be built depending on physical and operational characteristics of the appliances. Additionally, the aggregated response of the models within the local network (microgrid) should reflect reasonable load profile for the controlled power network.

In this Chapter, number of the appliance models is presented. In addition to the household appliance models, the electric vehicle (EV) battery is used as onsite storage element for the home. Solar panel and small wind turbine generation profile are used to represent the renewable energy resources within the low-voltage network. In the following sections details and tests for the consumption device, generation resources, and storage element are presented.

4.2 Residential load modeling

For controlling and coordinating the participation of the consumer in the smart power networks, number of residential load models is used. These models are used for testing the proposed algorithms in the next Chapters. For each consumer there is minimum consumption level or critical loads that must be served to avoid the intervention to the user' living activities. After these critical loads, the smart home management system can control and coordinate the other loads consumption to optimize the energy usage into the home. Models for shiftable and controllable appliances are required, for analyzing, developing control coordination algorithms for consumers' participation in the smart power network. Space cooling/heating (AC) units, water heater coils (WHC), clothes dryer machine (CDM), and ventilation device (VD) are models that are used as a consumption appliances. In the following section number of residential load models is presented.

4.2.1 Cooling and heating devices

The heating and cooling devices belong to the controllable load that can be controlled without a lot of notable effects to users' comfort level. The cooling and heating devices temperature set points can be used as a control variable to alter the energy consumption during the power peak consumption time [3]. The time of the start/stop can be used to keep the temperature between the desired temperature settings. Other control action, the temperature setting point for the appliance can be changed by one or two degree without big intervention to the users' preferences. The start/stop cycle depends on fixed and dynamic parameters related to the space. The fixed parameters for example are space area, surface, walls and the area of the windows. The dynamic parameters are the difference between indoor and outdoor temperature, the ventilation rate and the preference of the space's users. For modeling the operation model of the space heating/cooling, all of those parameters have to be taken into consideration. The refrigerator operation is different which it is operated between two setting points (maximum and minimum) and the control actions have to be only inside the operation range without changing these limits. There are number of assumption for formulating the operation model of the space cooling /heating process [125]. The start/stop of the space cooling/heating appliance during the operation horizon is divided into sub-interval *N, where n={1,...,N}*. The space temperature is checked each sub-interval to change the appliance state (*ON/OFF*). The air-condition (AC) device operates in a range of temperature around the user's set point (T_s) . The appliance aims to maintain the space temperature between the two temperature set points (the minimum and maximum points). When the space temperature exceeds the maximum temperature point, the AC unit is turned "*ON*" to return the room temperature to the minimum temperature point and then turned "*OFF*". If the current temperature within the temperature range, the device keep the current state. The space temperature model can be defined by using the following equation.

$$T_{n+1} = T_n + \Delta t.\frac{\alpha}{\Delta c}.W_{AC,n} + \Delta t.\frac{G_n}{\Delta c}$$

Where:

T_n : space temperature during time slot *n*,

Δt : period of time slot *n*,

G_n: heat gain rate for the room during the time slot n, positive if the temperature outdoor greater than the temperature indoor and negative if situation is opposite.

Δc : Energy needed to change the temperature one degree in the space.

α : cooling/ heating capacity of the *AC* appliance.

$W_{AC,n}$: state of the device (1/0 or *ON/OFF*) during time slot *n*.

The appliance status can be represented as follows:

$$Status_{AC}(n) = \begin{cases} 0\,(off) & T_n < T_{\min} \\ 1\,(on) & T_n > T_{\max} \\ Status_{AC}(n-1) & T_{\min} \le T_n \le T_{\max} \end{cases}$$

Where:

$T_{min} = T_s - \Delta T$

$T_{max} = T_s + \Delta T$

Where:

T_s : user setting temperature

T_{min} : minimum temperature

T_{max} : maximum temperature

T_n : temperature of the space during sub-interval *n*.

ΔT : temperature range of the *AC* operation.

Status$_{AC}$*(n)*: state of the air-condition at time slot *n (ON/OFF)*

Algorithm1: The Normal operation Algorithm for the AC appliance (thermostat control)

```
Start
   Repeat
       read the previous temperature (T_{n-1})
          Define the stat of the device (ON/OFF)
              define the maximum temperature setting (T_max(n))
               define the minimum temperature setting (T_min(n))
               define the current temperature from space temperature model (T_n)
              If (current temperature <=Minimum temperature)  Turn appliance "OFF "
             If ( current temperature > =Maximum temperature)  Turn appliance "ON"
           If  ( T_min < T_n <= T_max )      no change
   Until (n>N)
End
```

Algorithm2: Controlled operation algorithm of the AC device during the simulation

4.2 Residential load modeling

Start

Repeat

read the previous temperature (T_{n-1})

define the stat of the device (ON/OF)

Temp. control *change* T_s *according to the temperature control plan*

OR or AND

Time Control *change Period* $_{ON}$ *(start/stop) according to the optimized time control plan*

define the maximum temperature setting ($T_{max}(n)$)

define the minimum temperature setting ($T_{min}(n)$)

define the current temperature from space temperature model (T_n)

If (current temperature <=Minimum temperature) Turn appliance "OFF "

If(current temperature > =Maximum temperature) Turn appliance "ON"

If ($T_{min} < T_n <= T_{max}$) *Execute the time control plan*

Until (n>N)

End

Algorithm1 shows the operation algorithm for the device with only thermostat control. *Algorithm2* shows the controlled operation algorithm using user temperature setting control, by changing the temperature setting during the peak consumption time. Also, by using the optimized time control plan to define the start/stop time of the device as long as the temperature within the desired temperature rang. The time control plan can be used to distribute and optimize the start/stop times for a group of appliances to minimize power consumption or to minimize the number of devices simultaneously "ON". Those control options can be used within the building energy management system to optimize the repeated start/stop for a group of cooling/heating devices for optimizing the energy use in the building. Figure 1 shows three temperature profiles for the AC appliance (Thermostat control, optimized time control and thermostat control with user temperature setting control (Ts)). The first approach, temperature thermostat only defines the start/stop of the device depending on the user temperature setting. Figure 4.1 shows that the start/stop times are defined depending on the temperature bounders (T_{min} *and* T_{max}). The second approach, the start/stop is defined depending on the optimized time control plan which aims to avoid user setting Ts violation. Figure 1 shows that the start/stop of the device is defined within the operation range between the two bounders (T_{min} *and* T_{max}). The start/stop of the *AC* appliance is defined by using the optimization algorithm that is presented in the next Chapter. The third approach, temperature thermostat defines the start/stop time, with changing T_s (0.5 to 2 degrees) depending on the available power or during peak consumption times. For example, Figure 4.1 shows that T_s is increased by 1.5 degree during operation cycles 16 and 17. This action minimizes the normal "ON" period during operation 16 and shift the second "ON" period to be at the start of the operation cycle 18.

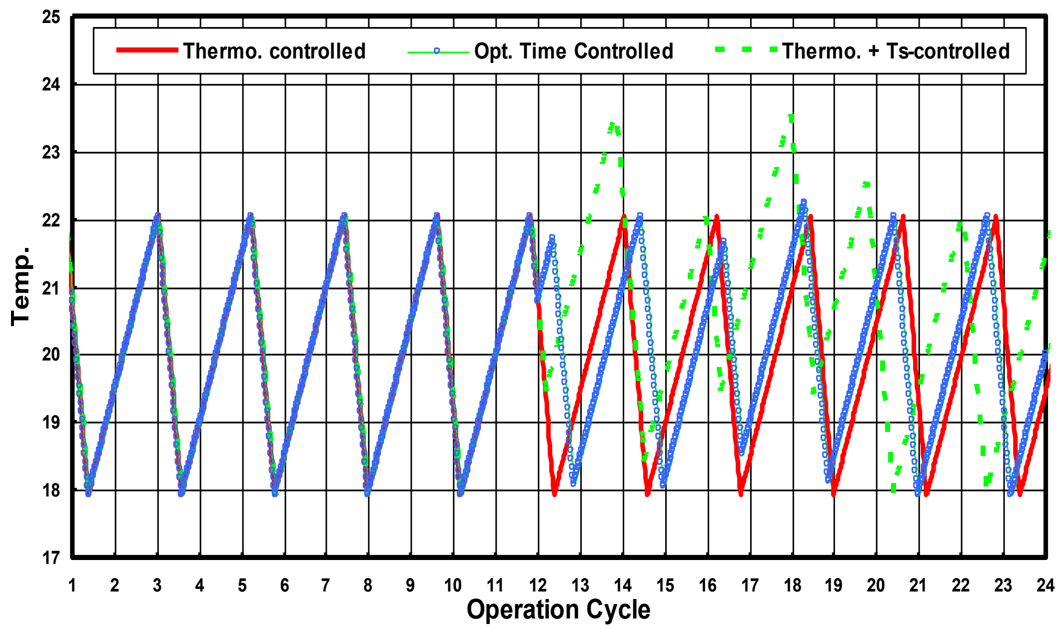


Figure 4.1: Temperature profiles for three control approaches for the AC applicance

(a) Thermostat control (b) optimized Time control (c) Thermostate+ user temperature setting(Ts) control)

4.2.2 Shiftable operation appliances

There are number of household appliances that can be shifted from the peak consumption times to the low consumption times. Washing machine and dryer machine are example of the shiftable appliances. The washing machine is needed to work for one or two hours per a day, which can be shifted to the low consumption times. The dryer machine (DM) can be shifted to the low consumption times or minimized its consumption during the operation time. In the following section the operation model of the dryer machine.

- **Operation model of the dryer machine(DM)**

The clothes dryer machine is operated for a certain time until the drying task is completed. The operation period can be divided into number of periods. This feature can be used to minimize the power consumption during the peak consumption times. The clothes dryer machine is turned "ON" as long as the accumulated "ON" periods are less than the required total time to complete a clothes dryer job. When the accumulated "ON" periods reach the required task total time, the clothes dryer is turned "OFF". A clothes dryer consists of a rotating tumbler and heating coils. The power consumption of the motor is usually in the range of several hundred watts (e.g. 300 watts), while the heating coils can be several kilowatts [9]. The operation model for the dryer machine (DM) is as follows:

$$Status_{DM}(n) = \begin{cases} 0(off) & T_n \geq T_{ac} \\ 1(on) & T_n < T_{ac} \end{cases}$$

Where T_{ac}, T_n are the total required time for the dryer task and the accumulated total "*ON*" periods of the dryer machine (DM) until the sub-interval *n*

- **Controlled operation of the dryer machine(DM)**

The total task "ON" period of the dryer machine can be divided into number of "ON" periods according to the available power (On-period control). Controlling On-period distributes the operation period to minimize the device consumption according to the available supply cap. Also, the total operation task can be totally shifted to the high generation or low consumption times. Figure 4.2 shows the consumption curves by using different operation schemes for the dryer machine. The uncontrolled operation make consumption peak during the low generation time. The first control scheme minimizes the consumption during the low generation by stopping or minimizes the heating coil operation time. However the total consumption still exceeds the local generation during the low generation time.

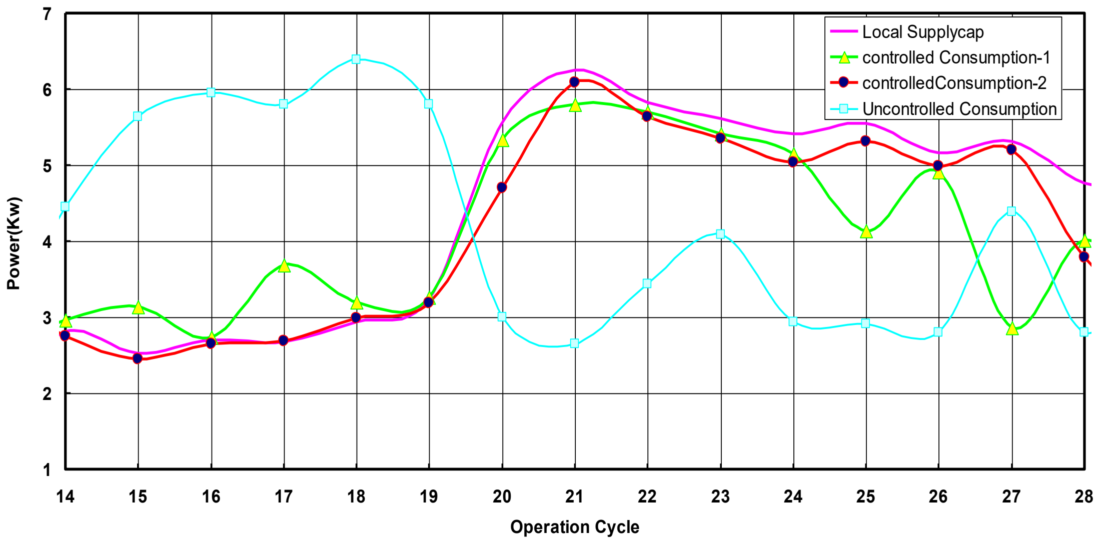


Figure 4.2: Consumption curve by using different control scheme for the dryer machine

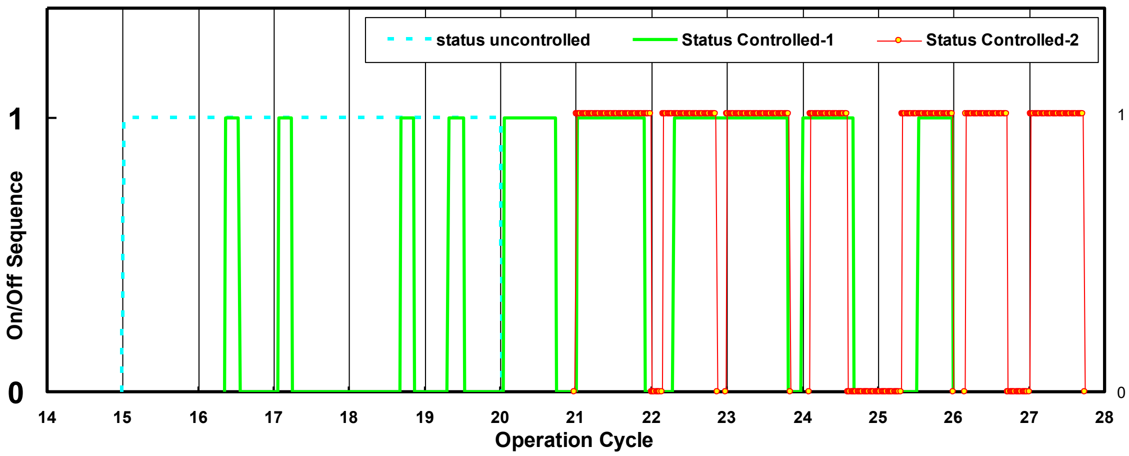


Figure 4.3: On/Off sequence of the dryer machine for controlled and uncontrolled operation

Figure 4.2 shows the start/stop sequence of the dryer machine by using the first control scheme. The second control scheme shifts totally the operation time to the high generation period. Figure 4.3 shows the On/Off sequence of the different operation scheme.

4.2.3 Ventilation appliances

Indoor air quality is affected by humidity, odors, and contaminants. The regular replacement of the indoor air with outside air controls the air quality. The number of air replacement per hour (ARH) is defined depending on the type of the building (e.g. normal house, commercial building, industrial building), the area of the building, and the occupation (number of persons). Ventilation can be mechanical/forced (using fans), natural (windows), mixed and infiltration. The number of replacement for the tightly insulated house is between 0.41 to 0.5 ARH and for the loosely insulated house is between 1.11 to 1.47 ARH [126]. The required air for ventilation is calculated by cubic feet per minute for each person (CFM/P) or for each square feet of the space area (CFM/f^2). The range of required outdoor air for each person is between 5 to 20 CFM/P. The range of required outdoor air for each square feet is between 0.12 to 2.14 CFM/f^2. Ventilation process increases the energy needs for heating/cooling in addition to the energy of ventilation process. The energy recovery ventilation can be used to mitigate the energy consumption. In our simulation, the ventilation appliance operates for certain period depends on the size of the space and the number of persons in it.

- **Operation model for the ventilation appliance**

For controlling and coordinating the start/stop of the ventilation fan/fans (VF), the operation horizon is divided into number of sub-interval *N (n= {1,...,N})*. The indoor air quality (IAQ) in the space is checked each sub-interval to change the VF operation state (*ON/OFF*). We assume that VF operates in a pre-setting air quality range (ex. between 0.2 and 1). The VF aims to maintain the space IAQ between the two IAQ setting points (minimum and maximum points). Measuring the air quality Model is described in the next section. When the space IAQ become below the IAQ_{min}, VF unit is turned "*ON*" to return the space IAQ to the maximum quality point and then is turned "*OFF*". If the current IAQ within the air quality range, the appliance keep the VF current state. The operation model is as follows:

$$Status_{VF}(n) = \begin{cases} 1\,(ON) & IAQ_n < IAQ_{\min} \\ 0\,(OFF) & IAQ_n > T_{\max} \\ Status_{VF}(n-1)) & IAQ_{\min} \le IAQ_n \le IAQ_{\max} \end{cases}$$

Where:

IAQ_n : indoor air quality during the sub-interval n

$IAQ_{\min}$: minimum indoor air quality setting point

$IAQ_{\max}$: maximum indoor air quality setting point

$Status_{VF}(n)$: status of the VF during the sub-interval n

- **Indoor air quality model**

Indoor air quality (IAQ) model can be defined using the following equations, these equations represent the role of the air quality sensor in reality to send the actuating signal to the VF. For each sub-interval n equation 1,2,3 and 4 are calculated to define the air quality level within the space to decide the status of the VF.

$IAQ(n) = (\nu_1(n) - \nu_3(n)) / \nu_2(j)$ (1)

$\nu_1(n) = \nu_1(n-1) + \Delta t * VFrate * Status_{VF}(n)$ (2)

$\nu_3(n) = \chi(n) * \nu_4 * \Delta t + \mu * \nu_5 * \Delta t$ (3)

$\nu_2(j) = \varphi(j) * \nu_4 * Pcycle + \mu * \nu_5 * Pcycle$ (4)

Where:

$IAQ(n)$: air quality during the sub-interval n

$\nu_1(n)$: outdoor air volume in the space during sub-interval n

$\nu_2(j)$: expected required outdoor air for the space during the operation cycle j

$\nu_3(n)$: exhausted outdoor air in the space during the sub-interval n

Δt : duration of the sub-interval n (minutes)

Pcycle : operation cycle period (minutes)

VFrate : ventilation fan rate CF/hour (cubic feet per hour)

$\chi(n)$: number of persons in the space during the sub-interval n (occupancy sensor)

ν_4 : required outdoor air in cubic feet per minute for each person (CFM/P)

μ : space area (square feet)

ν_5 : required outdoor air in cubic feet per minute for each square feet (CFM/F^2)

$\varphi(j)$: expected number of persons during the next operation cycle j

$Status_{VF}(n)$: ventilation fan status ON/OFF (1/0)

Algorithm3: the operation algorithm for the space ventilation device

Start

Repeat

read the previous outdoor air volume $(v_1\,(n-1))$

define the stat of the device (ON/OF)

During the peak consumption time

Time Control *change Period* $_{ON}$ *(start/stop) according to the optimized time control plan*

define the current LAQ(n) from space ventilation model (eq. 1,2,3, and 4)

If (current LAQ(n) $> LAQ_{Max}$ *) Turn appliance "OFF "*

If (current LAQ(n) $< LAQ_{Min}$ *) Turn appliance "ON"*

If ($LAQ_{Min} <= LAQ(n) <= LAQ_{Max}$ *) Execute the time control plan*

Until (n>N)

End

- **Controlled operation of the space ventilation**

Algorithm3 represents the operation algorithm of ventilation fan with and without control. Figure 4.4 and 4.5 show the controlled and uncontrolled operations of the ventilation fan during the low renewable energy generation. As shown in Figure 4.4, generation exceeds consumption until the operation cycle 9. Thus, the controlled and uncontrolled operation is identical. During operation cycles 9 to 19 the control/optimization algorithm is used to minimize and distribute the start/stop of the device without a lot of violation as possible to the air quality setting (The air quality setting between o.2 and 1).

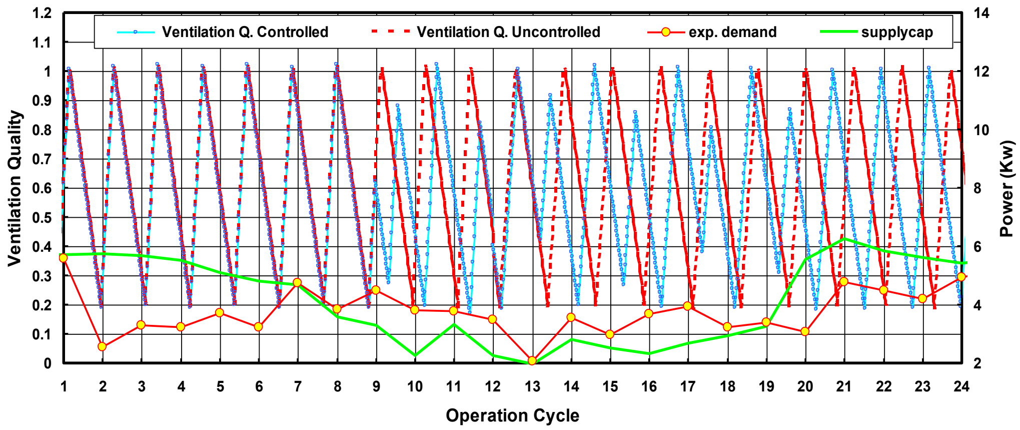


Figure 4.4: space ventilation quality of the controlled and uncontrolled operation

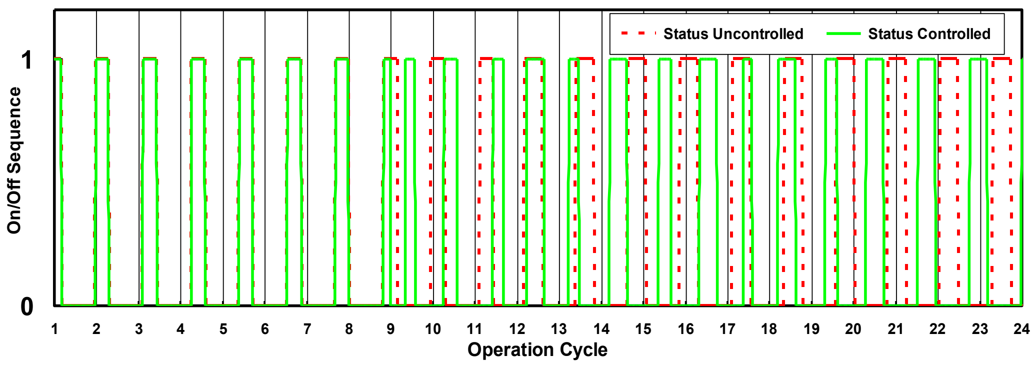


Figure 4.5: operation sequence of controlled and uncontrolled operation of the VF

4.2.4 Heating water coils

Normally, the user defines the setting temperature point (T_s) for the hot water tank. The heating water coil (HWC) tries to maintain the water tank temperature close to T_s defined by user. When the hot water temperature falls under defined minimum temperature, the heating appliance turned "*ON*". The heating appliance continues in the "*ON*" state until the water temperatures returns to the setting temperature by the user and then turned "*OFF*". The heating appliance keeps its status, if the hot water temperature is within the desired range. The status of the heating water appliance can be defined form the operation model as follows:

4.2 Residential load modeling

$$Status_{HWC}(n)=\begin{cases}0\ (off) & T_{tank}(n)>T_S\\ 1\ (on) & T_{tank}(n)<T_{min}\\ Status_{HWC}(n-1) & T_{min}\le T_{tank}(n)\le T_S\end{cases}$$

$$T_{min}=T_s-\Delta T$$

Where:

T_s : The user hot water tank setting temperature

T_{min} : The minimum temperature for the hot water tank

$T_{tank}(n)$: The temperature of the hot water during sub-interval *n*.

ΔT : The temperature range for the appliance operation.

Status_{HWC}(n): The state of the appliance at time slot *n (ON/OFF)*

- **The hot water tank temperature model**

The hot water tank temperature changes can be defined by using the following model:

$$T_{tank}(n+1)=T_{tank}(n)(V_{tank}-frate(n).\Delta t)/V_{tank}+T_{inlet}.frate(n).\Delta t/V_{tank}$$
$$+\Delta t.\frac{P_{hc}}{\Delta c_{tank}}.w_{hwc,n}-\Delta t.\frac{G(n)}{\Delta c_{tank}}$$

Where:

$w_{hwc,n}$: status of the water heater coil during time slot n (1/0))

A_{tank}: surface area of the tank

V_{tank}: volume of the tank

T_{tank}: mixed water temperature in the tank

T_{inlet}: inlet water temperature

Δt : duration of each time slot n

frate(n): hot water flow rate during time slot n

Δc_{tank} : power required to change the tank temperature by one degree.

G(n) : heat gain rate of the tank during the time slot n

R_{tank} : heat resistance of the tank

P_{hwc} : power capacity of the water heater (kW)

- **The controlled operation of HWC**

The status of the HWC can be controlled by using thermostat only, where HWC is turned "*ON*" when tank temperature falls under the minimum temperature and still "*ON*" until the tank temperature return to the user setting T_s and then is turned "*OFF*". If there is a prediction about the amount of the hot water required for the future use, the heating period (*ON* period) can be shifted before the actual time of use. Also, the heating period can be controlled (can be divided to a number of "*ON*" periods) according to the available power.

4.3 Storage units for the smart power grid

The energy storage units will play a crucial role for exploitation of the renewable energy resources. Several electricity storage technologies are under development (e.g. lithium-ion batteries, plug-in hybrid electric vehicles) [127]. On the other hand, new technologies for thermal energy storage are now available (such as hot salt tanks). The plug-in electric vehicles (PEV) are expected to play an important role for minimizing emission and to be an important storage element within smart power grid [36] [128]. The battery capacity and the charging rate are key factors for the battery operation and for studying the participation of the PEV batteries into the demand side management. The battery operation is normally limited to a given charging and discharging level to avoid damage and for increasing the battery life of use [122]. The allowed energy state of the battery is limited to state of charging maximum (SOC_{max}) and state of charging minimum (SOC_{min}). The available battery capacities and the available chargers are reported in [123] [36] [129]. In Belgian, government statistics states that there are three categories of PEV (10, 20 and 30 kwh) and two types of chargers available at home and at work (3.3 and 7.2 kw) [129]. In Australia, depending on limitation of the household wiring, the expected chargers rate range from 2.4 to 4 Kw for single-phase connection and about 16.6 kw for three-phase connection [36]. In PEVs market, the battery capacities range from 16 to 53 kwh and the charging rate range from 1.9 to 9.6 kw [9]. In the following section, PEV battery model is presented.

- **PEV battery model**

For simulating and analyzing the PEV batteries participation into the smart power grid, a battery model is required. The battery model for charging and discharging is non-linear depending on several variables, like the battery state of energy, the internal resistance, the output voltage, and the maximum and the minimum voltage allowed for the battery [121]. In this work for simplicity, a linear model for the PEV battery charging/discharging is used. The vehicle battery is used as own storage element for the smart home management system. This battery is charged or discharged for more exploitation of the local renewable energy resources. The operation status of the battery (charging, discharging, and stop) is defined depending on, the state of charge of the battery (SOC), the connectivity state (CS) and the supply-demand state (*SDS*). The battery operation model is defined using the following equations:

$$BA_{EV,n} = \begin{cases} 1 & disch. & SOC_n \geq SOC_{\max} \\ 0 & ch/disch & SOC_{\min} < SOC_n < SOC_{\max} \\ -1 & ch & SOC_n \leq SOC_{\min} \end{cases}$$

$$CS_{Ev,n} = \begin{cases} 1 & connected \\ 0 & not \end{cases}$$

$$SDS_j = \exp.demand / \exp.\sup ply$$

$$status_{EV}(n) = \begin{cases} 1 & disch & if\,(SDS_j < 1\ \&\ BA_{EV,n} \neq -1\ \&\ CS_{EV,n} = 1) \\ -1 & ch & if\,(SDS_j > 1\ \&\ BA_{EV,n} \neq 1\ \&\ CS_{EV,n} = 1) \\ 0 & stop & otherwise \end{cases}$$

The battery SOC can be updated as follows:

$$SOC_{EV}(n) = \begin{cases} SOC_{EV}(n-1) - status_{EV}(n) * (P_{disch} * \Delta t / C_{batt}) & if\ (status_{EV}(n) = 1) \\ SOC_{EV}(n-1) - status_{EV}(n) * (P_{ch} * \Delta t / C_{batt}) & if\ (status_{EV}(n) = -1) \\ SOC_{EV}(n-1)) & if\ (status_{EV}(n) = 0) \end{cases}$$

Where:

$BA_{EV,n}$: battery availability during the time slot *n*

$CS_{EV,n}$: connectivity state of the battery during the time slot *n*

SDS_{j} : expected supply and demand state during the operation cycle *j*

$status_{EV}(n)$: operation status of the battery during the time slot *n*

$SOC_{Ev}(n)$: battery state of charging during the time slot *n*

Δt : Length of the time slot *n* (minutes)

C_{batt} : Battery rated capacity (kWh)

$SOC_{\max}$: maximum state of charge of the battery

$SOC_{\min}$: minimum state of charge of the battery

P_{disch} : discharge rate of the battery (kw)

P_{ch} : charging rate of the battery (kw)

- **Analyzing the battery performance depending on charging/discharging rate**

In this section the battery model performance with different charging and discharging rates is presented. The ability of the storage element to reshape the local power curves and the local demand curve depends on a number of parameters, like the capacity of the battery, the charging rate, the discharging rate, and the running cost of the battery. There are number of technologies for building storage elements which is different in price, life cycle, capacity, charging and discharging rates [123] [129].

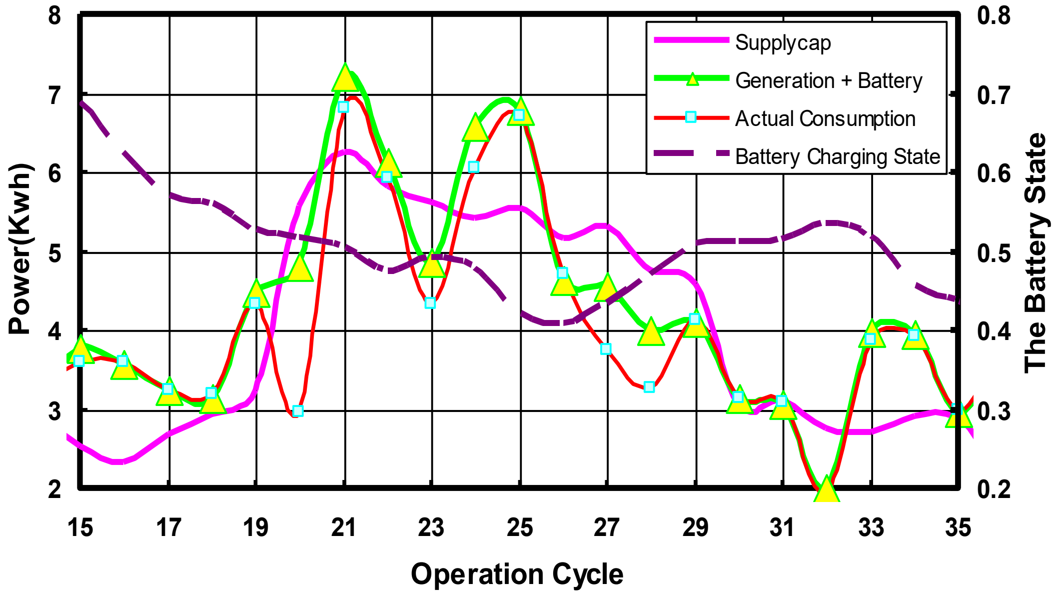


Figure 4.6: Power curves for the SBMS with depending on the local renewable energy resources and the storage elements

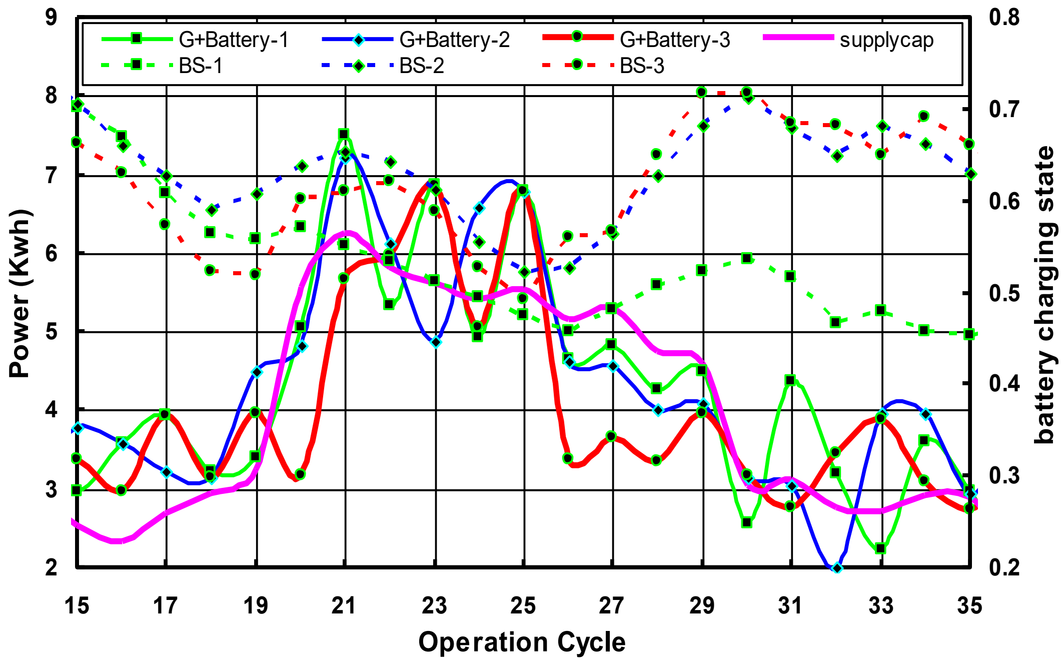


Figure 4.7: Local power curves with using batteries with different charging rate:

Battery-1) 1 kw, Battery-2) 2.5 kw, Battery-3) 6.5 kw, and discharging rate for all is 2.5 kw

While, discharging rate defines the ability of the battery to cover the consumption peaks, charging rate define the ability of the battery to clipping the variable generation peaks which also affects the amount of modification to the consumption curve. Figure 4.6 shows the power curves for a smart home energy management system (SHEMS), the onsite renewable energy supply curve, the modified local power curve by using battery, the actual consumption curve (using the developed optimization algorithm Chapter 7) and the battery charging state curve. When the modified generation curve (Generation+ Battery) exceeds the supply cap curve, this mean the battery in discharging state to cover the consumption peak. When the modified generation curve under the supply cap curve, this is mean that the battery in charging state to store the surplus power above the local consumption. When the modified generation curve and the supply cap curve identical, this is mean there is no charging or discharging for the battery or the battery is not available in this time.

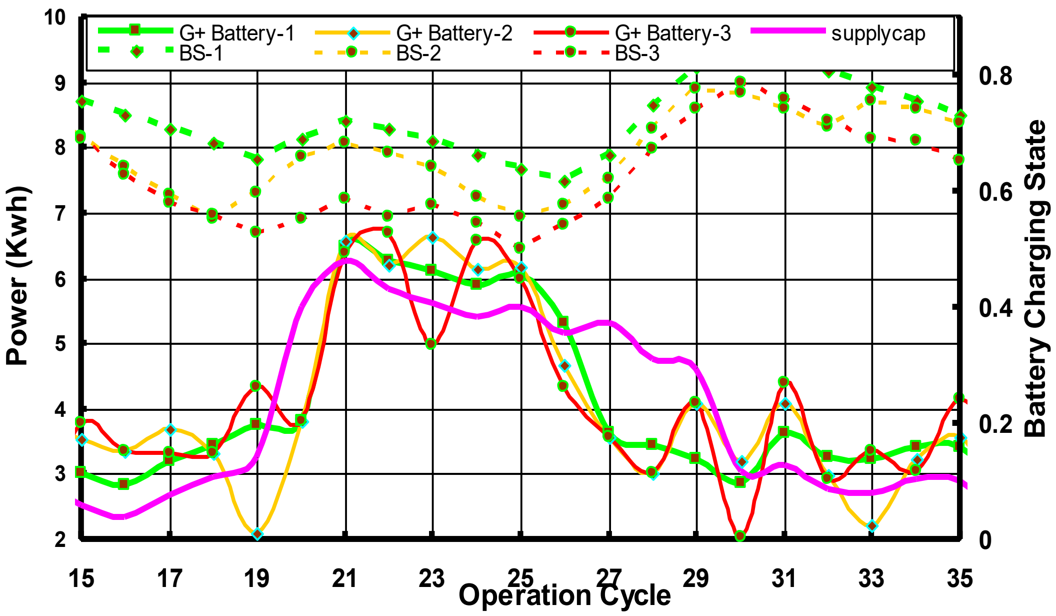


Figure 4.8: Local power curves with using batteries with different discharging rate

Battery-1) 1 kW, **battery-2**) 2 kW, **battery-3**) 2.5 kW and charging rate is 3.5 kW

Figure 4.7 illustrates modifications to the local supply cap curve by using the same renewable energy resources and batteries that have different charging rate and the same discharge rate. The higher battery charging rate produces lower peaks power curves (G+battery-3). This is because the battery able to cover the consumption peaks without a lot of consumption shifting. At the same time, the bottoms of the curve (G+battery-3) are deeper, which refers to more exploitation (storing) for the local renewable generation.

Figure 4.8 shows the comparison among the local supply cap curves by using the same renewable energy resources and batteries with different discharging rate and the same charge rate. The lower battery discharging rate produces lower peaks power curves, this is because the low discharge rate distributes the storage power over long operation period (G+battery-1 curve during operation cycle 21 to 26). This increases the power stress within the home, which is the unsatisfied power or the shifted power from the high consumption period to the low consumption period. When the consumption exceeds the generation by amount of power greater than the ability of the battery to cover totally, the modifications by the storage element to the local power curve is uniform (by the maximum rate). Whenever increasing discharge rate, waving in the local power supply curve appears (e.g. G+battery-2 and G+battery-3 curves during the operation cycles 21 to 26). The high consumption peaks appears because there is shifted consumption from the low generation operation cycle (before operation cycle 21). The high discharge rate makes high consumption peaks after the controlled consumption period. So, this is the place of the battery optimization algorithm that has to be used by the battery agent to define the amount of power and the time of participation for battery charging and discharging taking into consideration users' preference, technical and economic considerations.

4.4 Renewable generation resources modeling

The use of small-scale generation units for Onsite consumption is becoming more widespread due to efforts that aim to reduce greenhouse gas emissions, as well as the desire to improve system flexibility and security. With increasing dependence on distributed energy resources and intelligence in the electricity infrastructure, the possibilities for minimizing costs of household energy consumption increase [8]. As penetration of distributed resources increases, there are growing needs to studying, modeling and testing the composite behavior of groups of distributed generation (DG) resources.

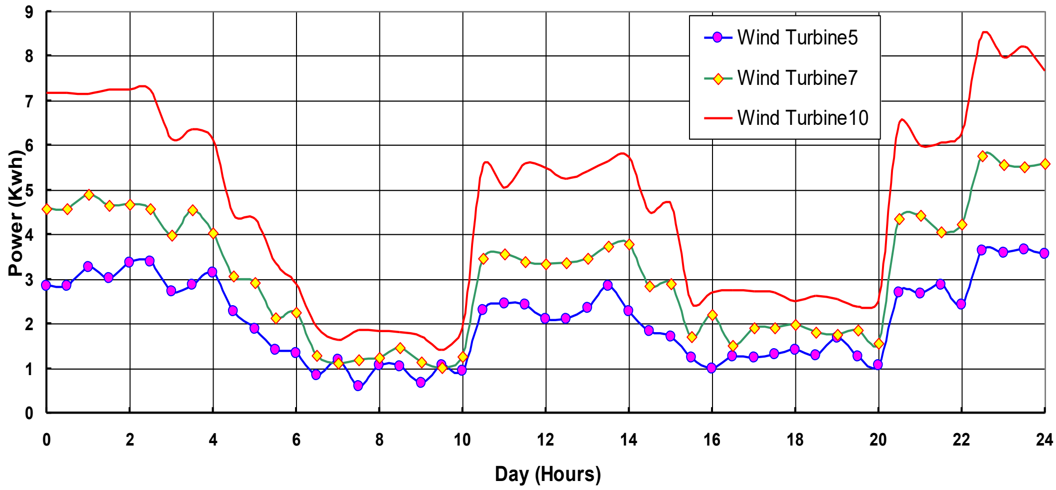


Figure 4.9: Three wind turbine generation profiles for a day (5 , 7, 10) kw

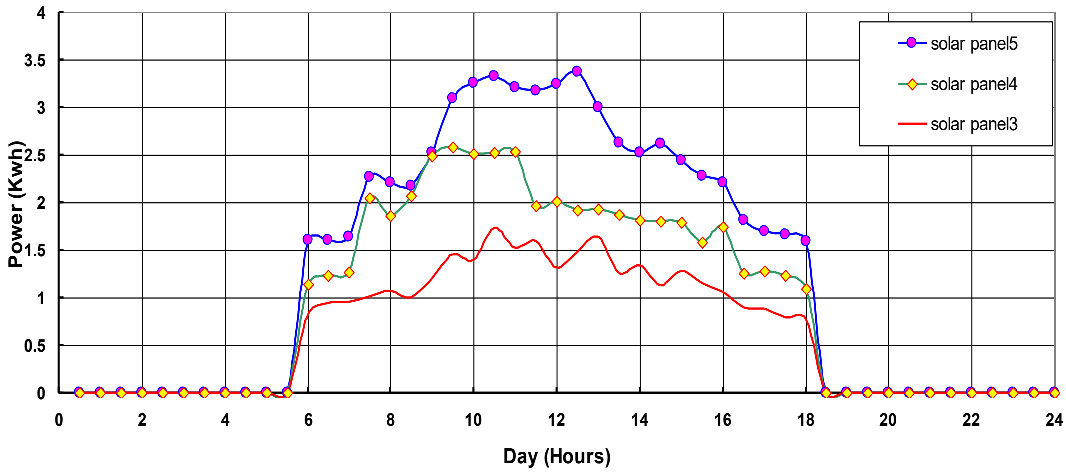


Figure 4.10: Three photovoltaic units' generation profiles for a day

Micro wind turbines, photo-voltaic arrays (PV), and micro combined heat and power (*MicroCHP*) are three technologies currently in use as a small scale DG. Wind turbines have been utilized for many years, and their operating characteristics are well known. Typically, a wind turbine has an associated power curve, which provides the relationship between the output power and the input wind speed. This graph can be used to determine the output power from any given input wind speed, whether this is a single wind speed, or a probability distribution of wind speeds [130]. Photovoltaic cells (PV) are an old technology, have only become viable for electricity production with the recent increase of semiconductor conversion efficiencies. PV generators derive their power output from solar irradiance over the area of the array. In the following section, the generation profiles for the residential renewable energy resources that are used in our work are presented.

- **Residential wind turbine generation profile**

The wind generation forecast is procured based on the typical wind power curve and generated wind speed data. The mean daily wind speed is 10 m/s, which follows a Weibull distribution function with Weibull coefficient equal to 2.1 [30]. The variations of the wind speed average over the seasonal, monthly, diurnal and even short term (less than 10 minutes) which affect the predicted generation from the wind turbine [130]. The wind speed is also very dependent on the location. Differences between two sites close to each other can be significant. For testing using onsite residential wind turbine in this work, generation function for the wind energy resources is implemented. Figure 4.9 shows the three generation curves for residential wind energy unit as a renewable energy rescores for feeding homes locally.

- **Residential photovoltaic unit generation profile**

Generation function for residential photovoltaic unit is used for emulating the generation profile of the household solar panel. Figure 4.10 describes three generation curves for small solar energy unit used as a renewable energy rescores for homes.

5 Quantum-Inspired Evolutionary Algorithm for Supply and Demand Matching

5.1 Introduction

Due to the current trend towards depending on the distributed energy resources (DER), coordination and optimization software is required. The distribution natural of the small scale and renewable energy resources entails depending on distributed software connected with communication networks to coordinate the resources operation. Recently, several coordination and optimization approaches have been proposed for optimally manage the diversified energy resources of the future Smart Grid. These approaches are classified in [39] into market-based and non-market-based. Market-based algorithms depend on modeling consumer and production units as bidding entities (amount of power and price). The central agent (coordinator) collects bids from consumer and production units, and sets the equilibrium market price for selling and buying power to match between supply and demand. Non-market-based coordination approaches depend on modeling consumer and production units as entities that have planning and modification abilities and can calculate the predicted levels of local consumption and generation. The central agent (coordinator) depends on a searching algorithm (learning, bio-inspired and genetic algorithms) and multi-objective functions for optimally allocating the available power for matching supply and demand.

The developed algorithm is a non-market-based coordination approach [41] [66] [47] uses coordination agents that collect consumption levels from sub-agents, and set the permitted consumption levels according to the multi-objective functions that takes the available supply cap and the system stability into consideration. In this chapter, a quantum-inspired evolutionary optimization that is used for coordinating multi-agent operation within the Smart Grid for matching supply and demand is presented.

The rest of the chapter is organized as follows: The next Section describes the quantum inspired optimization algorithm proposed. The third Section introduces the multi-objective functions evaluation.

5.2 The quantum-inspired evolutionary algorithm

Quantum-inspired evolution algorithms combine the evolution theory and the quantum information theory. There, the solution space is represented using quantum bits (qubits) and the evolution operators are designed using some features inspired from the quantum mechanics principles like the quantum bit evolution(quantum bit rotation), interference and superposition. In our implementation, we rely on the quantum-inspired evolutionary algorithm (QIEA) that is developed in [118] [108], which depend on a real-valued representation for the solution space for solving the coordination agent optimization problem. It is reported that this algorithm introduces superior performance when compared to classical and other quantum-inspired evolutionary algorithm.

The quantum-inspired evolutionary algorithm uses quantum chromosomes to represent solution individuals. Each chromosome consists of a number of qubits that represent the solution variables. We represent each device agent power requirements by a quantum-like gene g_i in optimization problem. The quantum genes represent the controller agents' consumption range (or period of consumption) in the quantum population space. The quantum population space contains a set of quantum individual $q_j \in Q$ $j \in \{1,\ldots,M\}$, where Q is the quantum population space and M is the size of this space. Each quantum individual contains N genes $q_j = [g_1, g_2, \ldots, g_N]$. Each gene is represented by two values, the mean and the width of the local controller agent consumption range x_i.

There is analogy between the mentioned quantum-inspired evolutionary algorithm and the quantum computation algorithm. Quantum computing algorithms have four main stages [79], the initialization stage, the superposition stage, entanglement stage and the measurements stage. Figure 5.1 shows the algorithm flowchart. The first stage is the quantum population space initialization. The initialization of the quantum population is carried out by generating number of quantum individuals with random mean inside the problem domain and with width equal to the total domain width. One of the advantages of the quantum inspired evolutionary algorithm over the classical genetic evolutionary algorithm(GEA) is the fair distribution of the solutions inside the problem domain which minimize the probability for tripping in local minimum or local maximum solutions which is one of the shortcomings of the classical GEA. The second stage is the superposition of the quantum individual genes. This step is accomplished by the probability density function (PDF) formulation for each quantum gene, where the individual quantum genes existence defines the probability distribution of different solutions in the problem domain. PDF is similar to the wave function $|\varphi>$ in the quantum mechanics world, which specifies the probability of the quantum particle existence in the space around atom [79]. There is no step represents entanglement in this quantum-inspired evolution algorithm. The last step is the measurement step, which is accomplished by constructing the cumulative distribution function (CDF). The main steps of the quantum-inspired evolutionary algorithm are as follows:

1. *Initialize the quantum population space depending on the collected data from the local controller agents.*
2. *Convert the quantum population space to the classical population space.*
3. *Evaluate the classical population space according to objective functions.*
4. *Select the best classical individual and use it to update the quantum population space.*
5. *Repeat steps 1 to 4 until the objective functions are satisfied.*

Next, we present the details about the algorithm and for each step in the following subsections.

5.2.1 The quantum population space representation

The used Quantum-inspired algorithm depends on real-coded population space, where the evolutionary genes are represented by real pulses. Each pulse spectrum covers the variable solution domain that it represents. Its height is defined based on the population space size. For example, if the real-coded quantum gene represents variable x in the population space where $5<x<45$ and the population space size is M. The gene spectrum will be 40 (mean of the gene is 25) and the height of the gene will be $1/(40*M)$. Through this representation, the summation of the areas of all genes of quantum individuals that represent the same variable is one.

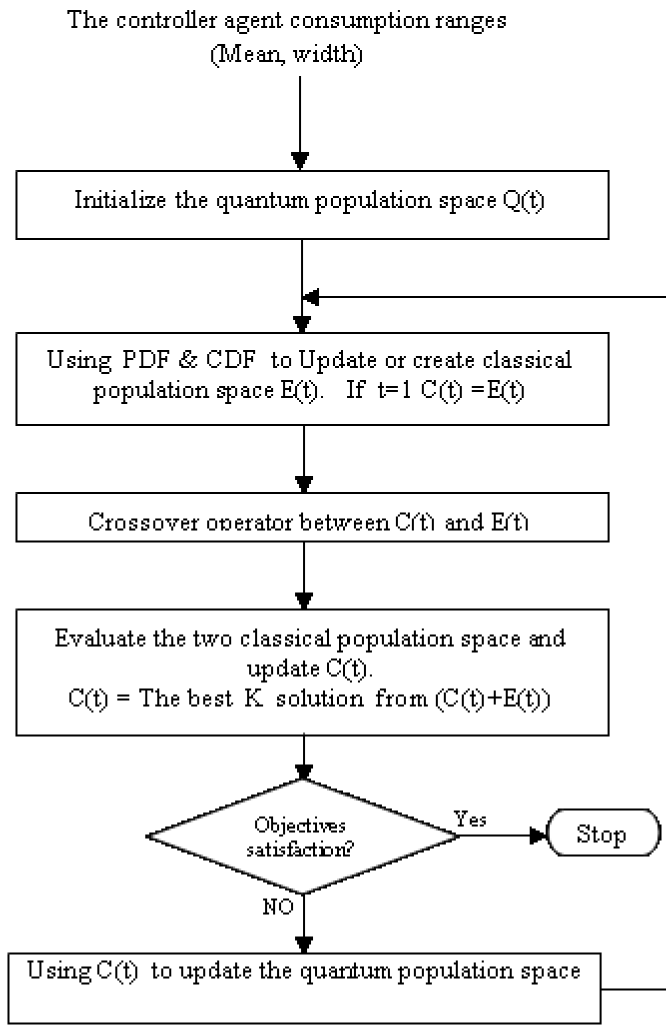


Figure 5.1: Quantum-inspired evolution algorithm

5.2.2 Initializing the quantum population space

Each local controller agent is represented by quantum-like gene in the quantum population space. A quantum gene represents the local controller agent's expected consumption range for the next operation cycle. Each gene is represented by two values, the mean and the spectrum of the local controller agent's consumption range. Each quantum individual consists of a number of quantum-like genes equal to the number of local controller agents that are coordinated by the coordination agent. Different quantum individuals can be generated in the population space by randomly generating centers for the quantum gene inside the consumption range and with spectrum value equals to the consumption range.

5.2.3 Converting the quantum population space to the classical population space

To evaluate the quantum individuals for reproduction according to their quality, a mapping between quantum population space and classical population space is required. The probability density functions (*PDF)* and cumulative distribution functions (*CDF)* of quantum genes are used to map the quantum population space to classical population space. The *PDFs* of the quantum genes are constructed depending on the different genes of all quantum individuals. This allow us to define the probabilities of the different solutions in the population space. Creating *PDF* functions for the different genes represent interference process between the quantum individuals. In this process, all pulses that represent certain quantum gene in the population space individuals are summed. Mathematically, the *PDF* of gene *j,* on generation *t* of the algorithm, is given by the following equation:

$$PDF_{jt} = \sum_{i=1}^{M} g_{ji}$$

Where *M* is the size of the population space

The *CDFs* are constructed depending on the *PDFs* by using the following equation :

$$CDF_{jt} = \int_{L_{lj}}^{Luj} PDF_{jt}(x)\,dx \, .$$

Where L_{lj} and L_{uj} are the lower and upper limits of PDF_{jt}, respectively.

Then, *CDFs* are used to define one value for each quantum gene in the solution space. Thus, we generate the random variable *x*, such that $x \in [0,1]$. This variable is used to define one solution for the quantum gene by using the inverse function of the cumulative distribution function $CDF^{-1}(x)$ for this gene.

The PDF and CDF functions for quantum gene evolve through the different generations of the algorithm until the appropriate solution is defined. Figure 5.2 and 5.3 track the *PDF* and the *CDF* functions of one quantum gene in four different generations (1, 15, 20, 55). The graphs describe the convergence to the appropriate solution. The gene's *PDF* and *CDF* in the first generation spread over a wide range of values (the total expected consumption range). During the evolution of the quantum gene, the range that is covered by the two functions is shrunk in the offspring. This means, by evolving the quantum genes in the population space, the randomness of converting quantum population space to classical population space (the quantum genes measurement $(CDF^{-1}(x))$) is decaying which leads to convergence to the appropriate solution according to the objective functions.

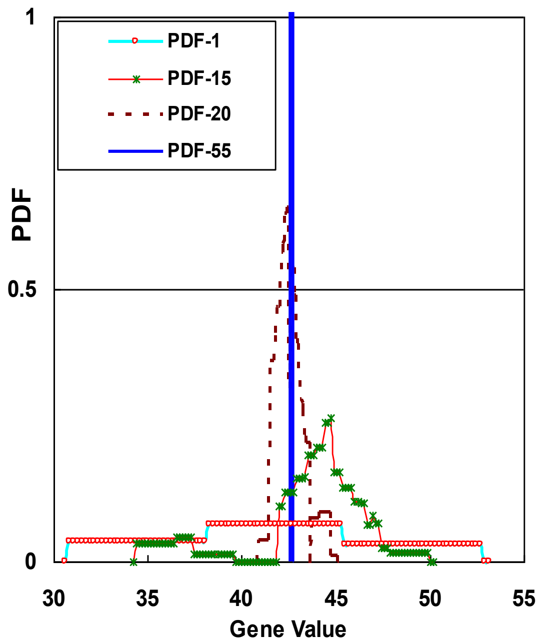


Figure 5.2: The probability distribution function evolution of a real-coded quantum gene for four generations (1, 15 , 20, 55)

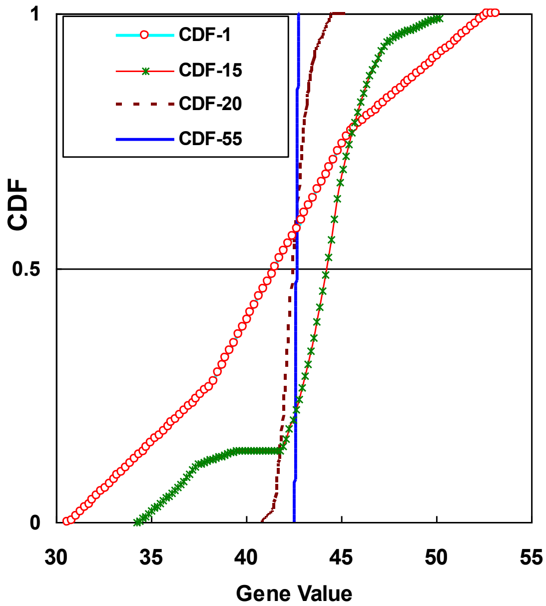


Figure 5.3: The cumulative distribution function evolution of a real-coded quantum gene for four generations (1, 15, 20, 55)

Depending on the *CDFs* the classical population space is created. This algorithm depends on quantum population space and two classical population spaces *E(t)* and *C(t).* In the first generation, *E(t)* and *C(t)* are identical. In the proceeding generations, *E(t)* contains the classical population of the current generations by direct mapping the quantum population using *CDFs.* After that, the crossover operator is used between *E(t)* and *C(t)* before evaluating the individuals in *E(t)* . Then, the best solutions in the current generation is selected and transferred to *C(t).*

5.2.4 Evaluating the classical population space

The developed algorithm depends on two classical population spaces. The first one is the temporary classical space *E(t)* for the current generation. The second one is *C(t)*, which contains the best classical solutions from all generations until the current generation. The classical population *E(t)* is updated using a crossover operator between *C(t)* and *E(t).* The number of individuals in the two classical population spaces is equal. The crossover operator takes each two individuals ($E_i(t)$ and $C_i(t)$) from the two classical spaces. Then, a random variable r is generated for each gene in the classical individual $E_i(t)$, such that $r \in [0,1)$. If r less than the crossover rate β (β< 1), the classical individual gene in $E_i(t)$ is updated by the corresponding gene in $C_i(t)$,otherwise there is no change in $E_i(t)$. $E(t)$ is then evaluated based on the *t-norm* of the objective functions. After that, the best individuals in both classical population spaces ($E(t)$ and $C(t)$) are selected to update $C(t)$.

5.2.5 Update the quantum population space

The new quantum population space is created by updating the center and the spectrum of each gene depends on the following two strategies:

1- Updating the gene center in the quantum population space by making the new centers equal the best classical individuals of the classical population space $C(t)$.

2- Updating quantum genes spectrum depending on the current classical generation rate of improvement (φ) over the previous generation. The *20%* rule is used to update the gene spectrum [118] [108]. To decide if the new genes spectrum is increased or decreased, the following rule is used :
   - If $\varphi < 20\%$ the genes spectrum is decreased
   - If $\varphi > 20\%$ the gene spectrum is increased
   - If $\varphi = 20\%$ there is no change

The rate of decreased or increased depends on the variable $\delta \in [0,1]$.

5.3 The multi-objective solution evaluation

The proposed coordination system formulates the supply and demand matching as a multi-objective optimization problem, where there are multiple criteria exist to evaluate the matching point quality, and there is an objective function attached to each of these criteria. For solving the multi-objective optimization problem, we have to consider number of decisions for implementing the appropriate algorithm for our optimization problem [131]. In the following section, the design points are presented.

5.3.1 Research and decision-making combination

There are three alternatives for combining research and decision making as follows:

1- **Decision-first and then search**. First, setting the objective functions and start search for solutions that satisfied these criteria.

2- **Search-first and then decision-making**. Search the solution space first for finding the set of feasible solutions after that identify the best one.
3- **Decision-making during search.** Decision-maker intervenes during the search in order to guide it towards promising solutions by adjusting the preferences in the process.

5.3.2 Combination of the objective functions

For evaluating the solution space in multi-objective optimization, method for manipulating objective functions is required. There are reported methods for manipulating objective functions for evaluating the solution space:

1- Combine the objectives. In this method the objective functions are combined to single objective function. After that this objective function is used for evaluating the individual solution in the solution space. The weighted sum of the objective functions is example for this method.
2- Alternating the objectives. In this method one criterion at a time is optimized while imposing constraints on the others. Here, important question arises, how to establish the ordering in which the criteria should be optimized, because this can have an effect on the success of the search.
3- Pareto-based evaluation. In this method, objective functions values for certain solution is arranged in a vector which represents the solution fitness. For comparing the individual solution, the dominance principle is used. A solution x is said to be non-dominated (optimal) if there is no other solution that is better than x in all the population space [131].

In the proposed coordination algorithm, we depend on "decision-first and then search" approach. There, we first set the objective functions and then search the solution space for the best solution for satisfying the objective functions. For evaluating population space depends on multi-objective functions, *t-norm* algorithm [132] is used. *t-norm* (triangular norm) is a binary operation on the unit interval which is commutative, associative, increasing and has neutral element 1. *t-norm* can be defined as follows:

$$T : [0,1]^2 \rightarrow [0,1]$$

For evaluating the solution space in the proposed coordination system, three t-norm methods are tested. Let A and B are two objective functions. The value of the two objective functions at solution x is $A(x)$ and $B(x)$. The t-norm value of the two objectives functions is calculated by one of the three t-norm method.

- t-norm-1 (A(x), B(x)) = min (A(x), B(x))
- t-norm-2 (A(x), B(x)) = A(x)*B(x)
- t-norm-3 (A(x), B(x)) = max (A(x) + B(x)-1, 0)

The *t-norm* value differs depending on the *t-norm* used. For example if *A(x) = 0.5* and *B(x) = 0.6*, the t-norm value for the two objective function will be 0.5, .3 and 0.1 for *t-norm-1*, *t-norm-2* and *t-norm-3* respectively.

The first method *t-norm-1* sets the evaluation for the solution as the value of minimum objective function among them; this means the evolution algorithm will improve this objective function until this objective function value becomes greater than another objective function. Then, the other objective function is selected and improved and so on until there is no improving for all objective functions. There is problem with this method, when one objective function is always the lowest among the rest objective functions, the solutions evaluation depends on this objective function only without concern to the rest of objective functions. In this situation, the selected solution is the best with respected to the lowest objective function only. When objective functions values are close to each other, all objective functions are improved until the min (maximum) objective function value among them. In all situations, the selected solution will be the min (maximum) value among all objective functions.

The second method *t-norm-2* combines the objective functions depends on the multiplication of the values of the objective function. This means all objective functions contribute in solutions evaluation. We cannot say the selected solution is the best solution for any objective function.

The third method *t-norm-3* combines the two objective functions values if the summation of the evaluation values greater than one otherwise the solution evaluation is zero. This means if the evaluation is low for all solutions in the population space, all solutions evaluation will be zero and there is no way to define what the best is and what the worst is in the solution space. Through using the third norm, there is no compromising among the different objective functions. For example, if we have three objective functions by using the third t-norm the following two solutions evaluation (0.1, 1, 1) and (0.7, 0.7, 0.7) are equally evaluated to 0.1.

5.3.3 Commensurability of the objective functions

Commensurable means the units used to measure the compliance with each of the objective function are comparable. Incommensurability of objective functions adds to the difficulty of the problem because the aggregation or comparison of different objectives is not straightforward. In the proposed coordination system, we use an application function for each objective function. Application function can be considered as measure for the goodness of the proposed solution [133]. If the objective function is *f(x)* where *x* is the proposed solution, the application function will be $H(f(x)) \in [0,1]$. The following application function for the objective functions is used:

$$H_i(x) = \begin{cases} 1 & f_i(x) >= M_i \\ 1 - (M_i - f_i(x))/(M_i - m_i) & m_i < f_i(x) < M_i \\ 0 & f_i(x) <= m_i \end{cases}$$

Where M_i= max $f_i(x)$ and m_i= min $f_i(x)$

We found that this conversion depends on the maximum and the minimum of the solutions of each generation. We rely on evolution algorithm to converge to the optimal or near-optimal solution for the multi-objective problem. So, comparison between solution generations (parents and their offspring) is needed to select the best from both. With this application function setting, solutions of successive generations for some objective function cannot be compared true because of different maximum and minimum of each generation (application functions setting are changed from one generation to another). So, we have to set the maximum and minimum of the application function to fixed values. We again face another problem, where the system is used to coordinate supply and demand for different situation and the gap between supply and demand changes dramatically from one operation cycle to another operation cycle; fixed values for maximum and minimum is not appropriate for all operation cycle. Finally, we depend on variable setting for application functions over all operation cycles and fixed in each operation cycle, where application functions setting depend on the maximum demand for each operation cycle. Using this setting, application function setting is fixed in each operation cycle, at the same time is appropriate for the demand in each cycle. Application function setting affects the overall system performance as will be shown in the simulation test in Chapter 8.

5.3.4 Confliction of the objective functions

The proposed coordination system in Chapter 8 depends on number of objective functions to optimize the coordination agent allocation of the available supply cap. One of these objective functions deals with the supply cap violation. There, the total permitted consumption levels have not to exceed the supply cap of the system. The second objective function aims to improve power system stability. There, we depend on the objective function to minimize the difference between the actual consumption levels of the current operation cycle and the permitted consumption levels for the next operation cycle. This objective function aims to avoid large overshoots in the local controller agents' consumption and smoothing the transition between the operation cycles. The third objective function is concerned with minimizing intervention in the local controller agents operation and maximizing power satisfaction level for the local controller agents, by maximizing the allocated power to each agent as possible according to the power network supply and demand.

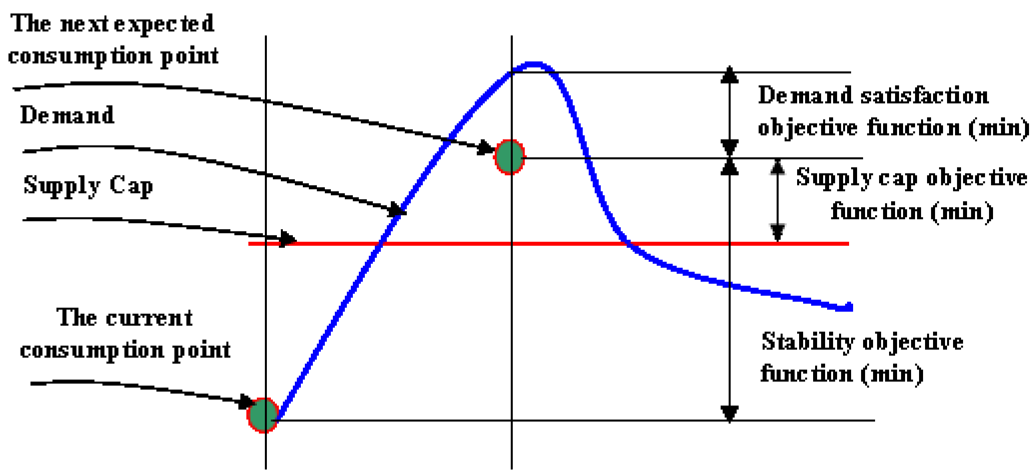


Figure 5.4: Objective functions roles for matching supply and demand

Figure 5.4 shows power curves (supply and demand) and where each objective function work. The supply cap objective function aims to remove or minimize the distance between the coordinated consumption point and the supply cap point. The demand satisfaction objective function aims to minimize the distance between the coordinated consumption point and the unconstrained demand curve point. The stability objective function aims to minimize the distance between the current consumption point and the coordinated consumption point to minimize the consumption overshoots between two successive operation cycles.

The position of the next consumption point defines if there is confliction or there is no confliction among the objective functions. As shown in figure 5, there is confliction between demand satisfaction function and supply cap objective function. Where demand satisfaction objective function aims to minimize the distance between the expected consumption point and the demand curve, at the same time, supply cap objective function aims to minimize or remove the distance between the expected consumption point and the supply cap curve. At this consumption point, there is no confliction between the supply cap objective function and stability objective function.

6 Simulation Environment of Smart Building Energy Management System

6.1 Introduction

Distributed energy resources (DERs) that depend on distributed power generators, electricity storages, and load management options can play an important role in supporting the objectives of market liberalization, combating climate change, increasing the amount of electricity generated from renewable sources, and enhancing energy saving. The widespread of DERs will affect the electricity infrastructure functioning: it will bring radical changes to the traditional model of generation and supply as well as to the business model of the energy industry [134]. With increasing use of distributed energy resources and intelligence in the electricity infrastructure, the possibilities for minimizing costs and shifting of residential power consumption increase. Technology is moving toward a situation in which households manage their own energy generation and consumption, possibly in cooperation with each other. About 40% of the worldwide energy consumed in building [135], smart building will play a crucial role in Smart Grid and in energy efficiency. The smart building energy management system (SBEMS) is expected to be the basic building unit for the virtual power plant (VPP). The proposed SBEMS include sensors, meters and a computer server. All household devices interact with the computer server through wireless and power-line communication. The SBEMS depends on the forecasted data about the local power resources generation, consumption and the charging level of the storage element (electric/heat) for a pre-defined operation period to optimize the energy utilization, device operation, and the storage element utilization (e.g. EV battery). SBEMS determines what the actions are that fulfill residential electricity and heat requirements depending on the local renewable energy resources and the local storage element. At the same time, coordinate the connection between the home and the local power network.

For simulating the SBEMS in this thesis, a multi-agent computing paradigm is assumed to represent the performance of the different devices and recourses in the simulation environments. A SBEMS simulation environment relies on number of agents for control and optimizes the local devices operation. The optimization agent and device agents are example of agents that are used for building SBEMS. The simulation environment entails developing different device models, the different control algorithms for each device, monitoring, optimization, and prediction and performance evaluation functions. The device models, EV battery model as storage element, the renewable energy resources generation profile (solar and wind) are presented in the previous chapter (chapter 4). EV battery is used as a storage element in the home environment for absorbing the excess onsite renewable energy generation above the local consumption. For controlling the connection between the SBEMS and local power network, optimization function takes place depending on the local power price and economical of storage and retrieving power from EV battery. In the next chapter development of an SBEMS optimization algorithm for managing household appliances and local generation units is presented.

In this simulation environment, number of device models is used to represent the variety of household appliances that can be used within the house. The energy power resources can be classified to stochastic generation resources, controllable resources and storage units. The stochastic generation resources (e.g. solar and wind generation units), their operation depend on unpredictable parameters such as weather conditions. Controllable resources (e.g. diesel generators) can be turned *ON/OFF* as required. The power storage units allow usage control based on market prices. The residential consumption devices can be classified into shift operation devices (e.g. washing and drying machines), thermal buffer devices (e.g. heating and cooling devices) and user action devices (e.g. audio and lighting loads). In [6] loads are classified into two categories: controllable and critical. Controllable loads are defined as the loads that can be controlled without noticeable effects to the consumers' comfort level. The available operational control of energy power resources and residential devices are presented [3]. Controlling demand response (DR) for a residential home can be classified with respect to the level of automation to manual DR, semi-automated DR and fully automated DR according to the automation levels exist [10].

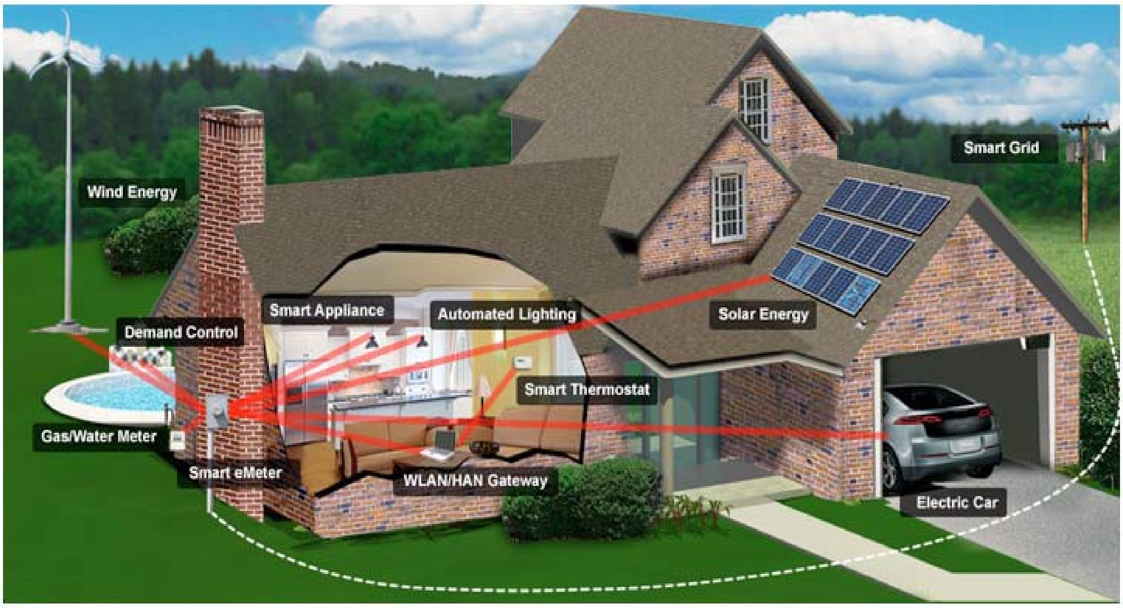


Figure 6.1: The expected prosumer model

With the development of the Smart Grid, dynamic load models are required. These models can facilitate the study of changes in electricity demand in response to customer behavior and/or signals from the energy service provider. Such load models are useful to evaluate the developed control and coordination algorithms effects to consumers' preferences, to the general performance of the power network (e.g. stability and reliability) and at the distribution circuit level (e.g. the power flow). For appropriate loads modeling, to be used in the demand response simulation, some characteristics are required [123]. For simulating the participation of the consumer/prosumer in the smart power networks, number of models for renewable and controllable power resources, storage units and residential load models are required. In this simulation, number of the resources/appliances agents is presented. These agents are used for testing the proposed algorithms in the next chapters. Space cooling/heating (AC) units, water heater coils (WHC), clothes dryer machine (CDM), ventilation fan (VF) are example of devices that are used as a consumption appliances. The electric vehicles (EV) battery is used as storage element. Solar panel and small wind turbine generation profile will be used to represent the renewable energy resources. In the following section details about the simulation environment of SBEMS is presented. Figure 1 shows the expected prosumer model [26].

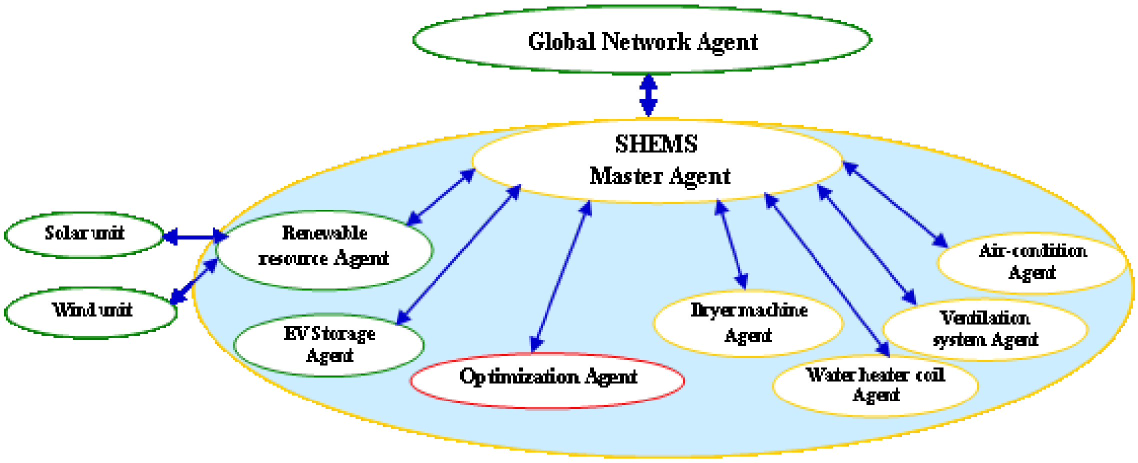


Figure 6.2: Proposed architecture for smart building environment simulation

6.2 The proposed SBEMS architecture

The proposed SBEMS depends on a number of agents for accomplishing the optimization and control task within the SBEMS environment. Figure 6.2 shows the main agents of the system that control and coordinate the SBEMS operation. Master agent, device control agent for each device within the home (building), optimization agent, the renewable resources agent and the EV battery agent are the main agents within the simulation environment. The master agent coordinates/optimizes the operation of a group of devices within a home (e.g. cooling, heating and ventilation devices). The master agent depends on device controller agents of different devices (e.g. air-conditioner, refrigerator, ventilation fan) to coordinate the operation of the device under its control. For optimizing the system performance, multi-objective functions for coordinating the multi-agent system operation for matching supply and demand within the SBEMS environment are used. The master agent depends on the ability of the device controller agents to maintain device operation within an area where power is consumed. This area is defined according to the user preference and the constraints related to the different devices' operation limits. Depending on a flexible operation of the device controller agents and the EV storage unit, more exploitation of the onsite renewable energy resources can be accomplished. Description about the proposed SBEMS components is presented in the following section.

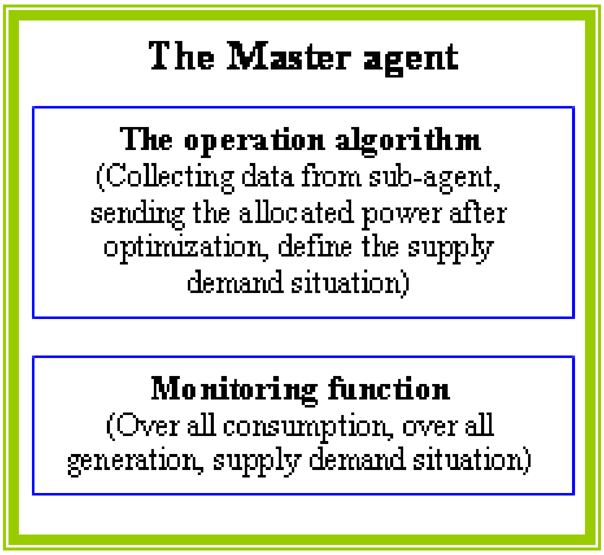


Figure 6.3: SBEMS master agent Components

6.2.1 The Master agent

Master agent is responsible for SBEMS operation in isolated mode or in connected mode with the local power networks depending on the local supply and demand situation. In this simulation, master agent makes early predictions about power critical time depending on the onsite consumption and generation curve for a pre-defined operation cycle. Figure 6.3 shows components of the Master agent. A pre-defined operation cycle period, the master agent collects data from sub-agents to define the expected supply, demand and the state of the battery of the next operation cycle. The master agent sends its request to the device controller agents asking for the minimal energy level and unconstrained (maximal) consumption level, and the time for consumption (start/stop) within the next operation cycle. These data is sent to optimization agent to allocate power for next operation cycle. After that, if SBEMS is a part of virtual power plant (VPP) or microgrid, the total expected consumption ranges (minimal and maximal) for the device group will be defined. These two levels, in addition to the actual consumption level of the current operation cycle, are sent to the

VPP agent to optimize the power consumption operation within the local power network (or microgrid) for the next operation cycle.

The monitoring function of the master agent records the overall consumption, the local renewable generation and the power supplied/taken to/from the local power network. In case the SBEMS participates in local coordination task, the master agent sends the consumption or generation range to the local power network coordination agent for optimization over the entire local power network. The master agent fills the following roles in the SBEMS:

1- Collects consumption levels from the device controller agents under its control, define the expected consumption range minimal and maximal and the time of consumption within the next operation cycle for each device (minimal, maximal, the best time for consumption).
2- Define the available local renewable generation from the power resources agent and the amount of power for charging/discharging the battery.
3- After receiving the coordinated consumption plan from optimization agent, send the coordinated consumption plans to the different devices and charging/discharging power to the battery agent.
4- If SBEMS is a part of virtual power plant (VPP) or microgrid, the total expected consumption range (minimal and maximal) for the device group will be defined, and send the consumption levels (minimal, maximal and actual consumption levels for the current operation cycle) to the VPP coordination agent.

6.2.2 The device controller agents

The device agent has a model for the device under its control by this model the expected consumption range for the next operation cycle can be defined. The device agent defines the minimal consumption level, unconstrained (maximal) consumption level, and the time for consumption (start/stop) within the next operation cycle. The minimal consumption level is determined by the device agent based on the constraints defined by the manufacturer or by the consumer. For example the cooling devices operate between two temperature levels. The task of the device agent is to maintain the temperature between these two levels. Depending on the current temperature of the device, device controller agent can define the minimum time of the "on" period (minimal power) that is required to maintain the temperature between these two levels during the next operation cycle. The maximum power is the device consumption without any intervention from the device controller agents. The main components of each device controller agent in the simulation environment are shown in Figure 6.4. Each device agent contains the device operation model, the task model, the different control algorithms, the monitoring functions and the power consumption prediction function. There is operation model for each device, for defining the device state (ON/OFF) and the power consumption. Also, there is task model for each device for tracking variation in the target variable (e.g. Temperature (AC), air-quality (VF), and state of charge (battery)).

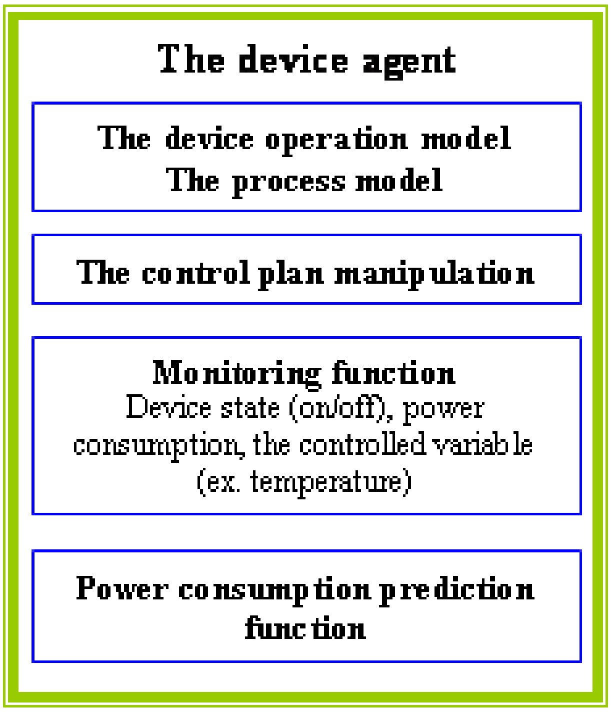


Figure 6.4: Device agent contents in the simulation environment

The controlled device operation depends on the controlled variable variation or depending on the optimize time control plan. Control function represents the actuator for start/stop times for each device. Also, there is control plan modification function for modifying the control plan after the optimization process. The monitoring function is for recording the device state during the operation horizon, the power consumption, the controlled variable variation, and other variables for analyzing the device operation. In complete SBEMS view, this data should be used for updating the device performance memory to be used for predicting the device consumption for the future operation cycle/cycles. The power consumption prediction functions are used for calculating the future consumption of the device for optimizing the device consumption. In our proposed SBEMS, the device controller agent is responsible for the following:

1- Define the appropriate consumption plan for the next operation cycle based on the device model it controls (air-condition, water heater coil, ventilation fan, etc.). The consumption plans include the minimal and the maximal consumption levels and the time of consumption (start/stop) within the next operation cycle.

2- Executing the coordinated consumption plan that is defined for the next operation cycle. Obviously, the plan which is determined for any particular device must not violate the operation limits of the device.

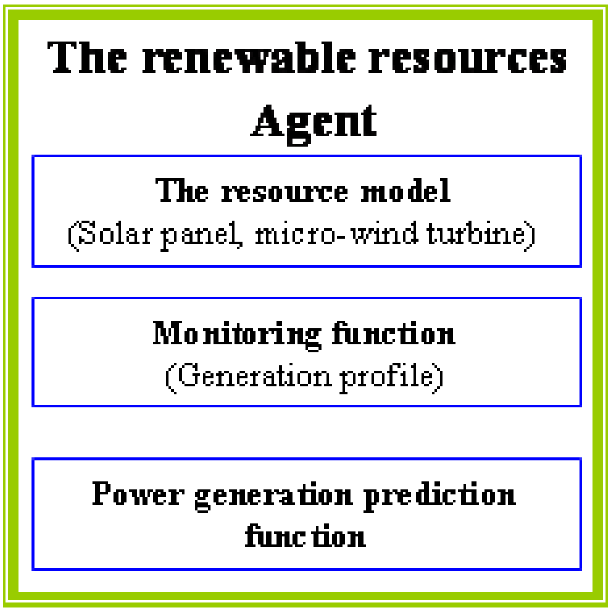


Figure 6.5: Renewable resource agent in the simulation environment

6.2.3 The renewable resources agent

The main components of the renewable resource agent are shown in

Figure 6.5. In this simulation two household renewable generation resources are used, the solar panels and micro-wind turbines. Normally, the renewable resources output depends on the predicted weather conditions (ex. wind speed) for the defining the expected output power. The monitoring function is used for recording the generation

profile for the future use of the unit generation prediction. The generation prediction function defines the expected generation level for the generation, depending on the weather conditions and the previous generation profile.

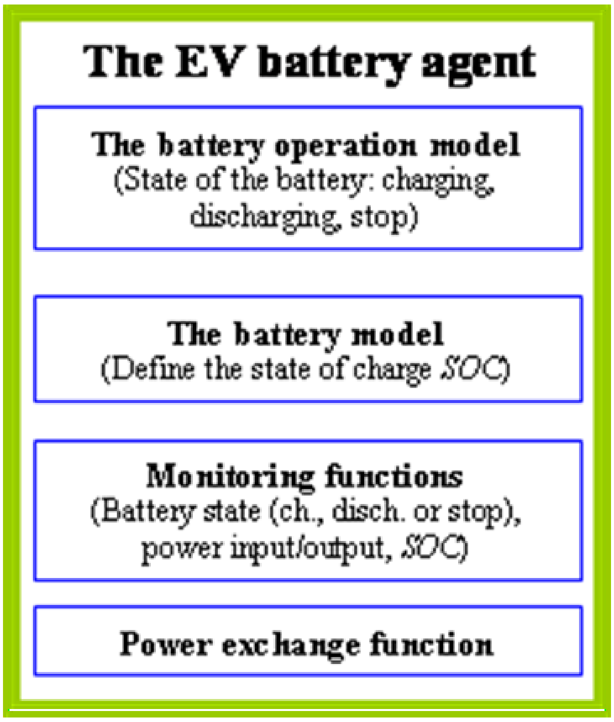


Figure 6.6: Components of the battery controller agent

6.2.4 The battery agent

The main components of the battery controller agent are shown in Figure 6.6. The battery operation model define the state of the battery depends on the state of charge (SOC), the driving profile , the connectivity state (connected/not-connected) and the supply-demand situation. The battery model defines SOC depending on the input/output power to the battery; this depends on charging/discharging rate, the available power and the time of charging/discharging. Normally, there is minimum SOC for each battery, this level is updated by user's driving profile. The monitoring function records the battery operation state, the state of charge, and input/output power. The exchange function defines the amount of power that can be discharged during the next operation cycle or the amount of power that is needed for charging the battery during the next operation cycle.

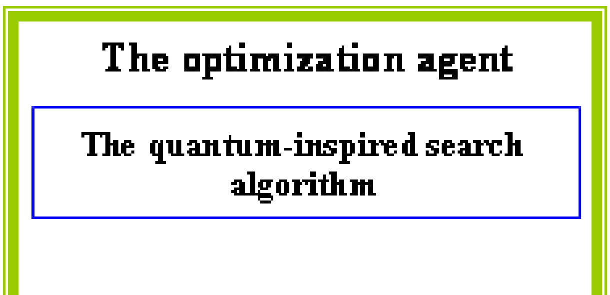


Figure 6.7: The optimization agent components

6.2.5 The optimization agent

The optimization agent depends on local demand and the available supply (local renewable resources generation, storage device and local power network) to optimize the power using by the device agents. The main components of the optimization agent are shown in Figure 6.7. The quantum-inspired algorithm is used for searching solution space for the optimal/sub-optimal solution each pre-defined operation cycle. The system objective functions are used for defining the quality of the different proposed solutions in the solution space. For example, to minimize the supply cap violation and to improve the satisfaction level of the different devices. The objective functions for the devices are used for defining the quality of the different proposed solutions in the solution space with respect to the optimal time (start/ stop) of using the allocated power. Solutions evaluation function used for leading the search algorithm to the optimal/sub-optimal solution for the system. For evaluating the control algorithm, device operation evaluation function required. Each device needs evaluation algorithm according to the required profile of the controlled variable.

6.3 Simulation framework

The proposed SBEMS system relies on an agent that coordinates a number of device controller agents which in turn control a number of device controller agents. The proposed algorithm depends on the multi-agent computing paradigm for testing the proposed algorithm in the next two chapters. Each device controller agent controls one device. For testing the proposed algorithms, an operation day is divided to 48 operation cycles where each cycle represents 30 minutes. Minimizing operation cycle periods increases processing and communication cost, at the same time increases the responsive of the coordination system to manipulate the variability of supply and demand within the power network. The last five minutes of each operation cycle is assigned to negotiation among the master agent and the device and power resources agents. Each device controller agent sends the expected consumption range of the next operation cycle and the time of consumption within the next operation cycle to the master agent. The master agent allocates the available local renewable supply (renewable generation and storage element) to the device controller agents according to the number of objective functions. It then sends the coordinated consumption levels to the device controller agents. The operation day has peaks for generations and peaks of consumption. We try to emulate different situations between consumption and the local renewable energy generation resources.

The proposed SBEMS coordinates consumption and local renewable energy resources of a home in an active power network or as a part of a virtual power plant (VPP). The SBEMS depends on the device controller agents' abilities to minimize or shift their consumption for certain operation cycles. Shifting or minimizing power consumption depends on the device types under control. For the real-life applications this performance can be obtained if the device agents control devices for cooling/heating, washing and drying clothes, and ventilation in the home, to name a few. For example, the temperature setting of cooling/ heating devices can be up (down) by one or two degrees during the peak demand without a lot of problems for the user. The device on/off cycle can be controlled to minimize and distribute the device consumption and to minimize the number of active devices during the same time. The ventilation devices operation period can be minimized or shifted before or after the peak demand. The operation time for the dryer device can be shifted to the predicted high renewable resources generation. Depending on the flexible operation of the consumption devices and the storage element maximizing the renewable energy exploitation can be accomplished. We assume that the device agents able to shift the power consumption without affecting the users' preferences.

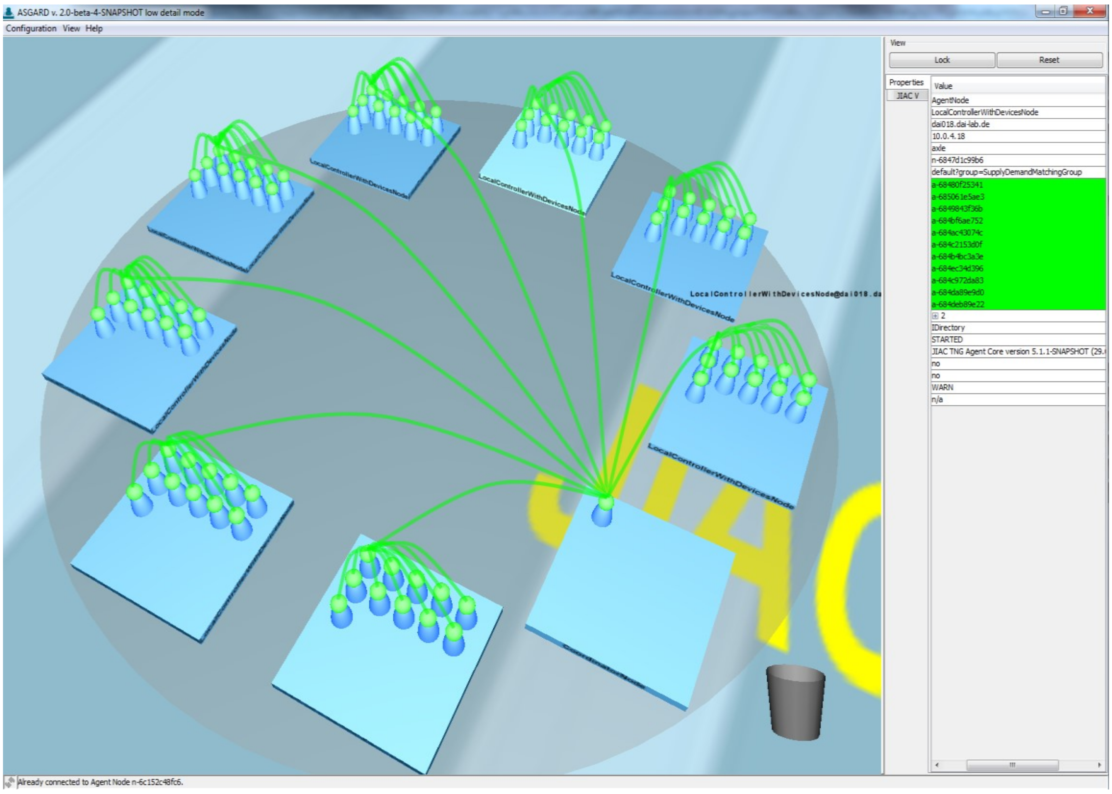


Figure 6.8: Snapshot for the virtual power plant supply and demand coordination system

Figure 6.8 shows the proposed VPP multi-agent system using the JIAC-V (Java Intelligent Agent Component ware version V) agent platform [136]. This snapshot is taken using the ASGARD (Advanced Structured Graphical Agent Realm Display) software [137] for monitoring multi-agent systems. The ASGARD monitor provides a method for monitoring and controlling multi-agent system infrastructures using an interactive 3D visualization. The snapshot shows a number of multi-agent platforms where agents can live and accomplish their tasks. The coordinator agent runs on a separate platform and is able to communicate with the local controller agents on the other platforms. Each local controller agent runs on one platform which contains ten device controller agents and the local controller agent able to communicate with them.

6.4 The performance monitoring functions

For monitoring, evaluating and analyzing the proposed power consumption coordination system performance, a number of monitoring functions are implemented, such as demand stress within the system function and the global system satisfaction level function. The demand stress function measures the difference between the aggregated total demand and the aggregated total coordinated consumption levels within the system. This function monitors the cycle of curtailed amount of demand during the peak demand time and the system recovery of this amount during the low demand time. The peak of this curtailed power within the system and the time for recovery is an important indication for the system stability. Demand stress monitoring function can be considered as measure for the quality of shifting the demand from the peak time to the low demand time. The global system satisfaction level function measures the global demand satisfaction level (social welfare) for all local controller agents in the area under the coordination system control.

7 Quantum-inspired Algorithm for Smart Building Energy Management System

7.1 Introduction

Depending on the smart Building energy management system (SBEMS) that is presented in the previous chapter, an operational algorithm for optimizing the performance of the SBEMS is presented. SBEMS considers as a building unit for virtual power plants (VPP) that is presented in the next chapter. The SBEMS depends on the forecasted data about the local power network, the predicted consumption of the building devices and the level of charging for the local storage element(thermal/electric) for the next operation period to optimize the device operation, the local energy utilization and optimizing the local storage elements utilization. SBEMS relies on a number of agents for control and optimize the local devices operation. In chapter 6, description about the SBEMS is presented. In chapter 5, the device models and the different control algorithms, are presented.

In this chapter development of a SBEMS optimization algorithm for managing household power-intensive appliances is presented. In this simulation environment, space cooling/heating (AC) units, water heater coils (WHC), clothes dryers (CD), ventilation fans (VF) and battery of electric vehicles (EV) is used. The level of load curtailments possible for residential customers can be interpreted as demand response (DR) potentials in residential markets with automated DR. Controlling demand response for a residential load can be classified to manual DR, semi-automated DR and fully automated DR according to the automation levels exist. While the first type depends on the manual response of the consumers according to price signals from the energy service provider or the network operator, the third type ignores the consumers' response and directly changes the setting of the devices under prior permission from the consumers. The approaches mentioned in this chapter depend on the third control type.

Depending on the automated response of the SBEMS, quantum-inspired optimization algorithm for the SBEMS is presented in this chapter. The objectives of SBEMS are to achieve a balance between different objectives within the system, such as optimize the renewable resource using, the demand satisfaction, and the comfort level of the users. For optimizing devices operation, objective functions are proposed and implemented. The supply cap objective function, the consumption distribution objective function, the devices consumption satisfaction objective function and improving device performance objective functions are example of the objective functions that are used. In this work, we depend on multi-objective functions for coordinating the multi-agent system operation for matching supply and demand within an active consumer area (controllable loads) or microgrid power network.

7.2 System architecture

We follow a hierarchal system approach that comprises two levels of control namely the master agent, and the device and power resources agents. In the first level the master agent coordinates the consumption of sub-groups of devices (e.g. cooling, heating and ventilation devices in home), and the second level comprises the agents of different devices (e.g. air-conditioner, water heater, ventilation fan) and power resources agent. A detail about the SBEMS simulation is presented in the previous chapter (Chapter 6). The SBEMS depends on the ability of the device agents to maintain the operation of a group of devices within an area where power is consumed. This area is defined according to the user preference and the constraints related to the different devices' operation limits. Depending on this flexible operation of device agents, the task of supply and demand matching can be accomplished.

The SBEMS task is to allocate consumption levels for the device agents within the expected consumption range according to certain number of objective functions related to the overall system performance. Number of objective functions is used to optimize the SBEMS allocation of the available supply cap. For example, one of the objective functions deals with the available supply violation. The aim of this function is to keep the total consumption levels around the available local supply by the renewable resources and the available local storage elements. Another objective function aims to distribute the devices consumption for minimize the number of devices that are "ON" in the same time. For each objective function there are application functions for preparing the objective functions to the evolution step.

The SBEMS master agent send consumption levels request to the device agents. Also, the generation level and state of charge (SOC) of battery requests are sent to the generation resources agent and battery agent respectively. The device agents define minimal, maximal and the time of consumption (start/stop) for devices operation under their control. The SBEMS sends this data to the optimization agent. Optimization agent depends on this data to allocate consumption levels for every device agent (between minimal and maximal level) and define the time of consumption within the operation cycle for each device avoiding the available supply cap violation. The available supply cap is the expected onsite local renewable energy resources generation and the available power from the storage element. If more power required for the next operation cycle, SBEMS connect to the local power network for supply the amount of the excess power. The SBEMS agent use a quantum inspired algorithm for optimizing the power allocating for the different devices and optimize the renewable resources using. Then, SBEMS agent sends the coordinated consumption levels to the device controller agents.

7.3 The SBEMS optimization algorithm

The optimization problem is formulated as a multi-objective optimization problem solved by quantum-inspired evolution algorithm. Let N be the number of device agents. Each agent i $(i \in \{1,2,\ldots\ldots N\})$ represented by $x_{ik} = [x_{ik}^{\min}, x_{ik}^{\max}, t_{ik}^{css}]$ for the next operation cycle k ($k \in \{1,2...\}$), where $x_{ik}^{\min}$, $x_{ik}^{\max}$, t_{ik}^{css} are the minimal and maximal expected consumption levels, and the center of operation period(start/stop) within the next operation cycle respectively. Let $X_k = (x_{1k}, x_{2k}, ..., x_{Nk})$ be the consumption data vector for all device agents. Each device controller agent is represented by real-coded quantum-like gene g_i in the quantum population space. The quantum population space contains a set of quantum individuals (chromosome) q_j ($j \in \{1,2,... M\}$) where M is the space size. Each quantum chromosome contains N genes as follows:

$$q_j = (g_1, g_2, ..., g_N)$$

$$q_j^{S_1} = \begin{matrix} c_{g_1} & c_{g_2} & . & . & . & . & . & . & . & c_{g_N} \\ w_{g_1} & w_{g_2} & . & . & . & . & . & . & . & w_{g_N} \end{matrix}$$

$$q_j^{S_2} = \begin{matrix} t_{g_1}^{css} & t_{g_2}^{css} & . & . & . & . & . & . & . & t_{g_N}^{css} \\ t_{g_1}^{ON} & t_{g_2}^{ON} & . & . & . & . & . & . & . & t_{g_N}^{ON} \end{matrix}$$

Where:

$q_j \in Q$, Q is the quantum population space,

$q_j^{S_1}$ and $q_j^{S_2}$ are the chromosomes of the first stage and second stage respectively

c_{g_i} and w_{g_i} are the center and the width of consumption range

$t_{g_i}^{css}$ and $t_{g_i}^{ON}$ are the center and the width of operation period of device agent i

The optimization algorithm contains two stages: 1) the first stage is the available power allocation stage 2) the second stage is consumption distribution and the device performance optimization. The quantum genes in the first stage represent the device agents' expected consumption for the next operation cycle in the quantum population space. Each gene is represented by two values, center and width of consumption. The quantum genes in the second stage represent the device agents' center and width of operation period ("*ON*" period) within the next operation cycle. each t_{ik}^{ON} For device *i* for the operation cycle k is defined after the first optimization stage depending on the allocated power for each device for the next operation period.

During the first stage, different quantum individuals can be generated in the population space by randomly generating centers inside the consumption range and with width equal to the consumption range. After that, the Q space is converted to the classical population space X with the same size M to be evaluated. In this stage, the optimization algorithm task is to allocate consumption levels for the device agents within the expected consumption range, take into consideration the satisfaction of objective functions related to the overall system performance. Two objective functions are used in the first stage to optimize the available supply cap allocation. The first objective function deals with the supply cap violation. The aim of this function is to make sure that the total consumption levels do not exceed the available supply cap. The second objective function is concerned with minimizing intervention into the device agents operation and maximizing power satisfaction levels for the device agents, by maximizing the allocated power to each agent as possible according to the expected supply and demand.

The proposed optimization algorithm consists of two stages, The first stage defines the allocated power for each device according to the expected consumption power from the device and according to the available supply cap. The first stage depends on two objective functions, the supply cap violation objective function and the consumption satisfaction objective function. The second stage of the algorithm defines the place of the "ON" period within the operation cycle for each device. This stage for improving the performance of the devices (improving the controlled variable of the device for example the temperature profile within the room with respect to the air-condition devices) and to distribute the operation periods which leads to power consumption distribution. The second optimization stage depends on objective functions for improving each device operation and the consumption distribution objective function. The two stages depend on a quantum inspired algorithm (Chapter 5) for defining the appropriate solution for each operation cycle.

7.4 Multi-objective formulations

The optimization algorithm depends on number of objective functions for optimizing the SBEMS performance with respect to the renewable resources utilization and the different device performance and the users' comfort level. There are two system objective functions and four device objective functions. The system objective functions are the supply cap violation and consumption distribution objective functions. The device objective functions are the device consumption satisfaction objective function and three functions for improving the device performance (air-condition device, water heater coil and the ventilation fan) and avoiding violation of the normal device's setting. The optimization algorithm contains two stages:

- The first stage is the available power allocation stage
- The second stage is consumption distribution and the device performance optimization.

Two objective functions are used in the first stage to optimize the available supply cap allocation. The first objective function deals with the supply cap violation. The aim of this function is to make sure that the total consumption levels do not exceed the available supply cap. The second objective function is concerned with minimizing intervention into the device agents operation and maximizing power satisfaction levels for the device agents, by maximizing the allocated power to each agent as possible according to the expected supply and demand. The mathematical formulation for the two objective functions is as follows:

- The supply cap objective function

$$\max_{x_j \in X} \left(P_k^{cap} - \sum_{i=1}^{N} x_{ik} \right)$$

Subject to $x_{ik}^{\min} < x_{ik} < x_{ik}^{\max} \quad \forall i \in \{1,2,\ldots. N\}$

Where p_k^{cap} is the maximum available power for the operation cycle k

- The consumption satisfaction objective function

$$\min_{x_j \in X} \sum_{i=1}^{N} \left(x_{ik}^{\max} - x_{ik} \right)$$

Subject to $x_{ik}^{\min} < x_{ik} < x_{ik}^{\max} \quad \forall i \in \{1,2,\ldots. N\}$

During the second stage, different quantum individuals can be generated in the population space by randomly generating centers within the range $[t_{g_i}^{css} - t_{g_i}^{ON}, t_{g_i}^{css} + t_{g_i}^{ON}]$

and with width equal to the operation period $t_{g_i}^{ON}$. After that, the Q space is converted to the classical population space X with the same size M to be evaluated. In this stage, the optimization algorithm task is to distribute the devices consumption periods("ON" periods) within the next operation cycle, take into consideration the satisfaction of objective functions related to the each device. In this stage, four objective functions are used. The consumption distribution objective function, the space cooling/heating objective function, the water heater coil objective function and the ventilation fan objective function. The mathematical formulation of the four objective functions is as follows:

- The consumption distribution objective function

This functions aims to distribute the device consumption by minimize the number of device "ON" in the same time. This function concerns with the place of the consumption period (device "ON" period) within the operation cycle. Aiming to minimize the number of devices "ON" in the same period. This function used during the peak consumption time to distribute the consumption particularly for the devices with repeated discontinuous operation time like ventilation and air-condition devices. The formulation of the objective function is as follows:

$$\max_{x \in \chi} \sum_{j=1}^{ns} \sum_{i=1}^{d} -(x_i(e_j) * P_i / P_{total}) \ln(P_i / P_{total})$$

$\forall x_{ik} \in \chi \quad i \in \{1,2,.... N\}$

d: number of devices under the master agent control

ns : number of time slots inside the prediction period.

$status_i$ (e_j): The state of device i (ON/OFF or 1/0) inside the prediction period e for the time slot j for the individual solution x, $x \in \chi$ where χ is the solution space.

P_i : The device i power capacity

P_{total} : The total power capacity (weight) of the devices under control

- The application function for the distribution objective function

$$H_i(x) = \begin{cases} 1 & f_i(x) >= M_i \\ f_i(x)/M_i & 0 < f_i(x) < M_i \\ 0 & f_i(x) = 0 \end{cases}$$

Where the maximum value M_i of the objective function calculated by assuming each device is "*ON*" and all other devices are "*OFF*" in the same time slot. This is the maximum value of the distribution objective function.

- The objective function of space cooling/heating device

The space cooling/heating objective function aiming to improve the temperature profile for the room by minimize the number of violation to the user's temperature setting and to keep the temperature around the temperature setting for the next proposed consumption plan. Normally there is temperature setting from the user, and the device operates in range of temperature above or under this setting by ΔT . ΔT is defined by the device manufacture setting. The objective function is as follows:

$$\min_{x \in \chi} \sum_{j=1}^{nump} V(T_{x_{AC}}(j))_{x \in \chi}$$

$$V(T_{x_{AC}}(j)) = \begin{cases} 0 & T_{\min} \le T_{x_{AC}}(j) \le T_{\max} \\ 1 & T_{\max} < T_{x_{AC}}(j) \,\|\, T_{x_{AC}}(j) < T_{\min} \end{cases}$$

$$\forall x_{ik} \in \chi \qquad i \in \{1, 2, ... N\}$$

Where:

$T_{\max}$: The maximum temperature

$T_{\min}$: The minimum temperature

x_{AC} : The proposed consumption of the space cooling/heating device in the solution *x*

$T(x_{Ac})$: The expected temperature profile when the power consumed by the device is x_{AC}

$T_{x_{AC}}(j)$: The expected room temperature in the time slot *j* when the power consumed by the device is x_{AC}

$V(T_{x_{AC}}(j))$: The temperature profile violation in the time slot *j.*

- The application function for the AC objective function

If the objective function is $f_{AC}(x)$ where x the proposed solution is, the application function will be $H((f_{AC}(x)) \in [0,1]$. The application functions is as follows:

$$H_i(x) = \begin{cases} 1 & f_{AC}(x) >= M_i \\ 1 - (M_i - f_{AC}(x)) / (M_i - m_i) & m_i < f_{AC}(x) < M_i \\ 0 & f_{AC}(x) <= m_i \end{cases}$$

Where M_i and m_i is the maximum and the minimum for the objective function i respectively.

- The objective function for the Water heater coil (WHC)

The objective function aims to improve the temperature profile for the water tank by minimizing the number of violation to the temperature setting and to keep the temperature around the temperature setting for the next proposed consumption plan. Normally there is temperature setting from the user, and the device operates in range of temperature under this setting by ΔT . ΔT is defined by to the device manufacture setting.

$$\min_{x \in \chi} \sum_{j=1}^{nump} V(T_{x_{WHC}}(j))$$

$$V(T_{x_{WHC}}(j)) = \begin{cases} 0 & T_{\min} \le T_{x_{WHC}}(j) \le T_s \\ 1 & T_s < T_{x_{WHC}}(j) \parallel T_{x_{WHC}}(j) < T_{\min} \end{cases}$$

T_s : The setting temperature

$T_{\min}$: The minimum temperature

x_{WHC} : The proposed consumption for the water heater coil device in the solution *x*

$T_{x_{WHC}}(j)$: The expected tank temperature in the time slot *j* when the power consumed by the device is x_{WHC} .

$V(T_{x_{WHC}}(j))$: The temperature profile violation in the time slot *j.*

- The application function for the WHC objective function

If the objective function is $f_{WHC}(x)$, where x the proposed solution is, the application function will be $H((f_{AC}(x)) \in [0,1]$. The application functions model is as follows:

$$H_i(x) = \begin{cases} 1 & f_{WHC}(x) >= M_i \\ 1-(M_i - f_{WHC}(x))/(M_i - m_i) & m_i < f_{AC}(x) < M_i \\ 0 & f_{WHC}(x) <= m_i \end{cases}$$

Where M_i and m_i is the maximum and the minimum for the objective function i respectively

- The objective function for the ventilation fan (VF)

The ventilation fan objective function aims to improve the ventilation quality profile for the room by minimizes the number of violation to the ventilation quality setting by the user for the next proposed consumption plan. The ventilation quality (VQ) depends on the period of "*ON*" and "*OFF*" time of the ventilation fan and the ventilation space parameter like the number of persons in the space and the activities in this space ($VQ \in [0,1]$). The objective function is as follows:

$$\min_{x \in \chi} \sum_{j=1}^{nump} V(VQ_{x_{VF}}(j))$$

$$V(VQ_{x_{VF}}(j)) = \begin{cases} 0 & VQ_{\min} \le VQ_{x_{VF}}(j) \le VQ_{\max} \\ 1 & VQ_{\max} < VQ_{x_{VF}}(j) \parallel VQ_{x_{VF}}(j) < VQ_{\min} \end{cases}$$

Where:

$VQ_{\max}$: The maximum ventilation quality

$VQ_{\min}$: The minimum ventilation quality setting

x_{VF} : The proposed consumption for the ventilation device in the solution *x*

$VQ_{x_{VF}}(j)$: The expected room ventilation quality in the time slot j when the power consumed by the device is x_{VF}

$V(VQ_{x_{VF}}(j))$: The ventilation quality profile violation in the time slot j.

- The application functions for the ventilation device(VM)

If the objective function is $f_{VD}(x)$ where x the proposed solution is, the application function will be $H((f_{VD}(x)) \in [0,1]$. The application functions model is as follows:

$$H_i(x) = \begin{cases} 1 & f_{VF}(x) >= M_i \\ 1-(M_i - f_{VF}(x))/(M_i - m_i) & m_i < f_{VF}(x) < M_i \\ 0 & f_{VF}(x) <= m_i \end{cases}$$

Where M_i and m_i is the maximum and the minimum for the objective function i respectively

7.5 The simulation framework

The proposed SBEMS system relies on one agent that coordinates a number of device controller agents which in turn control a number of device controller agents. The proposed algorithm implemented as a multi-agent computing paradigm for testing the system performance. Each device controller agent controls one device. For testing the proposed algorithm, an operation day is divided to 48 operation cycles where each cycle represents 30 minutes. The last five minutes of each operation cycle is assigned to negotiation among the home master agent and the device controller agents. Each device controller agent sends the expected consumption range of the next operation cycle and the actual consumption of the current operation cycle to the master agent. The master agent allocates the available local renewable supply (renewable generation and storage element) first to the device agents according to the number of objective functions. It then sends the coordinated consumption levels to the device agents. The operation day has peaks for generations and peaks of consumption. We try to emulate different situations between consumption and the local renewable energy generation resources.

The proposed SBEMS coordinates consumption and local renewable energy resources of a home in active power network or as a part of a virtual power plant VPP. The home management agent depends on the device controller agents' abilities to minimize or shift their consumption for certain operation cycles. The shifting or minimizing power consumption depends on the types of the devices under control. For the real-life applications this performance can be obtained if the device controller agents control devices for cooling/heating, washing and drying clothes, and ventilation in the home, to name a few. For example, the temperature setting of cooling/heating devices can be up (down) by one or two degrees during the peak demand without a lot of problems for the user. The device on/off cycle can be controlled to minimize and distribute the device consumption and to minimize the number of active devices during the same time. The ventilation devices operation period can be minimized or shifted before or after the peak demand. The operation time for the dryer device can be shifted to the predicted high renewable resources generation. Depending on the flexible operation of the consumption devices and the storage element maximizing the renewable energy exploitation can be accomplished.

7.6 The effectiveness of the optimization algorithm

In the following area, the responses of the optimization algorithm with and without the proposed objective functions are presented. The first case illustrates the consumption distribution function effectiveness. The system performance show the effectiveness of this function for distributing the devices consumption and minimize number of device "ON" in the same operation period. The second case illustrates the space cooling/heating objective function. Depending on using space cooling/heating objective function, the device avoids the temperature setting violation when the overall consumption exceed the available generation. In the following area, the performance of the system in the two cases is presented.

7.6.1 Consumption distribution objective function effectiveness

Consumption distribution objective function aims to distribute the period of consumption for the household devices to minimize the number of "ON" devices in the same operation slot. Figure 7.1 and 7.2 show the effectiveness of the consumption distribution objective function for minimizing the number of simultaneous devices operation times. This function can be used during the peak consumption times to minimize the consumptions peaks.

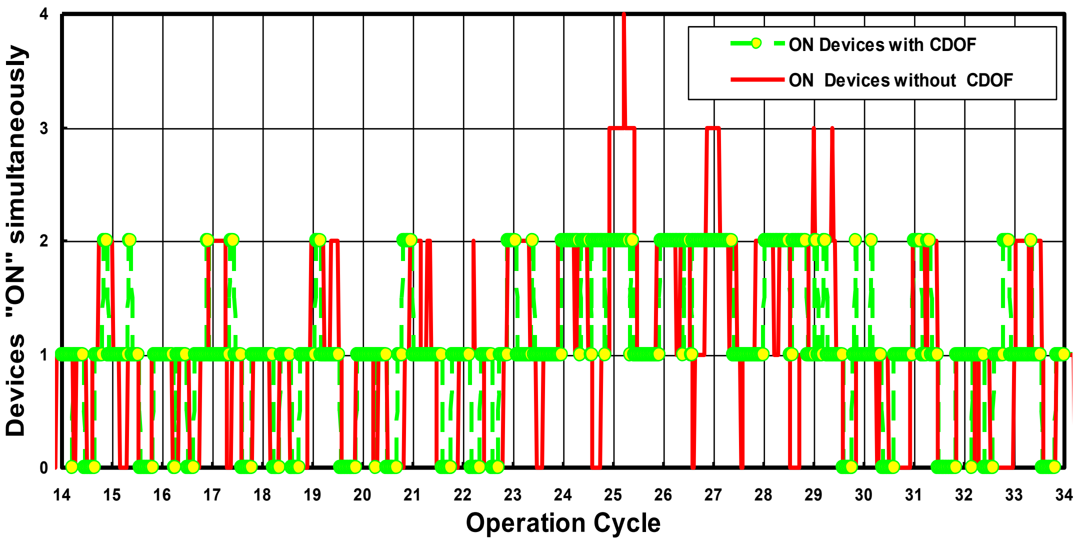


Figure 7.1: Number of simultaneous devices "ON" with and without the Consumption distribution Objective Function (CDOF)

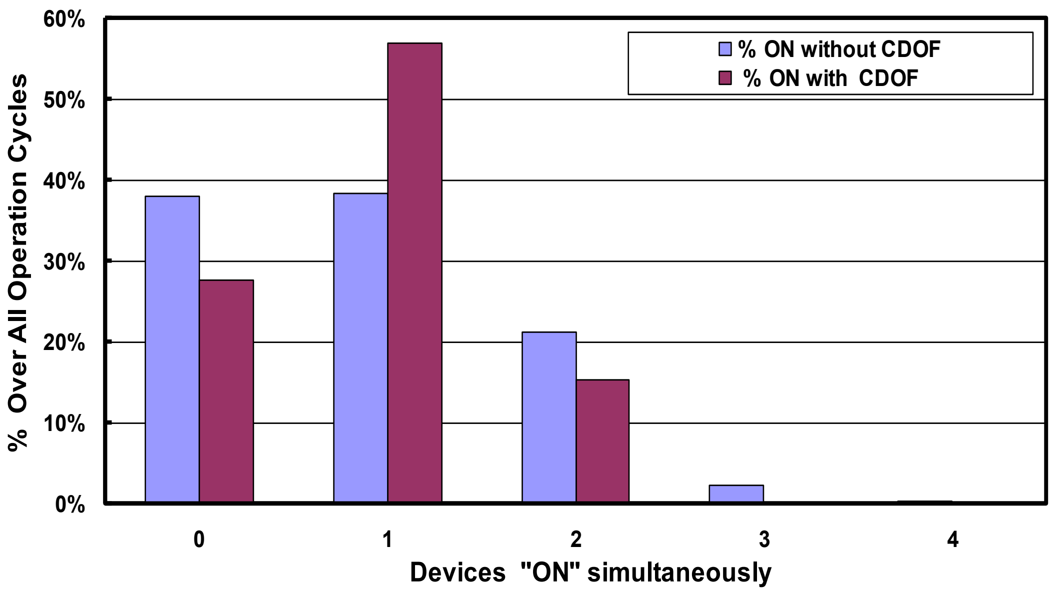


Figure 7.2: Percentage of number of simultaneous devices "ON" over all operation cycles with and without the Consumption Distribution Objective Function (CDOF)

it's normal, there are contradiction between the consumption distribution objective function and the different device operation optimization function. Figure 7.1 shows that without using consumption distribution objective function, the number of "*ON*" devices reaches 4 (maximum) during operation cycle 25 and reaches 3 during operation cycles 27 and 29. Figure 7.2 shows comparison between the system performance with and without consumption distribution objective function. The unoccupied time is minimized from 38% to 28% over all operation cycle by using consumption distribution objective function. Depending on using consumption distribution objective function the most operation times for the devices is 1 or 2 devices each operation slot (72% (57% + 15%)) and just 0.1% of the operation time is 3 devices each operation slot.

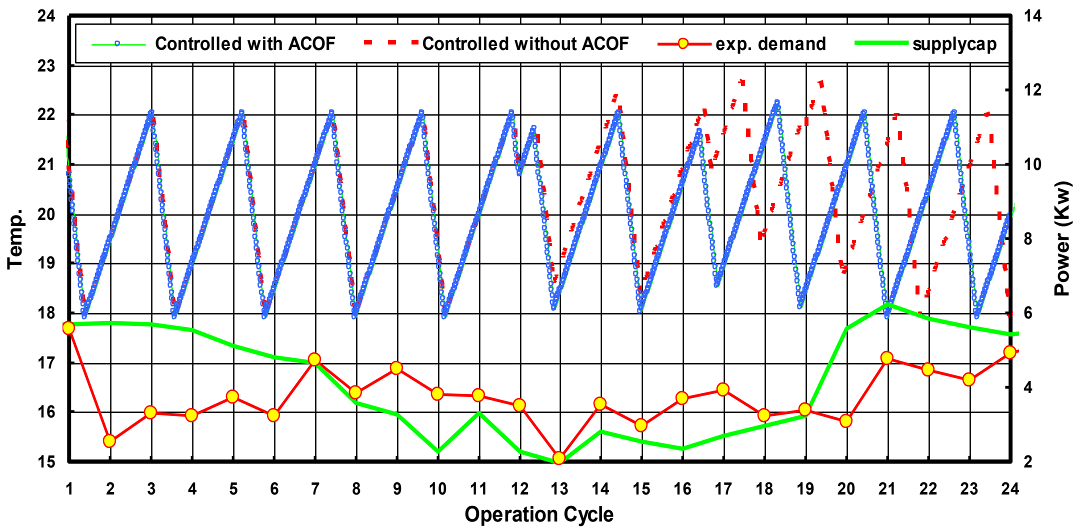


Figure 7.3: Temperature profile of the controlled operation with and without the air-condition objective function (ACOF)

7.6.2 The space cooling/heating objective function effectiveness

The space cooling/heating objective function aims to avoid the temperature setting violation during the low generation periods. The objective function aims to define the best solution in the solution space that optimizes the position of the device operation period (start/stop) within the next operation cycle. The best operation period for the cooling/heating device (the optimal solution) is the period that is not violate the device temperature setting or that minimize the violation to the temperature setting as possible when the allocated power to the device is low. Figure 7.3 and 7.4 show the air condition device operation with and without the objective function. As shown in

Figure 7.3, there are temperature setting violations during the operation cycles 14, 17 and 19.

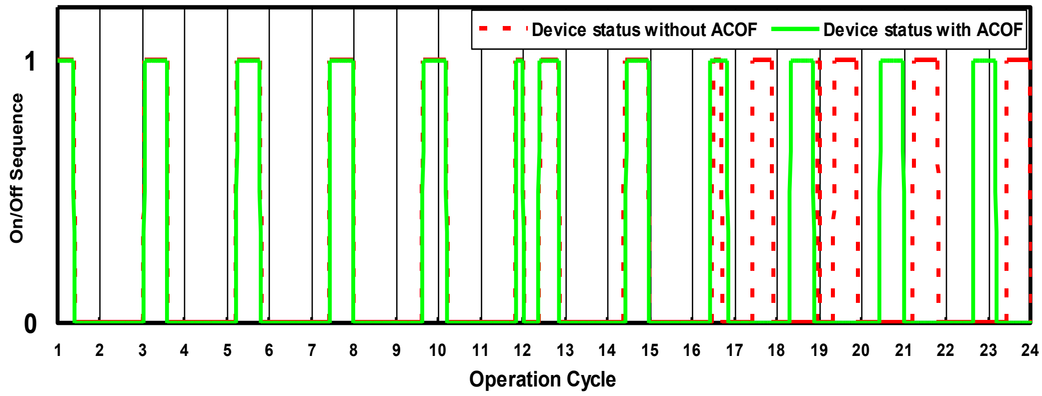


Figure 7.4: Air-condition operation sequence (start/stop) of the controlled operation with and without the air-condition objective function (ACOF)

8 Developing Controlling and Coordinating algorithm For Virtual Power Plant Operation

8.1 Introduction

Due to the current trend towards depending on the distributed energy resources (DER), coordination and optimization software is required. The distribution natural of the small scale and renewable energy resources entails depending on distributed software connected with communication networks to coordinate the resources operation. Virtual power plant (VPP) is a software paradigm for managing a collection of distributed generation resources, controllable loads, and storage systems, to behave like autonomous real power plant for the rest of the power network. VPP Software takes advantages of the emerging trend towards microgrids depend on distributed generation resources, communication network technology and the controlled operation by remote controller. This new concept is one of the techniques that can cope with the new development in the future Smart Grid which depends on the distributed renewable energy resources instead of the classical central fossil power plant. VPP can be used for more flexible response to the load and price variations [138] [139]. It has shown that, on the premise of an advanced Information and

Communication Technology (ICT) infrastructure, VPP represents a feasible solution to be implemented [139].

There are number of different VPP models that are used in the previous researches [134] [140] [8] [127]. According to the aims from building the VPP, VPP can be classified into commercial virtual power plant (CVPP) and technical virtual power plant (TVPP). While the first one directed to the market activities like maximizing the profit of generation, the second one directed to provide the power system quality, reliability and security. In [138], VPP is defined as an entity/Energy Management System that aggregates multi-fuel, multi-location and possibly multi-owned DER units via advanced ICT infrastructure either for the purpose of energy trading or to provide system support services. The developed coordination algorithm in this chapter depends on the VPP definition in [141]:

"The virtual power plant (VPP) is an aggregating software approach for centralized control number of controllable distributed energy (CDE) units. This aggregation aims to optimize the local power network performance which CDE units involved in and coordinates the participation of CDE units in the power markets"

The controllable loads in this work are a group of SBEMS (Chapter 5) that are represented by number of local controller agents. In this chapter, a control and optimization algorithm for the VPP is developed, utilizing the quantum-inspired evolutionary algorithm. We depend on a model for the virtual power plant that optimize and coordinate a group of consumer or prosumers operation. The expected prosumer Energy management system in the future Smart Grid will be able to smartly mange the production and the consumption of energy to maximize the local profit for the prosumer, at the same time contributes to provide the local power network that is involved in. The model that is used in the current study depends on number of different consumption, generation and storage units as described in (Chapter 4, Chapter 5).

The developed algorithm is a non-market-based coordination approach uses VPP coordination agents that collect consumption levels from the local controller agents, and set the permitted consumption levels according to the multi-objective function that takes the available supply cap and the system stability into consideration. In this chapter, an optimization approach that combines quantum-inspired evolutionary algorithm with multi-agent computing paradigm to coordinate the supply and demand for VPP in the future power networks is presented.

The rest of the chapter is organized as follows: Next Section describes the architecture of the proposed system. Third Section introduces the operation algorithm. Fourth Section introduces the Mathematical formulation of the optimization algorithm. Fifth Section illustrates the simulation framework. Sixth Section presents the performance analysis of the proposed algorithm. Finally, seventh Section is the conclusion.

8.2 System architecture

The developed agent-based VPP coordination approach relies on a hierarchal system that comprises three levels of control namely the coordination agent, the local controller agents and the device controller agents. In the first level the coordination agent coordinates the consumption of a number of local controller agents (e.g. SBEMS units). The second level consists of the local controller agents for controlling sub-groups of devices, and the third level comprises the controller agents of different devices (e.g. air-conditioner, refrigerator, ventilation fan). Figure 8.1 shows the architecture of the proposed system.

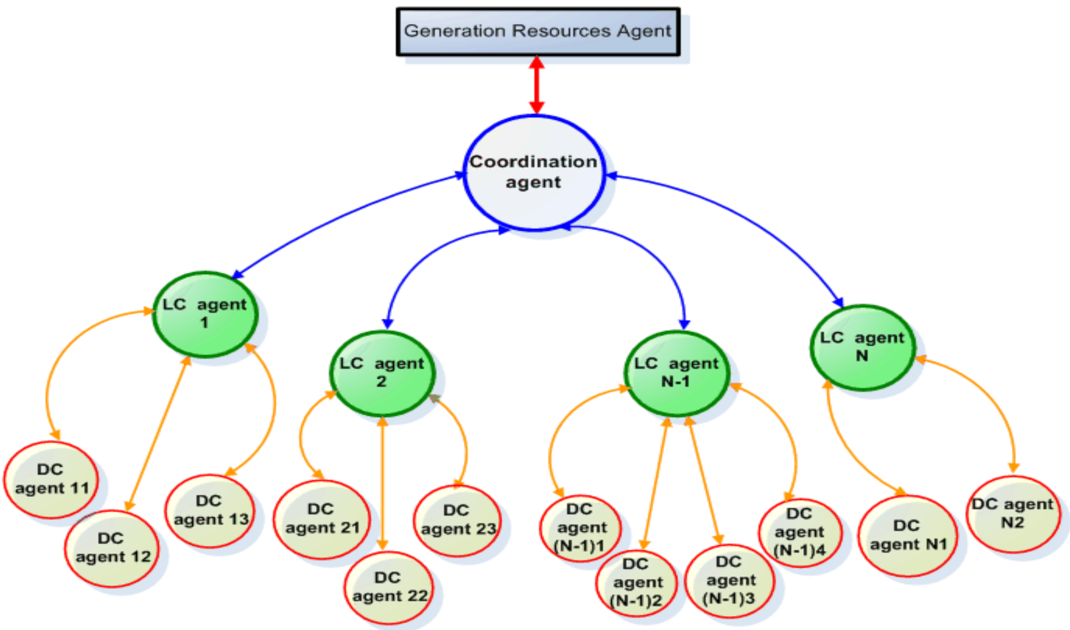


Figure 8.1: Architecture of the hierarchical coordination system

In this work, we depend on a non-market-based approach for coordinating multi-agent system for matching supply and demand within a VPP or a microgrid power network. The non-market based coordination algorithms depends on the ability of the SBEMS to maintain the operation of a group of devices within an area where power is consumed. This area is defined according to the user's preference and the constraints related to the different devices' operation limits. Depending on this flexible operation of the SBEMS, a central coordinator for a group of local controllable loads can be implemented. The coordinator allocates the dynamically available power among the different SBEMS, without violating the constraints for the different local SBEMS.

8.3 The coordination algorithm

The VPP coordinator depends on a number of local controller agents to control and coordinate the consumption in an active consumer area (VPP or microgrid). The task of the local controller agents is to define the minimal energy necessary for the operation of devices under their control taking into account the possibilities offered by device control agents (such as load shifting and load reduction). This minimal level is defined by the constraints related to the device operation within the limits that are defined by device setting or by the consumer. Local controller agents define their maximum consumption level, that is, the consumption of devices without any intervention during their operation. These two levels, in addition to the actual consumption level of the current operation cycle, are sent to the coordinator. Figure 8.2 depicts the operational interaction among the agents in the system. The details are as follows:

The local coordination agent sends consumption levels requests and supply cap request to the local controller agents and the generation market agent respectively. The local controller agents define minimum, maximum and actual power levels for the devices operating under their control, taking into account the possibilities offered by the device controller agents (e.g. load shifting and load reduction). Depending on such data from local controller agents, the coordination agent allocates consumption levels for every local controller agent (between minimal and maximal level). Such consumption level must not violate the available supply cap, that is, the expected local renewable energy resources generation which is defined by the generation market agent.

8.3 The coordination algorithm

The main goal of the proposed coordination system is to achieve a balance between different parameters in the system, such as resource consumption, the demand satisfaction, and the stability within the system. The local coordination agent sends the coordinated consumption levels to the local controller agents and receives the expected actual consumption levels for the next operation cycle. If more power is required for the next operation cycle, the coordination agent sends the new supply cap to the generation market agent. The generation market agent is responsible to define and order the classical generation units to supply the required additional power for the next operation cycle. In the next subsections, we explain the agent roles in more detail.

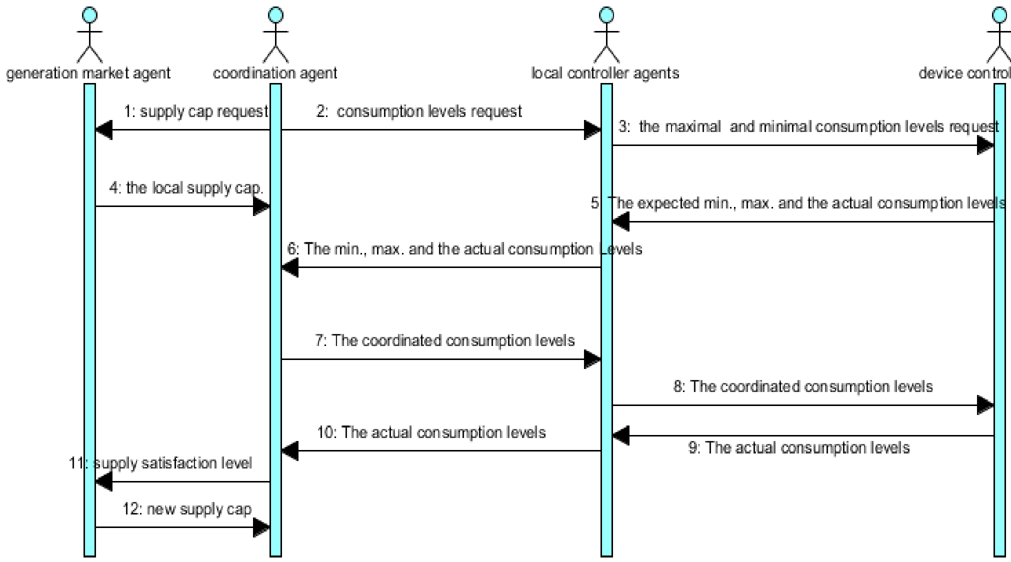


Figure 8.2: The sequence of the data flow among the multi-agent system

8.3.1 Roles of agents in the coordination system

The coordination system for matching supply and demand consists of three main agent types: the device controller agents, the local controller agents and the coordination agent. In the following section, different agent roles in the coordination system are presented.

8.3.1.1 The device controller agent

It must be mentioned that controlling energy power resources and consumption vary according to their availability to be controlled. In other words, controlling energy power resources that are stochastically operating (e.g. solar and wind generation units) depends on unpredictable parameters such as weather conditions, controllable resources (e.g. diesel generators), and power storage units which allow usage control based on market prices. Also, consumption devices can be shift operation devices (e.g. washing and drying machines), thermal buffer devices (e.g. heating and cooling devices) or user action devices (e.g. audio and lighting loads). In our work, we depend on a device model for simulating the thermal buffer devices behavior. Air-conditioners are one example of such devices where we can change the temperature setting to minimize the consumption during the peak time or change the on/off time periods. In our proposed coordination system, the device controller agent is responsible for the following:

1. Creating consumption plans for the next operation cycle based on the device model it controls (air condition, refrigerator, ventilation fan, etc.). The consumption plans include the minimum and the maximum consumption levels of these devices.
2. Responding to the local controller agent with the best suitable plan to meet the coordinated consumption level defined for the next operation cycle. Obviously, the plan which is determined for any particular device must not violate the operation limits of the device.

8.3.1.2 The local controller agent

Local controller agents' task (SBEMS) is to define the expected minimal energy necessary for the operation of sub-groups of device controller agents under their control taking into account the possibilities offered by device control agents. This minimal level is defined by the constraints related to the device operation within the limits that are defined by the manufacturer or by the consumer. Also, local controller agents define their unconstrained (maximum) consumption level, that is, the consumption of devices without any intervention during their operation. Each local controller agent collects consumption levels or plans from all device controller agents under its control. After that, it defines the minimum and the maximum consumption levels for the device group depending on the different consumption levels from the device controller agents. These two levels, in addition to the actual consumption level of the current operation cycle, are sent to the coordinator agent to optimize the power consumption operation within the local (microgrid) power network for the next operation cycle. The local controller agents fill the following roles in the coordination system:

1. Collect the minimum and the maximum consumption levels from the device controller agents under their control.
2. Aggregate the devices consumption levels and defines the expected consumption range (maximum and minimum) for the device group.
3. Send the consumption levels (maximum, minimum and the actual consumption levels) to the coordination agent.
4. After receiving the permitted consumption level from the coordination agent use the quantum-inspired evolution algorithm to allocate the permitted consumption level to the different devices under its control.
5. Send the proposed consumption levels to the device agent and receive the actual consumption for the next operation cycle. Aggregate all actual consumption levels from devices and send it to the coordinator.

8.3.1.3 The VPP coordination agent

The coordination agents' task is to allocate the dynamically available power (that depends on renewable energy resources) among the different local controller agents without violating the consumption constraints for the different local controller agents. The coordinator defines consumption levels for each local controller agent (between minimal and maximum level), without violating the available supply cap. The coordination aims to optimize the power consumption according to number of parameters, such as the cost of consumption, resource consumption and stability within the system. These parameters are interdependent, which means that changing one affects the others so the coordinator must compromise among those parameters to achieve the balance among them. The coordination agent roles are as follows:

1. Collects the consumption levels from local controller agents
2. Allocates the expected available supply to local controller agents using the quantum-inspired evolution algorithm.
3. Sends the allocated coordinated consumption levels to the local controller agents and receives the modified consumption levels from local controller agents and defines the total consumption for the next operation cycle.

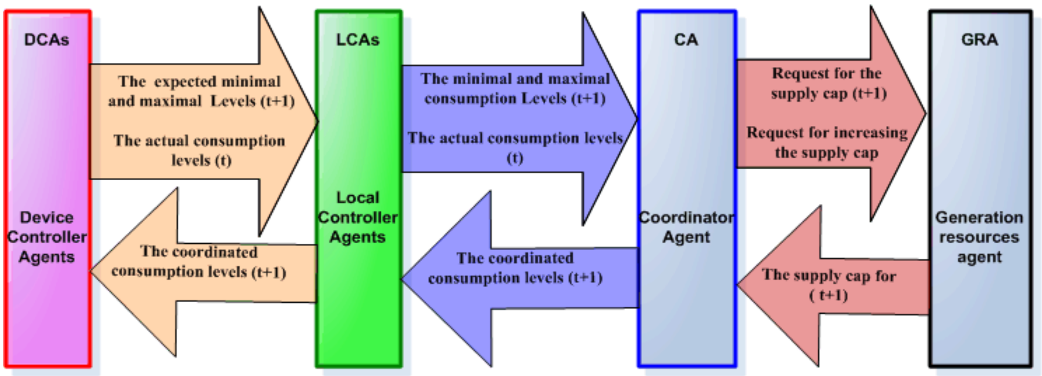


Figure 8.3: Information flow among the coordination system agents

Once the data is available to the coordination agent, it defines if the expected supply is sufficient for the next operation cycle or not. If the total consumption exceeds the expected supply, the coordination agent sends the request to the market generation agent to provide classical fuel resources to increase the supply cap for the next operation cycle.

Figure 8.3 shows the sequence of the data transfer between the different agents.

8.4 Mathematical formulation of the optimization problem

We formulate the coordination agent problem as a multi-objective optimization problem solved by quantum-inspired evolution algorithm. Let N be the number of local controller agents. Each agent i ($i \in \{1,2,..., N\}$) provides the expected consumption level $x_{ik} = [x_{ik}^{min}, x_{ik}^{max}]$ for the next operation cycle k ($k \in \{1,2...\}$), where x_{ik}^{min} and x_{ik}^{max} are the minimum and maximum expected consumption levels respectively. Let $X_k = (x_{1k}, x_{2k},..., x_{Nk})$ be the consumption range vector for all local controller agents. Each local controller agent is represented by real-coded quantum-like gene g_i in the quantum population space. The quantum population space contains a set of quantum individuals (chromosome) q_j ($j \in \{1,2,..., M\}$) where M is the space size. Each quantum chromosome contains N genes as follows:

$q_j = (g_1, g_2, \ldots, g_N)$

$$q_j = \begin{matrix} c_{g_1} & c_{g_2} & . & . & . & . & . & . & . & c_{g_N} \\ w_{g_1} & w_{g_2} & . & . & . & . & . & . & . & w_{g_N} \end{matrix}$$

Where:

$q_j \in Q$, Q is the quantum population space, c_{g_i} and w_{g_i} are the center and the spectrum of the local controller agent i consumption range.

The quantum genes represent the local controller agents' expected consumption for the next operation cycle in the quantum population space. Each gene is represented by two values, the center and the spectrum of the local controller agent consumption range. Different quantum individuals can be generated in the population space by randomly generating centers inside the consumption range and with spectrum equal to the consumption range. After that, the Q space is converted to the classical population space X with the same size M.

As mentioned in the previous section, the coordination agent's task is to allocate consumption levels for the local controller agents within the expected consumption range according to certain number of objective functions related to the overall system performance. Three objective functions are used to optimize the coordination agent allocation of the available supply cap.

The first objective function deals with the supply cap violation. The aim of this function is to make sure that the total consumption levels do not exceed the supply cap of the system. The second objective function aims at improving the power system stability. This function allows us to minimize the difference between the actual consumption levels of the operation cycle k and the coordinated consumption levels for operation cycle k-1. The third objective function is concerned with minimizing intervention in the local controller agents operation and maximizing power satisfaction levels for the local controller agents. This is done by maximizing the allocated power to each agent as possible according to the power network supply and demand. The mathematical formulation for the objective functions is as follows:

- The supply cap objective function is given by

$$\max_{x_j \in X} \left(P_k^{cap} - \sum_{i=1}^{N} x_{ik} \right)$$

Subject to $x_{ik}^{\min} < x_{ik} < x_{ik}^{\max} \quad \forall i \in \{1,2,\ldots. N\}$

Where p_k^{cap} is the maximum available power for the operation cycle k

- The system stability objective function is as follows

$$\min_{x_j \in X} \sum_{i=1}^{N} (x_{ik} - y_{i(k-1)})$$

Subject to $x_{ik}^{\min} < x_{ik} < x_{ik}^{\max} \quad \forall i \in \{1,2,\ldots. N\}$

Where $Y_{k-1} = (y_{1(k-1)}, y_{2(k-1)}, \ldots, y_{N(k-1)})$ represents the actual consumption vector for the local controller of the previous operation period.

- The consumption satisfaction objective function is

$$\min_{x_j \in X} \sum_{i=1}^{N} (x_{ik}^{\max} - x_{ik})$$

Subject to $x_{ik}^{\min} < x_{ik} < x_{ik}^{\max} \quad \forall i \in \{1,2,\ldots. N\}$

To evaluate the solutions of the above mentioned objective functions, we use the *t-norm* algorithm proposed in [132]. The following two steps are used to evaluate solutions depending on the multi-objective functions [142].

Firstly, each objective function is converted to an application function that measures the quality of the solution individuals [133]. If the objective function is $f(x)$ where x the proposed solution is, the application function will be $H((f(x)) \in [0,1]$. The application functions model is as follows:

$$H_i(x) = \begin{cases} 1 & f_i(x) >= M_i \\ 1 - (M_i - f_i(x))/(M_i - m_i) & m_i < f_i(x) < M_i \\ 0 & f_i(x) <= m_i \end{cases}$$

Where M_i and m_i is the maximum and the minimum for the objective function i respectively.

8.4 Mathematical formulation of the optimization problem

The setting of the maximum M_i and the minimum m_i of the application functions that represent the objective functions affect the system performance. Section 5.2 elaborates on system performance for two settings of the stability application function.

Secondly, *t-norm* (triangular norm) [132] is used to combine application functions to evaluate the population space individuals. For evaluating the solution space in the proposed coordination system, three t-norm methods are tested. In more details, consider we have A and B as two objective functions. The value of the two application functions that represent the two objective functions at solution x is $H_A(x)$ and $H_B(x)$. Then, the *t-norm* value of the two application functions is calculated by one of the three following *t-norm* method:

- *t-norm-1* $(H_A(x), H_B(x)) = \min(H_A(x), H_B(x))$
- *t-norm-2* $(H_A(x), H_B(x)) = H_A(x) * H_B(x)$
- *t-norm-3* $(H_A(x), H_B(x)) = \max(H_A(x) + H_B(x) - 1, 0)$

The *t-norm* value differs depending on the *t-norm* used. For example if $H_A(x) = 0.5$ and $H_B(x) = 0.6$, the *t-norm* value for the two objective function will be *0.5*, *0.3* and *0.1* for *t-norm-1*, *t-norm-2* and *t-norm-3* respectively. The coordination agent relies on the quantum-inspired real-coded evolutionary algorithm (chapter 5) for solving this multi-objective optimization problem. In the following section, a description of this algorithm is presented.

For evaluating solutions depending on the previous three objective functions the t-norm [5] algorithm is used. In our implementation, we use the following two steps to evaluate the solution depending on the multi-objective functions [142]. The first step aims to convert each objective function to an application function that measures the goodness of the proposed solution [133]. The second step combines application functions to single objective function depending on the t-norm algorithm [132]. The combined objective function is used to evaluate the individual solution in the solution space. The coordination agent relies on the quantum-inspired evolutionary algorithm (chapter 5) for solving this multi-objective optimization problem.

8.5 The simulation framework

The proposed coordination system relies on one coordination agent, number of local controller agents which in turn control number of device controller agents. For testing the proposed algorithm, an operation day is divided into 48 operation cycles where each cycle is 30 minutes. The last five minutes of each operation cycle is assigned for negotiation among the coordination agent and the local controller agents. Each local control agent sends the expected consumption range of the next operation cycle and the actual consumption of the current operation cycle to the coordination agent. The coordination agent allocates the available supply cap to the local controller agents according to the objective functions presented in Section 4. It then sends the coordinated consumption levels to the local controller agents. The operation day has two main consumption peaks, the first one between 7 and 10 AM and the second one between 17 and 21 PM. We try to emulate the natural power consumption peaks in real life [124].

The proposed coordination system is able to coordinate the total consumption of the active consumer networks under its control depending on the local controller agents' abilities to minimize or shift their consumption for certain operation cycles. One or more shifting strategies can be used for the local controller agents. Each local controller agent defines the unsatisfied consumption of a certain number of previous operation cycles and updates the demand for the next operation cycles. We assume that the local controller agents are able to repeat this shifting strategy without affecting the device operation. This assumption is based on real life applications where device controller agents control devices for cooling, heating and ventilation. For example, the temperature setting of an air condition can be up by one or two degrees during the peak demand which can be easily controlled by the agent. The cooling device on/off cycle can be controlled to minimize and distribute the device consumption and to minimize the number of active devices during the same time. The ventilation devices operation period can be shifted before or after the peak demand. Depending on the flexible operation of the consumption devices the coordination task can be accomplished.

For monitoring, evaluating and analyzing the proposed coordination system performance, a number of monitoring functions are implemented, such as demand stress within the system function and the global system satisfaction level function. The demand stress function measures the difference between the aggregated total demand and the aggregated total coordinated consumption levels within the system. This function monitors the cycle of curtailed amount of demand during the peak demand time and the system recovery of this amount during the low demand time. The peak of this curtailed power within the system and the time for recovery is an important indication of the system stability. Demand stress monitoring function can be considered as measure for the quality of shifting the demand from the peak time to the low demand time. The global system satisfaction level function measures the global demand satisfaction level (social welfare) for all local controller agents in the area under the coordination system control.

8.6 The coordination algorithm convergence

For testing the coordination algorithm, one coordination agent and 100 local coordination agents are used. Each local controller agent controls 3 to 10 device controller agents. The average time required by the quantum-inspired algorithm that is used by the local coordination agents to allocate the available power to the 100 local controller agents is 4.6 second/cycle. The required time by the quantum-inspired algorithm changes depending on the maximum number of generations allowed for the quantum-inspired algorithm to converge to the appropriate solution. Such convergence depends on the situation of supply and demand. Figure 5 shows the relation between the average time required by the algorithm for convergence to the solution and the maximum number of generation allowed for running the quantum-inspired algorithm.

In Figure 8.4, we show that the required average time is nearly constant after 150 generation/cycle. The required number of generations changes from cycle to cycle depending on the situation between supply and demand. In this case, the time required for convergence to the appropriate solution during the peak demand increases up to 10 second/cycle. The average number of generations required for convergence is 102 generation/cycle.

Also, for investigating the system performance, we repeated the proposed algorithm several times (>5 times) in the same operating conditions. After that, the operating conditions are changed and the test is repeated again number of times.

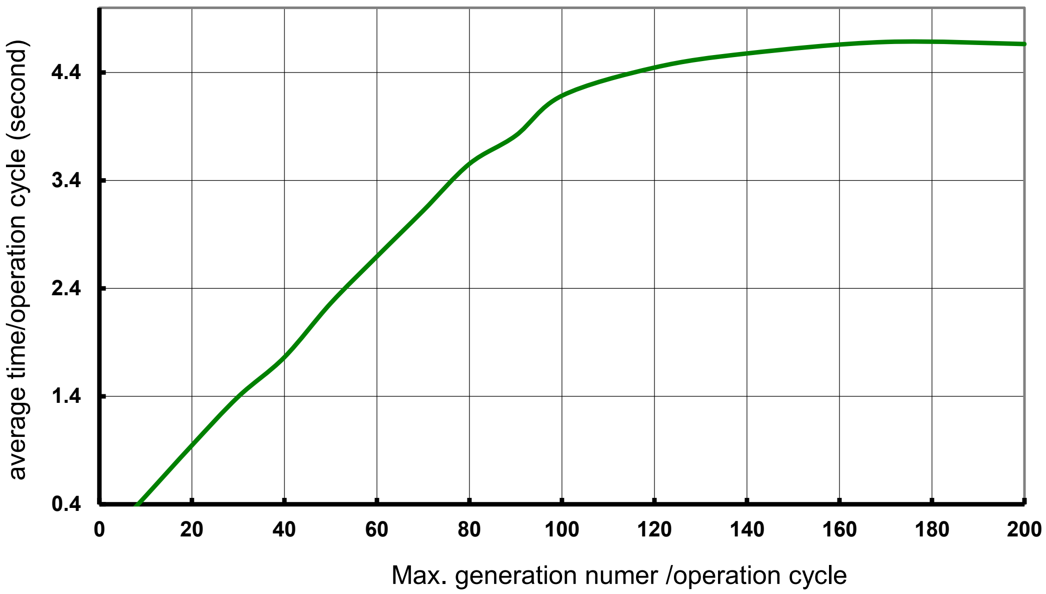


Figure 8.4: The quantum-inspired algorithm convergence average time/ cycle

The algorithm response in each case is nearly identical which reflect the stability and the reliability of the proposed algorithm in different operating conditions. One of the main advantages of the quantum-inspired evolutionary algorithm [30] is the balanced distribution of the population space which avoids trapping in local optima.

8.7 The proposed system performance analysis and monitoring

In order to explore the proposed approach abilities to coordinate and control the power consumption of number of local controller agents to match between supply and demand, the proposed coordination algorithm with simulated supply and demand profiles under different operation conditions is tested. First, the system is tested under different combination of the objective functions to illustrate the role of each objective function in the system performance. Second, the system is tested under different setting for the objective functions. Third, the system is tested under different evaluation method (t-norm).

For monitoring and analyzing the performance of the coordination system, number of monitoring function for evaluating the coordination system under different operation conditions is needed. These monitoring functions are required for testing system performance under different operation conditions and for evaluating the proposed coordination system. We depend on number of monitoring function for the system performance to analysis the system performance. The following monitoring parameters are used to evaluate the system performance:

- **The global system satisfaction function**: this function measures the global demand satisfaction level for all local controller agents in the area under the coordination system control.
- **The power change/cycle:** this function measures the power difference between two successive operation cycles. When this parameter is small system stability is better, where there is no large overshoots for the demand in the system. This parameter measure the ability of the coordination system to coordinate the consumption without affect the overall system stability.
- **The variance of the satisfaction levels of the local controller agents**: this function measures the variance of the individual satisfaction levels of the local controller agents. This parameter measures the fairness of the power allocation among the local controller agents.
- **Stress within the system**: this function measures the difference between the aggregated total demand and the aggregated total coordinated consumption levels within the system. This parameter monitors the cycle of curtail amount of demand during the peak demand time and the system recovery of this amount during the low demand time. Where the peak of this curtails power within the system and the time for recovery is important indication for the system stability. This parameter defines the ability of the coordination algorithm to satisfy the system power consumption and in the same time improve the system technical parameter.

Depending on these monitoring functions, we can evaluate the system performance according to the effects of the coordination system to the different consumption units, the quality of matching between supply and demand, and the overall system stability. In the following area, results and analysis for the simulation tests for the proposed coordination system is presented.

8.7.1 Objective functions roles and system performance analysis

The coordination system depends on number of objective functions to coordinate the power consumption in microgrid or local consumption area for matching supply and demand. In this item, the performance of the coordination system for different combination of objective functions is presented. We aim to illustrate the role of each objective function for improving the coordination system performance. First, the supply cap objective function is used for coordinating the power consumption during the peak demand in the microgrid to match between supply and demand. Figure 8.5 shows the system four power curves: supply cap, demand, the modified demand and the coordinated consumption curve of the system. The coordination system with this objective function able to prevent supply cap violation by minimizing the consumption of the local controller agents without violates the consumption range of each local controller agent. The coordination system force local controller agents to minimize their consumption during the peak demand times. The curtail amount of power from demand is large and this amount of power is recovered partially during the next low demand times. This is means, there is amount of power is shifted again to the next operation cycles. This leads to the modified demand increases continuously because there is always amount of unsatisfied demand moves to the next operation cycles. This consumption behavior is not possible in the power system because local controller agents able to shift or minimize their consumption for certain operation cycle depend on the device types that are controlled by the local controller agents. With only depending on the supply cap objective function, the system just minimizes the overall consumption to maintain it under the total supply of the system without concern to the system stability or the local controller agents demand satisfaction. This mean there is future expected expanding gab between supply and demand by using supply objective function only. Consequently, performance degradation arises, like low voltage rate and low power system frequency which leads to system unstability.

For improving the system performance, let us concern with the other part of the system, the local controller agents. The satisfaction objective function is added to the system for improving the satisfaction levels of the local controller agent to minimize the intervention in their operation and to minimize the curtail power from demand during the peak demand time.

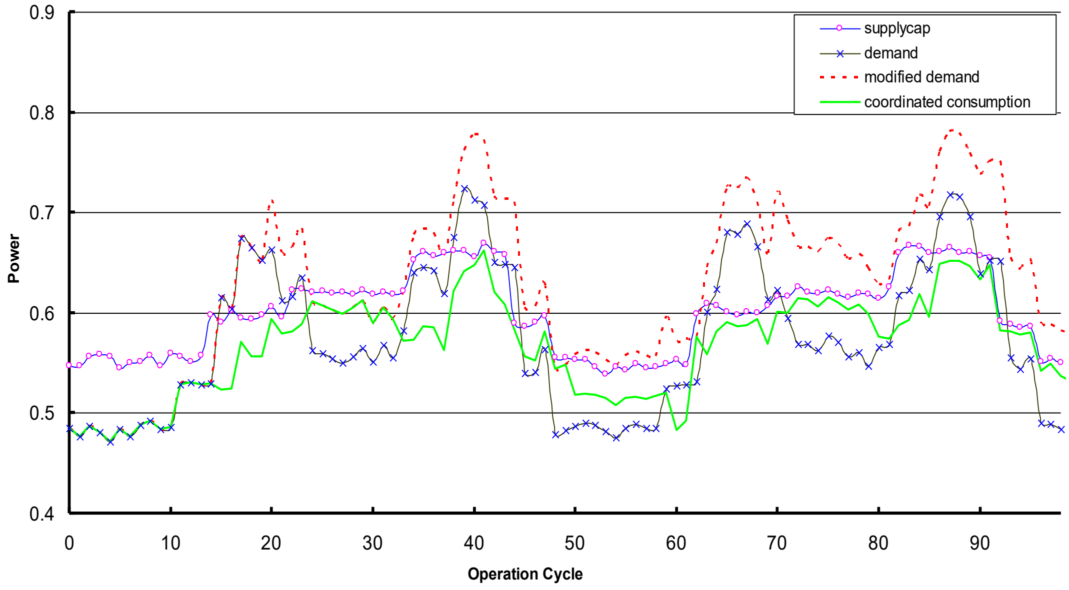


Figure 8.5: Coordination system with using supply cap objective function when demand exceeds supply

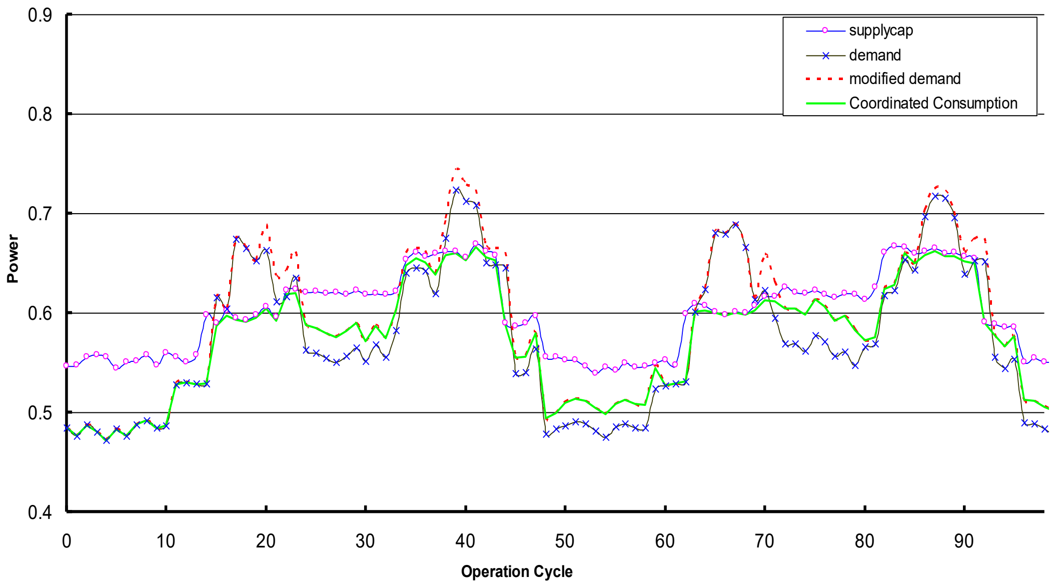


Figure 8.6: Coordination system with using supply cap and the consumption satisfaction objective functions

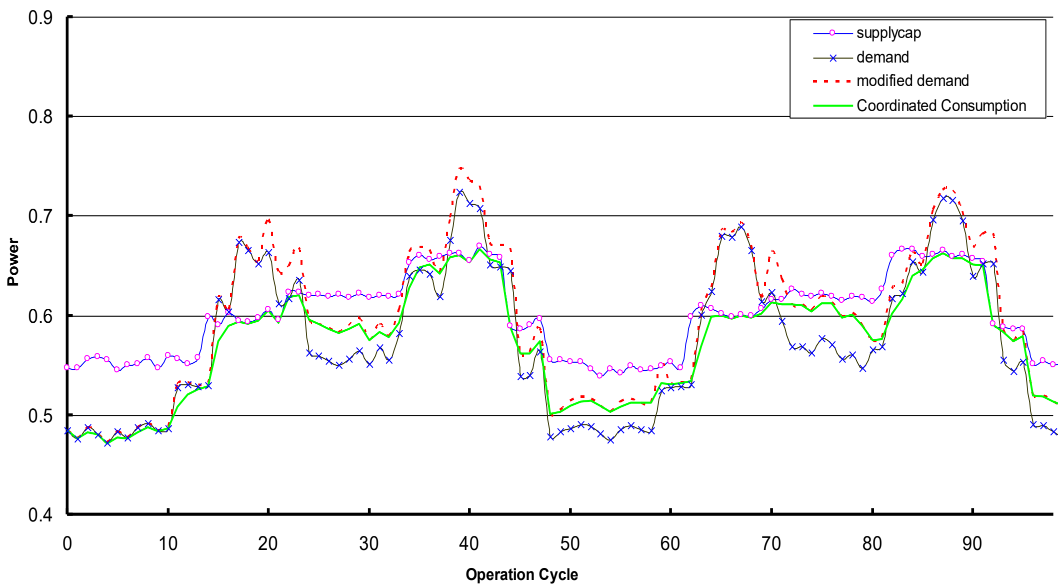


Figure 8.7: Coordination system with using three objective functions (supply cap, consumption satisfaction and the system stability objective functions)

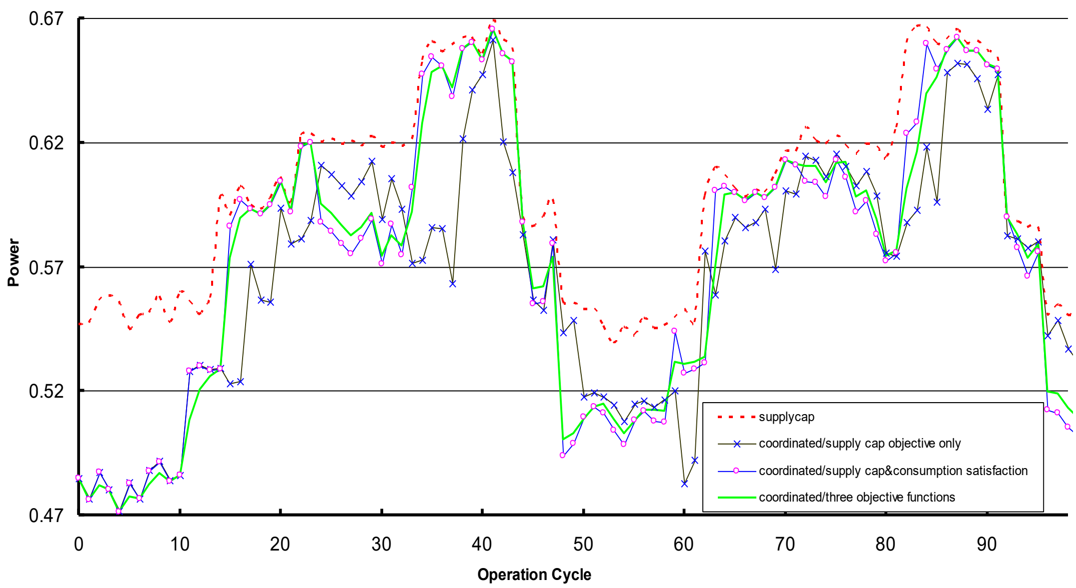


Figure 8.8: Coordinated consumption with different combinations of objective functions

8.7 The proposed system performance analysis and monitoring

Figure 8.6 show the four power curves of the system. For comparing the system performance before and after using the satisfaction objective function, Figure 8.9, 8.10, 8.11 and 8.12 show the two systems performance. Improvement in the demand stress within the system and global satisfaction level of the local controller agents can be seen clearly. At the same, the global system consumption still under the total supply cap of the system. Figure 8.9 shows the highly improvement in the demand stress within the system, where the demand stress waves in certain range of power depends on the times of peak and low demand. Additionally, the peaks of the waves decrease with time. Figure 8.10 shows that the power changes between each two successive operation cycles are also improved. Figure 8.11 shows that the global demand satisfaction for local controller agents is improved totally. Figure 8.12 shows that the local controller agents' satisfaction variance is minimized. Large consumption overshoots affect the system stability. The stability objective function is added to the system for minimizing the power overshoots between the successive operation cycles, for smoothing the system consumption performance and for minimizing the effects of the demand and supply variation on the system performance.

Figure 8.7 shows the four power curves of the system with the three objective functions. This objective functions combination able to coordinate the local controller agents consumption and minimize the effects of the supply and the demand variation on the system stability. For comparing the system performance, Figure 8.13, 8.14, 8.15, and 8.16 shows the comparison between the two systems performance before and after using the stability objective function. The improvement in the demand stress within the system and the global satisfaction level of the local controller agents can be seen clearly. Figure 8.14 shows the minimization of the power changes between each two successive operation cycles. This improvement in stability come at the expense of increasing demand stress within the system (Figure 8.13) and reduction in the global demand satisfaction within the system (Figure 8.16).

Figure 8.8 shows the three coordinated consumption curves for the previous three combinations of the objective functions. There is no supply cap violation for the three systems and the systems able to match between supply and demand. The system performance can be improved by Adding objective functions. Using those objective functions, technical, social and commercial parameter can be identified and improved.

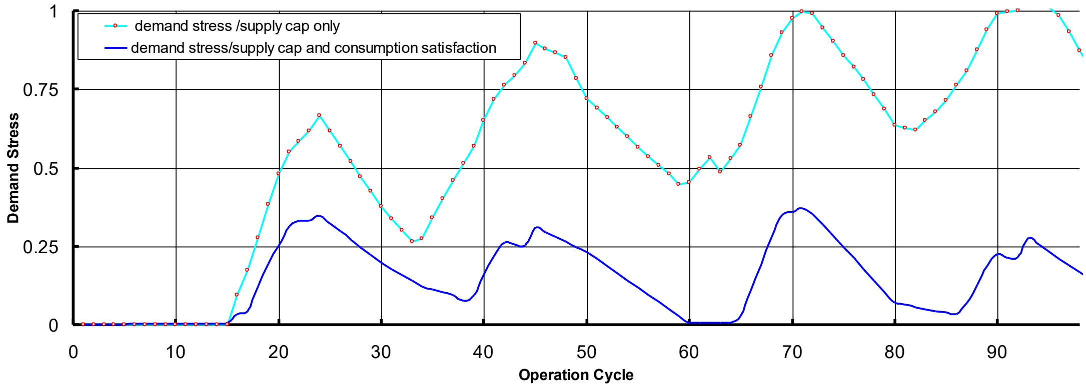


Figure 8.9: Demand stress within the system for supply cap only vs. supply cap and consumption satisfaction

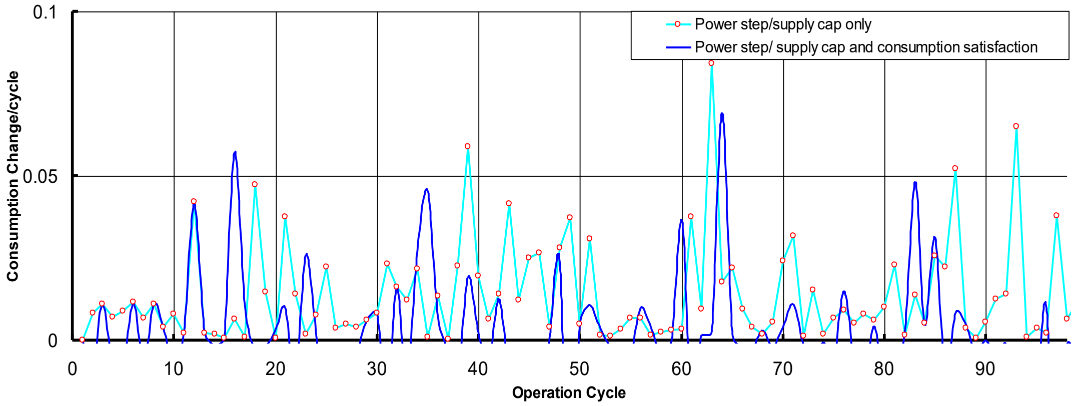


Figure 8.10: Power consumption change /cycle for supply cap only vs. supply cap and consumption satisfaction

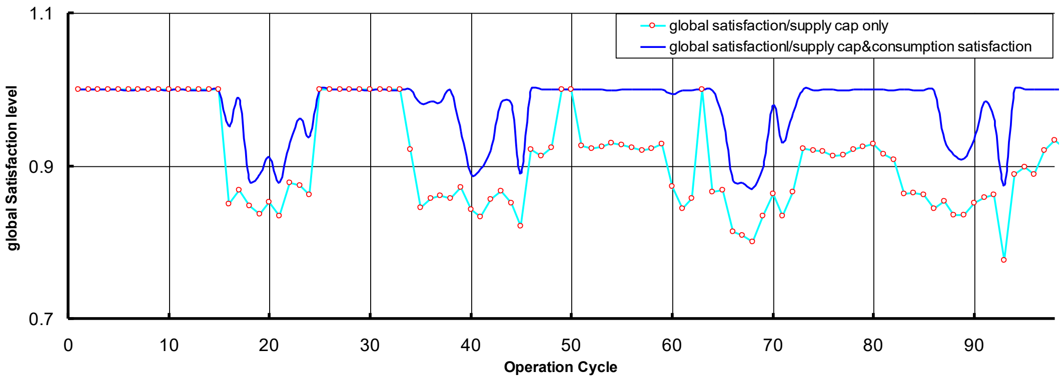


Figure 8.11: Global satisfaction level for supply cap only vs. supply cap and consumption satisfaction

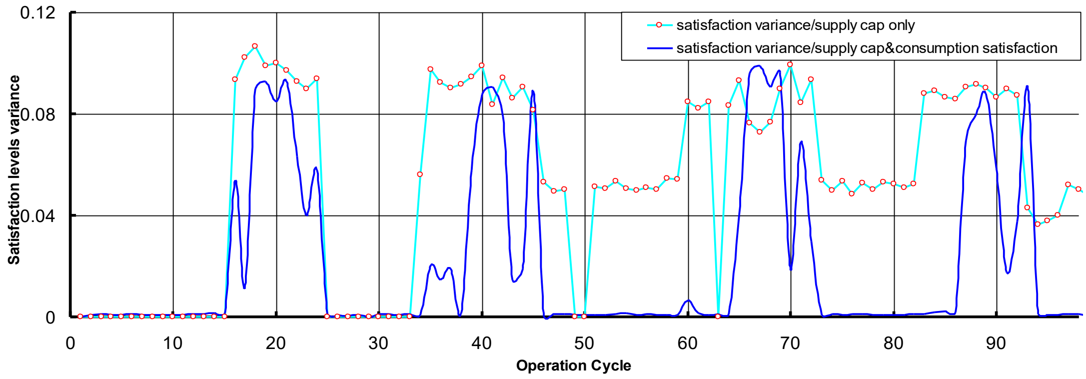


Figure 8.12: Satisfaction levels variance for supply cap only vs. supply cap and consumption satisfaction

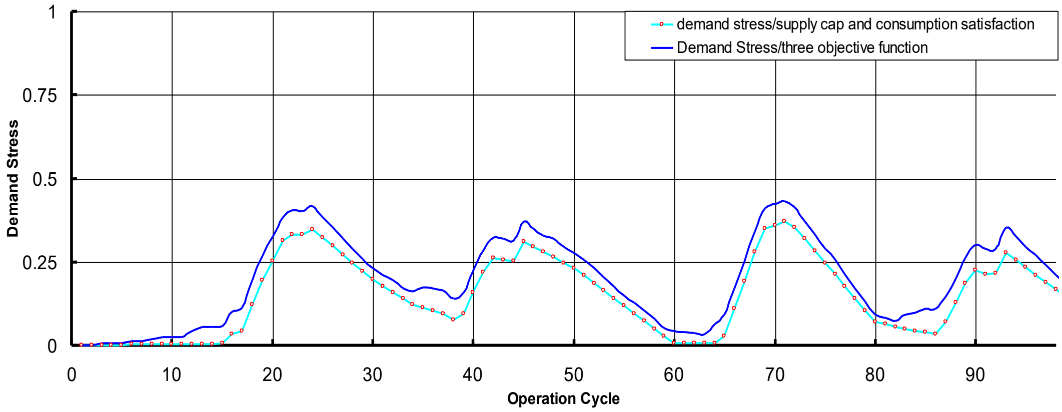


Figure 8.13: Demand stress within the system for supply cap and consumption satisfaction vs. the three objective functions

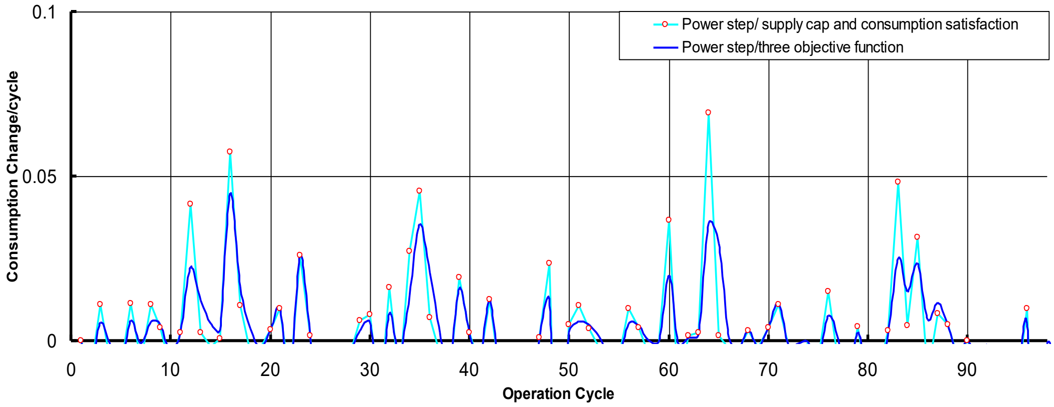


Figure 8.14: Power consumption change/cycle for supply cap and consumption satisfaction vs. the three objective functions

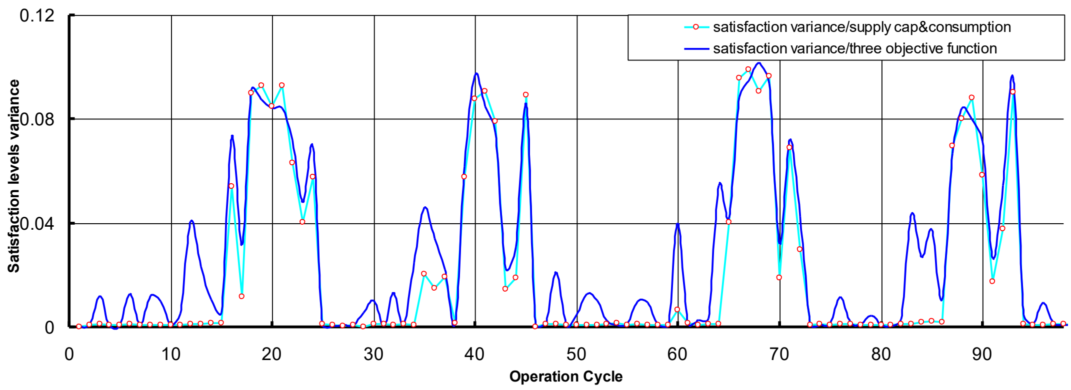


Figure 8.15: Global satisfaction level for supply cap and consumption satisfaction vs. the three objective functions

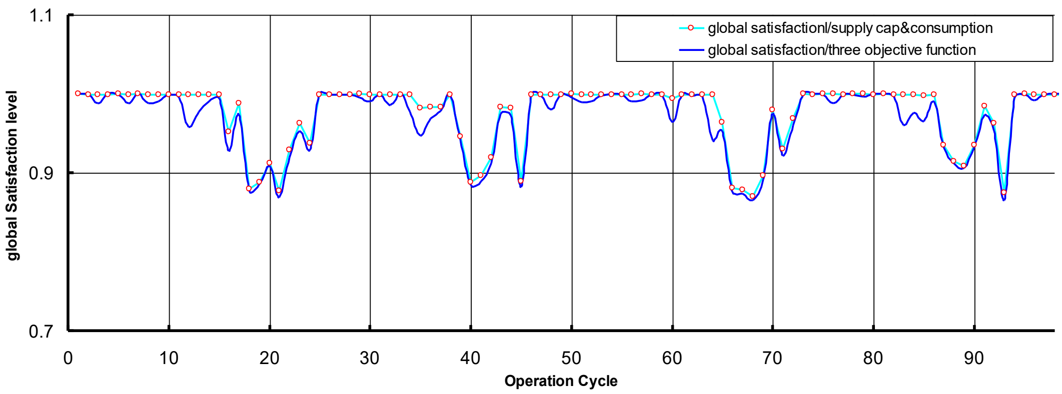


Figure 8.16: Satisfaction levels variance for supply cap and consumption satisfaction vs. the three objective functions

8.7.2 The system performance with different objective functions setting

The coordination system depends on number of objective functions for coordinating the power consumption within the controlled local power networks. This entails repeated decision-making for the coordinated joint consumption point of the system each operation cycle. Because of we depend on evolutionary algorithm, population space evaluation each operation cycle is required. For evaluating the solution space depends on multi-objective functions, application functions for those objective functions are required [133]. Depending on our tests, application functions setting affect the system performance. For illustrating this point, we tested the coordination system for two setting for the stability objective function.

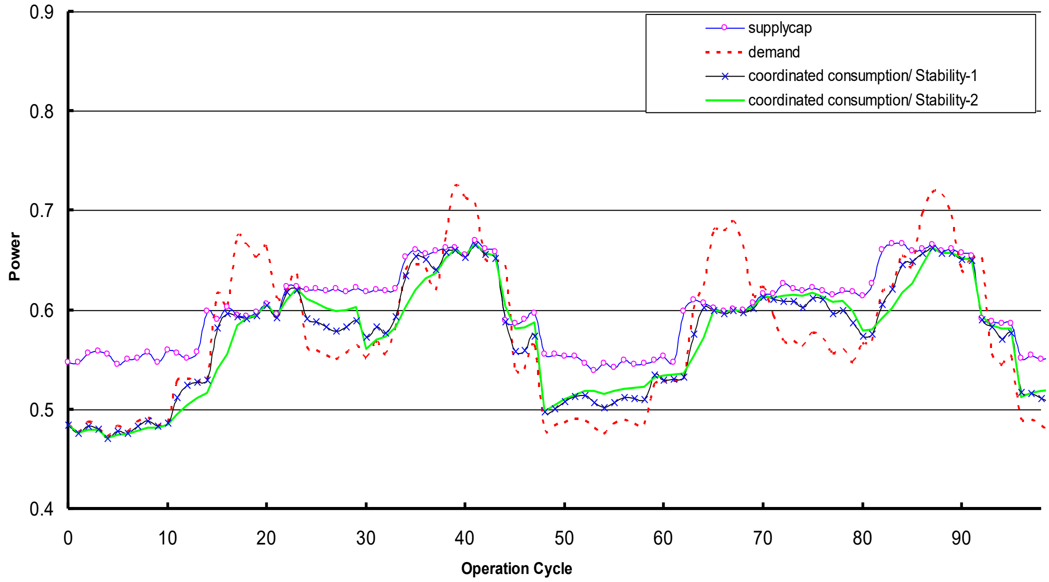


Figure 8.17: Coordinated consumption for two setting of the stability objective function

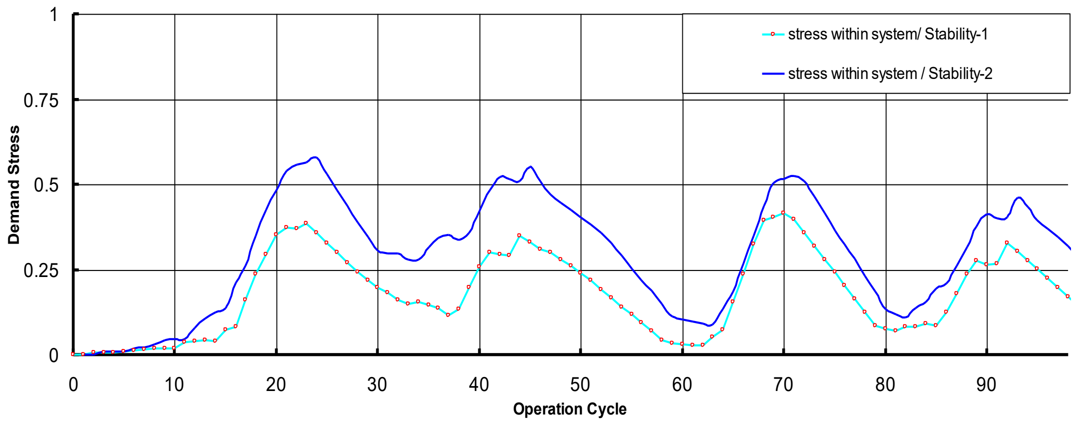


Figure 8.18: Demand stress within the system for two setting of the stability objective function

Figure 8.17 shows the consumption curves for two setting for the system stability function. The figure shows that, the coordinated consumption curve with the second setting is smoother and less in oscillation than the first coordinated consumption curve. Depending on the test, by appropriate setting of the stability objective function, more stable and smoother performance can be obtained. The setting of the stability function considers as damping factor for the coordination system. Where, by decreasing this factor, the coordinated consumption curve will be less sensitive to the supply and demand variation. At the same time, demand stress within the system will increase by decreasing this factor. Demand stress increasing leads to peaks of consumption in other consumption points. So, we should compromise between minimizing the total consumption variation and improving the system stability and increasing stress within the system. Figure 8.18 shows the demand stress within the system for the two setting. The demand stress of the second setting is greater than the first setting. Figure 8.19 shows that the average consumption variation between two successive operation cycles in stability-2 system is less than stability-1 system. This improvement in stability come at the expense of increasing demand stress within the system (Figure 8.18) and reduction in the global demand satisfaction within the system (Figure 8.20).

We can conclude that stability-2 function setting can be used when there is large variation in demand and supply and the demand and supply close to each other.

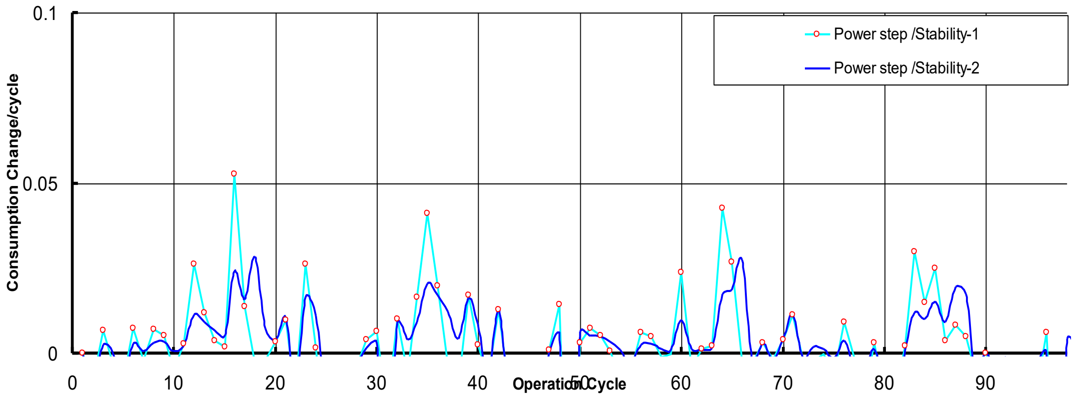


Figure 8.19: Power consumption change/cycle for two setting of the stability objective function

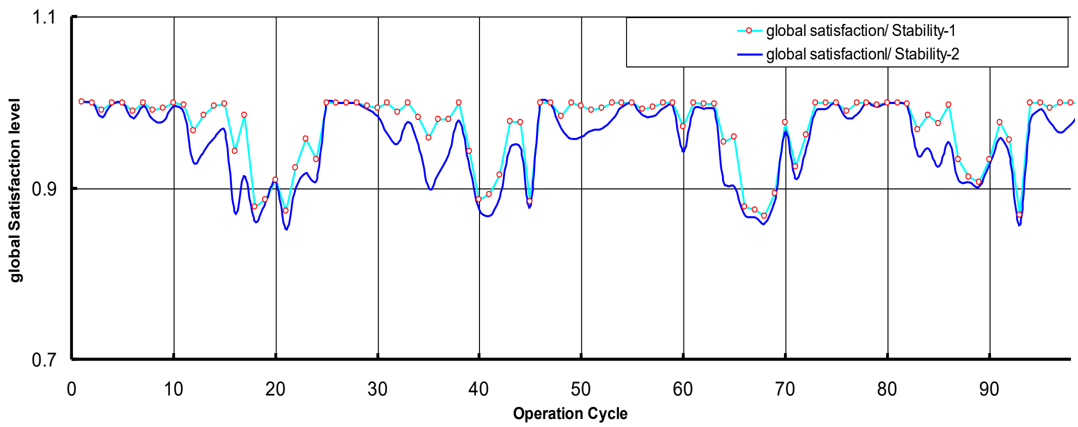


Figure 8.20: Global satisfaction level for two setting of the stability objective function

8.7.3 The system performance with different objective functions evaluation (t-norm)

The system performance under the same operation condition with different t-norms is tested. Figure 8.21, 8.22, 8.23 and 8.24 show the system performance with the different t-norm. From these figure, the solution evaluation way affects the system stability and may be leads to unstability in the system. From Figure 8.23, the third t-norm give random solution in some operation cycle. When the summation of the individual objective functions evaluation is less than one, solutions evaluation will be zero. This leads to random suboptimal selection for the solution because all solutions are equal. This in turn may lead to consumption point much lower than the actual demand point, which means amount of power that should be consumed in this operation cycle is shifted to the coming operation cycles. The modified demand curve will be higher than the original demand curve because there are repeated unsatisfied requests for power from the local controller agents which increases the future demand for the local controller agents. There are demand peaks for the modified demand curve higher than the demand peaks of the original demand curve. As shown in Figure 8.21 and 8.22, the first and the second t-norm modified demand peaks nearly as the original one in the level and shifted to another consumption time. Which means the demand curve is modified, at the same time the local controller agents satisfy their needs of power during the low consumption time without shifting to the next consumption peaks. As shown in Figure 8.24, the system with the second t-norm gives more robust performance than the first t-norm. Figure 8.25 shows that the power changes between each two successive operation cycle for the third t-norm is high compared to the first and the second t-norm.

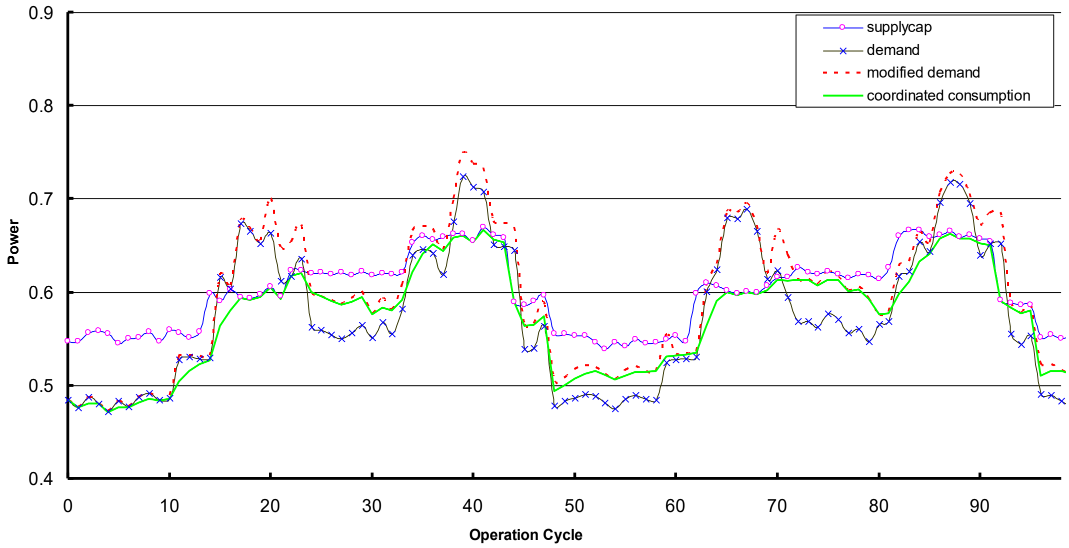


Figure 8.21: System performance with the first t-norm

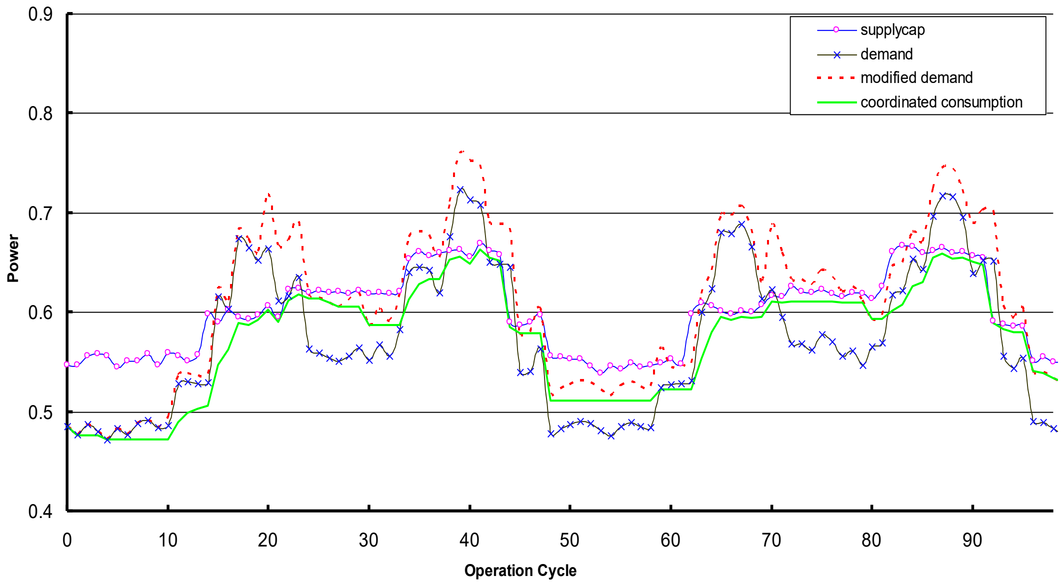


Figure 8.22: System performance with the second t-norm

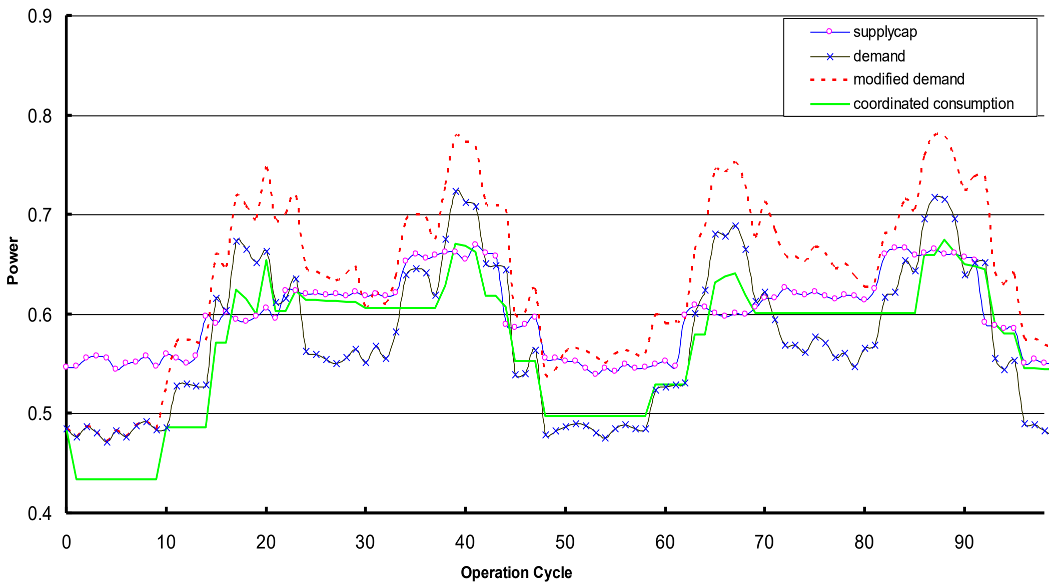


Figure 8.23: System performance with the third t-norm

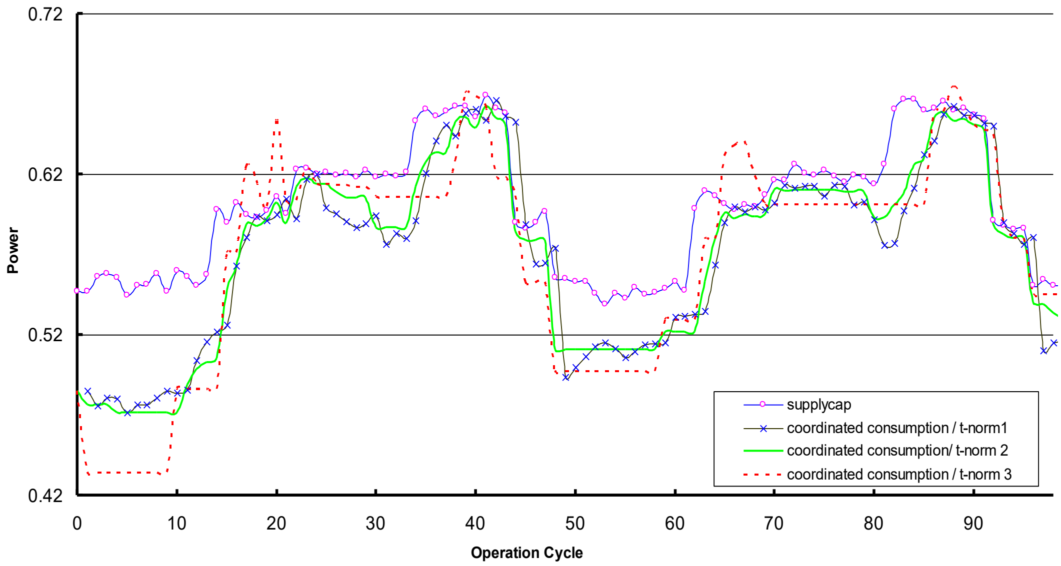


Figure 8.24: Coordinated consumption for the three t-norms

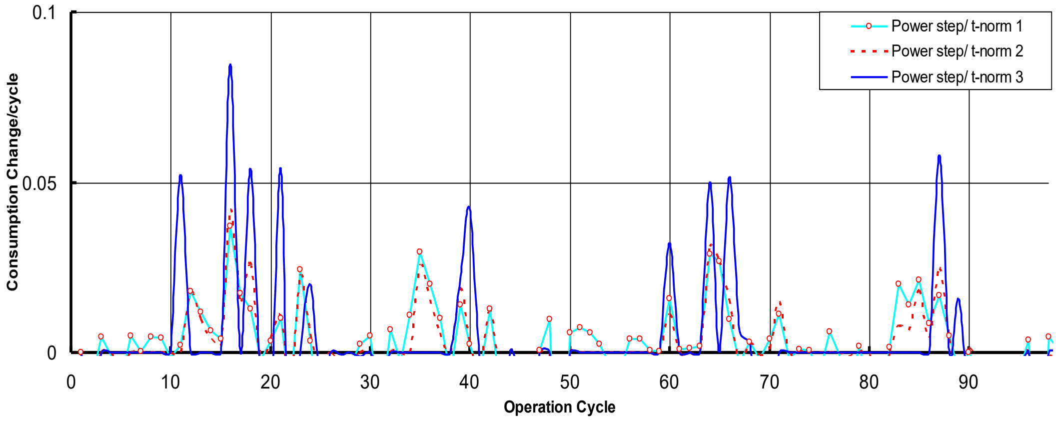


Figure 8.25: Power consumption changes for two successive operation cycles for the three t-norms

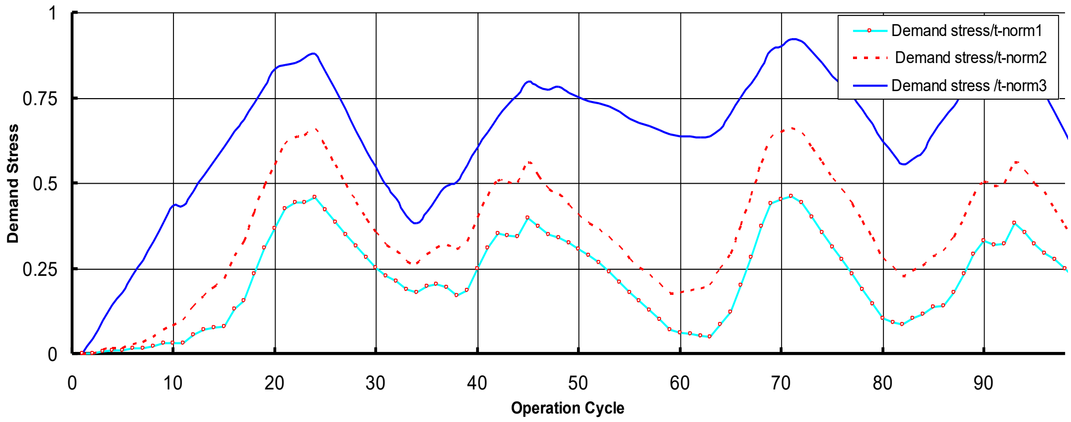


Figure 8.26: Stress within the system for the three t-norms

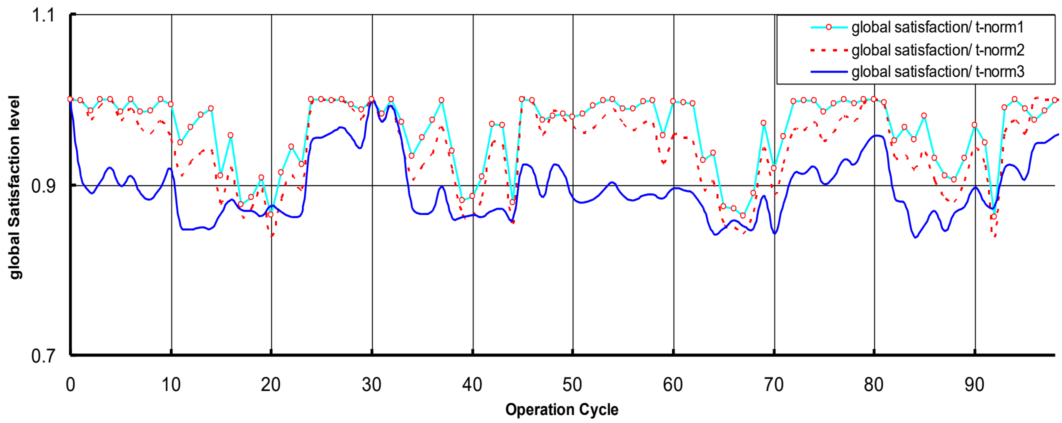


Figure 8.27: Global satisfaction level for the three t-norms

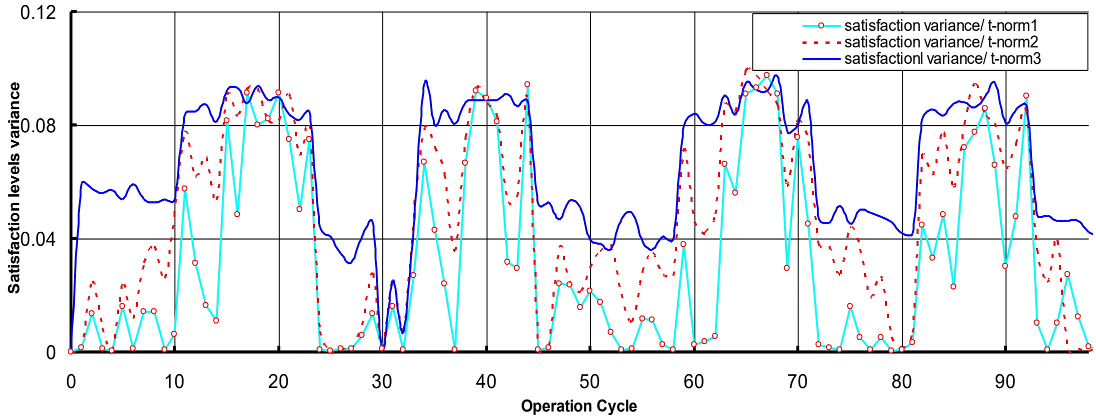


Figure 8.28: Satisfaction levels variance for the three t-norms

Figure 8.26 shows that the third t-norm affects the system stability where the demand stress within the system increase continuously which means the system goes to unstable state. On the other hand, for the first and the second t-norm demand stress within the system oscillates in certain range and decreases with time which means the system is stable. Figure 8.27and 8.28 show that the first t-norm gives the highest global satisfaction level and the lowest satisfaction level variance within the system, while the third t-norm is the worst one.

8.8 Conclusion

A quantum-inspired evolutionary algorithm for coordinating supply and demand matching for the future power networks is presented. The proposed system depends on multi-agents as control and information resources for the consumption and production units. The local coordinator agent and the local controller agents depend on quantum-inspired evolutionary algorithm for optimize the overall system performance. The simulation result shows that the proposed algorithm can be used to optimize energy consumption to match between supply and demand and to improve the overall system performance. The system is tested under different operation conditions. The first test illustrates the roles of the different objective functions for modifying the system performance. The second test shows that by appropriate setting for the objective functions smooth and robust performance can be obtained. The different performance parameters within the system have to be compromised. The third test shows that the evaluation method (t-norm) affect the total system performance and can cause system unstability.

8. Developing Controlling and Coordinating algorithm For Virtual Power Plant Operation

The proposed system can be used for monitoring a local power network (microgrid) consumption to define the general consumption behavior of the network. Thereby using the proposed system, the system performance parameter can be analyzed as a first step for improving the consumption performance for the power area under control. For example, depending on knowing the demand stress curve within the system, we can define the best time for using storage elements (charging or discharging). Depending on knowing the consumption changes between each successive operation cycle, times for the system performance degradation can be defined. Depending on knowing the global satisfaction level for local controller agents, the intervention in the user behavior can be minimized.

9 CONCLUSION AND FUTURE WORK

The future smart grid is predicted to depend on a large number of renewable energy resources that are directly connected to the low and medium voltage power network. For controlling demand and supply within future smart grid, information and communication systems will play the central role. To maintain stability and reliability within the smart grid, an effective load controlling mechanism is necessary. Matching between supply and demand aims to minimize the oscillation and the voltage flicker within power networks that depend on the renewable and distributed resources, which affect the general system stability as well as the generation and consumption units. We can control the device consumption to minimize the oscillation and the voltage flicker that affect the network as well as the generation and the consumption devices. Controlling the consumption devices improves the future energy system's performance that is depended on the intermittent and variable energy resources. This applies especially given the amount of devices used by consumers and their operation constraints. Furthermore, the ability to coordinate the consumption and generation of such devices depends on the type of the device unit under control. It also depends on the time of the day, the weather situation, and users' preferences. The aforementioned conveys two major challenges in coordinating supply and demand in the smart grid: First, at the local level (namely the users' level), operation constraints must be accounted for to meet the users' preferences and comforts. Second, at the global level, coordination and optimization solutions must take into consideration the supply capacity and the sustainability of the smart grid. Intelligent coordination approaches are an essential step toward integrating the renewable energy resources into the smart grid.

To address these challenges, we propose and develop in this thesis coordination and optimization algorithms to control and coordinate the operation among different entities within the smart grid. Our work belongs to the research efforts directed to developing optimization and coordination techniques for the future smart grid. Because of the distributed nature of the problem, multi-agent systems are proposed as the computing paradigm for development and performance of the proposed control and optimization algorithms. For controlling and coordinating the power-resource-controlling multi-agent actions, intelligent coordination and optimization techniques are required.

Exploiting quantum-computing principles to improve the performance of intelligent systems is one of the active research areas nowadays. For example, quantum-inspired evolution algorithms combine the evolution theory and the quantum information theory to improve the evolutionary algorithm's performance. It was proven that the performance of the quantum-inspired evolutionary algorithm outperforms classical and other quantum-inspired evolution algorithms.

In this work, two quantum-inspired algorithms for developing coordination and optimization algorithms for the future smart grid were presented. We proposed coordination algorithms that depend on integrating a quantum-inspired algorithms and a multi-agent system, which in turn controls the power consumption for matching supply and demand. The coordination problem was formulated as a multi-objective optimization problem solved by a quantum-inspired evolution algorithm. The system performance was tested. The test result showed that the proposed coordination system is able to coordinate the consumption of the active consumer networks under its control during the peak consumption times, depending on the local controller's (for consumption units) abilities to minimize or shift their consumption for a certain period. The test revealed that the system performance can be adapted according to the relation between supply and demand and according to the nature of supply (intermittent and variability).

9. Conclusion and Future Work

The thesis contributions may be summarized as follows:

- The second Chapter introduced a comprehensive review for the pervious developed algorithms for coordinating supply and demand for the smart grid. Additionally, comparison and analysis for the different algorithms were presented.
- The third chapter of the thesis introduced an introduction for the quantum and the quantum-inspired computing principles and features.
- Modeling of different consumption and generation units that are used in the thesis were presented in Chapter 4.
- A detail about the evolutionary optimization algorithm that is used for supply and demand matching within the smart power grid was presented in Chapter 5. Also, the evaluation of the multi-objective functions was presented.
- The simulation environment of the smart building energy management system was presented in Chapter 6. Monitoring and control functions that were used in the simulation environment were also presented.
- The seventh chapter represented the first proposed algorithm for supply and demand matching. In this chapter, we introduced a non-market-based approach for coordinate supply and demand within the smart Building energy management environment. The mathematical formulation of the optimization problem was presented. A number of objective functions was formulated for optimizing the different consumption devices' performance and the smart home energy management system performance. The developed algorithm compromised between device performance and system performance. This algorithm aimed to minimize the simultaneous "ON" time for consumption devices in home/building under control aiming to distribute the devices consumption and to minimize consumption peaks.
- The second proposed algorithm for supply and demand matching was presented in Chapter 8. In this chapter, we introduced a non-market-based approach for coordinating supply and demand within a virtual power plant (VPP) or microgird. VPP is a group of distributed energy resources and a group of consumer bundled together with a communication network that behaves like power plant. The mathematical formulation of the optimization problem was presented. The objective functions for satisfying the system optimal

performance requirements were formulated. The system performance was tested under different operation conditions.

Future work

The proposed algorithms in this thesis are considered as the first step into the direction of implementing a coordination system able to manipulate the real power networks optimization problem for the future smart grid, which depends on a large number of renewable energy resources directly connected to the low and medium-voltage power network.

Concerning future work, we plan to develop and test the proposed system for more realistic power optimization scenarios. In this regard, we aim to test the proposed system depending on more realistic models for the energy demand, more device types and with a larger number of local controller agents. We are planning to perform a comprehensive comparative study in all aspects of the proposed system versus similar existing studies. The other part of the future work will concern with integrating/exploiting other quantum-inspired algorithms for improving the optimization and coordination algorithms within smart grid.

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