MATHEMATICAL FRAMEWORK FOR DESIGNING ENERGY MATCHING AND TRADING WITHIN GREEN BUILDING NEIGHBOURHOOD SYSTEM

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Declaration

I declare that the research contained in this thesis was solely carried out by me. It has not been previously submitted to this or any other institute for the award of the degree or any other qualification.

Nomenclature

Acronym	
GB	Green building
GBNS	Green building neighbourhood system
NSO	Neighbourhood system operator
CGE	Centralized generation of electricity
DGE	decentralized generation of electricity
NDG	Non-dispachable distributed generation
DGU	Dispatchable generation unit
DER	Distributed energy resources
WT	Wind turbine
PV	Photovoltaic
MT	Micro-turbine
CHP	Combined heat and power
FC	Fuel-cell
ES	Energy storage
MCP	Market clearing price
DR	Demand respond
DSM	Demand side management
TOAT	Taguchi orthogonal array testing
PSO	Particle swarm optimization
BA	Bat algorithm
ACO	Ant colony optimization
GA	Genetic algorithm
DE	Differential evaluation
RLD	Responsive load demand
NRL	Non-responsive load

GBO	Gas boiler
TSP	Thermal solar panel
ESP	Electrical solar panel
HHW	Hot water heating
TD	Thermal dump
AEL	Aggregated electrical load
REF	Refrigerator
DW	Dish washer
EB	Electrical boiler
EHP	Electrical heat pump
ATL	Aggregated thermal load
FPC	Flat plate collector
SOC	State of charge
BIO	Biomass
EV	Electrical vehicle
Parameter	
P_t^A	Power produced by A at time t (kW)
$A \in \{PV, WT, FC, \cdots\}$	
v	Wind speed (m/s)
v_r	Wind nominal speed (m/s)
v_{ci} / v_{co}	Cut-in/out speed (m/s)
A_c	Area of the array surface (m^2)
η	Efficiency of the PV system (%)
I_t^β	The amount of solar variation over surface with β (kWm^2)
$\tilde{v}_t$	the forecasted wind speed at the height of the measurement (m/s)

H_{hub}	the hub height and the height (m)
H_{meas}	height of the measurement (m)
$E_{(t,s)}^{A,th}$	Thermal produced by A at time t (kWh) $A \in (WT, PV, FPC, BIO, GRID)$
$E_{(t,s)}^{A,ele}$	Thermal produced by A at time t (kWh) $A \in (WT, PV, FPC, BIO, GRID)$
$E_{(t,s)}^{D,ele}$	Electrical consumed at time t (kW)
$E_{(t,s)}^{D,wp}$	Electrical power generated by wp at time t (kW)
Z	Surface roughness length (%)
S^{pv}	solar cell array area (m^2)
η^{pv}	Module reference efficiency (%)
p^f	Packing factor (%)
$G_{(t,s)}$	forecasted hourly irradiation
λ^{SSP}	thermal energy extracted from the water (kWh)
η^{FPC}	Efficiency of the solar (%)
A^{FPC}	area and the forecasted hourly irradiation (m^2)
Δt	energy management time step (t)
$E_{(t,s)}^{BIO}$	thermal energy extracted from the BIO (kWh)
$R_{(t,e)}^{k,i}$	electrical revenue (£)
$R_{(t,e)}^{ES^-,i}$	Energy storage revenue from electrical discharge (£)
$R_{(t,h)}^{j,i}$	Thermal revenue (£)
$R_{(t,h)}^{TES^-,i}$	Thermal energy storage revenue from thermal discharge (£)
$C_{(t,h)}^{j,i}$	thermal power cost (£)
$C_{(t,e)}^{k,i}$	electrical power cost (£)
$R_{(t,e)}^{GR-,i}$	revenue from selling power (£)
$C_{(t,e)}^{GR+,i}$	Cost of buying power (£)
$C_{(t,h)}^{p,i}$	Thermal cost related to consumer (£)
$C_{(t,e)}^{m,i}$	Electrical cost related to consumer (£)
$P_{(t,e)}^{k,i}$	Power generated by electrical generators (kW)
$P_{(t,e)}^{ES^-,i}$	Power generated by energy storage (kW)
$P_{(t,e)}^{GR^-,i}$	Power generated by grid (kW)
$P_{(t,e)}^{m,i}$	Power consumed by consumer (kW)
$P_{(t,e)}^{GR^+,i}$	Power consumed by Grid (kW)

$P_{(t,h)}^{j,i}$	Thermal generated by generators (kW)
$P_{(t,h)}^{TES^-,i}$	Thermal generated by thermal energy storage (kW)
$P_{(t,h)}^{P,i}$	Thermal consumed by consumer (kW)
$P_{(t,h)}^{TES^+,i}$	Thermal consumed by thermal energy storage (kW)
λ^{SBP}	System buy price (£/kWh)
λ^{SSP}	System sell price (£/kWh)
$\pi_{(t,e)}^{a+,i}$	Offer Price for buying power (£/kWh) $a \in (TES, ES, EV, ESP, CHP, GBO, TSP, DW, HHW, REF)$
$\pi_{(t,e)}^{a-,i}$	Offer Price for selling power (£/kWh) $a \in (TES, ES, EV, ESP, CHP, GBO, TSP, DW, HHW, REF)$
$P_{(t,e)}^{CHP}$	Power produced by combined heat and power (kW)
FU_t^{CHP},i	Fuel consumption by combined heat and power
$\zeta_h^{CHP,i}$	Thermal efficiency for combined heat and power (%)
$\zeta_{e2}^{CHP,i}$	Power Efficiency 2 for combined heat and power (%)
$\zeta_{e1}^{CHP,i}$	Power Efficiency 1 for combined heat and power (%)
$FU_{(t)}^{GBO,i}$	Fuel consumption rate by gas boiler (m^3)
$P_{(t,e)}^{TCP,i}$	Power consumed by total consumption power (kw)
$P_{(t,e)}^{TGP,i}$	Power produced by total generation power (kw)
$P_{(t,h)}^{TD,i}$	Thermal power produced by thermal dump (kw)
$T_{(t,e)}^{REF,i}$	Temperature of hot heating water ($^{\circ}C$)
$T^{RED,i}$	Reduced temperature ($^{\circ}C$)
$T_{(t,h)}^{HHW,i}$	Temperature of hot heating water ($^{\circ}C$)
$T^{INC,i}$	Increased temperature ($^{\circ}C$)

Abstract

Nowadays, energy efficiency, energy matching and trading, power production based on renewable energy resources, improving reliability, increasing power quality and other concepts are providing the most important topics in the power systems analysis especially in green building in the neighbourhood systems (GBNS). To do so, the need to obtain the optimal and economical dispatch of energy matching and trading should be expressed at the same time. Although, there are some solutions in literature but there is still a lack of mathematical framework for energy matching and trading in GBNS. In this dissertation, a mathematical framework is developed with the aim of supporting an optimal energy matching and trading within a GBNS. This aim will be achieved through several optimization algorithms based on heuristic and realistic optimization techniques. The appearance of new methods based on optimization algorithms and the challenges of managing a system contain different type of energy resources was also replicating the challenges encountered in this thesis. As a result, these methods are needed to be applied in such a way to achieve maximum efficiency, enhance the economic dispatch as well as to provide the best performance in GBNS. In order to validate the proposed framework, several case studies are simulated in this thesis and optimized based on various optimization algorithms. The better performances of the proposed algorithms are shown in comparison with the realistic optimization algorithms, and its effectiveness is validated over several GBs. The obtained results show convergence speed increase and the remarkable improvement of efficiency and accuracy under different condition. The obtained results clearly show that the proposed framework is effective in achieving optimal dispatch of generation resources in systems with multiple GBs and minimizing the market clearing price for the consumers and providing the better utilization of renewable energy sources.

Chapter 1- Introduction

1.1.Motivation

Energy consumption in the building sector has been continuously increasing over the last decade, up to the point where energy efficiency in this sector has become a main concern for states, producers and customers. Furthermore, the building stock in the world expends nearly 45% of all energy utilised and emits one fourth of the all greenhouse gases' emissions. Therefore, green building neighbourhood systems (GBNS) (in both isolated and grid-connected operating modes) have attracted increasing attention particularly with regard to enhancing performance in terms of energy-saving, comfort thermal energy (energy that allows thermal comfort) and being environment- friendly. A GBNS can be considered as a collection of different green buildings (GBs) which jointly handle local electrical/thermal load demands (Fang et al., 2015). Proper control and trading of energy between GBs is essential for stability and for the economically efficient operation of these systems (Truong, Dodoo, and Gustavsson 2014).

Much research has been carried out to address different aspects in GBs relating to energy efficiency. For example, in relation to energy matching in green buildings, researchers have presented a comprehensive framework for investigating the influence of different types of consumers and producers (M. Marzband, Javadi, et al. 2018). Furthermore, research reported on by (M. Marzband, Parhizi, et al. 2016) concentrated on the energy matching problems of individual GBs. However, little research has been conducted to explore energy matching and energy trading among multiple GBs with different owners who may have different objectives such as reduction of cost (M. Marzband, Ghazimirsaeid, et al. 2017), maximisation of profits (M. Marzband, Javadi, et al. 2018), reduction of CO2 emissions (Ramchurn et al. 2011) etc. Furthermore, any consideration of uncertainties in consumption and production resources based on renewable resources is still not well explored. In addition, the current approaches do not propose a general framework for analysing and modelling the producers and do not investigate consumers and procumers' behaviour within a deregulated competitive electricity structure for energy matching and trading at the residential distribution level. They fall short in investigating the influence of distributed energy resources on the residential diffusion systems from an economic point of view and in implementing the appropriate conditions with full consumers' and prosumers' participation through probabilistic methodology in the future (Fotuhi-Firuzabad et al. 2014). Moreover, current research does not implement the operation of demand response combined with energy storage in a neighbourhood system efficiently (Fouladfar, Loni, et al. 2019a). To overcome these shortcomings, the aim of this research is to develop a mathematical framework based on optimization techniques that can explore energy matching and energy trading between green buildings to improve the energy efficiency of existing GBs in neighbourhood systems.

1.2. Aims, objectives and research questions

The aim of this research is to consider a mathematical framework to support optimal energy matching and energy trading within a green building neighbourhood system (GBNS). This aim will be achieved through the following objectives:

1- To establish mathematical models to represent the behaviour of various agents such as producers, consumers and prosumers which is necessary for modelling energy matching and energy trading;
2- To implement a mathematical framework for energy matching within a single building that can optimize the use of renewable energy, maximize profit, reduce cost and minimize the mismatch power between generation and consumption;
3- To implement a mathematical framework that can facilitate energy matching and energy trading within a green building neighbourhood environment;
4- To extend the above mathematical framework to support different ownership structures (single and multi-ownership) which will demand different optimization objectives;
5- To demonstrate the validity of the mathematical framework through case studies according to their associated objective function.

The research questions which have been addressed in this thesis are as follows:

1- How can the behaviour of producers, consumers and prosumers be modelled to support energy matching and trading in a neighbourhood system?
2- How can one construct a mathematical framework to support energy matching in a single building?
3- How can one construct a mathematical framework to support energy trading within a green building neighbourhood system?
4- How can different objective functions be optimized, arising due to multi-ownership of GBNS?

1.3. Research scope

A GB including dispatchable and non-dispatchable distributed energy resources, energy storage assets and a response load demand has been modelled in this study. It is assumed that a GB can either supply its local loads independently or in connection with other GBNS and the upstream grid (or retailers). Furthermore, the interoperability of GBs is considered in the proposed energy matching and trading structure where the excess energy in one GB can be stored or dispatched to another GB. Few studies have explored the economic incentive for participants to become involved in a GB. Therefore, this thesis aims to address this gap by involving consumer engagement and interaction.

1.4. The research's contribution

The contribution in this thesis is based on a scalable and comprehensive energy matching and trading within the realm of the consumer, producer and prosumer environment**.** Three issues are covered in this thesis: firstly, an impartial economic clearing scheme (market clearing price) for participants in GBs is proposed. Secondly, an electrical and thermal shift price and unit capacity selection are proposed with regard to customer energy demands. In addition, energy matching for a green building neighbourhood system is achieved, whereby producers, consumers and procumers try to minimize their total energy cost and reduce the peak demand from the grid to maximize the profit. Thirdly, the issue concerning the distribution of cost among GBNS is considered. Within the GBNS each GB competes with other neighbour to minimize the price based on the market clearing price. The contributions of this thesis can be thus be summarized as follows:

1. A comprehensive mathematical framework that is flexible and extendible in order to modify itself to other type of GBs as well as supporting the plug-and-play operation of the distributed energy resources and storage assets;
2. An optimization technique for future distributed energy forecasts;
3. A mathematical approach for novel optimal energy matching and energy trading operations for a day-ahead to minimize the total cost of operation;
4. A responsive load demand programming, integrated with energy storage, is developed under the existence of renewable energy generated power to indicate its ability for distributed energy resource (DER) production in order to decrease the market clearing price.
5. Presentation of a stochastic bidding strategy for several green buildings in order to participate in the local energy market to apply the uncertainties of load demand and available production power of non-dispatchable resources.

1.5.Structure of the Thesis

This thesis is divided into six chapters. Chapter 1 presents the research motivation, aim and objectives. It also provided the scope and methodologies utilized in this research.

Chapter 2 describes the background and gives the literature review that presents an overview of previous production studies and particular theories. The literature review will provide information and background on the studies that people have undertaken in the past.

Chapter 3 will investigate the proposed methodology. This chapter surveys the techniques and theories relevant to this research and looks at how these techniques can present the guidelines for this research. There are seven guideline and the following chapters are structured based on these guidelines. In guideline 1 which is ‘design as an artefact’ (chapter 4), the mathematical model of green building in a neighbourhood system is presented for energy matching and trading. In guideline 2 which is ‘problem relevance’ (chapter 1), the global challenge of reducing environmental pollution is presented. In guideline 3 which is ‘design evaluation’ (chapter 5), the proposed mathematical framework is evaluated. In guideline 4 which is ‘research contribution’ (chapter 1), the contribution of this thesis is itemized. In guideline 5 which is ‘research rigor’ (chapter 2), the obtained results from different methods are compared with each other. In guideline 6 which is ‘design as a search process’ (chapter 4), the different stages of the project are presented. Each stage is evaluated in chapter 4. In guideline 7 which is ‘communication of research’ (the published papers), some papers are presented and my papers have already been published in the top level of journal.

Chapter 4 presents the design of the artefact. The main objective is to provide a framework which can effectively support and facilitate green building in a neighbourhood system.

Chapter 5 presents the problem formulation which covers neighbourhood system operator (NSO) and the central NSO mathematical implementation. The proposed real time operational architecture for both the simulation and experimental evaluations is presented in Chapter 3 which is divided into different subsections to explain about the proposed algorithms. The application of this architecture to test the systems is demonstrated in chapter 5. Chapter 5 presents the simulation and experimental results and discusses them.

Finally, the thesis is concluded in chapter 6 this chapter summarizes the whole of the PhD research work. It starts with a summary of the research and this is followed an assessment of the research, its contribution & impact, and possible future work.

1.6.Summary

This chapter has illustrated the scope of this research. It presents the motivation, the aim and the objectives in this thesis. Moreover, it presents the structure of the thesis. The next chapter provides the background and presents a literature review of the topic. The main definitions are presented in this chapter 2. In addition, chapter 2 also presents the different type of optimization techniques.

Chapter 2- Background and Literature Review

2.1.Introduction

The main objective of this chapter is to introduce the components of green buildings, and the different types of distributed energy resources in neighbourhood systems as well as presenting the various optimization techniques which can be developed for such applications (Sharma et al. 2016). This chapter presents a summary of several theory and concept frameworks that are necessary to look at in order to understand and support energy matching and trading in green building neighbourhood system (P Palensky and Dietrich 2011). In addition, this chapter describes the general concepts within centralized electricity generation and decentralized energy provision. It also includes an overview of, and explains, the key concepts relevant to this study. Firstly, it presents distributed energy resources (DER) including fuel cells, photovoltaics, wind turbine, solar thermal energy, biomass and energy storage. Secondly, it presents definitions for consumers, green buildings, neighbourhood systems, and market clearing price, considering single ownership and multi-ownership. Furthermore, a literature review of energy matching and the concept of energy trading between GBs in the neighbourhood system is presented. In addition, this chapter concentrates on demand side management and on demand response, including the drivers and benefits, shiftable load scheduling methods and peak saving techniques (Guan, Xu, and Jia 2010). An awareness of all these issues is important for both consumers and the owners of green buildings. From a consumer’s point of view, they can participate in demand side management to decrease the market clearing price. From the point of view of an owner of green buildings, they can maximize their own profit. Demand side management techniques and demand control techniques are also presented in this chapter. In the following sections in this chapter there is also an overview of demand side management, demand response and the limitations in these two factors. With regard to this, the amount of demand response has been estimated based on the mismatched power between generation and consumption in order to obtain the market clearing price as accurately as possible. The uncertainty of generation and demand are also taken into account using appropriate statistical models based on Taguchi and Monte-Carlo techniques. The main reason for choosing Taguchi is that the examining scenarios can consider a fair result with a low number of results in the uncertain operating area (Asghar, Raman, and Daud 2014). It can provide much shorter examining scenarios and leads to reducing computing time that reduces the testing burden increasingly. Greatly, it is worth to mention that it is necessary for modelling energy matching and trading by taking uncertainty into account. Subsequently, a comprehensive simulation study based on optimization technique is then carried out to determine the effectiveness of the proposed method to mitigate the market clearing price (MCP). Finally, last section of this chapter focuses on optimization methods and the literature concerning these techniques. Different types of optimization techniques have been developed in this study to compare the obtained results with each other. As will be shown in this study, the optimal operation of consumers and the owner of green buildings will be calculated by using these optimization techniques.

2.2.Centralized and decentralized generation of electricity

Electric energy generation can be totally structured and operated as centralized generation of electricity (CGE) or decentralized generation of electricity (DGE) frameworks (Daki et al. 2017). In CGE frameworks, as shown in Figure 1, the bulk of electric energy production by central power plants goes to industry and households (Worthmann et al. 2015). Most of central power plants use various energy resources such as large fossil-fired steam turbine generating plants, coal boilers, or nuclear boilers (Worthmann et al. 2015). These enormous types of power plant require access to the deployment of large-scale infrastructures. CGE based power plants are susceptible to exhibiting pulsating instability under unwanted events, and are, therefore, susceptible to attacks (Somani and Tesfatsion, 2008). Due to these limitations, researchers and policy-makers have given more attention to using renewable energy resource in order to provide better efficiency and lower environmental impact as well as higher stability (H. Li, Member, and Tesfatsion, 2009).

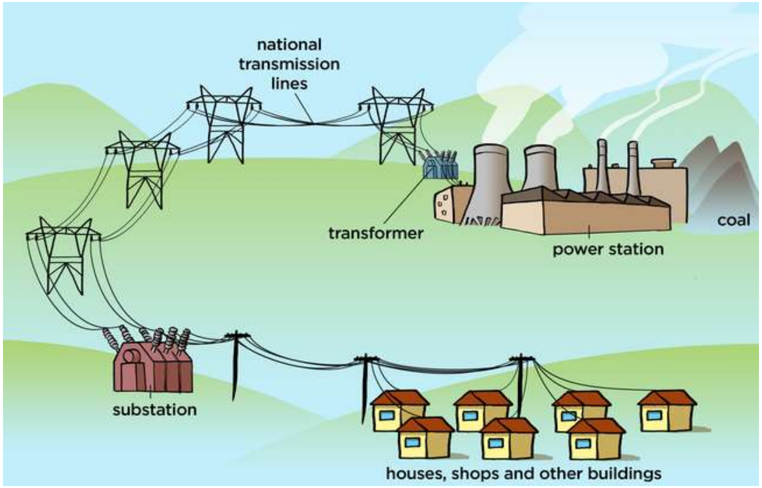


Figure 1 Centralized generation of electricity framework (Tavakoli, Shokridehaki, Funsho Akorede, et al. 2018)

The second type of electric energy generation is based on DGE frameworks. As shown in Figure 2, energy generation units in this kind of framework are located close to energy consumers rather than in power plants based on CGE and the produced power can be dispatched through to the national grid if there is an excess power (Alizadeh and Jadid, 2014). In addition, this local generation within the CGE framework reduces transmission losses and has lower carbon emissions (Xiang, Liu, and Liu, 2015). The security of the power supply can be nationally increased because the generation units are closer to the customers and the control and management of these generation units are easier when compared to the CGE framework (Zoka et al., 2007). The DGE framework can offer more competitive prices than the CGE framework (Mousa Marzband et al. 2014; Worthmann et al. 2015). Although the initial installation costs are higher due to using non-dispatchable distributed generation (NDG), a special DGE tariff can provide more stable pricing (Basu et al., 2012; Sousa et al., 2012). For consumers, DGE is a cost effective route to achieving lower carbon targets (Zhou, Zhao, and Wang, 2011). Several studies were conducted to study the main drawbacks of CGE and to promote the use of DGE as a primary source of electricity (Duvvuru and Swarup 2011). The main reasons for utilising a DGE, as listed in the literature, are summarized below (Guerrero et al., 2013).

1- Transmission bottlenecks: a CGE framework will require an increasingly heavy usage of communication systems, especially as the phasor measurement units are deployed. Expensive, dedicated communication systems are needed.

2- Power losses: a proportion of electricity is converted to heat and losses when it flows into transmission and distribution lines.

The advantages of a DGE framework can be summarized as follows:

1- Reduction of energy consumption.
2- Reduction in the amount of energy waste.
3- Minimization of energy production pollution.
4- Minimization of the life-cycle costs of renewable energy resources.

Because of these advantages, this thesis has chosen to utilized the DGE framework (Vasiljevska, Peças Lopes, and Matos, 2013).

Figure 2 decentralized generation of electricity framework (Che, Khodayar, and Shahidehpour 2014)

2.3.Distributed energy resources

Distributed energy resources (DER) and energy storage (ES) technologies are respectively small scale renewable/non-renewable energy resources and store energy as needed (Pantoja and Quijano, 2011). ES can be changed/discharged from/to an upstream grid/residential size electricity supply (Vasiljevska, Peças Lopes, and Matos, 2012). The world is dramatically switching from large centralized power plants to small-scale distributed generation ones. The introduction of in CO2 emission reduction programs has played an important role in increasing small-scale DER use in recent years (Mohd et al., 2010). For example, there are many types of motivation programs for the installation of small-scale solar power plants all over Europe. As a result, the purchase prices of the energy produced by these plants sometimes reaches as much as four times the normal retail price of electricity. Generally, DER can be categorized into renewable (non-dispatchable), non-renewable (dispatchable) sources and energy storage as shown in Figure 3 (Tavakoli, Shokridehaki, Funsho Akorede, et al. 2018). Renewable energy resources exploit natural resources (e.g. solar power and wind) and the energy produced by such resources is termed as non-dispatchable since it cannot be generated on request but depends on the availability of natural energy sources at a given time (Marzband et al., 2015). The energy generators that are based on renewable energy sources are, therefore, referred to as non-dispatchable generation units (e.g. wind turbine (WT), photovoltaics (PV)) (Lee, 2014). In contrast, non-renewable energy sources that use fuel (e.g. coal, gas and oil) are fully dispatchable on request (Lee, 2014). Diesel generators and micro-turbines (MT) can be included in this category. There are many advantages to renewable energy resources. Firstly, they can alleviate total energy flow through transmission and distribution networks and, therefore, can reduce problematic and associated wastes and the electricity price (Marzband et al., 2015). Secondly, technologies like CHP (combined heat and power) made locally increase the usage of large amounts of generated thermal/electricity power which can be utilized for space and water heating (Zhang and Li, 2010). Ultimately, DER creates islanding which is a significant issue in regard to the reliability, safety and security of a system (Carvalho, Pedroso and Saraiva, 2015; Soroudi et al., 2011; Yu, Chung and Wong, 2011). In this content, energy storage (ES) is used to simply store excess energy generated during time periods of low demand which can then be used during the time periods of high demand (Mohammadi-Ivatloo et al., 2013; Soroudi et al., 2011; Yu, Chung and Wong, 2011). Furthermore, ES and electrical vehicles (EV) are considered as prosumers in this study which can be operated as both producers and consumers. DER devices can be widely utilized within green buildings (Soroudi and Afrasiab, 2012). In summary, DER refers to advanced renewable/non-renewable power generation resources that can be directly/indirectly connected to green buildings (M. Marzband, Ardeshiri, et al. 2017; Tavakoli, Shokridehaki, Marzband, et al. 2018). As shown in Figure 4, DER includes both generation units such as photovoltaics, micro-turbines, fuel cells, etc., and energy storage technologies like superconducting magnetic energy storage, flywheels and batteries. A further explanation of these technologies and their potential applications is presented in the following sections. (M. Marzband et al. 2011; Pourakbari-Kasmaei et al. 2019; J. Valinejad et al. 2017) illustrates the technologies that can support emerging DER technologies. DER can be driven by different types of technologies such as combustion engines, fuel cells, micro-turbines, photovoltaic systems, wind turbines, geothermal systems, etc. DER technologies can take place on two levels: the local level (inside green buildings) and the end-point level (Javadi et al. 2018; Jaber Valinejad, Marzband, et al. 2018). Local level power generation plants often include renewable energy technologies that are site specific, such as wind turbines, geothermal energy production, solar systems (photovoltaic and combustion), and some hydro-thermal plants (Moafi et al. 2016; Jaber Valinejad, Barforoshi, et al. 2018). At the end-point level, the individual energy consumer can apply many of these same technologies with similar effects. One example of an end-point level technology is the modular internal combustion engine (M Marzband and Sumper 2014; Mehrasa et al. 2019; Mehrasa, Pouresmaeil, Pournazarian, et al. 2018; Rodrigues et al. 2018).

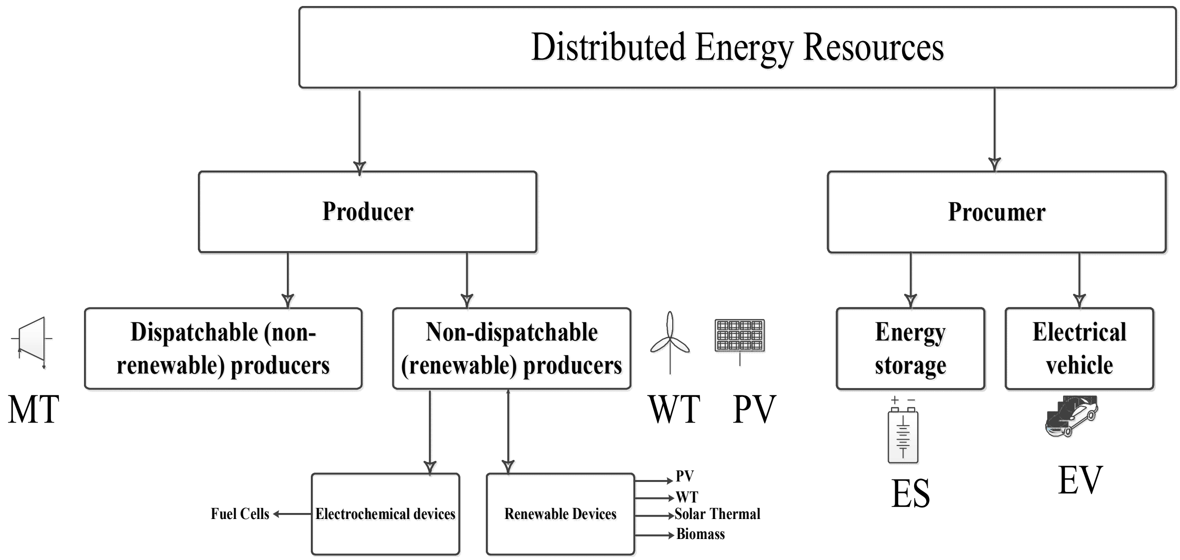


Figure 3 presentation of the parameters of DER (Mousa Marzband et al. 2014)

2.3.1. Fuel cells (FCs)

Fuel cells are able to directly convert chemical energy into electrical and thermal energy. This process could be likened to energy storage (ES) technology, since they both use a series of electrochemical processes created by a conversion of hydrogen and oxygen. ES and fuel cells are similar and consist of two electrodes which are separated by an electrolyte. Fuel cells can be totally characterized by the type of material of the electrolyte used. Presently five major types of fuel cells in different stages of commercial availability exist (Sharaf and Orhan 2014). They are the alkaline fuel cell, the proton exchange membrane fuel cell, the solid oxide fuel cell, the molten carbonate fuel cell, and the phosphoric acid fuel cell (though alkaline fuel cell is not suitable for DER application). Physically a fuel cell plant consists of three major parts, namely (1) a fuel processor that removes fuel impurities and may increase the concentration of hydrogen in the fuel; (2) a power section (the fuel cell itself) which consists of a set of stacks containing catalytic electrodes, generating the electricity, and (3) a power conditioner that converts the direct current produced in the power section into alternating current to be connected to the grid (Méndez et al., 2006). The advantages of this technology are high efficiency in the controlling of the load demand, reduction of emissions and noiselessness due to the non-existence of moving parts, and a free adjustable ratio (50 kW–3MW) between electric and heat generation. The energy savings result from the high conversion efficiency, which is typically 40% or higher, depending on the type of fuel cell.

2.3.2. Photovoltaic systems (PVs)

Solar energy has been directly converted to electricity technologically since the 1940s by using photovoltaic systems (PVs). PVs are generally known as solar panels. PV solar panels include divided multiple cells, connected to each other in both series and parallel, that transform light radiation into power. PVs can be operated as stand-alone or can be connected to the grid. The electricity generation of PVs is directly proportional to the surface area of the cells and the cell sizes. Thus, cells should be relatively large. Although, the energy efficiency of a PV system may be relatively low, nonetheless, it is better to utilize these renewable energy systems (Aryanpur et al. 2019; Ghasemi et al. 2019; Behnam Mohammadi-Ivatloo et al. 2013).

2.3.3. Wind turbines

The conversion of wind energy to electrical power is possible by the utilization of wind turbines. It has been shown that wind speeds between the 4–25m/s (meter/second) range can generate enough power to be worthwhile (Shotorbani et al. 2019; Jaber Valinejad, Marzband, Busawon, et al. 2019). The sizes of wind turbines have been growing steadily over recent decades and the largest units of wind turbines are now about 4MW (megawatt) whereas in 1980 they were less than 30kW (kilowatt) (Jaber Valinejad, Marzband, Barforoshi, et al. 2019). Wind turbines are integrated with a variable speed system. The power quality depends on the design of the protection system. A direct connection of several generators at the same time can lead to increased flicker levels and a relatively big value of active power. At the moment, wind power is recognized as the most important power among all the renewable energy resources (Amin et al. 2019; Shotorbani et al. 2019).

2.3.4. Solar thermal

Solar thermal technology exploits solar energy to generate thermal energy. To achieve this, a concentrating solar power system produces solar power by using dish systems that are made of glossy material which are used to concentrate the solar radiation onto a central container to generate temperatures in excess of 1000°C. Steam can be generated from these high temperatures in order to run either chemical processes or electric turbine generators (Ghasemi et al. 2019). Solar thermal energy has been categorized as low-, medium-, or high-temperature collectors by the USA Energy Information Administration. Low temperature collectors have typically been used to heat swimming pools. Medium-temperature collectors that are flat plates have been used to create hot water for buildings and commercial use, whereas high-temperature collectors focus on solar for using mirrors or lenses. These are typically used for electric power generation. Solar thermal technology has the potential to supply over 85% of grid power, and different solutions has been proposed to mitigate environmental problems (Ghasemi et al. 2019).

2.3.5. Micro-turbines (MTs)

One of advantages of Micro-turbines (MTs) in comparison with other DER technologies is that they can start quickly. As a result, they can be suitable for integrating heat and power usage. They are one of the most important technologies used to power electric vehicles. MT systems are basically limited to a range covering 40 to 350kW (Pourakbari-Kasmaei et al. 2019), while conventional gas turbines are limited to a range covering 450kW to more than 250MW (Moafi et al. 2016). Generally, MT efficiencies are between 30% and 40%, particularly with an 85% effective recuperator (Borbely et al., 2006) but they can achieve efficiencies of above 80% in a combined heat and power (CHP) application. MTs can be operated in the same method as that for conventional gas turbines (Mirzaei, Yazdankhah, et al. 2019). MT systems show advantages within reciprocating engine generators, such as higher power density, with regard to footprint and weight, especially in terms of low emissions. In addition, MTs have the advantage of having the majority of their heat loss included within their relatively high-temperature exhaust, while reciprocating engines' waste heat will be between its exhaust and cooling system (Amin et al. 2019). However, reciprocating engine generators are quicker as regards changes in output power requirement and are generally more efficient, although the efficiency of micro-turbines is developing. Additionally, MT lose more efficiency at low power levels than reciprocating engines (Amin et al. 2019)

2.3.6. Biomass

Biomass is credited with being one of the most significant energy sources among renewable energies in the future. Biomass is fundamental material created from plants and animals. It is considered as a renewable energy source because more plants and crops can always be grown, and it utilizes waste from them. According to the US International Energy Agency, 15% of the world's energy, especially heat and power, is presently supplied from biomass. Some instance of biomass fuels are wood, crops, manure and some rubbish. Generally, biomass is considered as a valuable element that can meet the global energy demand in the world. When biomass is burnt, chemical energy is produced as heat that is used to release steam which can, in turn, be used to either drive a turbine for the generation of electricity or to supply heat to residences and factories. Biomass combustion release burning the biomass in air at a flow rate of 5–6 kg of air per kg of biomass. This procedure on a small-scale can be applied for thermal applications, whereas a large-scale combustion plant with a steam cycle is essential for power generation (Kirubakaran et al., 2009). Biomass can generate fuel for cars that is significantly cleaner than oil.

2.3.7. Energy storage technologies

Electric energy generation needs the transformation of energy into electricity. Although, transformation processes such as solar, wind, and hydro depends on a fluctuating fuel source, in these situations, the power system utilizes some energy storage capability to overcome the variation in the energy supply. In other cases, energy storage can store excess energy production; for instance, when energy production produces more excess electricity during the night. Energy storage usually happens through a transformation process from electrical energy form to another form of energy. There are many options for large-scale energy storage including battery energy storage, flywheels, compressed air energy storage, and pumped storage (S. S. Ghazimirsaeid, Fernando, and Marzband 2016).The main function of the battery energy storage system is to supply a spinning reserve in the event of a power plant or conduction line equipment failure. For these systems, the electricity can be stored in rechargeable batteries in the form of chemical energy. To provide the energy storage requirements, the battery must be of high energy density, high power, high charge efficiency, good cycling ability, long life and have a low initial cost. The contents of available utility-scaled battery storage systems are created of several numbers of lead-acid cells, utilizing technology such as that found in vehicle batteries (Mirzaei, Yazdankhah, et al. 2019; Tavakoli, Shokridehaki, Funsho Akorede, et al. 2018). Additionally, other applications where batteries are being investigated for utility power systems comprise load levelling, and frequency. Batteries supply a fast respond time; response to load changes happen in about 25ms (millisecond). Furthermore, they are noiseless and non-polluting and are ideal for installation in suburban areas, close to load centers. The following technologies have been used and/or are proposed for energy storage applications (Mohammad Amin Mirzaei, Ahmad Sadeghi Yazdankhah, Behnam Mohammadi-Ivatloo, Mousa Marzband, Miadreza Shafie-khah 2019): lead-acid batteries, nickel-metal hybrid batteries, lithium ion batteries, and lithium polymer batteries.

2.3.8. Consumers

Another concept that needs to be defined when researching into green building is ‘consumers’. Consumers can be categorized into two types of appliances, namely responsive and non-responsive, based on the flexibility of the demand (Soroudi, 2012; Soroudi et al., 2011; Tina, Gagliano and Raiti, 2006). For example, energy for lighting, heating, computers and musical systems needs to be utilized instantly on request and, therefore, the energy demand for such utilities are considered as a non-responsive load (NRL) (Houman Jamshidi Monfared, Ahmad Ghasemi, Abdolah Loni 2019; Nastaran Gholizadeh, Gevork B Gharehpetian, M Abedi, Hamed Nafisi 2019; Pourakbari-Kasmaei et al. 2019). However, a user has the flexibility of choosing to operate home appliances (such as dish washers and washing machines) during low peak periods and, therefore, such energy demands can be considered as responsive load demands (RLD) (Houman Jamshidi Monfared, Ahmad Ghasemi, Abdolah Loni 2019). RLD is fundamentally obtained through varying the load; as a result the power consumed matches the power generated. Therefore, the mismatch power will be mitigated under this condition. The common method to maintain a power balance between load demand and power generation is to change the amount of generation to meet the load demand (i.e., the load following). But an advanced and new methodology is to use RLD for matching the load demand with the available power generation (i.e., generation following). The results of past studies are shown that RLDs (e.g. dish washing and refrigerators) can be controlled to smooth out the load demand curve while maintaining energy matching (Yu, Chung and Wong, 2011). Dish washing and refrigerators make up 11% of residential loads and can increase up to 30% during on-peak hours (Chatthaworn and Chaitusaney, 2014; Zeng, Bo ; Zhang, Jianhua ; Zhang, Yuying ; Yang, Xu ; Dong, Jun ; Liu, 2014). Therefore, the control of aggregated dish washing and refrigerators can be a viable option for RLD. DER devices and consumers are main constituents of green buildings. Green buildings will be explained in further detail in the following section.

2.4. Green buildings

A green building (GB) is a typical integrated energy and communication system consisting of interconnected loads either RLD or NRL and DER (including both dispatchable and non-dispatchable) (Ameena Saad Al-Sumaiti, Magdy Salama, Mohamed El-Moursi, Tareefa S. Alsumaiti 2019; Mirzaei, Yazdankhah, et al. 2019; Mohammad Amin Mirzaei, Ahmad Sadeghi Yazdankhah, Behnam Mohammadi-Ivatloo, Mousa Marzband, Miadreza Shafie-khah 2019). A typical configuration of a GB is shown in Figure 4. Green buildings mainly operate in standalone (or isolated) mode or in parallel with the grid (or in grid connected mode) in cases of emergency (M. Marzband, Javadi, et al. 2018). The ability to be a multiple energy carrier and the ability to isolate green buildings from a upstream grid provides highly reliable electric power to GB consumers (Tavakoli, Shokridehaki, Marzband, et al. 2018). In addition, green buildings are considered as a driving technology in achieving energy efficient neighbourhoods (Chauhan & Saini, 2014; Diakaki et al., 2013). Figure 6 shows a representation of these different producers and consumers in a typical green building (Fouladfar, Sumaiti, et al. 2019; Mehrasa, Pouresmaeil, Marzband, et al. 2018).

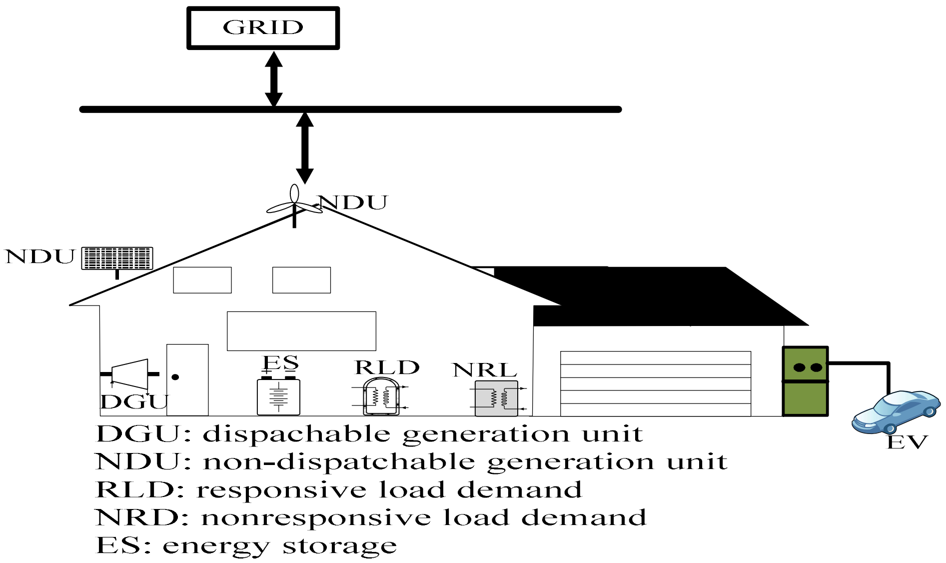


Figure 4 A typical configuration of a GB (S. S. Ghazimirsaeid, Fernando, and Marzband 2016)

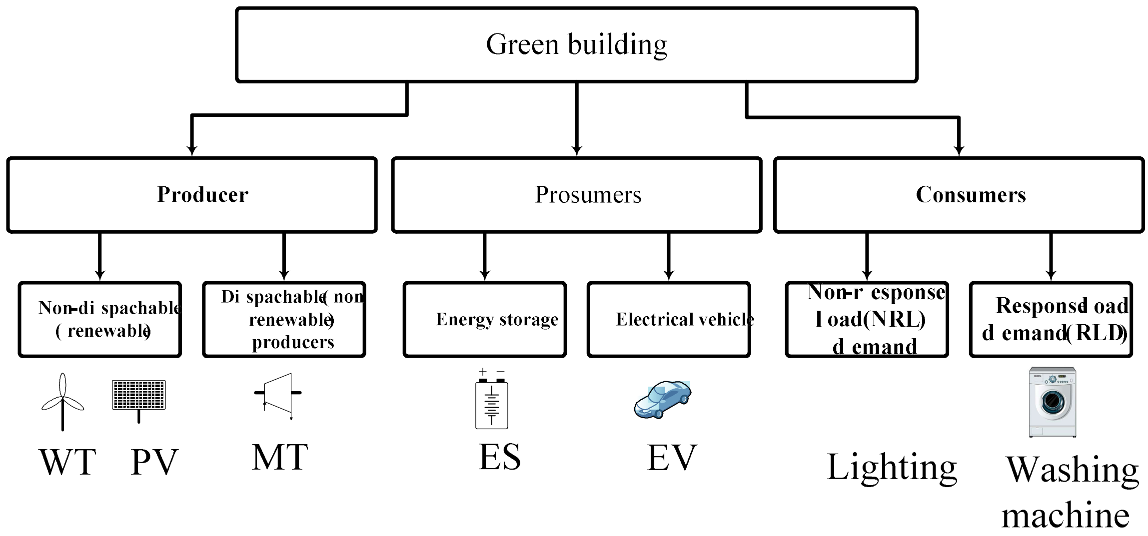


Figure 5 Characterization of Producers and Consumers (S. S. Ghazimirsaeid, Fernando, and Marzband 2016)

2.5. Neighbourhood systems

Green buildings in neighbourhood systems (GBNS) have significantly received more attention in recent years and are in line with the policy objectives within and across countries in order to avoid climate change (Pedrasa, Spooner, and MacGill, 2011; Quiggin et al., 2012). Figure 6 shows multi-green buildings connected to an upstream grid. The most distinctive feature of GBNS is the use of on-site renewable energy resources to compensate for the energy demands of each building (S. S. Ghazimirsaeid, Fernando, and Marzband 2016). Renewable energy resources inherently suffer from a lack of an on-demand energy production capability due to unforeseen weather conditions (Jiang and Fei, 2011; Cappers et al., 2012). Therefore, energy matching is a vital first step in obviating mismatched energy at each time interval (C M Colson and Nehrir 2011). In addition, the difficulties in achieving GBNS targets arise when buildings are located far from upstream grids or in urban areas where the built environment of the buildings is limited in terms of the ability to install renewable energy generation sources (Jiang and Fei, 2011; Guan, Xu, and Jia, 2010; Cappers et al., 2012). Therefore, it might not be possible for every single building to contribute to GBNS goals (Bajpai & Dash, 2012; Lu, Wang, Zhao et al., 2015; Sfikas et al., 2015). Hence, it is more realistic to look beyond a single building and consider promoting the GBNS concept at a community level (or on a wider scale such as a city) (Basu, 2013; Olivares, Canizares, and Kazerani, 2011). As a result, this can offer the opportunity to consider a cluster of buildings as an energy system where buildings can optimally interact with each other through an upstream grid in order to increase the energy and environmental efficiency of the community (Baños et al., 2011; Ondeck et al., 2015; Anvari-Moghaddam et al., 2015). Energy trading among all GBs within a neighbourhood system should be promoted as a good solution for achieving energy efficient neighbourhoods (Rastegar, Firuzabad, and Aminifar, 2012; Shi, Luo, and Tu, 2014). In this regard, it is necessary to provide a foundation for creating low carbon communities by promoting energy trading strategies whereby buildings within neighbourhood systems can interact with each other (El-Sharkh, Rahman, and Alam, 2010; Mohammadi, Hosseinian and Gharehpetian, 2012). The energy demand of a neighbourhood should be continually controlled and monitored in a GBNS (Hart and Jacobson, 2011). Furthermore, it is important to go beyond a consideration of the energy demand of buildings and consider also the energy demands for urban infrastructures (such as waste and water management, public lighting and transport) (Grohnheit, Andersen and Larsen, 2011; Ruiz-Álvarez et al., 2012). Renewable energy could be expanded to include solar, wind and hydro power, as well as other forms of solar energy, bio-fuels and heat pumps (ground, rock or water), whereby the supply facilities can be placed in a GBNS where it is most efficient and sustainable (Vahidinasab and Jadid, 2010). A typical configuration of a GBNS is shown in Figure 7. In this configuration, micro-turbines, photovoltaic solar panels, storage devices and associated load demands (such as electrical vehicles) should be considered within the neighbourhood system (Saeedian et al. 2019). These interactions can be served by establishing an independent system operator which is a controller that can be installed in GBs (Dodoo, Gustavsson, and Tettey 2017). Furthermore, at the top level, the coordination and management of all GBs can be carried out by a central controller. In this thesis, this concept will be explained in detail in chapter 6.

In addition, according to National Energy Technology Laboratory in the USA, the benefits of a GBNS can enhance systems' operation and application, as per the list below (Obara 2015):

1. Reliability: by reducing the possibility of widespread blackouts.
2. Economics: by reducing costs of electricity prices; creating new jobs.
3. Energy efficiency: by keeping downward the production cost, easier delivery, and managing electricity consumption.
4. Environment: reducing emissions by using renewable energy resources and improving the efficiency of production, transfer, and consumption.
5. Security: by decreasing the possibility, and consequences, of human attacks and natural disasters.
6. Robustness (Aalami, Moghaddam, and Yousefi, 2010; Abedi et al., 2012; Bayod-Rújula, 2009; Dietrich et al., 2012; Morais et al., 2010; Ipsakis et al., 2009; Kuznetsova et al., 2015; Sfikas, Katsigiannis, and Georgilakis, 2015): From robustness point of view can be itemized as follows:
    1. Performance improvement system meter.

2. Better customer consent.
3. More reliable and economic delivery of energy improved by data flow and secure communication.
4. Life cycle management, reduction in cost, and improved end-to-end power delivery in the GBNS design.
5. Input visibility of utility operation to property management.
6. Impact access to historical data for strategic planning

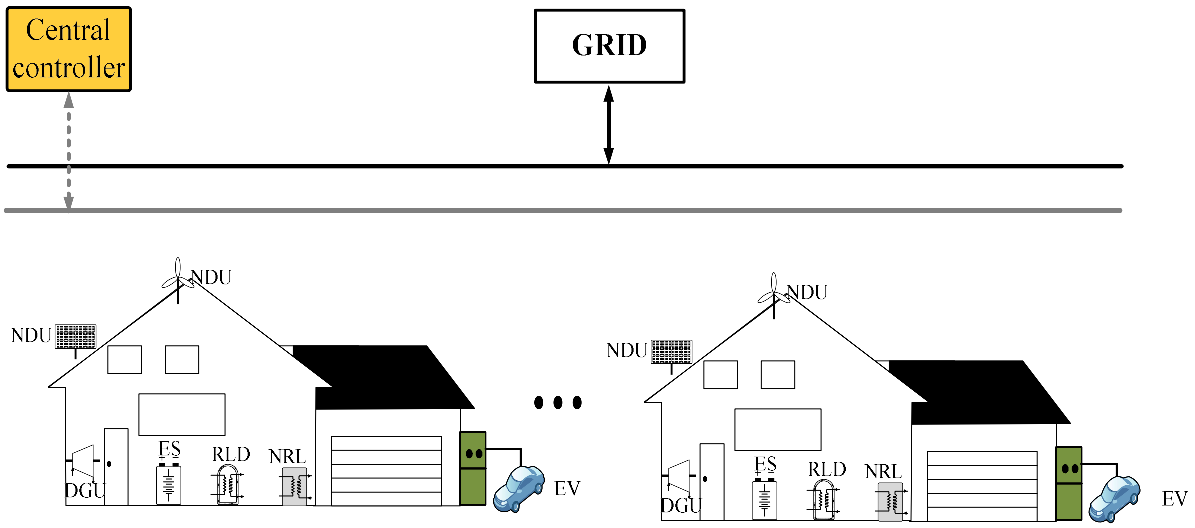


Figure 6 Multi grid-connected green buildings in a neighbourhood system (S. S. Ghazimirsaeid, Fernando, and Marzband 2016)

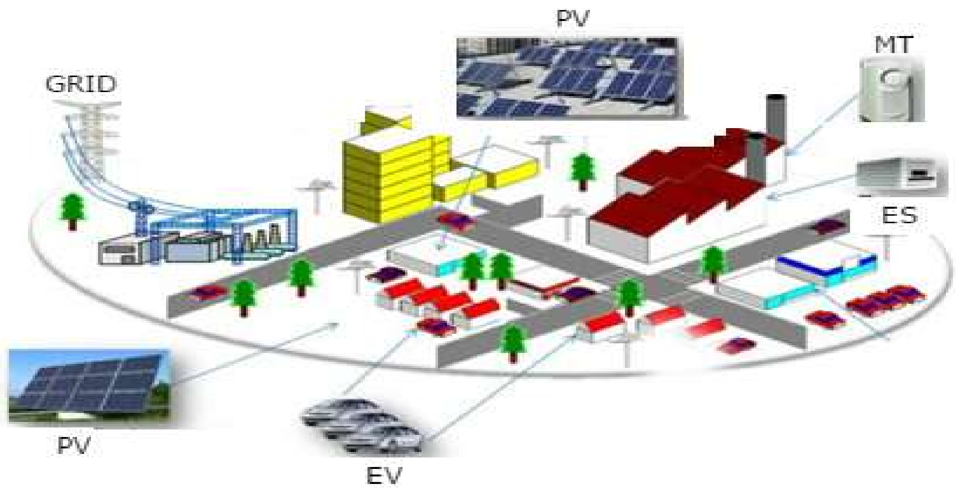


Figure 7 Characteristics of a GBNS (Roh, Shahidehpour, and Wu 2009)

2.6. Owners in green building neighbourhood systems

GB owners are people who own a GB (land and property) although may not actually live at the property (Basak et al., 2012; Che et al., 2015; Samari et al., 2013). They could potentially live in the GB or rent it to other people for extra income (Paul and Taylor 2008; Sailor, 2008). The owners of a GB can appeal against a decision which is made concerning which type of generation technology (electrical or thermal) is best to be installed in the building (Ali and Al Nsairat, 2009; Nguyen, Toroghi and Jacobs, 2016). Furthermore, the method of generation technology will be managed, restricted and decided upon by the owner of GBs in order to control the exchange of power between GBs in the neighbourhood system and the upstream grid (Boudreau, Chen and Huber, 2008). All GBs in a neighbourhood system can be handled by either one owner (the so-called single ownership system) or by multiple owners (the so-called multi-ownership system).

2.6.1. Single ownership system

The single ownership system in a GBNS structure is one where the GBNS is solely owned by an individual (Fouladfar, Loni, et al. 2019a; Mirzaei, Yazdankhah, et al. 2019; Morteza Nazari-Heris, Mohammad Amin Mirzaei, Amjad Anvari-Moghaddam, Behnam Mohammadi-Ivatloo 2019). This system is an integrated form of several types of distributed energy resources such as PV, WT, ES, etc. (Mirzaei, Yazdankhah, et al. 2019) with the facility of localized generation thus minimizing or maximizing one objective function (Hamzeh, Karimi and Mokhtari, 2012; Sun et al. 2015). A single ownership system can be individually assigned to each consumer. In other words, different objective functions can be constructed and assigned to the incentive factors of the consumers (i.e., lighting, refrigerators) (Hakimi and Moghaddas-Tafreshi, 2014; Mahmoud, Azher Hussain and Abido, 2014; Piagi and Lasseter, 2005). The general picture of a single ownership system is presented in Figure 8. All the GBs are run by only one owner and each of them has independent consumer.

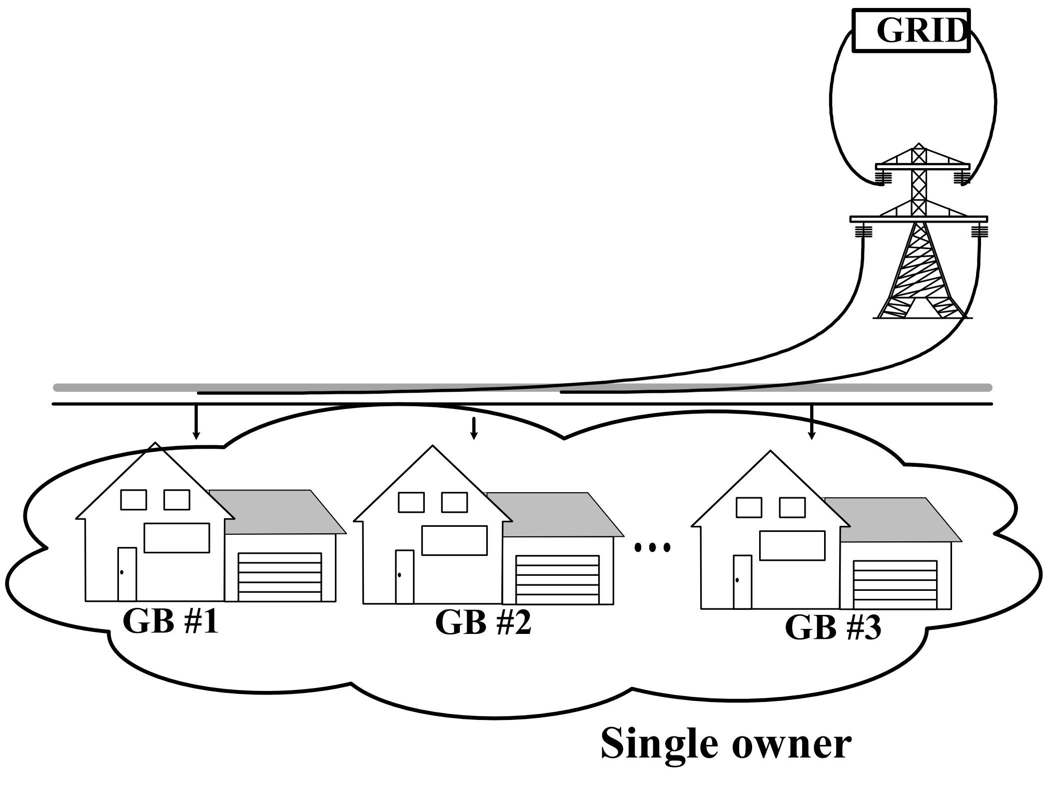


Figure 8 schematic diagram of the single ownership structure (M. Marzband, Yousefnejad, et al. 2016)

2.6.2. Multi-ownership system

The expressivity of a multi-ownership system is slightly different from the single ownership system whereby each owner has an exclusive right to use a specific GB (which is regarded as a right in achieving its revenue goal) (Loh et al., 2013; Patrao et al., 2015). Therefore, the objective function can typically be formulated as minimizing the operation cost of each GB or even maximizing the probability of making the profit of the owner of each GB individually as great as possible (Bahramirad, Reder and Khodaei, 2012; Mohamed, 2006).

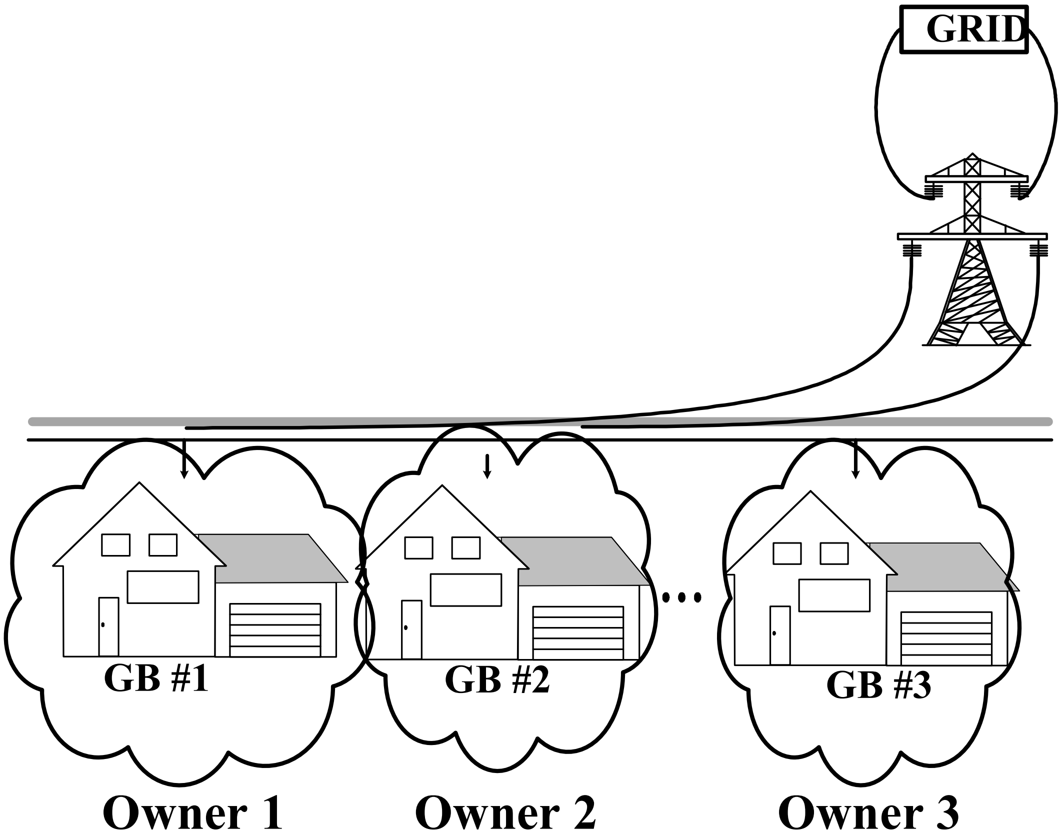


Figure 9 schematic diagram of the multi ownership structure (M. Marzband, Alavi, et al. 2017)

2.7. Market clearing price

When both producers and prosumers operate as a producer, they attempt to maximize their profit. Similarly, when both the consumers and prosumers operate as a consumer, they try to minimize the market clearing price (MCP) as well as participate in the energy matching and trading structure to obtain an operation that will minimize the cost (Arsalan Najafi, Mousa Marzband, Behnam Mohamadi-Ivatloo, Javier Contreras, Mahdi Pourakbari-Kasmaei, Matti Lehtonen 2019). MCP is defined as the price that is available when an electricity market is clear of surplus and shortage as shown in Figure 10 (Saebi et al., 2010; Yan, 2014). It is the outcome of the market bidding price (Dehghan et al. 2018; Gholizadeh et al. 2019; Mirzaei, Nazari-Heris, et al. 2019). When electricity MCP is specified, every supplier whose offering price is under or equivalent to the electricity MCP will be caught to supply electricity at that hour (Yan and Chowdhury, 2014b) It should be paid at the same price based on the electricity MCP, not at the price offered (Conejo, Nogales and Arroyo, 2002; Yan and Chowdhury, 2014a). The motivation for this is to establish fairness in the market and to prevent market chaos (Karsaz, Mashhadi and Mirsalehi, 2010). The anticipation of the electricity MCP is a forecasting of the future electricity price based on the given prediction for electricity demand, temperature, sunshine, fuel costs, and other related effects (Mohammad Amin Mirzaei, Morteza Nazari-Heris, Behnam Mohammadi-Ivatloo, Mousa Marzband 2019). Fair electricity MCP forecasting can help producers and consumers in providing their electricity usage and in the bidding strategy to maximize their profits (Ye et al., 2017). Offering a valid bidding price for a suitable electricity amount at the appropriate time is the first priority (M. Marzband, Javadi, et al. 2018). Presently, in electricity price anticipating studies, short-term anticipation of the electricity MCP is the most important research area (Zhang and Luh, 2005). It is also generally known as 24-hours day-ahead electricity price forecasting (Conejo et al., 2005; Independent Electricity System Operator, 2013; O'Neill et al., 2005).

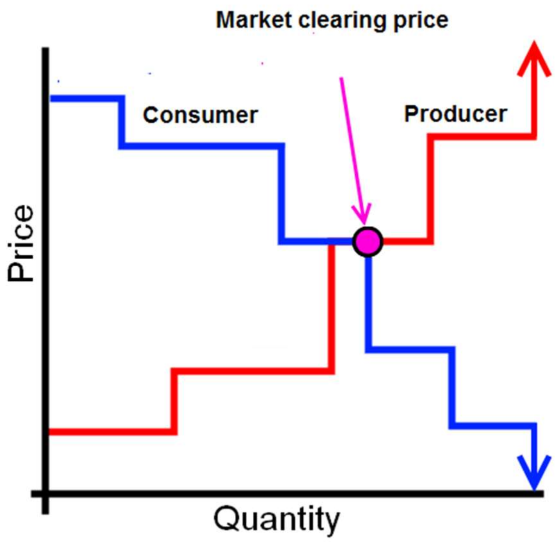


Figure 10 market clearing price (Pourakbari-Kasmaei et al. 2019)

2.8. Energy matching and energy trading

Energy matching and energy trading are key aspects that need to be considered when creating GB neighbourhood systems (Hamdy, Hasan and Siren, 2013; Malatji, Zhang and Xia, 2013; Pezzini, Gomis-Bellmunt and Sudri-Andreu, 2011; Ramachandran et al., 2011). The concept of energy matching occurs between the production and the consumption of energy (Soares et al., 2012). However, when renewable energy is introduced into buildings, energy matching becomes a challenging issue since there could be a mismatch between the energy produced by the non-dispatchable generation units and the non-responsive load demand at a given time for a particular building (Kaki, Salo and Talluri, 2014; Silva et al., 2006). Therefore, mechanisms for serving the energy demand of a given building need to be put in place by introducing energy storage and by shifting the response load demand when renewable energy is available (Alhelou et al. 2019; Basak et al. 2012; Gu et al. 2014; Jiayi, Chuanwen, and Rong 2008; Daniel E. Olivares et al. 2014; Shuai et al. 2016; W. Su and Wang 2012). Furthermore, if the objective of the consumer is to minimize the cost of energy consumption and reduce CO2 (Che et al., 2015; Huang, Lu and Zhang, 2011; Kaur, Kaushal and Basak, 2016), an overall energy management control mechanism (Basak et al., 2012; Dimeas and Hatziargyriou, 2005; Katiraei et al., 2008; Khodaei, Bahramirad and Shahidehpour, 2015; Kriett and Salani, 2012) needs to be included to decide when to purchase energy from the grid, when to store or when to consume renewable energy etc. (Cho et al., 2011; Nejabatkhah and Li, 2015).

The ever-increasing demand for green buildings (GBs) creates new challenges, but also creates new opportunities for researchers to invest in possible solutions to address these challenges (M. Marzband, Azarinejadian, et al. 2018). Such opportunities for investigation can be summarized as energy trading in a neighbourhood system, load flexibility through demand response (DR) programs, and diverse storage technologies. To fully exploit the potential of the emerging opportunities, neighbourhood systems' operational philosophy and strategies should be revisited. In the light of the new paradigm, the prosumer concept was born as an enabling strategy for modern and smart GBs in neighbourhood systems (GBNS) (M. Marzband, Azarinejadian, et al. 2018). The prosumer concept is defined as the ability of future electricity consumers to become active elements in GBNS' operations through local generation, demand flexibility, and storage. From the definition, one can realize the necessity for a new energy matching and energy trading structure with modern functionalities to enable interactions around energy and ancillary services products. It should be scalable to accommodate any number of participants, e.g., consumers, the owner of GBs and retailers (or the upstream grid).

In addition, energy matching and trading mechanisms are needed to provide local interactions among different consumers and the owner of GBs. A comprehensive operational solution should be proposed for every type of demand flexibility, distributed energy generation, and storage technology at the neighbourhood level to exploit the existing potential. The multiple GBs in a neighbourhood system concept is yet another useful tool which can be used in developing new energy trading structures to improve the resilience of the power system in a smart grid platform (Guerrero et al., 2013; Hu and Li, 2013; Mojica-Nava, Barreto and Quijano, 2015; Nekouei, Alpcan and Chattopadhyay, 2015; Nguyen and Le, 2015; Nunna and Doolla, 2012; Ribeiro, 2015). Basically, every GB host's local generation demands flexibility resources and storage devices to encourage the possibility of short- or long-term autonomous operation of the system in severe conditions.

In the last decade, many studies have addressed energy matching, trading strategy and challenges regarding the optimization formulation within a GB with/out energy storage (ES) units (Jia and Tong, 2016; Nekouei, Alpcan and Chattopadhyay, 2015; Savaghebi et al., 2013; Wei, Liu and Mei, 2015) (Guerrero et al., 2013; Hu and Li 2013; Mojica-Nava, Barreto and Quijano, 2015; Nguyen and Le, 2015), and GBs' interoperability in a neighbourhood system (Nunna and Doolla, 2012; Ribeiro, 2015).

The application and control of prime movers (such as gas engines in a GB) to compensate for various load demands and the intermittent output of renewable energy resources. Furthermore, (Behnam Mohammadi-Ivatloo, Moradi-Dalvand, and Rabiee 2013) evaluated the pitch angle and twister speed controller of wind power in GB to maximize the production of power and stabilize the GB voltage during short faults. The authors in (Moradi-Dalvand et al. 2012) studied energy matching and trading in a GB which varied the generator output power to ensure the stability of the operation and to minimize fuel consumption price (Mehrasa, Sepehr, et al. 2018). Moreover, the authors in (B. Mohammadi-Ivatloo et al. 2011) presented multiple control and energy management system strategies in a GB with various distributed energy resources in order to compensate for the shortage of power.

Recent research undertaken by (B. Mohammadi-Ivatloo et al. 2012; Mohammadi-ivatloo et al. 2012; Rabiee, Mohammadi-Ivatloo, and Moradi-Dalvand 2014; Razmjoo et al. 2019) presented evaluated frameworks for energy trading among different GBs, as well as between GBs and a central power company (Ameena Saad Al-Sumaiti, Magdy Salama, Mohamed El-Moursi, Tareefa S. Alsumaiti 2019). This research was to ensure that any deficiency from the local energy resources was solved, and that any excess power or shortage power which is either stored or sold in order to maximize the profits of the various GB owners. For instance, the authors in (B. Mohammadi-Ivatloo et al. 2012) proposed a neural network to forecast the energy algorithm of a GB's renewable energy resources and to optimize the GB's scheduling and trading decisions. In (Behnam Mohammadi-Ivatloo et al. 2013), the authors presented a novel algorithm for forming coalitions among GBs, in a cooperative game-theoretic framework, with the aim of optimizing and reducing energy loss. Research undertaken by (Abbaspour et al. 2013; B. Mohammadi-Ivatloo, Shiroei, and Parniani 2011) analyzed the cost competition among interconnected GBs by using the game theory approach. Similarly, the authors in (Behnam Mohammadi-Ivatloo, Rabiee, and Ehsan 2012) proposed an optimization framework for energy matching and trading between GBs, whereby sellers declared, firstly, the amount and the cost of energy they wished to trade and buyers responded by declaring their unit cost bid to the sellers (Tavakoli, Shokridehaki, Funsho Akorede, et al. 2018). The authors in (Dodoo, Gustavsson, and Tettey 2017) proposed a case where two GBs in a neighbourhood system, operating in islanded mode, can trade energy in order to minimize the total energy production and transmission price. In other words, the authors in (Sharma et al. 2016) utilized the weighting effect, from the framework of prospect theory, to account for the irrational behaviour of each GB, originating from the uncertainty of the trading strategy of its opponents. Furthermore, the authors in (Xu, Hu, and Spanos 2017) proposed the implementation of a coalition control system to provide control and communication between GBs' neighbourhood systems efficiently.

Recently, in addition to proposing energy matching and trading, considerable attention has been paid to using the ES abilities of GBs to improve the resilience and the reliability of the GBs against emergency events such as natural disasters or security defects (e.g. the sudden shutdown of DER units). The GBs' resilience reflects their capability to avoid the disconnection of their critical services when faced with problems (Dodoo, Gustavsson, and Tettey 2017). In this regard, different academic and industrial research (Ling and Masao 2011; D. Liu and Cai 2005; Mirzaei, Yazdankhah, et al. 2019; Misra et al. 2016) have presented GBs' storage capacity which can mitigate the impact of the power loss of generation during emergency events by supplying the most amount of non-response load demand in GBs. Actually, ES and DER units, the integral components of GBs, play an important role in preserving the operation of critical load demands such as those for the rescue services centers, police stations, hospitals, fire stations and emergency situations in the US (Bassanino et al. 2016; S. S. Ghazimirsaeid, Fernando, and Marzband 2016). For example, there have been several cases during natural disasters (such as hurricanes Katrina and Rita, and the wildfires) which interrupted the electricity in parts of Utah in 1995 and 2003; additionally there was the 2003 North American Northeast blackout (S. A. Ghazimirsaeid et al. 2014). In addition to the different reports (Baraldi and Zio 2008; Misra et al. 2016; Yuce, Rezgui, and Mourshed 2016) encouraging the usage of ES in GBs to improve grid resilience and grid reliability, a number of similar researches (Mohanty, Bhuvaneswari, and Balasubramanian 2012; Siano 2014) have also reviewed the issues relating to power quality, that might arise, when a couple of non-linear non-response loads are supplied by DERs in GBs.

To summarize, the main body of study (Rao et al. 2012; Xiang, Liu, and Liu 2015; Han Yu, Chung, and Wong 2011) has focused on producing an autonomous GB that relies on its internal production and storage units to supply its demand in a stable and efficient manner, while minimizing cost and power losses. The topic of GB storage for increasing grid resilience has been supported by several technical reports (C.M. Colson and Nehrir 2009; R. H. Lasseter 2011; Rao et al. 2012). A summary of the literature review on energy matching and trading is presented in Table 1.

Table 1 the summary of literature review of energy matching and energy trading

Number	Decision variable	Objective	Method	Reference
1.	Use of prosumers and electricity consumers	Minimization of cost	ABC	(Marnay et al. 2008; M. Marzband, Fouladfar, et al. 2018; Mousa Marzband et al. 2015; Tsikalakis and Hatziargyriou 2008)
2.	Local interactions among different consumers and the owner of GBs	To improve the resilience of the power system	Game Theory	(M. Marzband, Javadi, et al. 2016, 2018)
3.	Development of the application and control of prime movers	To compensate the various load demands and the intermittent output of renewable energy resources		(Anastasiadis et al. 2014; N. D. Hatziargyriou et al. 2009; N. Hatziargyriou et al. 2007; Lidula and Rajapakse 2011; Ton and Smith 2012; Zamora and Srivastava 2010)
4.	To evaluate the pitch angle and twister speed controller of wind power	To maximize the production of power and stabilize the GB voltage during short faults		(Jiayi, Chuanwen, and Rong 2008; Justo et al. 2013; P. Piagi and Lasseter 2006; Ustun, Ozansoy, and Zayegh 2011)
5.	To utilize various generator output powers	To minimize the fuel consumption price	Qualitative analysis	(Abu-Sharkh et al. 2006; Funabashi and Yokoyama 2006; R. Lasseter et al. 2002; Z. Sun and Zhang 2012; Z. Zhang et al. 2010)
6.	To utilize various distributed energy resources	To compensate for the shortage of power		(Nejabatkhah and Li 2015; Zhi, Zhang, and Liu 2011)
7.	To evaluate frameworks for energy trading among different GBs	To maximize the profits of various GB owners	Game Theory, Iterative method	(Bi, Ding, and Xu 2010; Katiraei et al. 2008; Salomonsson et al. 2008)
8.	To propose a neural network to forecast the energy algorithm of a GB	To optimize the GB's scheduling and trading decisions	Neural network	(Alvial-Palavicino et al. 2011; Geelen, Reinders, and Keyson 2013)

9.	To present a novel algorithm for forming coalitions among GBs	Ti optimize and reduce energy loss	Game theory	(Gangale, Mengolini, and Onyeji 2013)
10.	Using the game theory approach.	To analyse the cost competition among interconnected GBs	Game Theory	(C.M. Colson and Nehrir 2009; Payne and Frow 2005)
11.	Operating in islanded mode	To minimize the total energy production and transmission price.	Iterative method	(D. Lu and François 2009)
12.	To implement a? coalition control system	To provide control and communication between GBs neighbourhood systems efficiently.	Multi-agent system	(Thillainathan Logenthiran et al. 2012)
13.	To present the GBs' storage capacity	To mitigate the impact of the power loss of DERs during emergency events.		(Carley 2009)

2.8.1. Limitations of the current energy matching and trading in GB neighbourhood system

Based on the literature review, it can be seen that the current body of work related to energy matching and trading is lacking in multiple aspects:

1- There has been a lack of literature about energy trading schemes in order to motivate GBs to cooperate with each other and in covering all the non-response load demands in a neighbourhood system. Moreover, models should be developed to evaluate incentive schemes that encourage GB operators to store part of their excess energy to provide enhanced retailers' resilience. Such excess could be utilized in the case of a power blackout resulting from a natural disaster or a malicious attack.

2- A number of conducted works (Carley 2009; Chauhan and Saini 2014; Gabbar et al. 2012; Ismail, Moghavvemi, and Mahlia 2013) have proposed multiple game-theoretic models to study energy matching and trading among GBs. However, these works assume that, when choosing optimal action, every operator has complete information regarding the system's architecture, the central power company, and other GBs. However, in a real-life application, GBs will rarely have complete information. In reality, in a GB setting, given the intermittent output of renewable energy sources, a GB will find it challenging to predict its opponents' available energy output and storage level. In the proposed methodology presented in this thesis, GBs don't need to share a lot of information with each other.

3- With the exception of the research undertaken in (Gabbar et al. 2012), the current literature on energy matching and trading in GBs assumes that all decision makers are logical. However, as shown by the studies in (Divya and Østergaard 2009), consumers will deviate from the origin of the classical game theory significantly, when faced with uncertainties. Some uncertainty could possibly be caused by the consumers' inadequate information regarding GB system abilities and the renewable energy resources/storage levels.

According to the aforementioned items, the proposed techniques have flexibility and plug-in/plug-out capabilities. It means that the proposed techniques can easily realize a new connection between DER and a new green building in a GBNS. The proposed methodology is able to distinguish this new change and it can perform its appropriate action. In addition, a few data and information can be exchanged between consumers and the owner of green buildings in the proposed techniques. It means that the security and privacy of consumers and the owner of green buildings can be taken into account in the model. Moreover, the different types of uncertainties have been taken into account in the proposed technique for increasing accuracy. On the other hand, the uncertainty of load demand, the renewable energy resources and the market clearing price have been included in the proposed techniques and the impacts of these types of uncertainties over each other have been investigated totally in the proposed technique.

2.9. Demand side management

An extension in using the number of renewable energy resources in GBs has already been started and it is anticipated to increase further in the future (Mirzaei, Yazdankhah, et al. 2019). Reliable operating of a GB with renewable energy resources is principally dependent on a perfect power balance between the power supply and the load demand at each time interval (Mohammad Amin Mirzaei, Ahmad Sadeghi Yazdankhah, Behnam Mohammadi-Ivatloo, Mousa Marzband, Miadreza Shafie-khah 2019). It is a difficult task to properly maintain and accomplish the power balance, assuming there is a little control on the demand side (the generation side can be controlled according to the load demand) (Arteconi, Hewitt and Polonara, 2012; Gelazanskas and Gamage, 2014; Warren, 2014). It gets even more complicated when the renewable-based DER generation increases (Logenthiran, Srinivasan and Shun, 2012). Renewable energy resources (renewable-based DER) changes with weather conditions and it is not usually easy or favorable to model the output of renewables to imitate a particular load demand profile (Mazur and Goater 2014). Furthermore, peaks in renewable-based DER resources during some time intervals do not necessarily match with the high load demand, so the produced energy needs to be either consumed or stored for other consumption in the next time intervals (Ensor and Cooper, 2004). Electricity networks could continuously rely on fossil fuels' peaks during peak hours but, in order to increase the variability in production, consumers would be finally forced to keep higher margins of reservoir, which would dramatically increase the total price of electricity at the end of daily operation (Mohsenian-Rad et al., 2011; Mohsenian-Rad et a,l. 2010). The alternative way to maintain the power balance is to use the new technologies or methods, particularly the ones that are based on user behaviour or user engagement (Gelazanskas and Gamage, 2014; Gellings, 2017). To summarize, all the required load demand is supplied by the classical approach whenever it happens, but the new strategy states that the load demand might be managed by engaging consumers based on the current state of the network (Li et al., 2016; Pina, Silva and Ferrão, 2012). The introduced inherent variation of renewable-based DER units could be controlled by matching the load demand to the power supply, which is where the demand side management (DSM) might come into consideration (Davito, Tai, and Uhlaner 2010). There is an important role for DSM in contributing to improving the efficiency and use of system assets (Mohammad Amin Mirzaei, Morteza Nazari-Heris, Behnam Mohammadi-Ivatloo, Mousa Marzband 2019). It can be considered as a useful tool for carrying out the different objectives of load shaping, such as peak load curtailment, flexible load consumption, strategic conservation, strategic load demand growth, valley filling, and load demand shifting (as shown in Figure 11) (Zehir and Bagriyanik, 2012). The load shape follows production as closely as possible by the combination of the mentioned methods (MortezaNazari-Heris, Mohammad Amin Mirzaei, Behnam Mohammadi-Ivatloo, Mousa Marzband 2019). It could decrease the amount of assets needed to fulfill the current load demand using existing techniques (mostly fossil-fuel) and would significantly increase the load demand factor (Ramchurn et al., 2011a, 2011b). On the other hand, DSM is the implementing, planning, and monitoring of consumer activities that are designed to influence the existing generation of electricity (Gottwalt et al., 2011; Torriti, 2015). This could potentially create an ideological power balance between load demand and supply more effectively. It would also reduce the peak of load demand and make the whole network more robust, secure and efficient (Lunden, Werner and Koivunen, 2013). Thus, it manages the time pattern and value of the utility's demand. Generally, the main purpose of DSM is to encourage consumers (including the responsive/non-responsive load demand) to use less consumption during peak hours or to shift energy consumption to off-peak hours in order to flatten (or smooth) the load demand curve. Occasionally, it is more favorable to follow the production pattern instead of flattening the curve. Under this condition, there will be a need to design some control strategies to optimize energy use.

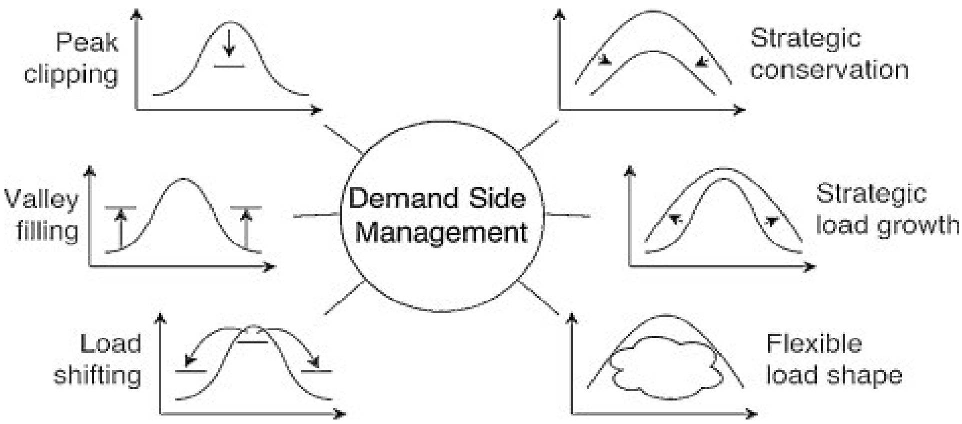


Figure 11 basic load shaping techniques (Ameena Saad Al-Sumaiti, Magdy Salama, Mohamed El-Moursi, Tareefa S. Alsumaiti 2019)

Another important aspect to investigate within a DSM is that it should be able to charge consumers with a variable electricity price (Lunden, Werner and Koivunen, 2013). When electricity is cheap, the load demand can be increased then the electricity prices will significantly rise. Under these circumstances, customers will intend to buy less energy and they will reduce their consumption. Owing to the fact that electricity is a local commodity and inherently as a result it is economically a non-storable and transport constraint. On the other hand, as electricity has to be consumed the moment it is produced, markets constantly experience short-term changes as capacity fluctuates from surplus to shortage of power. This is because of the hourly and daily fluctuation in load demand. A fixed electricity tariff is simply very archaic and introduces cross-subsidies between consumers. In a fixed electricity tariff, there is no incentive for consumers to contribute to making the network more efficient (Gelazanskas and Gamage, 2014). If variable pricing was implemented, the price elasticity of the demand side would become opposed to the fixed price tariff. On the other hand, increasing the number of renewable-based DERs because of their stochastic nature would also change the power supply curve. During the times when renewable-based DERs are scarce, the electricity price for the same value of energy would increase, and load shifting is relatively more flexible and effective. This happens because renewable-based DER, like solar or wind power, has very low operating cost. On the whole, demand response (DR) techniques in DSM would allow consumers to become both environmentally friendly and save more money.

DSM schemes should be utilized in GBNS in order to ensure that energy consumption matches production and to save on electricity costs by avoiding peak consumption hours and by better control of the grid's energy consumption. Consumers can currently participate in DSM schemes, seeking to gain advantage from the offering of financial incentives by GBs and they can, therefore, reduce their electricity costs. A variety of research studies (S. X. Chen, Gooi, and Wang 2012; Passey et al. 2011; Tan, Li, and Wang 2013) have presented scheduling models and load shifting to evaluate the effectiveness of DSM schemes. Authors in (Bracco et al. 2012) have presented various frameworks that attempt to flatten the demand curve based on DSM consumption scheduling. For instance, the authors in (Bracco et al. 2012) proposed a DSM model which exactly applied previous data and based on that anticipated the consumption pattern of the consumers' water heaters and, eventually, they proposed a load shifting scheme for peak shaving. The authors in (Y. Zhang, Gatsis, and Giannakis 2013) proposed a pattern for scheduling consumers' air conditioning devices, based on energy consumption scheduling requirements. In addition, the work in (T. Logenthiran et al. 2012) defined a load management control strategy in order to optimize electric vehicles' charging, with the aim of enhancing peak demand shaving and voltage regulation. Furthermore, the work in (Mohammad Amin Mirzaei, Ahmad Sadeghi Yazdankhah, Behnam Mohammadi-Ivatloo, Mousa Marzband, Miadreza Shafie-khah 2019) surveyed the topic of various electric vehicles in a grid, trying to choose the optimal time to start charging in order to reduce an individual's price (which is mostly related to the total grid power).

The work in (Amin et al. 2019) presented a market clearing price scheme for a day-ahead schedule while proposing a cost proportional to the ratio of peak to average. In (Mirzaei, Nazari-Heris, et al. 2019), the authors presented an effective scheduling of consumer-owned generation and energy storage, based on a DSM scheme, to flatten the aggregate demand in consumption. In (Amin et al. 2019), the authors proposed a day-ahead DSM scheduling based on heuristic evolutionary algorithms in residential, commercial and industrial consumers. In (Houman Jamshidi Monfared, Ahmad Ghasemi, Abdolah Loni 2019), the authors proposed a mechanism design framework based on game theory approach to persuade a power company to operating cost effectively and better demand management contracts to consumers. The results from these multiple works show that the load curve can be more actively managed and flatten on a daily basis by fully distributed DSM schemes.

In addition, variety of research work have proposed DSM schemes, with the aim of production matching with consumption in order to reduce intermittent renewable energy resources (Thillainathan Logenthiran, Srinivasan, and Shun 2012; Strbac 2008; Vytelingum et al. 2011). For instance, the authors in (Nastaran Gholizadeh, Gevork B Gharehpetian, M Abedi, Hamed Nafisi 2019; Warren 2014b) explained a number of optimization algorithms for operating and scheduling a large renewable energy resources plant which reduced the energy use of external energy sources and managed to serve all its consumers under various delay rates. Furthermore, the author in (Davito, Tai, and Uhlaner 2010; Kyriakarakos et al. 2013) proposed a framework based on the game theory approach in order to match the anticipated output of wind turbines with the total demand, and this has shown a significant reduction in the supply/demand mismatch. The work in (Müller et al. 2015; Suganthi and Samuel 2012) proposed an application based on price and on a direct-load based DSM scheme, in order to match production and consumption in the future network.

A large amount of literature concerning DSM is emerging from game theory modelling and solutions (Adner and Zemsky 2006; Atzeni et al. 2012; Gelazanskas and Gamage 2014) in order to capture the fact that the actions of producers, consumers and procumers can be combined with the objective of managing the total grid load. Furthermore, a large number of research studies (Gellings et al. 1986; Gottwalt et al. 2011a, 2011b) have studied the optimization framework in order to investigate the interaction between a utility company and the grid's consumers hierarchically. This is owing to the fact that, in an energy matching and trading setting, a utility company proposes a certain motivation or pricing strategies, to which consumers react by altering their consumption method. For instance, the paper in (Pina, Silva, and Ferrão 2012) proposed an optimization framework in order to deal with a high level of uncertainties based on real-time pricing in residential buildings. In particular, the authors in (Goulden et al. 2014; Z. Wu, Tazvinga, and Xia 2015) studied an optimization approach between GBs and various consumers, with the objective of smoothing the aggregated load in the system, while increasing the revenues of all producers, consumers and prosumers. The authors in (Arteconi, Hewitt, and Polonara 2012) presented a multistep optimization model among energy producers, energy consumers and energy retailers while trying to maximize the retailers' procurement and pricing decisions. The authors in (Adika and Wang 2014) presented an optimization approach between a power company and consumers, while also studying the impact a destructive attack could have, through the handling of pricing data.

Moreover, a large amount of work in DSM literature has looked at the subject of irrational consumers in energy matching and trading scenarios, using the Nobel-winning framework of prospect theory. For example, the authors in (Arteconi, Hewitt, and Polonara 2013; Aryanpur et al. 2019; Morteza Nazari-Heris, Mohammad Amin Mirzaei, Amjad Anvari-Moghaddam, Behnam Mohammadi-Ivatloo 2019) introduced a storage management framework wherein storage owners can decide to sell or store energy, while accounting for their subjective perceptions, using a prospect-theoretic framework.

In (Strbac 2008), a prospect-theoretic framework is also used to analyze a DSM scheme, whereby consumers try to minimize the price of their energy consumption by choosing the best time to participate in the market. In summary, this DSM section in this thesis focuses on flattening the load curve (Behrangrad 2015; Paulus and Borggrefe 2011), besides matching demand to the intermittent nature of large-scale renewable energy resources (Meyabadi and Deihimi 2017; Suganthi and Samuel 2012). The different kind of DSMs presented in the literature has been summarized in Table 2.

Table 2: different DSM models presented in literature

Number	Decision variable	Objective	Method	Reference
1.	To apply previous data and based on that to anticipate the consumption pattern	The energy consumption matches production and saves on electricity costs by avoiding peak consumption hours and by better control of the grid's energy consumption	Mont Carlo	(João Soares et al. 2016; TIAN et al. 2007)
2.	To define a load management control strategy in order to optimize electric vehicles' charging		Game Theory	(A.-H. Mohsenian-Rad et al. 2011; Saad et al. 2012)
3.	Trying to choose the optimal time to start charging electrical vehicles		Game Theory	(H. K. Nguyen and Song 2012)
4.	To present a market clearing price scheme for a day-ahead schedule while proposing a cost proportional to the ratio of peak to average		Game Theory	(N. Zhang et al. 2015; Y. Zhao et al. 2010)
5.	To present an effective scheduling of consumer-owned generation and energy storage.		Realistic method	(Yunpeng Wang et al. 2014; World Energy Council 2016; Y. Zhang, Gatsis, and Giannakis 2013)
6.	To persuade a power company to offer effective costs and to make demand management contracts to consumers		Game Theory	(Javadi et al. 2018; M. Marzband, Javadi, et al. 2016, 2018)
7.	To match the anticipated output of wind turbines with total demand.		Game Theory	(Devine-Wright 2005; Marden, Ruben, and Pao 2013)
8.	To propose an application based on price and on the			(D. Li, Jayaweera, and

	direct-load based DSM scheme.			Naseri 2011; Wei, Liu, and Mei 2015; Zhong, Xie, and Xia 2013)
9.	To propose an optimization framework in order to deal with the high level of uncertainties based on real-time pricing.		Stochastic dynamic program	(Kelly, Pástor, and Veronesi 2016; Wei, Liu, and Mei 2015)
10.	To propose a prospect-theoretic framework in order to minimize the electricity price of a consumer's energy consumption by choosing the best time to participate in the market		Game Theory	(D. Zhang et al. 2013; Zugno et al. 2013)

The shortcomings of the DSM proposed by other researchers can be summarized as follows:

1- While integrating variable renewable energies into a grid is well established in looking at DSM in the literature, the small-scale demand on the consumer side are relatively less studied. As most DSM schemes focus on day-ahead consumption scheduling, consumers might be forced to deviate from such consumption, given the unpredictable nature of their renewable energy resources' output. This has an effective impact on DSM programs and can, potentially, require the power company to buy additional energy in real-time, especially at higher cost, in order to compensate for the deviation.

2- Current research has not fully accounted for an assessment of the energy left in storage in DSM. Actually, this assessment is typically based on the consumer's perceived future energy price, which is unknown given the variable nature of dynamic energy pricing. Changes in this assessment will undoubtedly impact on a consumer's decision to buy or sell energy when participating in DSM schemes.

3- Optimization is widely studied in terms of the interaction between producer and consumers (M. Marzband, Fouladfar, et al. 2018; Parandehgheibi et al. 2018), assuming that the producer declares its pricing strategy first, before consumer responds. All the studies discussed in this thesis utilize the expectation that consumers are fully rational players and will thus play out their strategy according to classical game-theoretic analysis. However, the behaviour of consumers, who are human players, can significantly deviate from the rational ideology of classical theory, when faced with the uncertainty of probabilistic outcomes.

4- The work in (Bozchalui et al. 2012; D. T. Nguyen and Le 2014; Pedrasa, Spooner, and MacGill 2010) proposed that, in terms of consumers' irrational behaviour, the uncertainty from which this behaviour stems is usually associated with the probabilistic strategies of opponents. These works fail to account for other different sources of uncertainty on the consumer side of the grid (which include the intermittent output of their renewable energy generators, and the future cost of any energy kept in their storage devices).

According to the aforementioned items, the proposed DSM in this study has been developed based on the impact of the uncertainty of renewable energy resources and market clearing prices. In addition, energy storage is accommodated in the model in order to reduce the pressure of consumers to participate in DSM. From the producers' perspective, their pricing strategy should be performed simultaneously with the DSM process.

2.9.1. Demand response

Demand response (DR) is a most important part of DSM and is defined as a particular tariff or schedule to encourage end-use customers to respond to changes in rate or in the availability of electricity during time by changing their normal patterns of electricity use (Marzband et al., 2016, 2018). On the other hand, DR has been becoming progressively popular in GBs recently. DR has been proposed extensively as a tool to provide better operations for consumers, and more efficient integration of renewable energy resources. In addition, DR can be proposed as an incentive payment program to decrease the utilization of electricity when grid reliability is imperiled (Palensky and Dietrich, 2011). Consumer actions can be categorized into three actions in response. Consumers can decrease the load demand during on-peak time and maintain (or increase) the normal load pattern during off-peak time (Ameena Saad Al-Sumaiti, Magdy Salama, Mohamed El-Moursi, Tareefa S. Alsumaiti 2019). This induces a decrease in consumers' comfort as they are forced to shorten electricity utility at certain times, but this also reduces the whole consumption so reducing the bill even further. The second action that could be executed to respond to high electricity prices or low availability is to offset electricity use during on-peak to off-peak time. This pattern flattens the load demand shape by both reducing the peak load and by filling low consumption hollows. It does not reduce the average amount of energy used by the end users but increases the distribution efficiency as the system operates in a more stable mode. Ultimately, consumers can use on-site production to decrease the demand seen by the utility. This would increase user autonomy, further dispatchable generation units (for example diesel generator) and reduce the average load demand on the distribution network. In other words, it would maximize system complexity. Many DR models are overviewed in the research of (Ameena Saad Al-Sumaiti, Magdy Salama, Mohamed El-Moursi, Tareefa S. Alsumaiti 2019) and (Al-Sumaiti et al. 2019) in order to accomplish these tasks. These models can be divided into two main groups: incentive-based programs and price-based programs. Incentive based programs can further be defined as classical or market based. Using a classical incentive-based program the end user is implemented in load shaping by agreeing to either give up control of certain appliances (direct load control) or to react by limiting the total use of electricity (load limiter or interruptible program). Consumers who agree to participate but do not respond should pay more penalties as per the program terms and conditions. Market based programs would allow consumers to participate in different incentive-based load reduction programs. In the time intervals, consumers could reduce their offer prices and the MCP, participate, etc. (Conejo, Morales and Baringo, 2010; Siano, 2014). The programs based on price would operate using a dynamic electricity pricing scheme that would reflect the availability of the electricity price (O'Connell et al., 2014). The simplest form of programs based on price is ‘time of use’ and consists of on-peak and off-peak rates (Kim and Shcherbakova, 2011). Such a program is already extensively implemented owing to the fact that it requires the least enabling technologies. Furthermore, time of use can be used to reduce peak shaving and the MCP. The most complex method is real time pricing. It can control the price in real time to shape end-use load demand. Information about implementing and on the experimentation results of DR programs can be found in Nolan and O’Malley (2015). Real time pricing is one of the most favorable DR techniques. It follows an economic and technical rule. Differently, to other encouragement-based programs, it does not directly limit a user’s consumption; therefore, consumers always have a choice to modify their load demand patterns. Such a program would not raise huge policy issues, as real time pricing does not involve any intervention from the generation side to the consumer’s premises. As opposed to encourage-based programs (Bartusch et al., 2011; Parvania and Fotuhi-Firuzabad, 2010). DR is encouraging from both the policy and technical prospects. Most DR techniques need a dependable connection in order to have a two-way communication between consumers and other elements of the network (e.g. the upstream grid, GBs) to transmit offer prices, the amount of generation, etc. In addition, DR is hardware intensive requiring participating consumers to install home energy matching and trading units and them having some smart appliances which are able to response on time, load demand and show price without any human interaction. DR will have intensive benefits for the consumers or the owner of GBs in making the overall network more secure as well as maximizing the total profit (Action and Efficiency, 2010; Ma et al., 2013).

Authors in (Parvania, Fotuhi-Firuzabad, and Shahidehpour 2013) have presented on the effect of DR on electricity markets and have proposed a market-clearing prices and demand shifting. They find that the system is more effective, and that social welfare has been increasing, as more consumers participate in DR (i.e. as the load participation factor is increased). Also, the author in (Parvania, Fotuhi-Firuzabad, and Shahidehpour 2013) presented the impact of DR implementation over variables of the network (e.g. market clearing price) by the formulating of the unit commitment problem.

(H. A. Aalami, Moghaddam, and Yousefi 2010) proposed a method for controlling load demand based on the elasticity of the offer price of consumers. The control of the load demand will be managed by the need of the supplier to reduce the consumption. The optimization problem is to minimize the operating cost subject to technical constraints. Some of these constraints are the maximum load reduction for a particular customer, the maximum increase for the cost of electricity, and the power balance.

In (M. Marzband, Fouladfar, et al. 2018) the authors proposed three different methodologies to integrate short-term reactivity into a generation technology mix with an optimization model by considering operational and economic constraints. Results showed that the integration of DR can relieve the network peaks, and reduce the required investment, reducing the valley filling.

Authors in (Gkatzikis, Koutsopoulos, and Salonidis 2013) examined the penetration of real-time electricity price in the residential sector in collaborating with renewable energy resources. The basic idea was that during periods of low renewable-based energy resources when only thermal generation was available and the forecasted demand was close to that of the production, then the real-time price signal would be high enough as per the pricing model and, therefore, bring in DR.

(Cappers, Goldman, and Kathan 2010) presented the DR scheduling process in order to model it and integrate it into the distributed energy resources' topology. This allows for the calculation of available DR at the point of transmission; thus it can help in the better monitoring and verification of the requested DR. A summary of the DR models presented in the literature is presented in Table 3.

Table 3: DR models presented in the literature

Number	Decision variable	Objective	Reference
1.	To propose a market-clearing prices and load demand shifting	The system is more effective and social welfare has been increasing.	(L. Chen et al. 2012; Gatsis and Giannakis 2013)
2.	To control load demand based on the electricity price elasticity of consumers	To minimize the cost for consumers	(Newsham and Bowker 2010; Schroeder 2011)
3.	To propose three different methodologies to integrate short term reactivity into a generation technology mix optimization	Decreasing the required investment of generation and increasing the network flexibility; facilitating the integration of variable wind power.	(Rentizelas, Tatsiopoulos, and Tolis 2009; Saele and Grande 2011)
4.	To present the DR scheduling process in order to model and integrate it into the distributed energy resources' topology	It can help in the better monitoring and verification of the requested DR.	(Law et al. 2012)
5.	To examine the penetration of the real-time electricity price in the residential sector when collaborating with renewable energy resources	The forecasted demand is close to the amount of production	(Allcott 2011; Z. Chen, Wu, and Fu 2012)

Limitations

The following shortcomings relating to energy matching and energy trading and DR modelling at the neighbourhood level can be identified in the existing studies which have been examined while preparing for this research:

1- A large number of methods have been presented to help consumers respond to the DR service automatically but most of these proposed methods lack real-time to adjust to different capabilities in the implementation of the processing of the change of working of consumers' appliances.

2- Models that propose to allow consumers to participate in the electricity market have not been extensively discussed or thought to be powerful enough to tolerate the uncertainty of consumer behaviour in order to respond to changes in the market clearing price. A number of consumers adjusting their demand (either load shifting or curtailment) in order to achieve same data would smooth the variations in costs by increasing the accuracy of the forecasted consumption and production. Thus, a real-time centralized neighbourhood system operator (CNSO) which can effectively process the DR events is expected to be implemented in this study based on the accuracy of the predicted consumption and production.
3- There is a lack of a general framework for analyzing and modelling the behaviour of the owners of GBs in a deregulated competitive energy matching and energy trading structure at the residential distribution level when (Gregoratti and Matamoros, 2015; Nunna and Doolla, 2012; Silva, Ili and Karnouskos, 2014; Z. Wang et al., 2016; Wu et al., 2015) considering uncertainties by using the concept of energy trading and energy matching as a solution in a multi-agent interaction problem by guaranteeing fairness among GBs.
4- There have been no investigations on the impact of prosumers on the economic operations of future residential neighbourhood systems looking at full prosumers' participation through probabilistic methodology (Houman Jamshidi Monfared, Ahmad Ghasemi, Abdolah Loni 2019; Y. Wu et al. 2015).
5- There is no supply bidding mechanism considering energy trading for all the owners of GBNs (Nastaran Gholizadeh, Gevork B Gharehpetian, M Abedi, Hamed Nafisi 2019; Linfeng Zhang, Gari, and Hmurcik 2014).
6- There is no market clearing price calculation based on energy matching and energy trading among the owner of GBs, among market bids and the double-side auction approach (Algarni and Bhattacharya, 2009; Su and Huang, 2014; Yang, Zhou and Xin, 2005; Zhang et al., 2015).
7- There has been no idea put forward for combining DR and ES in a satiable manner to exploit the full capabilities of these types of resources (Behboodi et al., 2016; Yang, Zhou and Xin, 2005).
8- There is no solution that can guarantee the benefit of all owners of GBs, consumers and prosumers with opposing objectives in a multiple ownership environment in (Amin et al. 2019; Khodaei, Bahramirad, and Shahidehpour 2015) is proposed. This is while proposed solutions in Chandler et al. (2014); Ipakchi (2011; Lopes, Algarvio and Coelho (2013); Poveda and Schumann (2016); Yang, Zhou and Xin (2005) does not guarantee to find a final optimal solution.
9- In Su and Huang (2014) and Zhang et al. (2015) retailers are not considered as a key element in the energy trading structure.
10- The interoperability of GBs with each other as well as with retailers is not considered in the proposed energy trading structures given by Chiu, Sun and Poor (2015) and Lee et al. (2015).

2.10. Uncertainly modelling

Optimization in electrical and thermal energy matching and trading is an intricate operation because of the variation in energy demand and the uncertainty of power production, exclusively because of the large penetration of renewable energy systems, such as wind and solar power. The majority of the available type of approaches have, first and foremost, concentrated on the question of solving the energy matching and trading problems in GBNS optimally. There are many optimization techniques (Momoh, 2012) that have been used in the optimization of GBs.

The duty of these techniques is to improve the stochasticity and the adaptive components. Some techniques such as realistic optimization methods are not suitable for complicated or large scale power systems (Melhem et al., 2017). The use of these methods is limited to reply new idea for the optimization of the GB. In order to achieve the global optimal solution, hybrid techniques should be integrated to connect the advantages of the multiple techniques, which make it possible for the application to be utilized for electricity in a GB (Zakariazadeh, Jadid and Siano, 2015).

It should be considered, as shown in most of the studies examined for this thesis that due to lacking uncertainty considerations optimization techniques are not accurate and simple enough, the influence of renewable-based DER resources, variation, and the fluctuation nature of these resources would increase the risk of operation. Furthermore, load demand cannot be exactly anticipated at each time intervals. Those two factors are very important in making decisions. Thus, the uncertainty parameters and the stochastic method should be applied to present the energy matching and trading due to different operational situations. Recently, a large number of studies have been presented in order to describe methods for dealing with uncertainties in energy optimization; these can be mainly divided into two categories (Jiang and Low, 2011). One of them is to class the uncertain factors by additional reserves, i.e., the more controllable non-renewable based DER resources can be employed in order to increase the robustness of the network from uncertainty point of view, load consumption for smoothing production power, and for satisfying the total load demand. However, this is expensive and the network may still have a capacity deficiency problem when the load demand changes (Bertsimas et al., 2013). On the other hand, stochastic (or probability statistic) and deterministic optimization techniques can be presented to deal with uncertainty problems. When considering uncertainty in the optimization problems The stochastic method (Mirzaei, Yazdankhah, et al. 2019) utilizes stochastic variables to demonstrate the uncertainty.

Two uncertainty methods including the Monte Carlo and Taguchi methods are considered in this thesis and the obtained results from those methods have been compared with each other. Brief explanations of each method are presented in the following section. These methods were selected because they are most widely used and their applications in green building studies are a relatively new method in comparison with conventional statistical methods. In addition, more importantly and far less explored, they have the potential to capture a representation of a network's complexity. These two methods used several methods in combination with improvement in both the sensitivity and the explanatory power of the analysis by applying the effects of the uncertainty parameters. The outcomes from these methods will advance new and emerging fundamental research in uncertainty simulations, in dynamic network analysis, and in computational models and architectures of optimization algorithms. These methods are widely involved in the techno-economic phenomena analysis of GBNS. The Taguchi method is offered as a better tool and technique to manage uncertainty parameters. Taguchi can reduce computational time more effectively thereby improving the precision of the results in comparison with the other known methods such as the Monte Carlo method.

2.10.1. The Monte Carlo technique

The Monte Carlo technique is investigated because it is an important simulation method that uses statistical sampling techniques to obtain a repeated experiment probabilistically. This method is helpful in providing an estimated solution using random numbers for solving problems that are difficult randomly or accidently using mathematical problems or functions (M. Marzband, Parhizi, et al. 2016).

Monte Carlo is one of the easiest applications to obtain a target amount; a suitable algorithm can be extended with extensive background knowledge including different mathematical formulations. Furthermore, the advantage of the Monte Carlo technique is that it can give a relatively precise amount through simulation without much processing. On the other hand, a disadvantage of the method is that the outcome is comprehensive if the probability distribution of the amount of input and the range denoted by the mathematical formulation are not accurate. The distribution of random numbers has a considerable effect on the analysis outcome. Therefore, the random numbers of the function should be formulated correctly according to the necessary range and distribution of the random numbers. Monte Carlo simulation has been carried out by constructing models of feasible outcomes that is replaced with an area of values (a probability distribution) for any part that has essential uncertainty as shown in Figure 12. Afterwards, it computes outcomes again and again, every time applying a variety type of random values from the probability distribution. Monte Carlo simulation could require several times of recalculations before it has been finished that is relying on the number of uncertainties values specified for them. Monte Carlo simulation creates distributions of feasible result values.

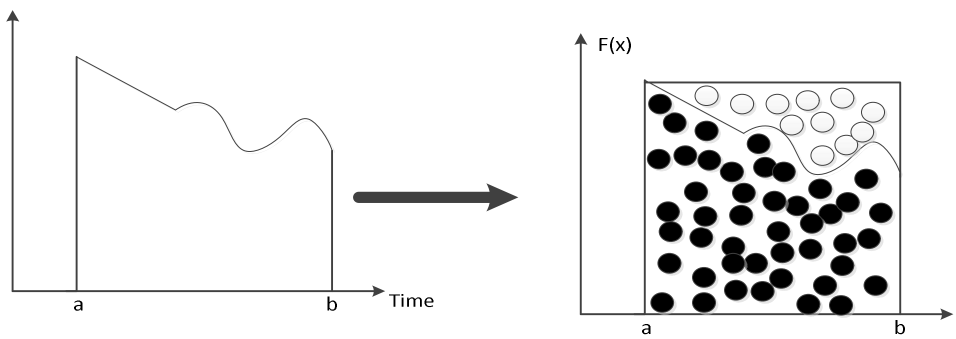


Figure 12: the Monte Carlo method (M. Marzband, Parhizi, and Adabi 2016)

2.10.2. Taguchi's orthogonal array testing

The powerful Taguchi orthogonal array testing (TOAT) method was presented by Taguchi (Tsui, 1994) to achieve robust solutions in experimental development problems in manufacturing. The TOAT method proposes the great testing scenario to minimize the scenario number in the uncertain operating space which can reduce the testing speed significantly. For increasable and quadratic models, TOAT has been demonstrated to have the capability to choose representative scenarios optimally in order to test all possible structures (Liu and Cai, 2005). When compared with the Monte Carlo simulation, TOAT proposes much smaller testing scenarios and obtains better designs in a shorter computing time. In spite of its capability, TOAT is only considered as an optimization algorithm to solve the energy matching and trading in GBs (M. Marzband, Javadi, et al. 2016). In this study, TOAT is proposed to be used to evaluate the gradient values of the cost function and the profit of the energy matching and trading in GBNS in adjacent optimization spaces. Subsequently, the cost function should be optimized according to the direction specified by the gradient values.

This thesis proposes that TOAT can be employed in the stochastic methods to determine the number of scenarios in the planning problems. The mathematical formulation is applied based on the scenarios generated by the TOAT method; then it is proposed to solve the energy matching and trading problems with regard to generation dispatching. The uncertainties of both the load demand and the renewable energy resources are modelled in this problem (Yu, Chung and Wong, 2011). The method of TOAT has been briefly explained in the following.

For a system with some uncertain inputs, the proper adjustment of the uncertainty parameters can make the system adaptable within various operating scenarios and less sensitive to random variations. Generally, some selected scenarios of the uncertain variables are validated to guide the controlling variables' adjustment. Suppose a system Y can be indicated by a function of $\boldsymbol{Y(\mathrm{x}_{1,} \ldots\ldots, x_F)}$ where $\boldsymbol{\mathrm{x}_{1,} \ldots\ldots, x_F}$ are F uncertain variables. If every variable in set $\{x_1, \ldots. x_F\}$ is indicated by **B** selected levels in its variation range, then the number of full combination of system states is $\boldsymbol{B^F}$. This last sentence seems to be complete. Usually if a sentence starts with 'if' there has also to be something like a 'then' within it. It is computationally expensive to test all the $\boldsymbol{B^F}$ cases when F is large. Hence, TOAT is employed to generate an optimal number of testing scenarios such that only a small number of tests need to be performed. In TOAT, testing scenarios are formed according to orthogonal arrays (OAs). An OA for F variables and B levels is represented by $\boldsymbol{L_H\left(B^F\right)}$, where H is the number of combinations of variable levels. $\boldsymbol{L_H\left(B^F\right)}$ is represented in the form of a matrix with H rows and F columns, and the variable levels are indicated by matrix element values. As an example, an OA $\boldsymbol{L_4(2^3)}$ is shown as follows:

$$L_4(2^3) = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 2 \\ 2 & 1 & 2 \\ 2 & 2 & 1 \end{bmatrix} \quad \textbf{(1)}$$

There are three levels of variables, including two levels of each variable, and four combinations in $\boldsymbol{L_4(2^3)}$. The testing scenarios determined by $\boldsymbol{L_4(2^3)}$ are shown in Table 4. Hence, for system Y, totally H testing scenarios can be formed based on OA $\boldsymbol{L_H\left(B^F\right)}$. Generally, H is much smaller than $\boldsymbol{B^F}$. For the above system with three random variables and each represented by two levels, the number of full combinations is 2^3.

Table 4: Four Testing Scenarios Determined By Orthogonal Array

No. of the Testing scenarios	Variables' levels		
	X1	X2	X3

1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

However, according to $L_4(2^3)$, only four testing scenarios are formed. Thus, the number of testing is minimized. An OA has the following features.

1- For the variable in each column, every level occurs H/B times. For example, in $L_4(2^3)$, H=4 and B = 2 and, because of that "1" and "2" occur two times in each column.

2- In any two columns, the combinations of two variable levels occur the same number of times. For instance, in any two columns of $L_4(2^3)$, the combinations of two variable levels, i.e., "11", "12", "21", and "22", appear one time (Yu, Chung and Wong, 2011).

3- The combinations determined by TOAT are uniformly distributed over the space of all the possible combinations. For example, the combinations of scenarios are shown in Figure 13 (Zhang and Leung, 1999).

4- If any two columns of an OA are exchanged (or some columns can be ignored), the resulting array still satisfies the OA features. OAs can be implemented by many other methods (Gautschi, 2005). The simplest way to get an OA is to choose a proper OA directly from OA libraries (Abido, 2002; Peace, 1993; Wysk, Niebel, Cohen, and Simpson, 2000). It is worth mentioning that it is possible that, for a given problem, there is no existent OA in the OA libraries whose number of columns is equal to the number of uncertain variables in the problem. In such a case, an OA whose number of columns is a few more than the number of uncertain parameters should be chosen. Then, according to OA's features mentioned above, this OA is used in TOAT by ignoring the redundant columns.

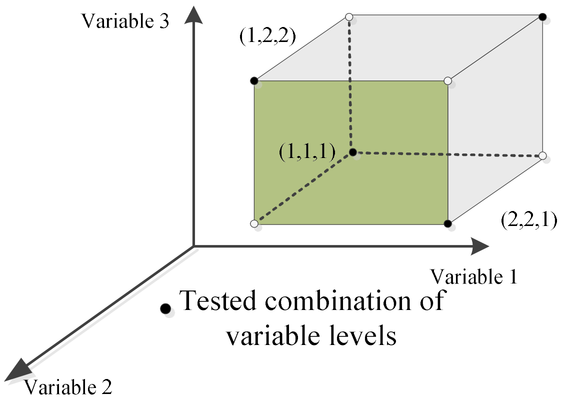


Figure 13: Orthogonal array $L_4(2^3)$

2.10.3. Literature review of uncertainty

In the literature, several issues relating to communication in GBs, renewable-based DER resources, and the different types of customers for establishing energy matching and trading in GBNS are addressed independently, such as in the studies of Chiu, Sun and Poor (2015); Jiang and Low (2011); Niyato et al. (2011);

Polasky et al. (2011); Soroudi 2012; Yan and Chowdhury (2014). These researchers treated all the renewable energy, load, energy storage as general demand resources of a GB and presented a new optimal operation framework (Polasky et al., 2011). Bakirtzis et al. (2007) discussed various uncertainty problem in GBs looking at the aspects of market risks, shortage of knowledge, several measurement errors, and so on. They employed various possibilities to examine the uncertainty problem in order to deal with it. Moreover, they did not consider the uncertainty problem from the energy production and distribution point of view which are the most important components in energy matching and trading in GBNS. (Bingnan Jiang and Fei 2011) presented a DR model presenting the uncertain modelling of renewable energy sources. The authors cooperated in order to optimize a supply-demand model using dynamic optimization programming. In such a scenario, two dynamic decisions were studied based on a day-ahead, and real- time. In the day-ahead policy, a primary DR was modelled throughout a day. In the real-time policy, the modelled DR is changeable dynamically according to the real-time situations. However, the authors only investigated the uncertainty in the supply of renewable energy (e.g. solar power and wind power generation). The influence of power loss in a GB communication network was studied by Niyato et al. (2011) in two different aspects: energy demand estimation and related operating cost. In such a scenario, the authors proposed that, with an increase in power loss in the communication network, the energy cost will increase to the grid and to the consumers increasingly. To solve this problem, they used a queuing model to measure the value of the packet loss at the data aggregator units. By measuring the amount of packet loss, the grid evaluates the demand from the customers and also assesses the energy cost. In (B. Li et al. 2016), the author proposed a distributed energy resources' (DER) impact evaluation tool for taking uncertainty into account. This uncertainty is associated with the various behaviours of renewable energy sources. The proposed evaluation tool combines two models: probabilistic (stochastic) and possibility (deterministic). The probabilistic scenario is employed to model some of the cases in a DER environment. On the other hand, the possibility scenario is employed to consider the rest of the cases for which the probabilistic model is not appropriate. Although, according to other available studies, the proposed model included only the uncertainty of renewable energy sources as an uncertainty component. Moreover, (Alireza Soroudi 2013) proposed a programming scheme under uncertainty due to the existence of renewable energy sources and plug-in electric vehicles. It showed that the real-time energy demand from consumers is different from the requested one as unit commitment in the presence of renewable energy sources. In addition, they proposed issues associated with controlling electric vehicles in GBNS. They utilized a particle swarm optimization (PSO) approach to consider optimal scheduling of DER resources under uncertainty. (Alireza Soroudi and Amraee 2013) discussed various decision-making strategies under different scenarios in energy matching and trading in GBNS systems as different solutions.

In the study of Yu et al. (2009), a chance constrained programming model was evaluated to solve energy matching and trading in GBNS systems with a consideration of the uncertainties of both the demand and the wind turbine output. Although, some research studies have investigated generation dispatch, the most significant method to propose the uncertainties was still to examine is still an examination the vast numbers of scenarios generated by the Monte Carlo method (Martinez et al. 2011). However, this surveying approach is unsuccessful in providing a solution for the matching and trading problem in practice because of its heavy computational burden. Other researchers solved the computational demand problem by using scenarios that are specified by the scenario selection method (J. Valinejad et al. 2017) or by operating experience (Zhao et al., 2009) to describe the uncertain operating conditions (Han Yu, Chung and Wong, 2011).

Battistelli, Baringo and Conejo (2012) proposed a stochastic optimization strategy for GBs with electric vehicles and renewable energy resources, presenting the uncertainty in production, energy storage and the demand relationship (Battistelli, Baringo and Conejo, 2012) and an integrating stochastic optimization algorithm with uncertain load, electricity price was designed in Mohammadi, Soleymani and Mozafari (2014). However, stochastic methods typically propose a probabilistic warranty for constraint satisfaction in order to use a deterministic probability curve to present the uncertain change of stochastic parameters which may not reflect the real case exactly. Additionally, robust optimization (Mirzaei, Yazdankhah, et al. 2019) is an effective tool for dealing with uncertain but limited data within an optimization model by uncertain sets with deterministic bound. However, it was proposed by (Alireza Soroudi 2012) to make a robust energy optimization model for GBs and an uncertain set was built to define the diversity of renewable resources. Then, the robust optimization problem was converted into a scenario-based deterministic problem. A scenario is a current and easy way to explain uncertain factors in deterministic status, e.g., the uncertainties of renewable resources and load demand can be proposed by chosen scenarios, but the key issue lies in how to diminish the huge number of testing scenarios. There are many reduction techniques comprising interval linear programming (Wang, Xia and Kang, 2011), a backward and forward scenario reduction technique (Lingxi Zhang et al. 2015), and a worst-case reduction method (Gao et al., 2013), etc.; these have all been previously applied in electricity market trading (Morales et al., 2009). In this thesis, the TOAT is introduced to select testing scenarios based on the theory of robust design (Beyer and Sendhoff, 2007). The testing method is based on the most likely scenarios, in which the uncertain factors are assigned to the values that have the largest probability to appear. Therefore, it is used to select a minimum number of testing scenarios with good statistical information in an uncertain set. It has been proven to have the ability to select optimally representative scenarios for testing all possible combinations (Taguchi and Rafanelli, 1994), especially for linear and quadratic model optimization (Han Yu, Chung and Wong, 2011). The method uses an equivalent deterministic way to describe uncertain factors and selects typical steady scenarios to be tested and analyzed, which results in significantly less testing scenarios and shorter computing time than that of the Monte Carlo simulation. A summary of uncertainty modelling which has been proposed in the literature is presented in Table 5.

Table 5: uncertainty modeling presented in literature

Number	Uncertainly Parameter	Objective	Method	References
1.	Renewable energy resources such as solar power and wind power	More controllable non-renewables in order to smooth generation power and satisfy demand.	Heuristic algorithm	(Fouladfar, Sumaiti, et al. 2019; Mousa Marzband, Fatemeh

				Azarinejadian, Mehdi Savaghebi 2015)
2.	To measure the amount of packet loss	The grid evaluates the demand from the customers and also assesses the energy cost	Queuing model	(M. Marzband, Parhizi, and Adabi 2016; M. Marzband et al. 2015)
3.	To propose two models: probabilistic and possibilistic	The probabilistic scenario is employed to model some of the cases in a DER environment. On the other hand, the possibilistic scenario is employed to consider the rest of the cases for which the probabilistic model is not appropriate	Stochastic method	(Mirzaei, Nazari-Heris, et al. 2019; Morteza Nazari-Heris, Mohammad Amin Mirzaei, Amjad Anvari-Moghaddam, Behnam Mohammadi-Ivatloo 2019)
4.	To propose a resource scheduling scheme under uncertainty (But even if it is 'uncertainty' this phrasing reads oddly.	To control electric vehicles in GBNS	PSO	(M. Marzband, Fouladfar, et al. 2018)
5.	To consider the uncertainties of both the load and wind energy	To solve the energy matching and trading in GBNS systems	Monte Carlo	(Fouladfar, Loni, et al. 2019b)
6.	To consider electric vehicles and renewable energy	Integrating a stochastic optimization algorithm with the uncertain load, and the electricity price	Stochastic optimization strategy	(Tavakoli, Shokridehaki, Funsho Akorede, et al. 2018; Tavakoli,

				Shokridehaki , Marzband, et al. 2018)
7.	To consider renewable resources and load	To reduce the vast number of testing scenarios	Scenario-based deterministic problem	(Houman Jamshidi Monfared, Ahmad Ghasemi, Abdolah Loni 2019; Mousa Marzband, Javadi, et al. 2016)

2.11. Optimization methods

The minimization of cost and the maximization of profit are the main objectives that must be achieved in this thesis. To reach this objective, optimal energy matching and trading should be implemented through some techniques and optimization algorithms in order to find the best solution in terms of cost minimization and profit maximization (Mirtaheri et al. 2019). In this thesis, a comparison between various techniques for operation scheduling is presented, and some logical results are presented, in order to offer a clear overview of each technique in terms of their advantages and disadvantages. Recent developments in optimization methods can be mainly divided into realistic and heuristic methods, as shown in Figure 14.

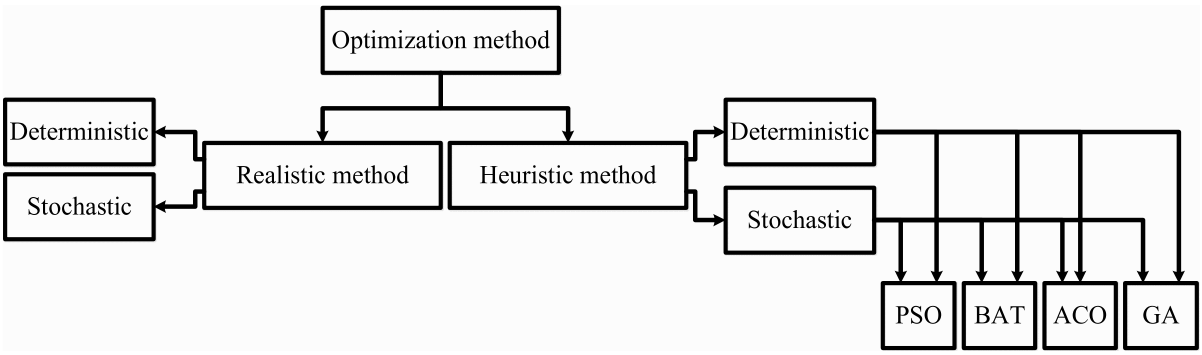


Figure 14: different types of optimization methods

2.11.1. Realistic method

There are many optimization techniques that are applied to deal with energy matching and trading problems. Some of techniques are developed based on realistic optimization methods, but some others use artificial intelligence based methods. Such realistic based optimization methods (Safari and Shayeghi, 2011) are extremely sensitive to the initial value of the starting points and may converge to a local optimum. There is no limitation on the cost curve nature in the dynamic programming method. It can produce global solutions even if the objective function has a nonlinear and discrete nature (A. Soroudi and Afrasiab 2012). However, dynamic programming has the obstacle known as the curse of dimensionality. It can create a lot of problems, resulting in much high computation times.

2.11.2. Heuristic method

Heuristic methods are methods that are inspired by physical and biological processes and nature and most of them act populationally. Heuristic search methods, as opposed to realistic methods, act randomly and does the space search in parallel. Another difference between these methods is not using the information of the space gradient. These methods only use the fitness function for guiding the search but by not having collective intelligence, they can find out the optimum point. In population methods, fundamental interaction and exchanges of data between extremity will be in different ways. Local interactions between members include random searches, positive and negative feedback and system cross-like interactions guide the system to its organizing position.

The heuristic method has been selected after a consideration of these optimization methods. One of the advantages of these algorithms is that they encounter iterative search processes. This subject can cause an efficient exploration and exploitation in the search space including the local and global optima. Generally, the advantages and disadvantages of the heuristic method can be summarized as follows:

Advantages

– Although there is a realistic optimization method that can solve the problem it cannot be used on the available hardware.

– The heuristic method is more flexible than the realistic methods, allowing, for example, the incorporation of conditions that are difficult to model.

– The heuristic method is used as part of a global procedure that guarantees finding the optimum solution to a problem.

Disadvantages

– No method for solving the problem of optimality is known.

– Escaping on the local optima

In this section, four types of heuristic algorithms (such as particle swarm optimization algorithm (PSO), bat algorithm (BA), ant colony algorithm (AC) and genetic algorithm (GA)) are compared to find the best optimal solution for this thesis.

Partial Swarm optimization (PSO) algorithm

The PSO method is used with a similar application for solving some of the optimization problems in the studies of Leeton et al. (2010). This method is a random search algorithm which is modelled from the social behaviour of a flock of birds. Initially, this optimization method was implemented to discover governing models on the simultaneous flight of the birds, the sudden changes in their path as well as the optimum formation of the flock of birds. Subsequently, this method was employed for optimizing non-linear continuous functions and it has been indicated that the PSO method is a super-innovative method based on population that is used for finding the minimum of the object function. In this algorithm, each member of society (which is called a particle) moves in the search space (M. Marzband, Fouladfar, et al. 2018). The displacement of the particles in the search space is affected by their experience and knowledge and by their neighbour's knowledge. Thus, the position of the other particles in a group affects the manner of a particle which is searching. Members in the group learn from each other, so that, based on the knowledge obtained, they move toward their best neighbour. The PSO method is based on the principle that, in each moment, each member adjusts its location in the search space based neither on the best place that is located in it so far or the best place that exists for all the neighbour of that member. In this method, an iteration process for improving the answer is undertaken and during this process the members of group repeatedly investigate the fitness of the different cases of the candidate and gradually move toward points which, in that position, have the best position. The best answer found by all the members of the group in each iteration is identified as the best position. Each of the group members put the found information at the disposal of their neighbour. Thus, the members of the group are able to identify the positions that the other members of the group are successful in. In fact, the movement strategy in the search space is based on global awareness and an awareness of the standpoints of the positions of the other neighbour and moves toward better point of solution (Fouladfar, Sumaiti, et al. 2019). The advantages and disadvantages of the PSO method are presented below.

Advantages:

1. The number of parameters is very low.

2. The convergence of particles in the PSO method is very fast.

3. PSO is easy to implement and there are few parameters to adjust.

4. In this method, unlike other optimization methods, none of the particles (solutions) is eliminated and only the amount of each particle is changed.

5. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas.

Disadvantages:

1. The PSO method needs a great deal of computer memory and it may implement slowly.

2. By increasing the particles, the efficiency of the algorithm will be decreased (Abido, 2002)

Bat Algorithm (BA)

Bat algorithm is a part of heuristic optimization method that is expanded by Xin-She Yang in (X. Yang and Hossein Gandomi 2012). The bat method has been founded on the echolocation action of bats with ranging pulse level of emission and loud voice. Echolocation is a kind of sonar that supports bat to discover the path of the prey. Furthermore, by helping the echolocation, Bats can also recognize form, place and angle of the prey. The explanation of the echolocation of bats can be defined as follows: Each particle flies randomly with different velocity vi at position xi with altering intermittence and loud voice Ai. The Particles are searching in order to gain the hunt, therefore intermittence, loudness, and pulse has been changed (M. Marzband, Fouladfar, et al. 2018). The searching has been increased by local pace randomly. Thus, this process has been continuing until find the best certain criteria.

This fundamentally utilize a intermittence-tuning technique in order to conduct the dynamic manner of a congestion of bats, and the equilibrating between exploration and exploitation can be monitored by adjusting parameter in bat algorithm.

The advantage and disadvantage of the bat method can be described as follows:

Advantage:

The bat algorithm can provide a very quick convergence at a very initial stage by switching from exploration to exploitation. This makes it an efficient algorithm for applications such as classifications when a quick solution is needed.

Disadvantage:

It can get trapped in local optima (Yang and Gandomi, 2012).

Ant Colony optimization (ACO)

Marco Dorigo and colleagues introduced the first ant colony optimization algorithms in the early 1990s (Song, Chou and Stonham, 1999). The development of these algorithms was inspired by the observation of ant colonies. Ants are social insects. They live in colonies and their behaviour is governed by the goal of the colony's survival rather than focusing on the survival of individuals. The behaviour that provided the inspiration for ant colony optimization is the ants' foraging behaviour and, in particular, how ants can find the shortest paths between food sources and their nest. When searching for food, ants initially explore the area surrounding their nest in a random manner. While moving, ants leave a chemical pheromone trail on the ground. Ants can smell the pheromone. When choosing their way, they tend to choose, in all probability, paths marked by strong pheromone concentrations. As soon as an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest. During the return trip, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone trails will guide other ants to the food source (M. Marzband, Yousefnejad, et al. 2016).

The advantages and disadvantages of the ACO method can be described as follows:

Advantages:

1. ACO can be used in dynamic applications.
2. Positive feedback leads to the rapid discovery of good solutions.

Disadvantages:

1. Convergence is guaranteed, but the time to gain the convergence is uncertain.
2. Coding is not straightforward.

Genetic algorithm (GA)

Another heuristic method is the genetic algorithm (GA) which is a probabilistic search technique that has its roots in the principles of genetics. It places more emphasis on the natural selection of surviving species and the process of reproduction of new offspring. The algorithm works on the process of mutation and crossover to create a new population (Song and Xuan, 1998). Since its conception, the genetic algorithm has been used widely as a tool in computer programming, artificial intelligence and optimization. GA is a heuristic optimization technique which is based on the principle of natural selection and genetics (He, Wang and Mao, 2008). In recent years, the interest in these algorithms has been rising fast, as they provide robust and powerful adaptive search mechanisms (Warsono et al., 2007). GA has an immense potential for application in the field of energy matching and trading systems and it has been successfully applied to solve various problems within electric power in neighbourhood systems. It searches multiple solutions simultaneously in contrast to conventional optimal algorithms. Therefore, the possibility of finding global optimal solution is increased. The main advantage of GA is that it finds s near optimal solution in a relatively short time compared with other random searching methods. Despite this aforementioned success, GA is only capable of identifying the high performance region in an affordable time and displays inherent difficulties in performing a local search for numerical applications (M. Marzband, Alavi, et al. 2017).

2.11.3. Literature review of optimization methods

Generally, in the field of realistic and heuristic methods, if a method has not been not considered as an uncertainty in an optimization method, it is called as a deterministic method. On the other hand, if it has survived uncertainly it can be explored as a stochastic method. In this thesis, for one green building the deterministic method has been used but the use of the deterministic method for multiple green buildings in a neighbourhood system is complex and time consuming when solving optimum problems with large dimensions. Thus, it is an applied stochastic method.

In this thesis, lots of optimization methods (including realistic and heuristic algorithms) are considered to implement the energy matching and trading in a green building neighbourhood system. Due to high non-linearity and the complications of the energy matching and trading problem, heuristic optimization methods fail to obtain optimal solutions. By the way, heuristic methods do not enforce any condition on an objective function shape which is a good choice for solving energy problems and has attracted a great deal of attention in recent years. In the past decade, a wide variety of heuristic optimization methods such as the genetic algorithm (GA) (Warsono et al. 2007), particle swarm optimization (PSO) (Chaturvedi, Pandit and Srivastava, 2009; Safari and Shayeghi, 2011; Zhang, Gari and Hmurcik, 2014), differential evolution (DE) (Pothiya, Ngamroo and Kongprawechnon, 2008), the Tabu search (TS) (Pothiya, Ngamroo and Kongprawechnon, 2008), the ant colony optimization (ANO) and the bat algorithm (BA) have been applied in order to implement energy in a neighbourhood system.

Differential evolution (DE) is heuristic search algorithm that was originally motivated by the mechanisms of natural selection. Like other evolutionary algorithms, DE is very effective for solving optimization problems with non-linear objective functions, since it does not require derivative information. The DE algorithm was successfully applied in the optimization of some well-known nonlinear, non-differentiable and nonconvex functions by Storn and Price (M. Marzband, Fouladfar, et al. 2018). The DE algorithm is an evolutionary algorithm that uses a rather greedy and less heuristic approach to problem solving than do other evolutionary algorithms, such as genetic algorithms, evolutionary programming and evolution strategies (M. Marzband, Fouladfar, et al. 2018). The fitness of an offspring competes with that of the corresponding parent in DE. This one-to-one competition will have a faster convergence speed than another optimization method. The potentialities of DE are its simple structure, easy use, local searching property and speediness. Nevertheless, this faster convergence yields a higher probability of searching toward a local optimum or getting premature convergence. This drawback could be overcome by employing a larger population. However, by doing so, much more computation time is required to estimate the fitness function (Mohammad Amin Mirzaei, Ahmad Sadeghi Yazdankhah, Behnam Mohammadi-Ivatloo, Mousa Marzband, Miadreza Shafie-khah 2019). A hybrid genetic algorithm approach based on differential evolution for economic dispatch by Bakirtzis, Petridis and Kazarlis presented a GA method and an enhanced GA to solve the energy matching and trading problem (Pourakbari-Kasmaei et al. 2019). According to their work, the results obtained are better than with the dynamic programming method. Chen and Chang developed a GA approach for implementing energy in a neighbourhood system, and the method was faster and more robust than other well-known methods in large-scale systems (Mirzaei, Yazdankhah, et al. 2019). Chiang suggested an improved genetic algorithm with multiplier updating to implement energy in a neighbourhood system with positive effects and multiple fuels (Su and Chiang, 2004). Simulation results shown that the PSO method is indeed capable to obtain higher quality solutions in comparison with the GA method (Baskar, Subbaraj and Rao, 2003). Park et al. designed a dynamic search-space reduction strategy to accelerate the optimization process in the PSO method for implementing energy in a neighbourhood system (Park et al., 2000). Coelho and Mariani combined the DE method with the generator to optimize the performance of implementing energy matching and trading (dos Santos Coelho and Mariani, 2006) and their proposed method outperforms other state-of-the-art algorithms in solving load dispatch problems.

Song and Xuan (Basu, 2013) employed an improved penalty function formulation for the GA to solve the energy matching and trading problem. Chang and Fu (Wang and Singh 2008) used a multi-objective method by using a fuzzy decision index and GA in a seven-generator sample system. (M. Marzband, Yousefnejad, et al. 2016) introduced an ant colony search algorithm approach to solve the energy matching and trading problem. (D. C. Gao and Sun 2016) employed a hybrid of a genetic algorithm to apply in several GBs in a neighbourhood system. Su and Chiang (Su and Chiang, 2004) used an incorporated algorithm for combined heat and power in a neighbourhood system based on an improved GA which was equipped with an improved evolutionary direction operator. Additionally, a multiplier updating has been used to avoid deforming the augmented Lagrange function but resulted in difficulties in the solution searching.

Song et al. presented a GA approach with fuzzy logic controllers to adjust its crossover and mutation probabilities to solve The energy matching and trading problem (Ahmad et al. 2017). Wong and Yurevich proposed an economic dispatch algorithm to solve the energy matching and trading problem (Koutitas 2012). Recently, Venkatesh et al. proposed GA techniques for the energy matching and trading problem with line flow constraints. Their paper claimed that GA was the best of the evolutionary method from computation time point of view. Orero and Irving presented a GA approach to the economic dispatch of generators and compared the results with the lambda-iteration method and the GA method (Mohammad Amin Mirzaei, Ahmad Sadeghi Yazdankhah, Behnam Mohammadi-Ivatloo, Mousa Marzband, Miadreza Shafie-khah 2019). El-Gallad et al. have implemented a PSO algorithm for resolving the energy matching and trading problem (Thongchart Kerdphol, Qudaih, and Mitani 2016). In their study, an advanced PSO algorithm implements energy in a neighbourhood system and the results are compared with GA (Yongli Wang et al. 2018).

Chen and Chang presented a GA method that used the system incremented cost as an encoded parameter for resolving energy matching and trading problems which could take into account network losses, and ramp rate limits (Yongli Wang et al. 2018). Fung et al. presented an integrated parallel GA incorporating simulated annealing and Tabu search techniques that employed the generator’s output as the encoded parameter (Yongli

Wang et al. 2018). Different reference system again. For an efficient GA method, Yalcinoz used the real-coded representation scheme, arithmetic crossover, mutation, and elitism in the GA to solve energy matching and trading more efficiently; it can obtain a high-quality solution with less computation time (Pipattanasomporn, Kuzlu, and Rahman 2012). Though the GA methods have been employed successfully to solve complex optimization problems, recent research has identified some deficiencies in GA performance. This degradation in efficiency is apparent in applications with highly non-linear objective functions (i.e., where the parameters being optimized are highly correlated) [the crossover and mutation operations cannot ensure better fitness because chromosomes in the population have similar structures and their average fitness is high toward the end of the evolutionary process] (Chang et al., 2007). Moreover, the premature convergence of GA degrades its performance and reduces its search capability which leads to a higher probability towards obtaining a local optimum (Baskar, Subbaraj and Rao, 2003).

Kennedy and Eberhart (1995) introduced PSO as one of the modern heuristic search techniques. It has gained a lot of attention in various power system applications (Yoshida et al., 2000). Generally, PSO is characterized as a simple heuristic of a well-balanced mechanism with the flexibility to enhance and adapt to both global and local exploration abilities. Compared to other heuristic searches, it has fast converging characteristics (Ciuprina, Ioan and Munteanu, 2002).

Recently, inspired by quantum mechanics, Sun et al. proposed a novel variant of the PSO, called the quantum-behaved particle swarm optimization (QPSO) algorithm (Sun, Xu and Feng, 2004). The QPSO outperforms the PSO in its global search ability and is a promising optimizer for complex problems. Furthermore, a hybrid multi-agent based PSO algorithm has been proposed by Gaing (2003) to implement energy in a neighbourhood system. Niknam proposed a fuzzy adaptive hybrid particle swarm optimization algorithm for the solution of non-clear energy matching and trading problems (Niknam, 2010). A local random search procedure is integrated with a modified PSO in the study of Naama, Bouzeboudja and Allali (2013) to improve the performance of the PSO algorithm in implementing energy in a neighbourhood system. In the modified PSO, particles are also made to remember their worst position. An improved PSO employing chaotic sequences combined with conventional linearly decreasing inertia weights and adopting an intersecting operation scheme is presented in the study of (Akbari Kaasgari, Imani, and Mahmoodjanloo 2017) and was tested on large scale neighbourhood system problems.

In the work of Sedighizadeh and Masehian (2009) and Koh et al. (2006), a parallel PSO algorithm, namely a synchronous parallel PSO (PSPSO), was discussed for implementing resolving energy problems. In PSPSO algorithms, the function evaluations of all the particles of the population are carried out in a parallel fashion by a cluster of computers and, at the end of the iteration, the positions of all the particles are updated as a whole. This makes the swarm react more slowly to the changes in the best position attained by any particle in the swarm and eventually reduces the convergence rate. To increase the convergence rate, an asynchronous version of the parallel PSO was proposed (Venter and Sobieszczanski-Sobieski, 2006). In asynchronous parallel PSO (PAPSO), the updating of the particle positions is undertaken in an asynchronous manner i.e. the social and cognitive knowledge of every particle is updated after its function evaluation. This leads to a quicker reaction by the swarm to the changes in the best function values, thereby increasing the convergence rate. In the work of (Mohan, Singh, and Ongsakul 2017), a parallel PSO algorithm was implemented on a cluster of personal computers (for solving the optimal energy matching and trading problem) in which the population is divided into several sub populations for evaluating the fitness functions. In the study of (Lin and Hu 2018) the use of a Java-based platform in the implementation of a parallel evolutionary algorithm has been highlighted and the problem of a 13-generator has been solved. The efficiency of the parallel evolutionary algorithms mainly depends on the dimensions of the problem.

Recently, PSOs have been successfully applied to various fields of energy system optimization such as power system stabilizer design (Pathak, Chatterji, and Narkhede 2012), reactive power and voltage control (Mohan, Singh, and Ongsakul 2015), and energy management systems (Kinhekar, Padhy, and Gupta 2015). The original PSO mechanism is directly applicable to the problems with continuous domain and without any constraints. Therefore, it is necessary to revise the original PSO to reflect the equality constraints of the variables in the process of modifying each individual's search. (Kinhekar, Padhy, and Gupta 2015) suggested a modified PSO to control reactive power and voltage when considering voltage security assessments. Since the problem was a mixed-integer nonlinear optimization problem with inequality constraints, they applied the classical penalty method to reflect the variables. (R. Mohammadi, Ghomi, and Jolai 2016) developed a revised PSO for determining the optimal values of parameters for an energy matching and trading system. In his study, the velocity of each parameter was limited to a certain value to reflect the inequality constraint problem in the dynamic process.

(J Soares et al. 2012) has proposed an interesting PSO procedure to solve the energy matching and trading problem by considering production constraints. The main advantages of PSO (Hurtado, Nguyen, and Kling 2015) are its simple concept, its computational efficiency and its easy implementation. However, the performance of the classical PSO greatly depends on its parameters, and it often suffers the problem of being trapped in local optima. Therefore, many variations have been proposed for the classical PSO by various researchers (Gudi et al. 2010) (Heo, Lee and Garduno-Ramirez, 2006) (Stutzman, 2006).

In the work of Victoire and Jeyakumar (2004) PSO is defined as one of the modern heuristic algorithms which can be used to solve nonlinear and non-continuous optimization problems. It has been used for many power system problems such as the optimal design of power system stabilization (Victoire and Jeyakumar, 2005a), distribution state estimation (J Soares et al. 2012), and optimal reactive power dispatch (Liu et al., 2005), (Chuanwen and Bompard, 2005) as well as for an energy matching and trading system. In the classical PSO, three aspects, namely, inertial, cognitive, and social, govern the movement of a particle. The cognitive behaviour helps the particle to remember its previously visited best position. In this direction a split-up in the cognitive behaviour is proposed. That is, the particle is made to remember its worst position also. This modification helps in exploring the search space very effectively to identify the promising solution region. Moreover, to exploit the promising region well, a simple local random search procedure, which is a modification of a direct search procedure (J Soares et al. 2012), is integrated with PSO. The resultant PSO algorithm is very effective in solving the energy matching and trading problems.

Furthermore, PSO has been found to be robust in solving continuous nonlinear optimization problems (J Soares et al. 2012). Recently, PSO has been successfully employed in solving the energy matching and trading problem while considering generator constraints (B. Jiang and Fei 2015) and non-smooth cost constraints (Neyestani, Farsangi and Nezamabadi-Pour, 2010). In order to solve the energy problem of units with valve point effects effectively, a hybrid solution methodology integrating PSO and a sequential quadratic program has been undertaken (Victoire and Jeyakumar, 2005a) (Victoire and Jeyakumar, 2005b).

Researchers including Yoshida et al. have presented a PSO for reactive power and voltage control when considering voltage security assessment. The feasibility of their method is compared with the reactive Tabu system and enumeration method on practical energy in a neighbourhood system, and this has shown promising results (Trelea, 2003). Naka et al. have presented on the use of a hybrid PSO method for solving efficiently the practical distribution state estimation problem (Gaing, 2003).

In this thesis, a scalable and comprehensive energy matching and energy trading structure by involving the owner of GBs, consumers and retailers is developed within the realm of a competitive environment. The partial swarm optimization (PSO) method is adopted to establish a scalable solution where any number of producers, consumers and prosumers can participate in trading energy and possibly ancillary services. In order to provide a comprehensive solution, the GB in the neighbourhood system concept is implemented in this study. It is proposed in this thesis that a GB consists of locally non-dispatchable/dispatchable energy resources, ES and responsive load (or DR). It is assumed that a GB can either supply its local loads independently, can supply other consumers in the neighbourhood system or in connection with the upstream grid; either way it enhances the resiliency of the neighbourhood system. Furthermore, the interoperability of the GBs is considered in the proposed energy trading structure whereby the excess energy of one GB can be stored or momentarily consumed in another GB. The optimum design of a system with multiple GBs leads to the simultaneous optimization of the GBs and the distribution network pay-offs. To solve this problem of dynamic programming, different optimization strategies are presented in this thesis. Complex integer programming in Marzband et al. (2013) and the gravitational search algorithm (Marzband et al., 2014) are examples of these techniques. Additionally, the stochastic nature of the load demand and renewable generation is considered in the proposed energy matching and trading. In this study, designing the new energy matching and trading structure is the primary focus and the PSO method is used in this thesis. A summary of the optimization techniques that have been summarized in the literature is shown in Table 6.

Table 6: optimization techniques presented in literature

Number	Objective	Advantage	Method	References
1.	To provide robust and powerful adaptive search mechanisms	Finds near optimal solution in a relatively short time compared with other random searching methods	GA	(A. H. Mohsenian-Rad, Wong, Jatskevich, and Schober 2010)

2.	Solving optimization problems with a non-linear objective function	Faster convergence speeds than other optimization methods	DE	(Das and Suganthan 2011; Peng et al. 2016)
3.	Implementing energy in a neighbourhood system	Is faster and more robust than the well-known methods in large-scale systems	GA	(Samadi et al. 2010)
4.	Multiplier updating to implement energy in a neighbourhood system	Positive effects and multiple fuels	GA	(Deilami et al. 2011)
5.	Implementing energy in a neighbourhood system	Capable of obtaining higher quality solutions than the GA method in neighbourhood problems	PSO	(Baziar and Kavousi-Fard 2013)
6.	A strategy to accelerate the optimization process in the PSO method for implementing energy in a neighbourhood system	Dynamic search-space reduction strategy	PSO	(Gudi et al. 2010)
7.	Employment of a hybrid of the genetic algorithm in order to apply in several GBs in a neighbourhood system		GA	(Giani et al. 2013)
8.	Using an incorporated algorithm for combined heat and power in a	Improved evolutionary direction operator.	GA	(Du and Lu 2011)

	neighbourhood system			
9.	To solve the energy matching and trading problem	With fuzzy logic controllers to adjust crossover and mutation	GA	(Shadmand and Balog 2014)
10.	System incremented cost as an encoded parameter	Solving energy matching and trading problems that takes into account network losses, and ramp rate limits	GA	(Raza and Khosravi 2015)
11.	To solve more efficiently the problems of energy matching and trading	This technique can obtain a high-quality solution with less computation time	GA	(Z. Zhao et al. 2013)
12.	To solve complex optimization problems	This technique reduces its search capability which leads to a higher probability towards obtaining a local optimum	GA	(Koutitas 2012)
13.	The QPSO outperforms the PSO in global search ability	Promising optimizer for complex problems	QPSO[1]	(Pedrasa, Spooner, and MacGill 2010)
14.	Implement energy in a neighbourhood system		PSO	(Faria et al. 2013)
15.	Solving optimal energy matching and trading problems in which the population is divided into several sub	Leads to a quicker reaction by the swarm to changes in the best function values, thereby increasing the convergence rate	PAPSO[2]	(Al-Bahrani and Patra 2018)

[1] Quantum-Behaved Particle Swarm Optimization
[2] Phase Angle Particle Swarm Optimization

	populations for evaluating fitness functions			
16.	Present a modified PSO to control reactive power and voltage when considering voltage security assessment		PSO	(T Kerdphol, Qudaih, and Mitani 2015)
17.	Solving the energy problem by considering the production constraints	This technique simple concept, computational efficiency and easy implementation	PSO	(Anwar and Mahmood 2014)
18.	To solve nonlinear and non-continuous optimization problems		PSO	(Y.-W. Zhao et al. 2012)
19.	To solve the energy problem while considering generator constraints and non-smooth cost constraints		PSO	(Baziar and Kavousi-Fard 2013)
20.	To present a PSO for reactive power and voltage control when considering voltage security assessment		PSO	(Moghaddam et al. 2011)
21.	To solve efficiently the practical distribution state estimation problem		PSO	(Xue et al. 2014)

2.12. Summary

The objective of this chapter was to investigate what the different parts of green buildings in neighbourhood systems are, as well as to showing how optimization methods can be useful in the design of optimal systems and to give an idea of the challenges involved. This chapter has analysed the optimization methods, the distributed energy resource models and the green building models to identify the theoretical aspects that should be considered in developing an optimal energy management system for operation assessment activities. Firstly, the collection of data from the literature review and the research questions helped to understand the different distributed energy resources models. Moreover, it also gave a way of understanding the community, subjects, objects, rules and tools involved in optimal operation and the economic dispatch assessments in green buildings in neighbourhood systems. Secondly, the optimization methods have identified (1) the optimal set-point of the DERs needed in order to deal with multi-objective optimization problems, and (2) the operating cost that needs to be minimized or the profit for the owner of green buildings that should be maximized. Finally, the DER models have been used to identify the information necessary for to deal with multi-objective problems. In the next chapter, the background to the present methodology, the good practices obtained in different approaches, and the organizational structure of those techniques dealing with optimal operation and energy matching and trading are presented.

Chapter 3: Methodology

3.1. Introduction

The purpose of a research methodology is to validate the rationale behind the selected research design and to present an explanation of why it is suitable to solve problems in the research area (Bell, 1999). There are several research strategies available to researchers such as experience, consideration, archival analysis, history, case study, and action research (Yin, 1994; Saunders et al., 2000). It is considered that using appropriate research strategies in a valid way at the valid time is always necessary for good research (Robson, 2002).

This research presents the design and implementation of an IT platform that can support energy matching and trading in GBNS. Designing effective IT artefacts is intricate because of the need for creating advances in a domain area where existing theory is often inadequate (Hevner et al., 2004). The design science methodology provided stand approach for extracting domain knowledge and then applying information system technology to create an artefact. The fundamental principle of design-science research contains seven guidelines for understanding, executing and evaluating the research. This research follows these guidelines in order to provide a discussion on theoretical foundation, scientific rigour, validation and validity.

3.2. Research methodology

There are different types of research approaches which can be used for exploratory, descriptive and explanatory research (Yin, 2009). Selecting the most suitable approach is vital for successful research (Robson, 2011).

According to Saunders et al (2007), some approaches can be considered to be deductive approaches and others as inductive approaches. As indicated by Burney (2008), the deductive approach works from the more general to the more specific which can also be referred to as the "top-down" approach. As a result, the deductive approach moves from theory to data and it is necessary to select samples of sufficient size in order to generalize conclusions (Easterby-Smith et al., 2008). Furthermore, in the deductive approach, the researcher develops a theory by testing a hypothesis and designs a research approach to check the hypothesis. In the inductive approach, the scientist collects information to develop a theory as a result of his/her information analysis. Additionally, the inductive approach starts from specific observations and extends to wider generalizations and theories and this research approach is also known as the "bottom-up' approach (Burney, 2008). The deductive approach comes from positivism, while the inductive approach is derived from the interpretivist philosophy (Saunders et al., 2009). Although these approaches are suitable for social science related research, they do not provide a good research methodology for a mathematical framework.

Therefore, as this research is IT based, a design science approach has been used in this research. Design science can utilize an analysis approach that mixes varied disciplines to support the development of artefacts. This requires an understanding and knowledge of a problem which can then be solved by artefacts (van den Hoven, 2001). Design science in information systems (IS) can be used to solve problems in innovative, efficient ways and can provide guidelines for the understanding, execution and evaluation of research. Since this research focuses on defining a mathematical framework to support energy matching and trading in green building neighbourhood systems, the design science method was chosen as the approach to be adopted to conduct this research. An overall picture of the research framework is shown in Figure 15.

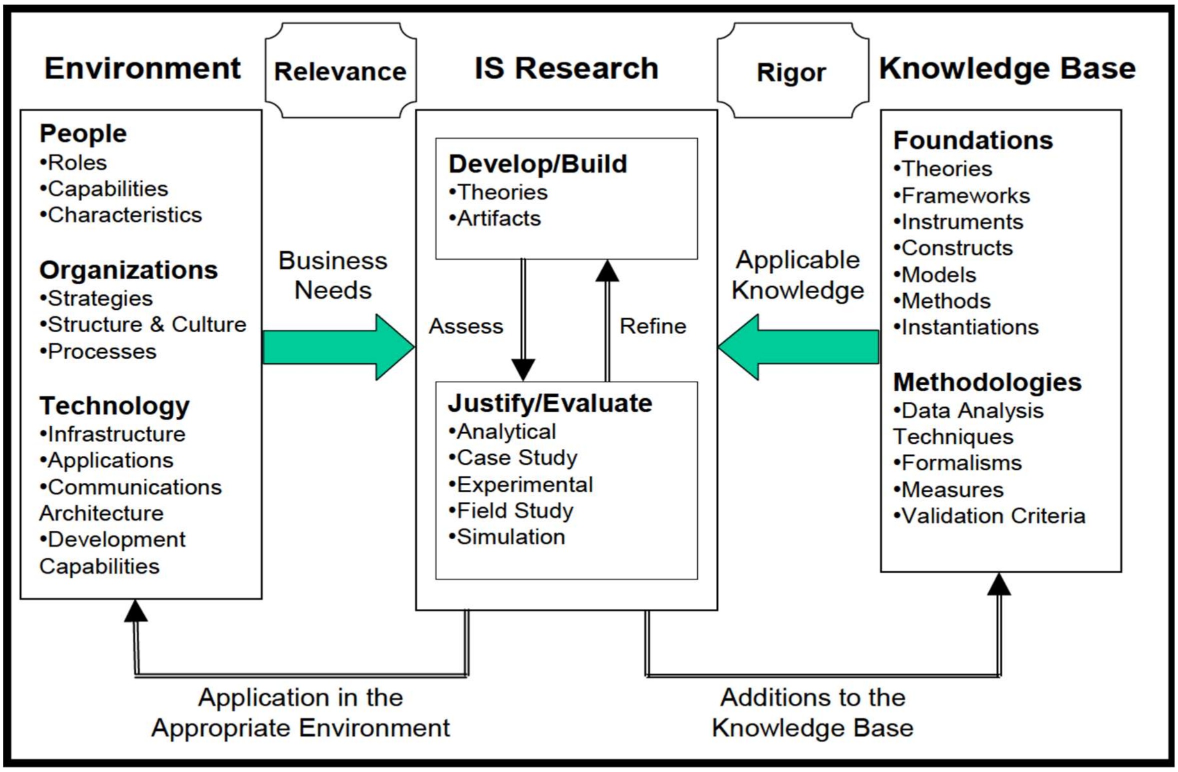


Figure 15: Information System research framework (Hever et al., 2004)

Figure 15 represents the main three sections in an IS research framework. Firstly, the environment column in IS research defines the problem and the existing phenomena which consist of people (their capabilities, roles and potential characteristics), organizations (their structure, culture, strategies and existing business processes) and existing technology (communication, infrastructure, architectures, applications and development capabilities). All of these together define the business need or problem as identified by Simon (1996) and Silver (1995). In this research, the business needs are designed by analyzing the requirements obtained from the built environmental factors for creating energy efficient neighbourhoods. The knowledge base (Figure 15) provides different types of materials that can be used to conduct the IS research. The knowledge base is comprised of foundations and methodologies. The foundations consist of instruments, theories, constructs, frameworks, strategies, models and instantiations utilized in the development phase of a research study. The methodologies include information analysis techniques, measures, formalism, and validation criteria guidelines utilized in the evaluation phase. In this research, techniques such as mathematical optimization are used in creating the artefact. A rigorous design is achieved through the application of existing theoretical foundations and methodologies. The environment and knowledge base are combined to produce the research which is the development of the theories or artefacts; in this case a mathematical framework for energy matching and energy trading. In this approach, these theories or artefacts can be improved by assessment and refinement. This can be carried out using various methods, such as case studies, experiments and field-testing. In this research, case studies are used to test the final artefact.

The fundamental principle of design science research utilized for this project contains seven guidelines (see Figure 15) for understanding, executing and evaluating the research. This research follows these guidelines in order to provide a discussion on the theoretical foundation, the scientific rigour and the validation and validity.

Table 7 Design science research guidelines

NO	Guideline	Comments
1	Guideline 1: Design as an artefact	This research will implement a mathematical framework for energy matching and energy trading
2	Guideline 2: Problem relevance	This research will address the global challenge of reducing environmental pollution and meeting growing energy demand through GBNS
3	Guideline 3: Design evaluation	This research will validate the proposed computational framework via case studies
4	Guideline 4: Research contributions	This research will improve the understanding of modelling energy matching and energy trading using mathematical techniques.
5	Guideline 5: Research rigour	Comparing the results obtained from two methods (i.e. particle swarm optimization (PSO) as a heuristic method and the realistic optimization algorithm)
6	Guideline 6: Design as a search process	The proposed mathematical framework will be developed through a series of iterative prototypes with increasing functionality. A strong literature review will be sought to refine the approach and achieve a practical system with the necessary accuracy.
7	Guideline 7: Communication of research	The intention is to publish in high level academic journals and international conferences. The targeted audience will be reached by utilizing journals in both the computer science and built environment fields

The following subsections discuss how each guideline was applied this research.

3.3.Design as an artefact

The artefact in this research is to implement a mathematical framework for designing energy matching and trading in GBNS. The designed artefact for this research is to model several GBs to support hourly day-ahead energy matching and trading in GBNS. Each GB included production, consumption and prosumers. Production includes controllable distributed energy resources (DER) and NDU, load (non-responsive load (NRL) and RLD), and ES devices. Every generation unit, DR during load reduction, and storage in the discharging mode are categorized as producer, while each load entity (i.e. RLD in charging mode) is considered as a consumer. Thus, GBs. can also supply the demand individually and can present elasticity in terms of production, consumption and prosumers. In addition, green buildings are capable of operating in neighbourhoods where they can trade energy with other green buildings.

In this situation, each GB is trying to satisfy its own objective(s), i.e., producers seek to maximize their profit while consumers try to minimize their operation cost. These GBs can sell their excess energy to other buildings or can supply their own shortages through neighbour instead of buying energy from the grid. Thus, each GB should have a neighbourhood system operator to assess the excess or the shortage of power. Additionally, a mathematical model was developed within this research to create GBNS that are economical, reliable, capable of exploiting DERs/RLDs and group action of various sources of energy. Each of the components has been modelled mathematically and the constraints of these components have also been defined in this model. Then, this model was developed based on optimization methods in the MATLAB and GAMS environments. GBNS can help facilitate the rapid integration of distributed energy resources (DERs), offering "plug and play" capabilities while not requiring the re-engineering of the distribution system control architecture.

3.4. Problem relevance

Increasingly, countries need to expand their resources and policies regarding energy and its related environmental pollutants for better future planning (Marzband et al,. 2013). Additionally, the key issue of energy consumption growth is related to other issues such as CO_2 emissions from oil and gas, global power system restructuring, electricity demand growth, concerns about global warming, and the high prices of fossil fuels. The influence of renewable energy resources within buildings has received considerable attention due to its ability to reduce fuel costs, operations and maintenance costs, and also the cost of carbon dioxide emission (Marzband et al., 2013). Solar power and wind power provide two of the potential renewable energy sources that have recently received appropriate attention as a result of their economic and technical advantages in view of the depletion of fossil fuels, global warming and increases in the cost of energy. This small scale model can be installed in a residential building which incorporates various demands and equipped with DERs and a two-way communication infrastructure. The GB concept has provided a platform for utilizing Distributed Energy Resources (DERs) (e.g., Photovoltaic (PV) Panels and Micro-Turbines (MTs)) as clean and cost efficient energy supplies, to fulfil many varieties of loads in residential and other types of buildings.

3.5. Design evaluation

Two concepts within this research will be validated: firstly, energy matching in GBs and, secondly, implementing energy trading in GBNS. Energy matching incorporates an optimization algorithm based on a realistic optimization technique that has been designed to simulate energy matching in a single green building which considers the interaction between producer, consumer and prosumers. This algorithm has been developed in GAMS environment and will be evaluated using a GB test case scenario. Energy trading in GBNS utilizes an optimization algorithm based on a PSO method and has been designed for considering energy trading between multiple GBs in neighbourhood systems. This algorithm has been developed in a MATLAB environment and has been evaluated for effectiveness using a test case scenario and has also been evaluated to ensure that the defined objectives are being achieved. For the evaluation, the obtained results by using optimization methods have been compared with the conventional method (without optimization).

3.6.Research contribution

The contribution of this study can be summarized as follows:

1- An advanced energy trading and matching framework based on optimization techniques is proposed for green buildings in neighbourhood systems and generally for active distribution networks. This framework is comprehensive, and it can be used for analysing and modelling consumers' behaviour in a deregulated competitive electricity market at the residential distribution level. The effect of prosumers on the financial operations of future residential distribution frameworks is additionally explored. Moreover, the usage of demand response and energy storage in an effective way is considered to exploit the full capabilities of these resources.

2- This framework is generally flexible, scalable and extendable. Various flexible distributed energy resources and numerous players (i.e. the owner of green buildings, consumers, retailers, etc.) can be accommodated conveniently in this framework. Having more players can improve competition and it can result in a reduction in the electricity price.

3- Maintaining green buildings' operational costs at a minimum level is one of the objectives. In addition, a power balance is attained between power supply and load demand in the proposed framework while the operational cost is minimized.

4- The uncertainty parameters such as the inherent nature of non-dispatchable distributed energy resources, load demand, and electricity prices are considered in the problem formation. The uncertainty of electricity pricing is incorporated into this model for the optimization of energy trading and energy matching and can increase the accuracy of the modelling significantly.

3.7.Research rigour

The determination of the optimal power set-point of distributed energy resources in multiple green buildings in a neighbourhood system is of great importance in smart grids. The determination of the optimal power set-point allows for higher benefits and the better use of renewable energy resources in GBNS. An effort has been made in this thesis to use totally different optimization approaches for determining the optimal set-points of distributed energy resources and to focus on optimal scheduling with the aim of improving the results obtained in the operation. The uncertainty parameters such as the electrical/thermal load demand, the market clearing price and the weather conditions were planned and conducted in keeping with Taguchi's method. Additionally, experimental information was used for developing mathematical models for the power generated by renewable energy resources and consumers. Mathematical models of all the devices and their technical and economic constraints were developed using different optimization algorithms in the MATLAB and GAMS environment. This thesis compares the quality of solutions obtained based on optimization algorithms by using partial particle optimization (PSO), the Bath algorithm (BAT), the ant colony optimization (ACO) and the recently developed improved genetic algorithm. The computer codes were developed in the MATLAB and GAMS environment to integrate the optimization models based on heuristic and realistic optimization techniques. For the purpose of comparison, some performance criteria such as minimization of operating cost and maximizing of profit were also used to schedule all the devices in GBNS. In addition, the merits and the limitations of the selected optimization methods were discussed.

3.8.Design as a research process

The fundamental part of this research is to propose an optimal design for energy matching and energy trading in green buildings. The search for an optimal design is often intractable because of realistic information systems' problems. Heuristic search strategies produce feasible, good designs that can be implemented in the business environment. Optimal design is essentially an important factor and it provides a key search process to discover an effective solution to a problem. This process of search can be used as an integral part of construction in the future. Problem solving can be seen as using an intelligent framework to achieve wanted outcomes while fulfilling constraints and the objective function existing in the problem formulation.

3.9.Communication of research

There is an intention to publish in high level academic journals and international conferences; thus the targeted audience will be reached by utilizing journals in both the computer science and built environment fields. So far, a conference paper has been presented and published in energy matching and trading within green building neighbourhoods based on a stochastic approach considering uncertainty. Furthermore, a journal paper entitled "Implementing Energy Matching and Trading based on Multi-agent System for a neighbourhood System Including Several Green Buildings by Considering Demand Side Management" is under the editing process.

3.10. Summary

The research methodology, the method of design, the problem, the design evaluation, the research contribution, research rigour and the research process have been explained in detail in this chapter. In the next chapter, each of these elements will be utilized.

Chapter 4: The Proposed Design Artefact

4.1. Introduction

This chapter is about the mathematical platform for energy matching and energy trading in the multiple green building in the neighbourhood systems. In this direction, this platform has been formulated mathematically based on several technical and economic constraints. The objective function has been also defined in this platform with the aim of satisfying the producers, consumers and upstream grid.

4.2. Green buildings in the neighbourhood system under study

The schematic of the GBNS under consideration is presented in Figure 16. The GBNS under study has i number of GBs. Several electrical/thermal DER technologies can be installed in them and the consumers of each building can be the same or different to each other. Each GBs, has electrical and thermal storage and a collection of generation resources such as PV, WT, ES, GBO, TSP, ESP, CHP as well as consumers consisting of NRL and RLD. Furthermore, it has been proposed that green buildings supply local energy such as electrical and thermal energy. The electrical grid network is available all the time to supply electricity when there is a shortage of power generated from the local DERs. If the excess electricity power generated in each GB is more than the local load demand, it can be sold to the upstream grid. Each GB possesses its own electrical/thermal load demand that depends on the kinds of household behavior and the lifestyle of the owners. Thermal load demands for each GB is given based on household types. Electrical appliances considered include dishwashers and washing machines. Therefore, the electricity load demand profile usually depends on the operation time of the domestic appliances in the GBs. As explained in chapter 2, the interactions among GBs can be served by establishing an independent system operator which is called hereafter a neighbourhood system operator (NSO). The main objective of the NSO is to reduce the mismatch of power between power generation and load demand consumption as much as possible, throughout by shifting a part of load demand consumption during on-peak periods and also improving the efficiency of energy matching. Furthermore, at the highest level, the coordination and management of NSOs and all GBs can be carried out by a central neighbourhood system operator (CNSO). This CNSO, placed at the highest level of the hierarchy, is responsible for the overall coordination of energy trading between the GBs and has several objectives such as reducing the operation price, and maximizing the profit in addition to minimizing of the greenhouse gas emissions. In this thesis, equipment capacities are also given and the operation or maintenance cost has been considered in the presented model. The real-time price of the electricity at each time interval is given one day in advance, thus it has been anticipated and can be predicted in the proposed model. The electricity offer price for each GB is provided based on their comparative energy consumption rate and it depends on several criteria such as the offer prices of GBs and obviating the mismatch of power. Since energy with a lower price as presented by the DER cannot be carried out on the load demands for all GBs in some time intervals, the GBs need to compete with each other to use the energy generated by the DERs in order to minimize their own energy price.

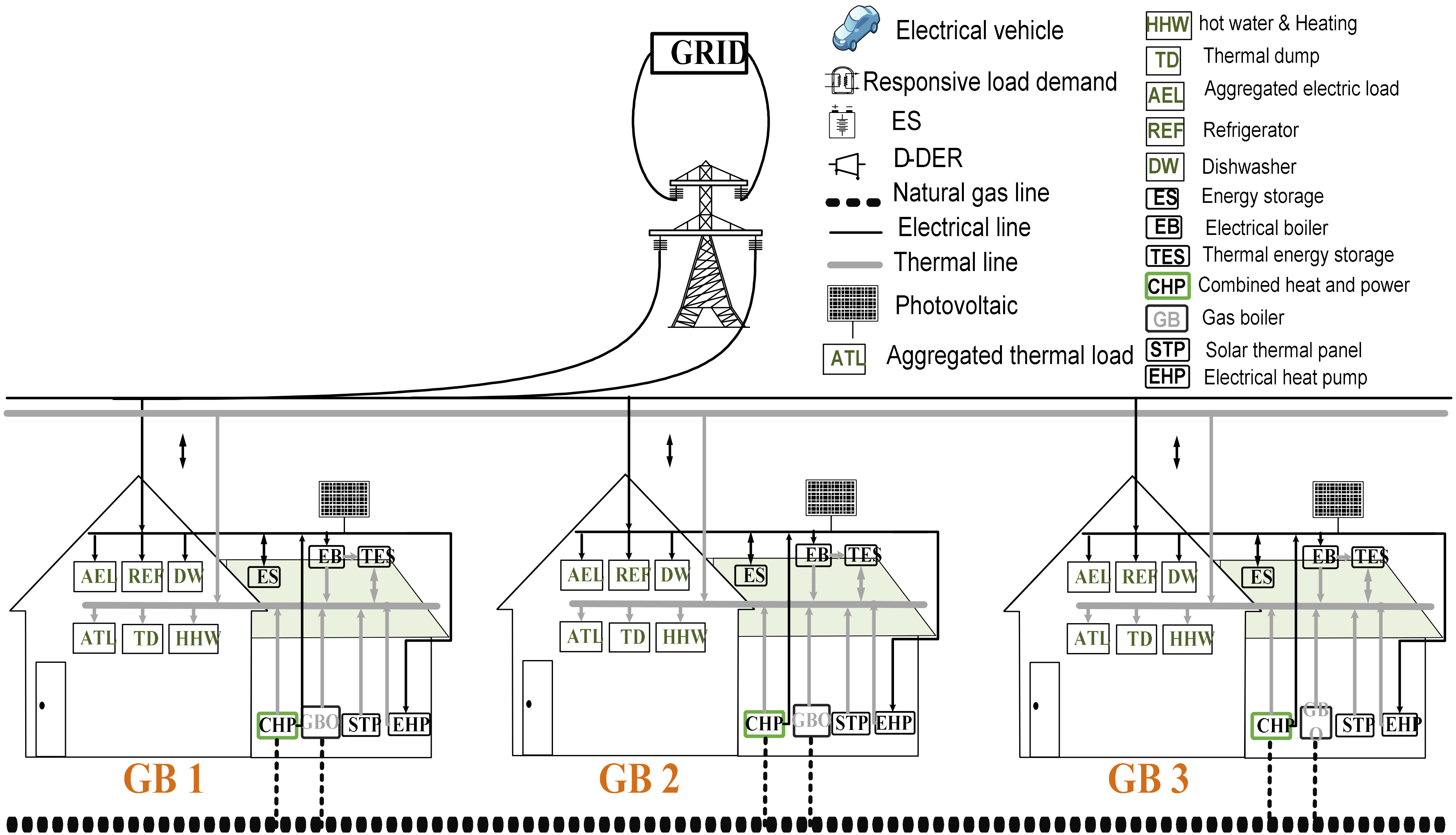


Figure 16: Schematic of a neighbourhood system with several GBs

4.3.The mathematical approach

The proposed structure for the GBNS in Figure 16 presents a solution for enabling a high share of participation by the DER. The aim of this market structure is to reduce the electricity price by maximizing the profit from the generation and consumption units through forming cooperation between each other. The proposed framework can provide this possibility for the owner of GBs and customers to select a proper method to utilize the optimal operation of DERs and to schedule load demand consumption. In the proposed framework, the household consumers play a most important role from several points of view such as better scheduling of DERs and better controlling of the responsive load demand (RLD). The owner of GBs in general and DER technologies in particular, can also enhance their cooperation with each other to obtain more profit. On the other hand, the consumers can manage their load demand profile and attempt to reduce the market clearing electricity/thermal price. To encourage GBs to undertake more participation and local generation and to reduce the MCP as well as improving the profit of owners (while consumers want to minimize their operation cost), a framework is presented in Figure 17. This framework is presented with the aims of ensuring a power balance, optimizing the demand side management, forming a coalition formation between GBs, and reducing the operating cost. The proposed algorithm structure consists of several units such as the TOAT unit, the energy matching and the trading unit. The Taguchi method is used for investigating the effect of uncertainty and this method is a balance between solution accuracy and the speed of reaching the optimum point. In this approach, the first stage (stage 1) is the forecasting of data. Therefore, the amount of energy produced by WT, PV and the non-responsive load (NRL) demand are forecasted. The second stage (stage 2) is the scenario generation. These scenarios can include situations such as the energy consumed by the NRL, and the energy generated by both WT and PV. These scenarios can be generated by using the information obtained from stage 1 depict in Figure 17. Subsequently, the uncertainty of the uncertainty parameters is carried out through the TOAT method in stage 3. The fourth stage (stage 4) is implemented by using the optimization techniques based on the heuristic method. This stage is implemented for the scheduling of the generation and consumption, taking technical and economic constraints into account. The last stage is then developed to derive results by calculating the profit by minimizing the operating cost for consumption and maximizing the profit for generation/GB owners.

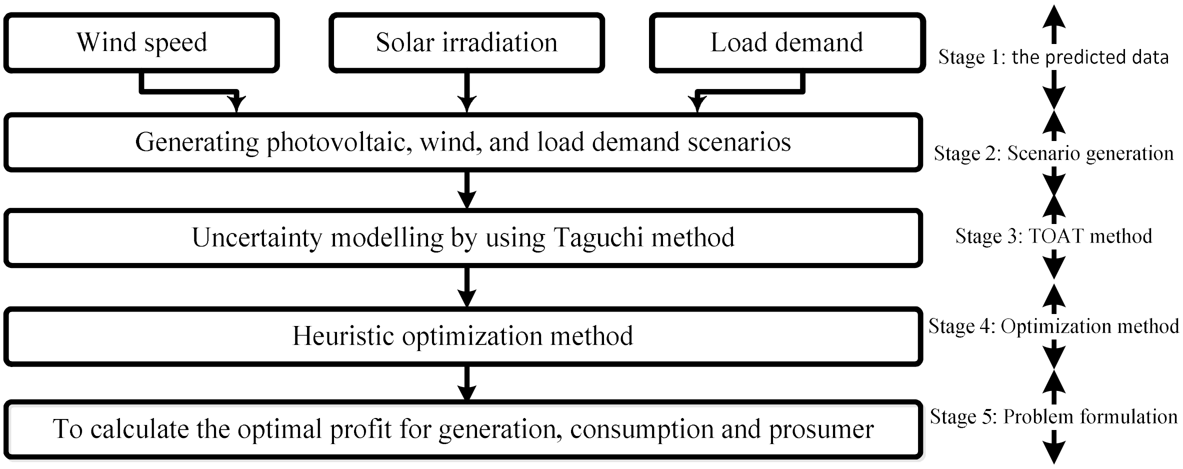


Figure 17: the process of implementing the proposed algorithm structure

4.3.1. Stage 1: the predicted data

The case study in this study is configured as the PV, WT and load demand which has been executed with real life data. The predicted PV/wind generation and load demand (i.e., NDU and NRL) for the entire day ahead can be used to generate the scenario. Wind data was obtained from the online records from the weather station at Museu de Badalona, Badalona (Spain)(affiliated with the Generalitat de Catalunya Weather Network). In addition, the solar data, such as the global and direct normal irradiance were obtained from the online records of Manresa, Barcelona (Spain) (affiliated with IREC (Estacions automátiques (XEMA). n.d.)). The load demand profile was also obtained from the Day-ahead energy market. n.d..

4.3.2. Stage 2: scenario generation

Since the market structure is based on predicted data and the fluctuating nature of the generation units needs to be noted, uncertainty must be considered in this structure. Probabilistic models are used to model the uncertainty.

Consumed load demand uncertainty modelling

The uncertainty of load demand using average parameters and standard deviation can be modelled according to the normal distribution curve. The average value in the load normal curve distribution is equal to the predicted load during each time interval. The standard deviation is obtained from the load prediction method based on experience and previous consumption patterns. To simplify the mathematical modelling, the normal distribution can be divided into several sections showing the load occurrence probability with the value equal to the mean value of that section. In this study, the normal probability distribution curve that is used as shown in Figure 18 (Rastegar et al., 2012; Ren et al., 2015).

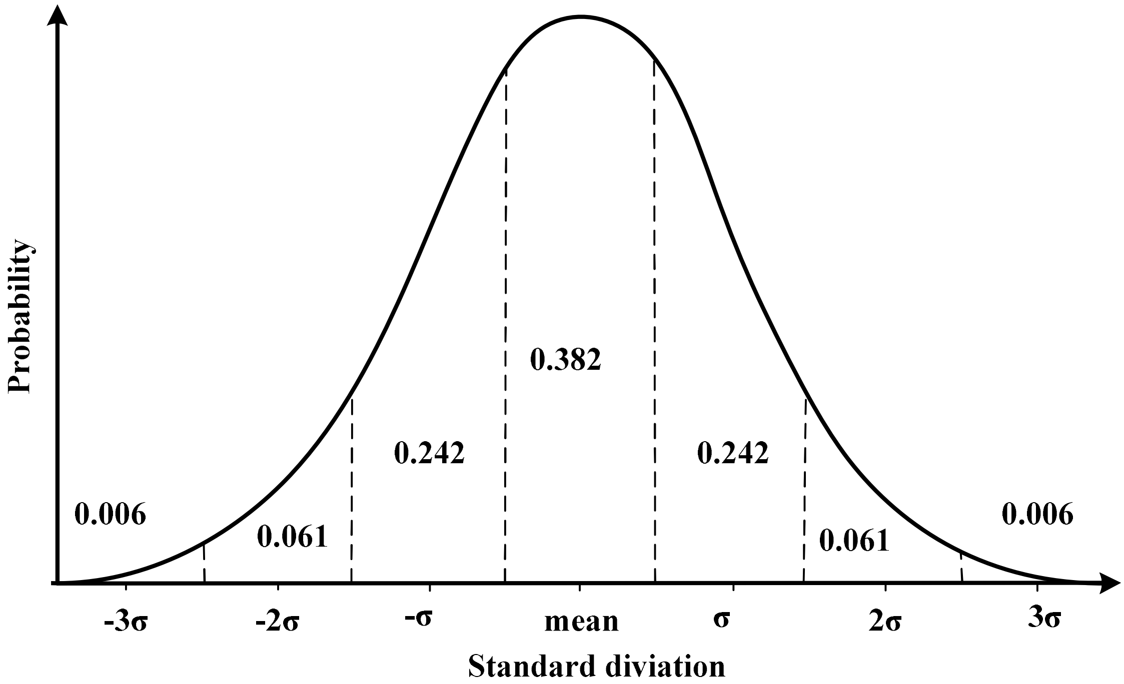


Figure 18: Seven pieces normal probability distribution curve

WT uncertainty modelling

It is worth mentioning that the wind speed is a random variable; as a result the calculation of the wind speed variability during 24 hours is undertaken by using the Weibull distribution. The average value of this distribution curve is the wind speed prediction datum. The Weibull distribution curve can also be divided into several separate sections. The possibility of occurrence of each interval is determined through the corresponding wind speed with the mode of each section. The wind speed probability distribution curve in this study is divided into the five pieces' distribution density function, as shown in Figure 19 (Quiggin et al., 2012; Ramachandran et al., 2011).

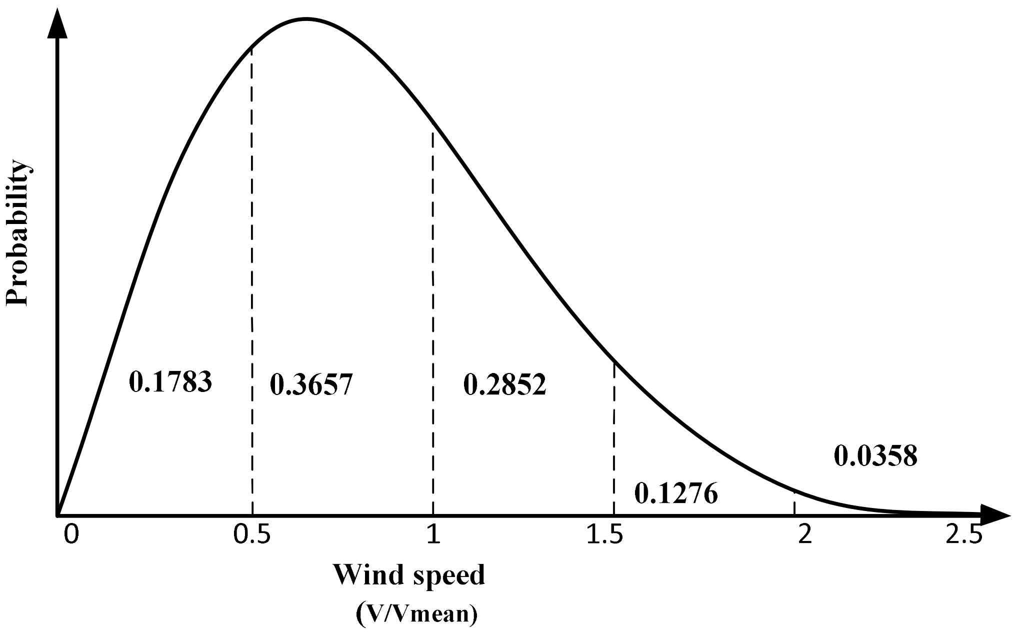


Figure 19: Wind speed probability distribution

The wind output power is determined from the power function based on the wind speed according to the following equation.

$$P_t^{WT} = \begin{cases} \left(\dfrac{P_r}{V_r - V_{ci}}\right)(v - V_{ci}) & V_{ci} \le v \le V \\ P_r & V_r \le v \le V_{co} \\ 0 & \text{others} \end{cases} \tag{2}$$

where P_t^{WT} (v) is the WT output power, v is the wind speed, P_r is WT nominal power, V_r is the wind nominal speed, V_{ci} is the turbine cut-in speed and V_{co} is the turbine cut-off speed. If the turbine generation starts at speed V_{ci} the output power will increase proportionally to the speed increase from V_{ci} to V_r and the nominal power P_r is generated when the wind speed is variable (between V_r and V_{co} . Because of security reasons, the turbine will turn off at speed V_{co} and the output power will be zero at a speed outside the mentioned limits. The wind output power curve is shown in Figure 20.

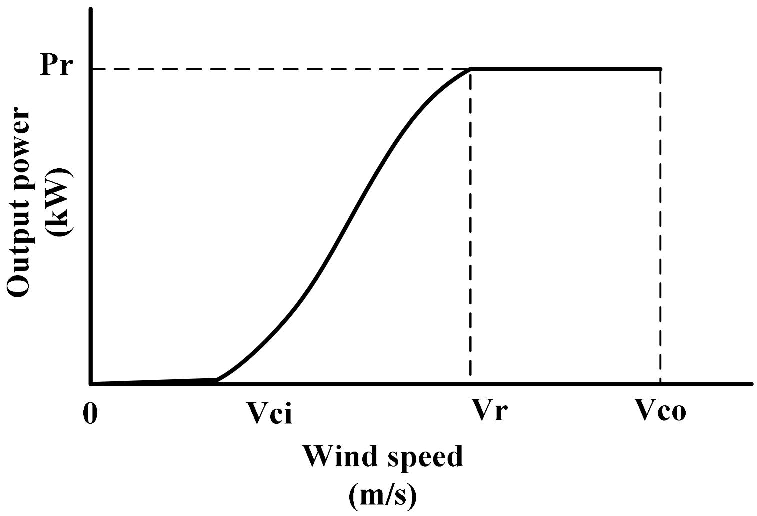


Figure 20: Wind output power curve

PV uncertainty modelling

The sum of the solar irradiation which comes to the earth, taking into account the external daily and yearly movement of the sun, depends on the geographic position (length, width and height) and the climatic conditions (for example, cloud cover). Many studies have shown that cloud cover is the main effective factor in the difference between the solar radiation measured outside the atmosphere and that over the earth's surface. Because of this, in the PV surfaces' yield the power is dependent upon the amount of solar radiation from the PV panel surface. The solar radiation hourly distribution can be divided into five sections and this is similar to the Weibull distribution model (which is illustrated in Figure 211) for wind speed (Arasteh et al., 2013). The PV system power distribution is obtained based on the radiation distribution. The PV system output power is calculated by:

$$P_t^{PV} = A_C . \eta . I_t^{\beta} \tag{3}$$

where A_C is the area of the array surface [m^2], I_t^β is the amount of solar radiation over a surface with β slop relation to the horizon surface [kWm^{-2}], and η is the efficiency of the PV system under realistic reporting conditions.

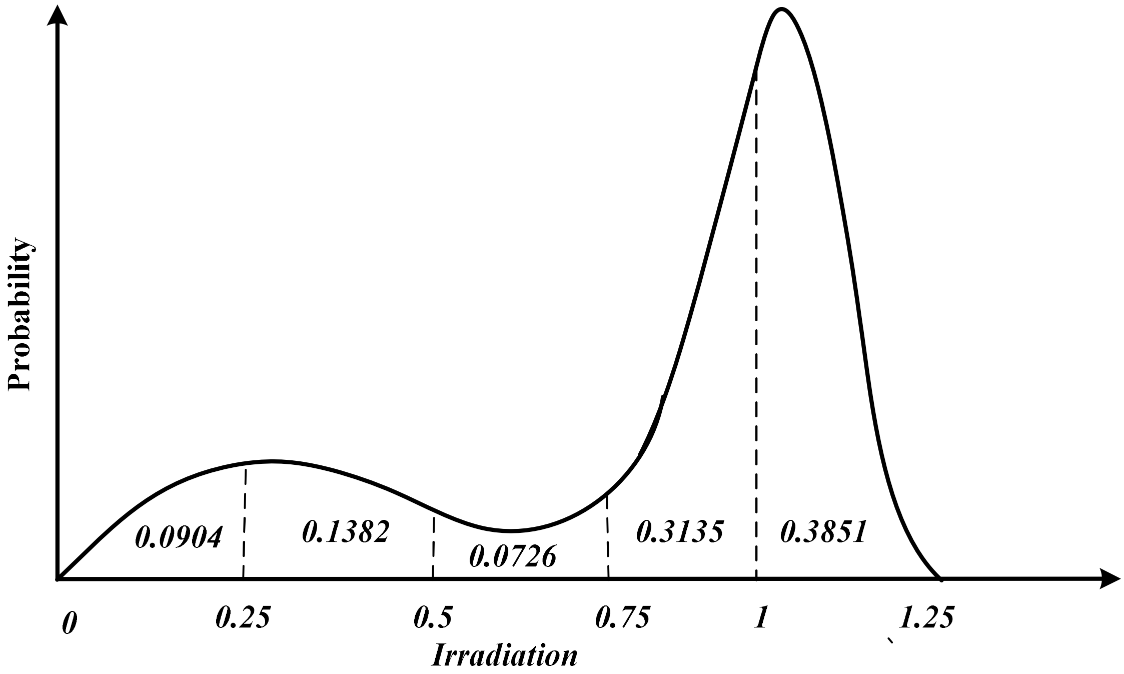


Figure 21: Solar radiation probabilistic distribution

4.3.3. Stage 3: The TOAT method

One of the benefits of using GBs is that the power produced by renewable based generation resources can be significantly improved. However, a giant drawback of renewable based generation devices (such as wind power generation and photovoltaic is their intermittent nature due to dependence on weather conditions. By the way, the obtained optimal solution under uncertainty may be desired or even feasible. Several widely different methods are used to represent the probability distribution of the intermittent supply from renewable resources and load flow. These techniques may be classified into several categories including analytical strategies, approximate techniques and the MonteCarlo simulation (MCS). MCS is the most simple, promising and appropriate one having the possibility of a fast response; however cumbersome efforts are its shortcoming which can limit its capability for large-scale application. Analytical strategies can usually use convolution techniques that lead to some simplifications. For example, the linear dependency of different random variables (especially for renewable based DERs) and linearization of the power system equations with losing accuracy are some of the simplifications in this techniques (Marzband et al., 2016). This is because the approximate techniques have an intermittent characteristic and this characteristic can provide a balance between speed and precision. The Taguchi orthogonal array test (TOAT) is recently well established and is widely-used in solving several complex problems particularly in the economic load dispatch in GB based systems (Do et al., 1995; Chatthaworn and Chaitusaney 2014; Yu et al., 2011). The TOAT ensures that the testing scenarios can provide good statistical information with a minimum number of uncertain operating spaces. This ability can also significantly reduce the testing burden. The TOAT has been well-tried in terms of possessing the flexibility to choose the optimal number of scenarios from all possible scenarios (Alizadeh and Jadid, 2014). In comparison with the MCS, the TOAT can generally provide much smaller testing scenarios which, as a result, leads to a shorter computing time. The proposed flowchart for implementing the TOAT is shown in Figure 2222. The TOAT method can generate the necessary scenarios along with the related occurrence probability (according to Figure 1818, Figure 19 and Figure 2121) for all the NDUs existing in the GBs by taking into account the weather conditions. Initially, the calculations on the probability of the created scenarios can be generated by selecting an orthogonal matrix for the existing uncertainties in the system. Subsequently, n values will be generated for the load demand, the PV and the MCP by using a normal distribution (according to Figure 188 and Figure 211). A further explanation of this method and why this method was chosen in this thesis can be found in Marzband et al., 2016.

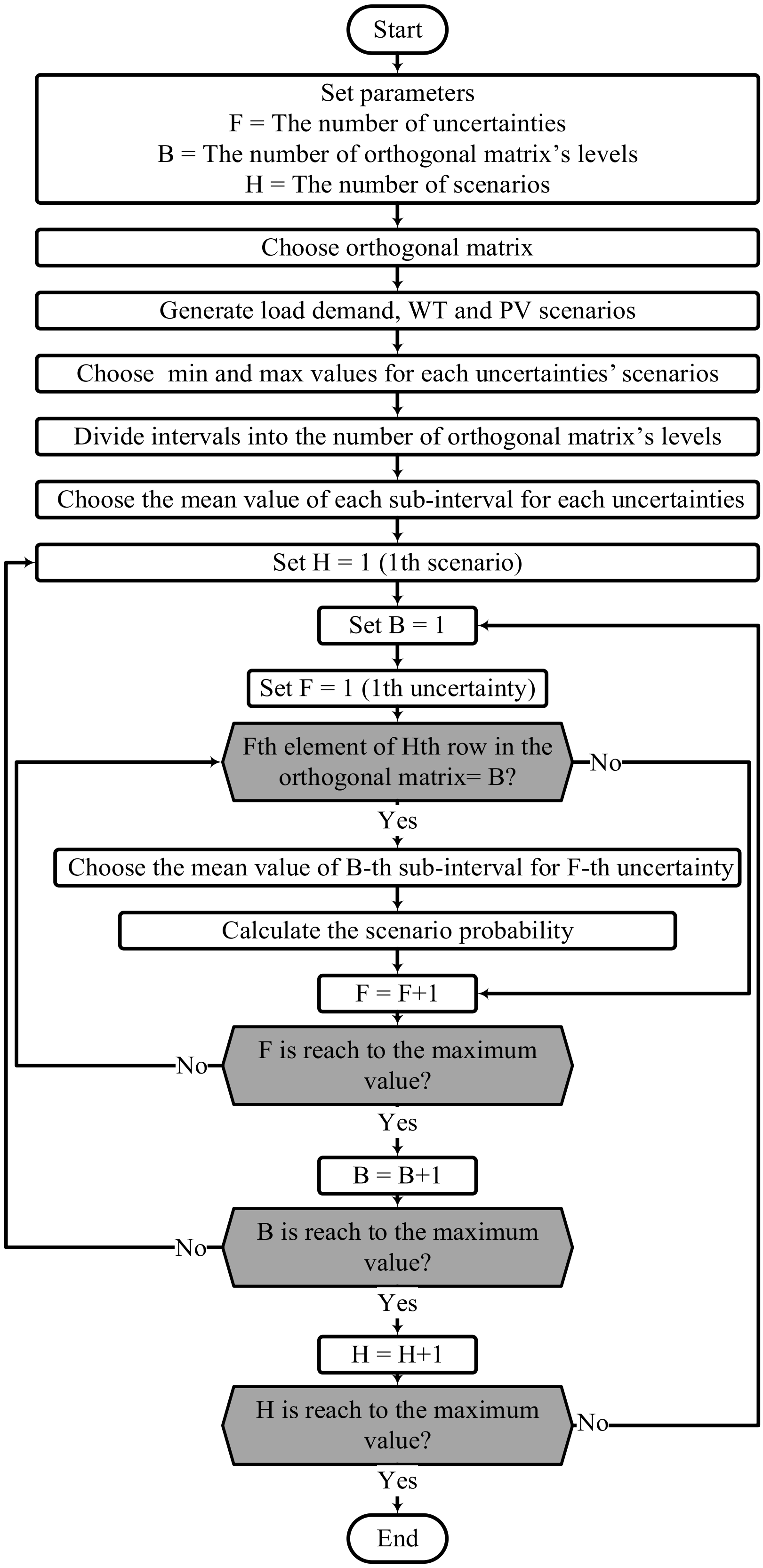


Figure 22: The Taguchi method

The capabilities and advantages of using the Taguchi method can be summarized as follows:

1- Reducing the number of experiments;

2- Reducing the costs and the time in reaching the optimum point;

3- Possibility of investigating discrete factors;

4- Possibility of estimating the results in optimum conditions;
5- Possibility of estimating the results in arbitrary levels;
6- Possibility of simultaneously obtaining optimum conditions for several responses;
7- Possibility of investigating factors with different levels.

4.3.4. Stage 4: Optimization technique

In order to run the PSO algorithm, an optimization problem should be formulated and solved in both the NOSs and CNSO. The topology of the GBNS consists of four different levels of producers, consumers and prosumers is shown in Figure 2323. These levels are contained in four levels including the Grid level, the CNSO level, the neighbourhood level, and the GB level. The process of sending and receiving information among the components can be considered as follows:

1- At the first step, a primary scheduling problem is solved in the NSOs (at the neighbourhood level) in the presence of participating producers, consumers and prosumers considering the electrical/thermal power shortage and the surplus of each GB. Then, each GB participates in the energy matching and trading framework by submitting two separate sets of electrical/thermal bids: a bid-in demand for purchasing excess electrical/thermal power from the GB, and a bid-in supply for selling electrical/thermal power in this structure to support GBs that have power shortage. Bids are submitted in the form of blocks of energy containing pairs of kWh and price values. NSOs are also required to send supply and demand bids for the day ahead to the energy matching and energy trading structure. In return, every GB and retailer receives optimal schedules from the energy matching and trading structure for the day-ahead operation.
2- The interoperability of the GBs is another feature in the proposed energy matching and trading framework which is solved to find the optimal values in the second step by the CNSO. When a GB experiences excess generation, after satisfying local needs, it tends to sell the excess power to other GBs or retailers in this structure based on the MCP. Alternatively, a GB with power shortage can purchase the cheapest available energy from other GBs or retailers. To encourage GBs to undertake more participation and local generation, their excess power, which has not been sold to other GBs, will be purchased by the retailers at the MCP (peer-to-peer energy trading pioneers in Britain n.d.). The interoperability mechanism in the proposed energy matching and trading framework further encourages participation from GBs by reducing the electricity prices for consumers from cheaper producers. It also reduces power losses by facilitating local generation and consumption.

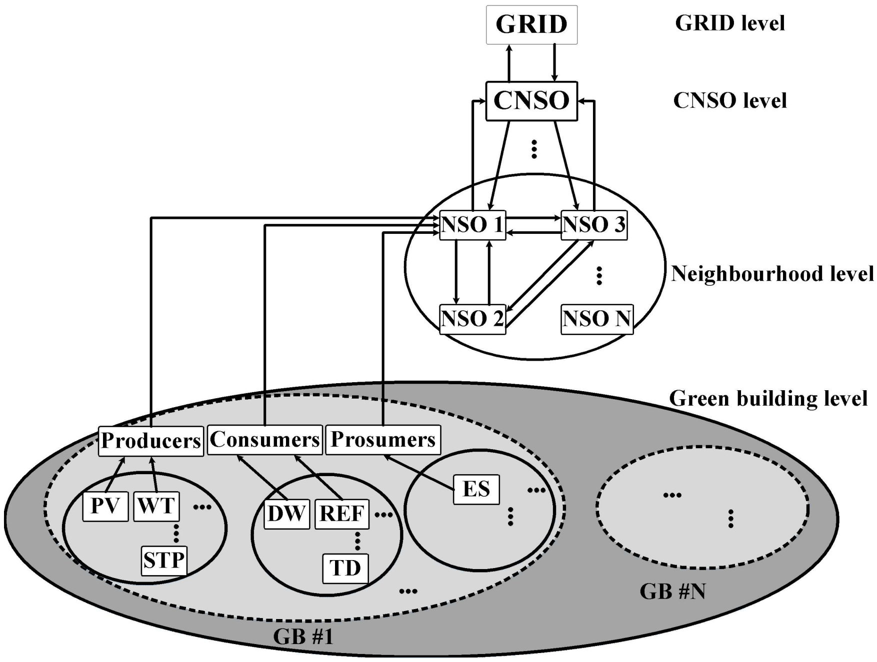


Figure 23: the topology of GBNS with various levels

Within this explanation it is worth mentioning that when uncertainly modelling is implemented then presenting an optimal solution by using a suitable method can be very challenging. To overcome this challenge, a few heuristic and realistic algorithms have been developed thus far. By a little modification, these heuristic algorithms can usually be applied to reducing the computational effort for simulation. The word of heuristic can be generally summarized as being evolutionary, and trial-and-error and experimentation methods. They are experience-based techniques and these techniques are inspired by learning processes that exist in nature (e.g., evolutionary inspired algorithms, collective animal behaviors) or in industrial processes and phenomena. A set of rules can define heuristic methods. These rules can be used in an iterative manner to find a solution in a search space inside GBNS. This search process will continue until no better solution is expected to be found in the iterations after a few times. As heuristic methods usually find pretty good solutions at the end of a program in a relatively shorter time, these methods can be applied in a lot of applications. Unlike realistic methods, heuristic methods sometimes produce an approximate solution close to the optimal solution. As, at convergence, reaching the optimal solution is not guaranteed in big problems, so the expression 'the near global optimum' is more appropriate. As a result, this kind of method is potentially more prone to get stuck in local minima or can even diverge and the final results completely depend on the parameter settings and the nature of the proposed model. To implement energy matching and trading units, different optimization techniques can be established depending on whether the computational time, the convergence rate and other capabilities are considered in terms of the nature of the proposed problem. In this research, in order to implement the mathematical model in MATLAB software, particle swarm optimization (PSO), harmony search (HS), ant colony (AN), bat algorithm (BAT) and other heuristic methods can be applied to the case study. These techniques use an optimal sizing of hybrid renewable energy resources (compared to each other) to pick out the perfect algorithm. In this research the PSO method has been used to define the optimum studies due to the following advantages:

1- The convergence speed of the PSO algorithm is better than the other optimization techniques.
2- The PSO algorithm is a very efficient method for finding the optimal solution and its convergence speed is much faster than the other algorithms.
3- The specific control parameters are not required for the design of the PSO algorithm.
4- The complexities associated with the mathematical analysis are relatively low, and it is able to easily adapt to changes in operating points.

Particle swarm optimization

The particle swarm optimization (PSO) technique was designed by Eberhart and Kennedy (Kennedy and Eberhart, 1995) and was gradually developed by other researchers. This method is inspired basically by the swarming actions of a set of birds, fish, of insect groups to find a food source. The social behavior of the animal groups can be simulated in this method by focusing on the position of the particles that can change at each iteration. It is worthwhile mentioning that every individual in the group is called a "particle". The main goal of this method based on swarming methodology is to reach the best solution by following the positioning patterns of the particles and the whole group. As an example, a flock of birds is investigated attempting to find a food source. When one of birds gets closer to the position of the food source, it chirps loudly and the others go towards that bird. Other birds adjust their velocities depending on their own position in comparison with the main bird. This process will continue up to a certain time depending on the variation of their positions and their velocity. This will happen iteratively until one of the members (birds in this case) reaches the food source in the search space. From a broader point of view, the swarm behaviors of animal groups can be categorized into two behaviors including exploratory and exploiting. Exploratory behaviors define the increasing search space. Exploiting behaviors describe the actions taken by the particles (birds in this example) in their attempt to reach the possible optimal solution in the search space (Baños et al., 2011; Erdinc, 2017). In the search space, every particle is defined as a solution. This solution has a fitness function (the objective function) to determine the velocity of birds in order to achieve a predefined goal. Each particle is represented by a vector matrix which can help to calculate, as well as estimate, the next movement of the particle. The fitness function based on this methodology takes a solution as a candidate vector and produces some random value inside the specific range. Then, the output of the function is compared with the other particles' output in the search space. In this way, every particle (or solution) contains four parameters, namely current position and velocity in the search space, current fitness value, and the memory which contains the best position ever achieved until now within the flock. The velocity and position of the particles at each iteration can be updated based on the current velocity, the best position of the particles achieved so far and the global best position. The global best position indicates the position of the particles closest to the target. The position and velocity of the particles can be given by including the population of the flock as the counter i and the dimension of the search space as the counter n (Erdinc, 2017). This equation is expressed by:

$$X_i = \left[x_{i,1}, x_{i,2}, \cdots, x_{i,n}\right], V_i = \left[v_{i,1}, v_{i,2}, \cdots, v_{i,n}\right], i = \{1, 2, \cdots, m\} \tag{4}$$

Generally, there is no regular method to see how the particles behave in the search space (Erdinc, 2017). However, there are some equations which can help to find the solution in every iteration counted by t to update velocity (v_i) and position (xi) of the i[th] particle, respectively (Erdinc, 2017).

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 \left[p_j(t) - x_j(t) \right] + c_2 r_2 \left[p_g(t) - x_j(t) \right] \tag{5}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{6}$$

where ω is the inertia weight, $p_i(t)$, and $p_g(t)$ denote the best position vector of the i[th] particle ever found and the whole swarm, respectively. $c_1\left(c_2\right)$ is the cognitive (social) accelerative coefficient, and $r_1\left(r_2\right)$ is the independent random uniformly distributed variable taken from the values in the range of [0,1]. The PSO technique encompasses three main factors, namely inertia, memory, and cooperation. These factors characterize the swarming behavior of the group particles which are supplied by the two main cognitive processes. These processes are the individual experience of each particle and the communication with the other particles. Thus, particles gather and share information to increase their quality of fitness function (Erdinc, 2017). As seen in Figure 2424, the PSO algorithm starts, firstly, by defining some constraints of the problem and the related parameters. Subsequently, the fitness function is evaluated for each of the particles to measure the optimality of the current results. Therefore, the velocity and position values of the particles are modified according to the procedure discussed in section 2.27 of this thesis by interacting with the other particles. The process will be repeated until the termination criterion is satisfied. The termination criteria of the algorithm can be imposed so that the minimum distance between the current position and target or the minimum number of iterations can be reached. Additionally, alternative stopping criteria can also be added for the case if no any optimal value cannot be found in the limit of the predetermined iterations (as seen in Figure 2525).

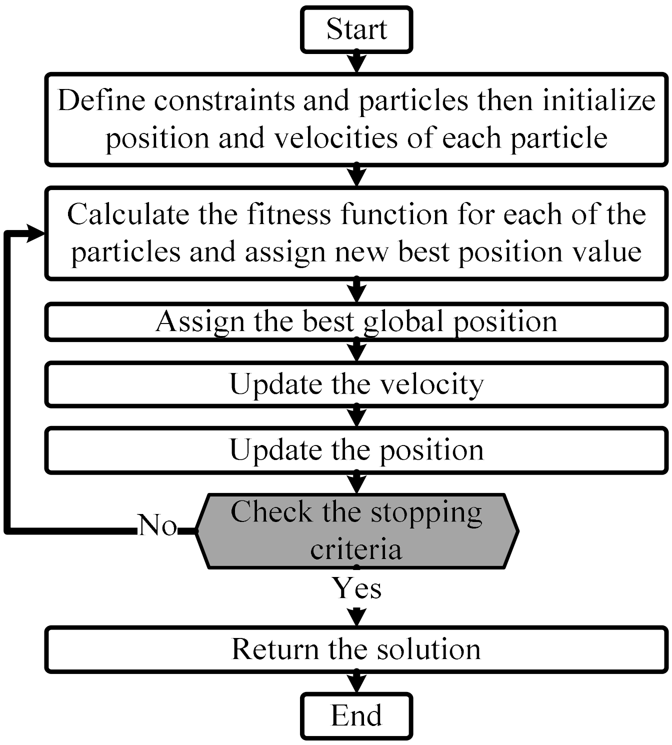


Figure 24: Flowchart of PSO techniques

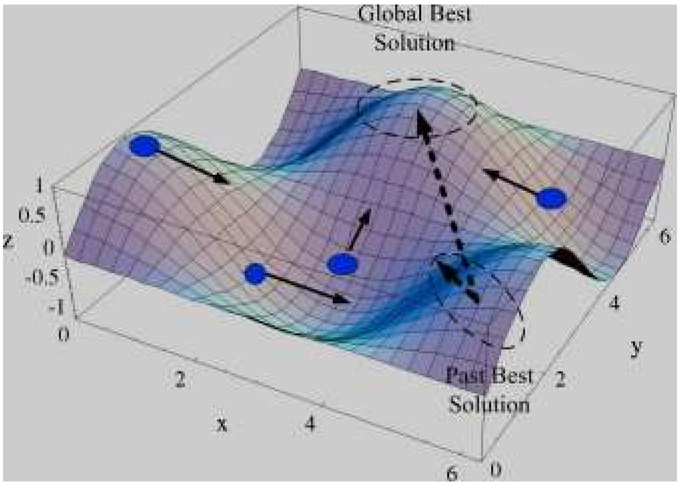


Figure 25: A particle swarm searching for the global minimum of a function

Initialization

At the beginning of the PSO algorithm, the initial value of the electrical and thermal variables must be initialized in the initialization section. The initial value given to the variables is presented in Figure 2626. As seen in this figure, if there is a shortage of power in the electrical section, firstly, the combined heat and power (CHP) swings into action to satisfy part of the electrical load demand. When the system suffers from more shortage of power, there is also the possibility of discharging the ES. If there is no way to supply a part of the load demand, firstly, the shifting of a part of the load demand from this time interval to other time intervals (in which there is sufficient supply of power) will be checked. Subsequently, if a shortage of power still exists, it can be mostly compensated for by buying power from the retailers. In addition, excess electrical power can be generated by generation units during some time intervals. Under this condition, the constraints of demand response (DR) can be defined at the beginning of the DR demand and the ES can also be exploited in the charging mode. Eventually, when a GB experiences excess generation, after satisfying all the local demand needs, dependent upon the value of the market clearing price (MCP), it tends to sell the excess power to other GBs or retailers in the energy matching and trading framework. Alternatively, a GB with a power shortage can purchase the cheapest available energy from other GBs or retailers. To encourage GBs to participate more in generation and supply their own local demand as much as possible, the remainder of their excess power will be purchased by retailers according to the value of the MCP (peer-to-peer energy trading pioneers in Britain n.d.). The interoperability mechanism in the proposed energy matching and trading framework will be caused to increase and further encourages participation from the GBs. The conclusion of this activity will reduce the electricity prices for the consumers and obtain more profit for the owner of the GBs. It also reduces power losses by facilitating local generation and consumption. In the case of thermal power shortage of, and surplus by, each GB, TES can be operated in charging/discharging modes if it is possible. Otherwise, the thermal shortage of power can be bought/sold from/to the GB neighbor.

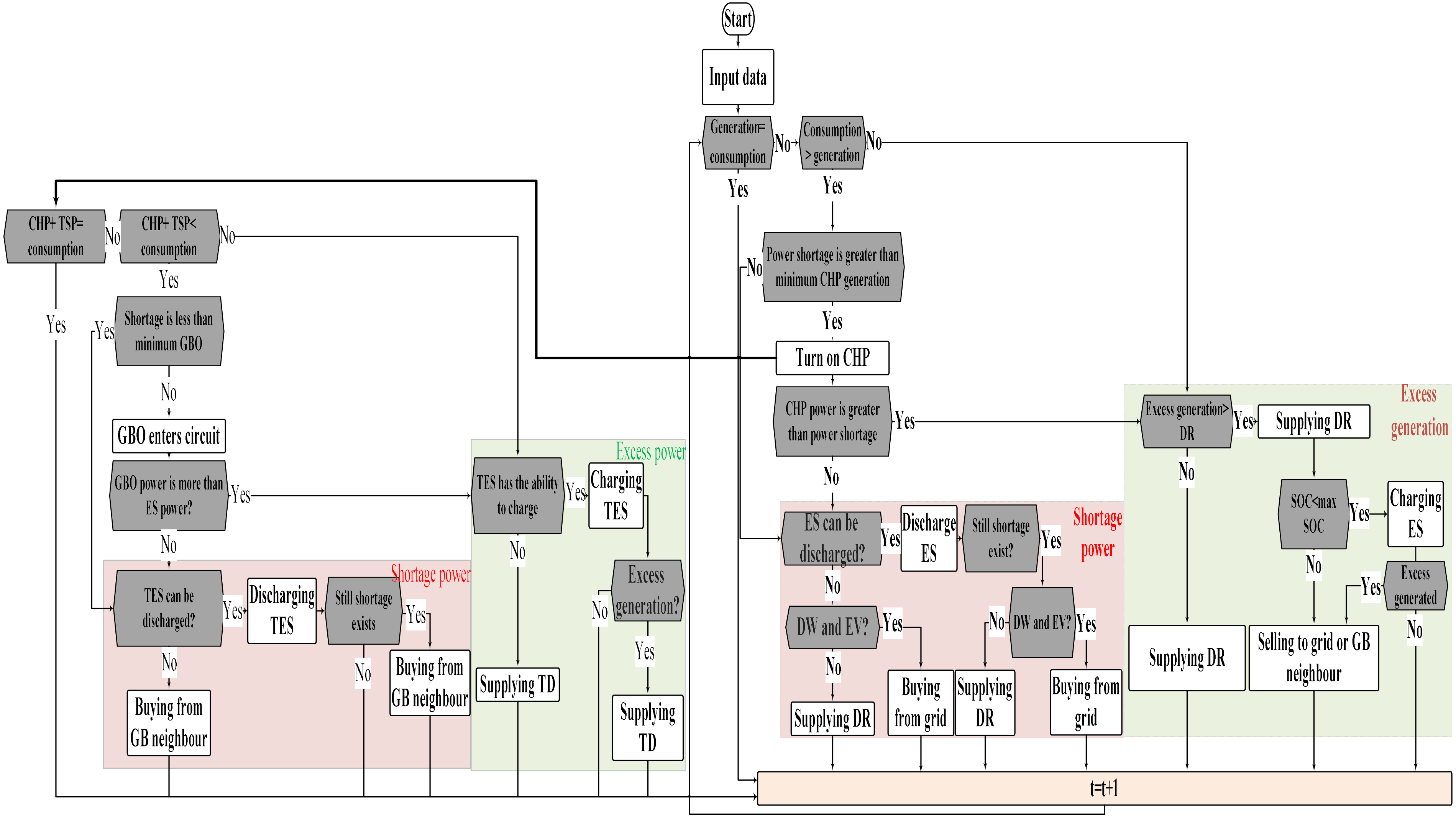


Figure 26: the proposed flowchart for initialization

4.3.5. Stage 5: Problem formulation

In this section, the mathematical formulation of the problem is presented by considering the key components of participation in the retail market. The general framework is easily expandable and adjustable with other electricity distribution systems with high levels of customers' participation. Two instances, namely, a single GB and a multiple GB in a neighbourhood system, are simulated in this study as follows.

Energy matching algorithm

The system under study is considered as a grid-connected green building containing non-dispatchable generation resources (wind turbine - WT, photovoltaics - PV and a flat plate collector - FPC), dispatchable generation resources (biomass - BIO) and energy storage (ES) supplying some non-responsive load demand (electrical and thermal demand and water pumping). The aim of the proposed EMS is to minimize thermal and electrical losses, to maximize the energy sold to the upstream grid, to increase the energy stored in the ES and to improve state-of-charge (SOC). The optimization problem is defined in the objective function given in Eq.(6).

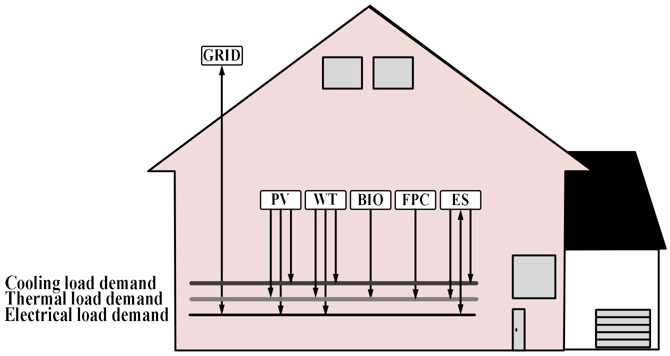


Figure 27: Energy flows between the hybrid system and the green household

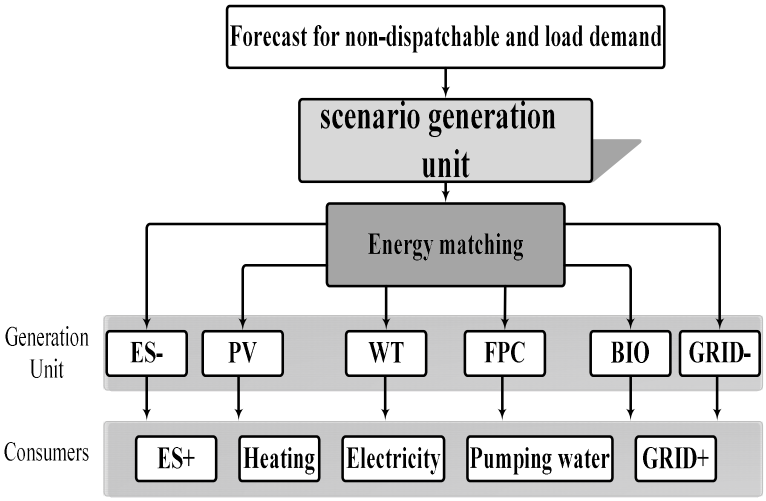


Figure 28: the proposed algorithm

Under this condition, each GB has a NSO which is responsible for meeting the objective function relating to the owner of the GB and local consumers. After management of all the local consumers and producers by NSOs, some information (such as the amount of power shortage or the amount of excess power for each time step for the next day ahead for each GB, and separate sets of supply and demand bids in order to sell and purchase energy) will be sent to the CNSO. Eventually, the CNSO can specify how GBs (including the rated capacity of the existing components and their operational constraints, and their cost functions, which does not change on a daily basis) can be mediated through interaction within the neighbourhood systems.

In this study, in the first step, a single ownership system is implemented in a typical case study; then a multi-ownership system is applied to a case study to help the owners of GBNS and consumers consider both the operating cost and the profit of the system in a real-world application. To this end, the objective function of each GB in the neighbourhood system should be independently defined in terms of achieving their goals.

Objective function

The defined objective function based on maximizing the generators' and retailers' profit as well as minimizing consumers' costs is as follows: the objective function (to be minimized) is characterized by the sum of different terms that are properly weighted: the deviation from the various demands (electrical, thermal, domestic water), the energy that is taken from the grid (i.e., the system has the objective not to depend on the grid but only on produced energy, when possible) and the energy in the storage system (which should be maximized during the optimization horizon and at the end of the optimization horizon). That is,

$$\min Z=\sum_{t=1}^{T}\left(\begin{array}{l}\alpha\cdot\left(\begin{array}{l}E_{(t,s)}^{WT,th}+E_{(t,s)}^{\mathrm{PV},th}+E_{(t,s)}^{\mathrm{FPC},th}+\\ E_{(t,s)}^{\mathrm{BIO},th}+E_{(t,s)}^{GRID,th}+\\ E_{(t,s)}^{ES,th}-E_{(t,s)}^{\mathrm{D},th}\end{array}\right)^{2}+\\ \beta\cdot\left(\begin{array}{l}E_{(t,s)}^{WT,\mathrm{ele}}+E_{(t,s)}^{\mathrm{PV},\mathrm{ele}}+\\ E_{(t,s)}^{GRID,\mathrm{ele}}+E_{(t,s)}^{ES,\mathrm{ele}}-E_{(t,s)}^{\mathrm{D},\mathrm{ele}}\end{array}\right)^{2}+\\ \theta\cdot\left(\begin{array}{l}\dfrac{\begin{array}{l}E_{(t,s)}^{WT,\mathrm{ele}}+E_{(t,s)}^{\mathrm{PV},\mathrm{ele}}\\ +E_{(t,s)}^{GRID,\mathrm{ele}}+E_{(t,s)}^{ES,\mathrm{ele}}\end{array}}{\rho g h}\cdot\eta_{ps}-\\ E_{(t,s)}^{D,wp}\end{array}\right)^{2}+\\ \varphi\cdot E_{(t,s)}^{GRID,ele}+\gamma\cdot E_{(t,s)}^{ES,\mathrm{ele}}-\rho\cdot SOC_{(t,s)}^{ES}\end{array}\right)a \tag{7}$$

The producer equations are defined as follows:

Wind turbine (WT)

The following model is used to simulate the electrical power generated by the WT:

$$\mathrm{P}_{(\mathrm{t,s})}^{\mathrm{WT}}=\begin{cases}0 & \mathrm{V}_{(\mathrm{t,s})}\le\mathrm{V}_{\mathrm{ci}}\\ \mathrm{P}_{\mathrm{r}}^{\mathrm{WT}}\times\dfrac{(\mathrm{V}_{(\mathrm{t,s})})^{2}-\mathrm{V}_{\mathrm{ci}}^{2}}{\mathrm{V}_{\mathrm{r}}^{2}-\mathrm{V}_{\mathrm{ci}}^{2}} & \mathrm{V}_{\mathrm{ci}}\le\mathrm{V}_{(\mathrm{t,s})}\le\mathrm{V}_{\mathrm{r}}\\ \mathrm{P}_{\mathrm{r}}^{\mathrm{WT}} & \mathrm{V}_{\mathrm{r}}\le\mathrm{V}_{(\mathrm{t,s})}\le\mathrm{V}_{\mathrm{co}}\\ 0 & \mathrm{V}_{(\mathrm{t,s})}>\mathrm{V}_{\mathrm{co}}\end{cases} \tag{8}$$

Where $V_{(t,s)}$ is the wind speed in time interval t under scenario s (m/s). It is worthwhile mentioning that the wind speed is predicted by some meteorological model and hence these predictions are retained as realistic ones. P_r^{WT} represents the rated electrical power, V_{ci}, V_{co} and V_r are the cut in, the cut off and the rated wind speed, respectively. Clearly, as the wind speed increases, the power output will increase with the cube of the wind speed. This model must be adapted to account for cut-in speed, rated speed, and cut-out speed. Low-wind speeds do not provide sufficient torque to the turbine blades to make them rotate. Power generation typically begins at wind speeds between 3 m/s and 4 m/s (6.71 and 8.95 mi/h). The wind speed at which power generation begins is called the cut-in speed. As the wind speed exceeds the cut-in speed, power generation will rise steeply as a function of the cube of the wind speed. However, when the speed reaches a threshold, the wind turbine will reach its rated power output and will no longer increase its power as the velocity increases. This typically occurs between 12 m/s and 17 m/s (26.84 and 38.03 m/h). With large turbines, the wind power is usually maintained at a constant level by adjusting the angle of the blades. As the speed increases above the rated speed, there is a danger that excessive forces will cause damage to the turbine. A braking system will engage and bring the rotor to a standstill. This occurs at the cut-out speed which is typically around 25 m/s (Figure 2929).

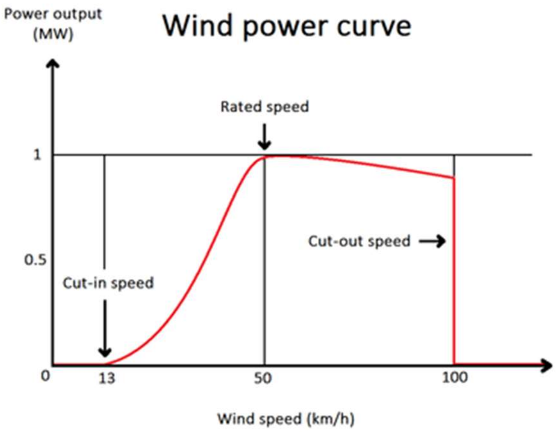


Figure 29: Wind Power Programme UK., (Renewable energy concepts n.d.)

In general, the wind speed measurements are given at a height different to that of the hub height of the wind turbine which can be expressed by

$$V_{(t,s)} = \tilde{V}_t \times \frac{\ln(H_{hub} / z)}{\ln(H_{meas} / z)}, \quad \forall t \tag{9}$$

Where H_{hub} and H_{meas} are the hub height and the height of the measurement, respectively. z is the surface roughness length and $\tilde{V}_t$ is the forecasted wind speed at the height of the measurement.

Photovoltaics (PV)

Solar irradiance is the amount of power that reaches the surface of the earth per unit area. For a given location, this amount will vary on a daily and yearly basis due to the motion of the earth relative to the sun. The amount of solar radiation also depends on the geographical location (latitude and longitude) and the climatic conditions. Cloud cover is the main factor affecting the amount of solar radiation that reaches the surface of the earth. Figure 3030 shows the seasonal and hourly variability in solar irradiance measured at Ames, Iowa. USA for the year 2015.

The power generated from the PV modules can be calculated using the following formula (Marzband & Sumper, 2014; Hocaoğlu et al., 2009):

$$P_{(t,s)}^{PV} = S^{PV} \cdot \eta^{PV} \cdot p^{f} \cdot \eta^{PV} \cdot G_{(t,s)} \tag{10}$$

where S^{PV} is the solar cell array area, η^{PV} is the module reference efficiency, p^{f} is the packing factor, η^{PV} is the power conditioning efficiency and $G_{(t,s)}$ is the forecasted hourly irradiation.

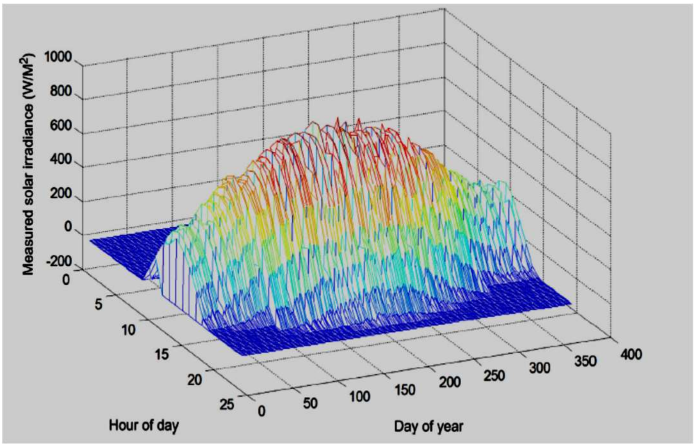


Figure 30: Measured Solar Irradiance for Ames, Iowa, USA in 2015.

Flat plate collector (FPC)

The useful thermal energy extracted from the water collector depends on the instantaneous incident solar irradiation, the plate area, and its efficiency (Fadaret al., 2009). It can be formulated as:

$$E_{(t,s)}^{FPC} = \eta^{FPC} \cdot A^{FPC} \cdot G_{(t,s)} \cdot \Delta t \tag{11}$$

where η^{FPC}, A^{FPC} and $G_{(t,s)}$ are the efficiency of the solar FPC, the area and the forecasted hourly irradiation, respectively. Δt is the energy management time step. During the summer period when normal heat supply to the district heating is required less, water for heating passing through the FPC may be stopped. This constraint can be formulized as follows:

$$E_{(t,s)}^{FPC} \geq E_{(t,s)}^{FPC,th} \tag{12}$$

Biomass (BIO)

Energy provided by the biomass heating plant depends on the used biomass quantity $u_{(t,s)}$, the biomass volumetric mass (VM) (i.e. the ratio between the dry mass and the volume), and the lower heating value (LHV).

The LHV assumes that the latent heat of vaporization of water in the fuel and the reaction of the products is not recovered. Subsequently, it can be calculated once the higher heating value (HHV) and moisture content (MC) are known. The HHV is the total energy release in the combustion with all of the products at 273 K in their natural state when water has released its latent heat of condensation. In the present work, the HHV is evaluated from the basic data analysis of biomass. The biomass MC represents the water amount present in the biomass and it can be expressed as a percentage of the dry weight. As regards the production plant, the plant is supposed to operate at maximum productivity level. The following equation provides the plant's developed energy (Dagdougui et al., 2012):

$$\mathrm{E}^{\mathrm{BIO}}_{(\mathrm{t,s})} = \mathrm{f} \cdot \eta^{\mathrm{BIO}} \cdot \mathrm{LHV} \cdot \mathrm{u}_{(\mathrm{t,s})} \cdot \mathrm{VM} \tag{13}$$

Biomass may not be used (especially during summer when heating is not necessary and thus cannot be sent to the network); as a result this constraint can be defined as follows:

$$E^{BIO}_{(t,s)} \geq E^{BIO,th}_{(\mathrm{t,s})} \tag{14}$$

Energy storage (ES)

ES can be operated as a prosumer because it can be used for the operating modes of charging and discharging.

$$SOC^{ES}_{(t,s)} \leq C^{ES}_{\mathrm{Tot},(t,s)} \tag{15}$$

$$E^{ES}_{(t,s)} = E^{ES,\mathrm{ele}}_{(t,s)} + E^{ES,th}_{(t,s)} + E^{ES,\mathrm{wp}}_{(t,s)} \tag{16}$$

$$E^{ES}_{(t+1,s)} = E^{ES}_{(t,s)} + E^{WT,ele}_{(t+1,s)} + E^{PV,ele}_{(t+1,s)} + E^{GRID,ele}_{(t+1,s)} \tag{17}$$

Energy trading algorithm

In this section, the problem formulation of the energy matching and trading framework is presented by using the key components (e.g. the owner of GBs, consumers, prosumers, upstream grid) in the local energy market. The characteristic of this framework is that it can be easily expandable to other electricity distribution systems with high levels of consumers' participation. In order to implement energy trading, it is considered that each GB has a NSO which is responsible for meeting the objective function relating to the owner of the GB and local consumers. After the management of all the local consumers and producers by the NSOs, some information (e.g. the amount of shortage of power or excess power at each time interval for the next day ahead for each GB) and submit a set of supply/demand bids (offer prices) in order to sell/purchase energy dispatched to the CNSO. Eventually, the CNSO can specify how GBs (including the rated capacity of the existing components and their technical and economic constraints, and cost functions) can be mediated through an interaction within the neighbourhood systems. It is worthwhile mentioning that the nature of the cost function cannot change on a daily basis.

Objective functions:

The defined objective functions, based on maximizing the generators' and retailers' profit and also on minimizing the consumers' costs, are as follows: the first part of Eq. (18) represents the income resulting from the electrical/thermal power produced by the producers existing in the GBs. The second part of Eq.18 is equivalent to the operating cost of the ES and the TES during the discharging mode required by the electrical/thermal resources. Eq. (19) expresses the income from selling the electrical power sold to the GBNS minus the cost of buying electrical power from the GBNS. This is while it should embrace the completion of its function of the power required in the GBNS and all constraints. Eq. (20) shows the value of the electrical power bought from the GBs for supplying the non-responsive and responsive load demands.

$$\max \sum_{\forall t} \sum_{\forall i} \sum_{\forall j} \sum_{\forall k} \begin{pmatrix} \square^{\mathrm{k,i}}{}_{(\mathrm{t,e})} + \square^{\mathrm{ES-,i}}{}_{(\mathrm{t,e})} + \square^{\mathrm{j,i}}{}_{(\mathrm{t,h})} + \square^{\mathrm{TES-,i}}{}_{(\mathrm{t,h})} \\ -\square^{\mathrm{j,i}}{}_{(\mathrm{t,h})} - \square^{\mathrm{TES+,i}}{}_{(\mathrm{t,h})} - \square^{\mathrm{ES+,i}}{}_{(\mathrm{t,e})} - \square^{\mathrm{k,i}}{}_{(\mathrm{t,e})} \end{pmatrix} \times \Delta \mathrm{t} \tag{18}$$

$$\max \sum_{\forall t}\sum_{\forall i}\left(\square^{GR\text{-},i}(t,e)-\square^{GR+,i}(t,e)\right)\times\Delta t \tag{19}$$

$$\min \sum_{\forall t}\sum_{\forall i}\sum_{\forall l}\sum_{\forall m}\left(\square^{p,i}(t,h)+\square^{m,i}(t,e)\right)\times\Delta t \tag{20}$$

where $\square^{k,i}(t,e)$ and $\square^{j,i}(t,h)$ are respectively the electrical and thermal revenue resulting from the DERs of k and j in GB i. $\square^{ES\text{-},i}(t,e)$ and $\square^{TES\text{-},i}(t,h)$ are respectively the revenue resulting from the ES and the TES electrical and thermal discharges related to GB i at time t. Also, $\square^{GR\text{-},i}(t,e)$ and $\square^{GR+,i}(t,e)$ are respectively the revenue/cost resulting from selling/buying electrical power from/to the retailer to GB i. In addition, $\square^{p,i}(t,h)$ and $\square^{m,i}(t,e)$ are respectively electricity costs relating to p and m consumers at GB i.

Technical and economic constraints:

$$\sum_{\forall i}\sum_{\forall k}\left(P^{k,i}(t,e)+P^{ES-,i}(t,e)+(1\text{-}X_t^{GR})\cdot P^{GR\text{-},i}(t,e)\right)=\sum_{\forall i}\sum_{\forall m}\left(P^{m,i}(t,e)+P^{ES+,i}(t,e)+X_t^{GR}\cdot P^{GR+,i}(t,e)\right) \tag{21}$$

$$\sum_{\forall i}\sum_{\forall j}\left(P^{j,i}(t,h)+P^{TES\text{-},i}(t,h)\right)=\sum_{\forall i}\sum_{\forall l}\left(P^{p,i}(t,h)+P^{TES+,i}(t,h)\right) \tag{22}$$

Eq.(21) and Eq. (22) express that the total power generated by the electrical/thermal generators during each time interval must be equal to the total load demand of the electrical/thermal consumers.

Retailer constraints:

$$\square^{GR\text{-},i}(t,e)=\pi^{GR\text{-},i}(t,e)\times P^{GR\text{-},i}(t,e) \tag{23}$$

$$0\le\pi^{GR\text{-},i}(t,e)\le\lambda_t^{SBP} \tag{24}$$

Eq. (23) shows the cost resulting due to buying electrical power from the retailer to the GB. Eq. (24) shows the offer price at each interval for buying power by the retailer to the GB.

$$\square^{GR+,i}(t,e)=\pi^{GR+,i}(t,e)\times P^{GR+,i}(t,e) \tag{25}$$

$$0\le\pi^{GR+,i}(t,e)\le\lambda^{SSP}(t,e) \tag{26}$$

Eq.(25) shows the revenue resulting from selling electrical power from the GB to the retailer. Eq.(26) shows the price bid interval for selling power by the retailer to the GB.

$$P^{GR+,i}(t,e)\le X^{GR}(t)\times P^{GR,\max} \tag{27}$$

$$P^{GR\text{-},i}(t,e)\le\left(1\text{-}X^{GR}(t)\right)\cdot P^{GR,\max} \tag{28}$$

$$P^{GR,\max}\le\left(P^{ESP,i}(t,e)+P^{CHP,i}(t,e)+P^{ES\text{-},i}(t,e)\right) \tag{29}$$

Eq.(27) and Eq. (28) show the exchanged power constraints between the GB and the retailer.

GB i constraints:

ES and TES constraints in GB i

$$\square^{ES+,i}(t,e)=\pi^{ES+,i}(t,e)\times P^{ES+,i}(t,e) \tag{30}$$

$$0\leq \pi^{ES+,i}(t,e)\leq \lambda^{MCP}(t,e) \tag{31}$$

$$\square^{ES-,i}(t,e)=\pi^{ES-,i}(t,e)\times P^{ES-,i}(t,e) \tag{32}$$

$$0\leq \pi^{ES-}(t,e)\leq \lambda^{MCP}(t,e) \tag{33}$$

where $\square^{ES+,i}(t,e)$, $\square^{ES-,i}(t,e)$, $\pi^{ES+,i}(t,e)$ and $\pi^{ES-,i}(t,e)$ show respectively cost, revenue, and price bid resulting from buying/selling electrical power by the ES in the GB i. Eqs. (34) to (39) present the maximum and minimum charge/discharge of the ES in the GB i.

$$E^{ES,i,min}\leq E^{ES,i}(t,e)\leq E^{ES,i,max} \tag{34}$$

$$P^{ES-,i}(t,e)\leq P^{ES-,i,max}\times X^{ES,i}(t),P^{ES-,i}(t,e)\geq 0 \tag{35}$$

$$P^{ES+,i}(t,e)\leq P^{ES+,i,max}\times X^{ES,i}(t),P^{ES+,i}(t,e)\geq 0 \tag{36}$$

$$P^{ES-,i}(t,e)\times\Delta t\leq\left(E^{ES,i}(t-1)-E^{ES,i,min}\right) \tag{37}$$

$$P^{ES+,i}(t,e)\times\Delta t\leq\left(E^{ES,i,max}-E^{ES,i}(t-1,e)\right) \tag{38}$$

$$E^{ES,i}(t,e)=E^{ES,i}(t-1,e)+\left(P^{ES+,i}(t-1,e)-P^{ES-,i}(t-1,e)\right)\times\Delta t \tag{39}$$

Eqs. (34) and (35) are the maximum limits of charging/discharging the energy existing in the ES. Eq.(38) states the energy equilibrium in the ES.

$$\square^{TES+,i}(t,h)=\pi^{TES+,i}(t,h)\times P^{TES+,i}(t,h) \tag{40}$$

$$0\leq \pi^{TES+,i}(t,e)\leq \max\left(\pi^{HHW,i}(t,h),\pi^{TD,i}(t,h)\right) \tag{41}$$

Eq.(40) shows the cost resulting from buying thermal power by the TES in the charging mode while Eq.(41) is the price bid at each interval for buying thermal power by the TES.

$$\square^{TES-,i}(t,h)=\pi^{TES-,i}(t,h)\times P^{TES-,i}(t,h) \tag{42}$$

$$0\leq \pi^{TES-,i}(t,h)\leq \min\left(\max\left(\pi^{CHP,i}(t,h),\pi^{GB,i}(t,h)\right),\pi^{TSP,i}(t,h)\right) \tag{43}$$

where $\pi^{TES-,i}(t,h)$ in Eq.(43) is the price bid variations' interval for selling thermal power by the TES and $\square^{TES-,i}(t,h)$ in Eq.(42) is the revenue resulting from selling the thermal power generated by the TES in the discharging mode.

$$E^{TES,i,min}\leq E^{TES,i}(t,h)\leq E^{TES,i,max} \tag{44}$$

$$P^{TES-,i}(t,h)\leq P^{TES-,i,max}\times X^{TES,i}(t),P^{TES-,i}(t)\geq 0 \tag{45}$$

$$P^{TES+,i}(t,h) \le P^{TES+,i,max}, P^{TES+,i}(t,h) \ge 0 \tag{46}$$

The maximum and minimum of the TES in charging/discharging limitations are shown in Eqs.(44) to (46).

$$P^{TES-,i}(t,h) \times \Delta t \le \left(E^{TES,i}(t-1,h) - E^{TES,i,min}\right) \tag{47}$$

$$P^{TES+,i}(t,h) \times \Delta t \le \left(E^{TES,i,max} - E^{TES,i}(t-1,h)\right) \tag{48}$$

$$E^{TES,i}(t,h) = E^{TES,i}(t-1,h) + \left(P^{TES+,i}(t-1,h) - P^{TES-,i}(t-1,h)\right) \times \Delta t \tag{49}$$

Eqs. (47) and (48) show the maximum limit of charging/discharging for the energy existing in the TES. Eq. (49) presents the energy balance in the TES.

EV constraints in GB i:

$$\text{if } X^{EV,i}(t,e) = 1 \Rightarrow P^{EV+,i,min} \le P^{EV+,i}(t,e) \le P^{EV+,i,max} \tag{50}$$

$$SOC^{EV,i}(t,e) \le SOC^{EV,i,max} \tag{51}$$

$$SOC^{EV,i}(t,e) = SOC^{EV,i}(t-1,e) - \frac{P^{EV+,i}(t,e) \times \Delta t}{E_{Tot}^{EV,i}} \tag{52}$$

$$SOC^{EV,i}(t,e) = SOC^{EV,i,max} \Rightarrow \begin{cases} X^{EV,i}(t,e) = 0 \\ P^{EV+,i}(t,e) = 0 \end{cases} \tag{53}$$

Eq.(50) states that $SOC^{EV,i}(t,e)$ automobile battery in the EV during each time interval related to GB i, must be less than its maximum value. It should be noted that Eq.(51) is the automobile battery power equilibrium constraint.

$$\square^{EV+,i}(t,e) = \pi^{EV+,i}(t,e) \times P^{EV+,i}(t,e) \tag{54}$$

$$0 \le \pi^{EV+,i}(t,e) \le \lambda^{MCP}(t,e) \tag{55}$$

Eq.(54) is the cost resulting from buying electrical power by the EV while Eq.(55) presents the offer price interval for buying power by the EV.

ESP constraints in GB i:

$$P^{ESP,i,min} \le P^{ESP,i}(t,e) \le P^{ESP,i,max} \tag{56}$$

The ESP generated power limitation is as shown in Eq.(56).

$$\square^{ESP,i}(t,e) = \pi^{ESP,i}(t,e) \times P^{ESP,i}(t,e) \tag{57}$$

$$0 \le \pi^{ESP,i}(t,e) \le \lambda^{MCP}(t,e) \tag{58}$$

Eq. (57) shows the revenue resulting from generating electrical power by the ESP whereas Eq.(58) shows the price bid interval for selling power by the ESP.

TSP constraints in GB i:

$$\square^{TSP,i}(t,h)=\pi^{TSP,i}(t,h)\times P^{TSP,i}(t,h) \tag{59}$$

$$0 \le \pi^{TSP,i}(t,h) \le \min\left(\pi^{TES\text{-},i}(t,e), \pi^{CHP,i}(t,h), \pi^{GB,i}(t,h)\right) \tag{60}$$

where Eq. (59) shows the generated thermal power income by the TSP and Eq.(60) shows the price bid interval for selling power by the TSP.

CHP constraints in GB i:

$$P^{CHP,imin} \le P^{CHP,i}(t,e) \le P^{CHP,i,max} \tag{61}$$

$$P^{CHP,i}(t,e) = FU_t^{CHP,i} \times \xi_{e1}^{CHP,i} + \xi_{e2}^{CHP,i} \tag{62}$$

$$P^{CHP,i}(t,e)=\xi_{e1}^{CHP,i} \times \frac{P^{CHP,i}(t,h)}{\xi_{h}^{CHP,i}} + \xi_{e2}^{CHP,i} \tag{63}$$

where Eq.(61) presents the power generation limitation by the CHP. In Eqs. (62) and (63), $FU^{CHP}(t)$, ξ_e^{CHP} and ξ_h^{CHP} are respectively the fuel, electrical efficiency and thermal efficiency of the CHP. Eq.(64) is the cost resulting from the power generation by the CHP. Eq. (65) shows the price bid interval for generating power by the CHP. In addition, Eqs. (66) and (67) state the revenue resulting from selling the electrical and thermal powers generated by the CHP.

$$\square^{CHP,i}(t,h)=\pi^{NG}(t) \times FU^{CHP,i}(t) \tag{64}$$

$$\square^{CHP,i}(t,h) \le \pi^{CHP,i}(t,h) \le 2\times\square^{CHP,i}(t,h) \tag{65}$$

$$\square^{CHP,i}(t,e)=\pi^{CHP,i}(t,e)\times P^{CHP,i}(t,e) \tag{66}$$

$$\square^{CHP,i}(t,h)=\pi^{CHP,i}(t,h)\times P^{CHP,i}(t,h) \tag{67}$$

GB constraints in GB i:

$$0 \le P^{GB,i}(t,h) \le P^{GB,i,max} \tag{68}$$

where Eq.(68) shows the limit of the power generated by the GB.

$$\square^{GB,i}(t,h)=\pi^{NG}(t)\times FU^{GB,i}(t) \tag{69}$$

$$FU^{GB,i}(t) = \frac{P^{GB,i}(t,h)}{\xi_h^{GB}} \tag{70}$$

$$\square^{GB,i}(t,h) \le \pi^{GB,i}(t,h) \le 2\times\square^{GB,i}(t,h) \tag{71}$$

where Eq.(69) shows the cost resulting from the thermal power generated by the GB. Eq. (70) shows the amount of fuel consumed by the GB. Eq.(71) shows the price bid at each interval for selling power by the GB. The revenue resulting from selling the thermal power by the GB is shown in Eq.(72).

$$\square^{GB,i}(t,h)=\pi^{GB,i}(t,h)\times P^{GB,i}(t,h) \tag{72}$$

Consumers, constraints (DR constraints):

$$P^{DR-,i}(t,e) \le (P^{TCP,i}(t,e) - P^{TGP,i}(t,e)).\ X^{DR-,i}(t,e) \quad (73)$$

$$P^{DR+,i}(t,e) \le (P^{TGP,i}(t,e) - P^{TCP,i}(t,e)).(1 - X^{DR-,i}(t,e)) \quad (74)$$

$$P^{DR+,i}(t,e) \le k_{\varepsilon} \times P^{n,i}(t,e) \times (1 - X^{DR-,i}(t,e)) \quad (75)$$

$$-k\ (t) \le P^{DR+,i}(t,e) - P^{DR+,i}(t-1,e) \le k\ (t) \quad (76)$$

where Eq.(73) shows that the value of the shiftable power must be smaller and equal to the subtraction sum of the total consumed power minus the total generated power.

Eq.(76) shows that the DR limit between two consecutive intervals must not exceed a certain limit.

ATL and AEL constraints:

$$\square^{AEL,i}(t,e)=\pi^{AEL,i}(t,e)\times P^{AEL,i}(t,e) \quad (77)$$

$$\square^{ATL,i}(t,e)=\pi^{ATL,i}(t,e)\times P^{ATL,i}(t,e) \quad (78)$$

$$\lambda^{MCP}(t,e) \le \pi^{AEL,i}(t,e) \le 2\times\lambda^{MCP}(t,e) \quad (79)$$

$$\begin{aligned}&\max(\pi^{TES-,i}(t,h),\pi^{CHP,i}(t,h),\pi^{GB,i}(t,h),\pi^{TSP,i}(t,h)) \le \pi^{ATL,i}(t,h)\\&\le 2\times\max(\pi^{TES-,i}(t,h),\pi^{CHP,i}(t,h),\pi^{GB,i}(t,h),\pi^{TSP,i}(t,h))\end{aligned} \quad (80)$$

where Eqs. (77) and (78) are the costs resulting from buying electric and thermal power by the AEL and the ATL. Also, Eqs.(79) and (80) show the price bid interval for buying power by the AEL and the ATL.

TD constraints:

$$\square^{TD,i}(t,h)=\pi^{TD,i}(t,h)\times P^{TD,i}(t,h) \quad (81)$$

$$0 \le \pi^{TD,i}(t,h) \le \min(\pi^{TES-,i}(t,h),\pi^{CHP,i}(t,h),\pi^{GB,i}(t,h),\pi^{TSP,i}(t,h)) \quad (82)$$

where Eq.(81) shows the cost resulting from buying thermal power by the TD while Eq.(82) states the offer price interval for buying power by the TD.

REF constraints:

$$\begin{cases}\text{if } T^{REF,i,\min} \le T^{REF,i}(t,e) \le T^{REF,i,\max} & X^{REF,i}(t,e)=0\\ \qquad\qquad \text{Otherwise} & X^{REF,i}(t,e)=1\end{cases} \quad (83)$$

$$X^{REF,i}(t,e)=1 \Rightarrow \begin{cases}P^{REF,i}(t,e)=P^{REF,i,\max}\\ T^{REF,i}(t,e)=T^{REF,i}(t-1,e)-T^{RED,i}\end{cases} \quad (84)$$

$$X^{REF,i}(t,e)=0 \Rightarrow \begin{cases}P^{REF,i}(t,e)=0\\ T^{REF,i}(t,e)=T^{REF,i}(t-1,e)+T^{RED,i}\end{cases} \quad (85)$$

$$\square^{REF,i}(t,e)=\pi^{REF,i}(t,e)\times P^{REF,i}(t,e) \quad (86)$$

$$0 \le \pi^{REF,i}(t,e) \le \lambda^{MCP}(t,e) \tag{87}$$

where Eq.(86) states the cost resulting from buying power by the FER and Eq.(87) states the offer price interval for buying power.

DW constraints:

$$\text{if } X^{DW,i}(t,e) = 1 \Rightarrow \begin{cases} P^{DW,i}(t,e) = P^{DW,i,max} \\ DT^{DW,i}(t,e) = DT^{DW,i}(t-1,e) + 1 \end{cases} \tag{88}$$

$$\text{if } DT^{DW,i}(t,e) = DT^{DW,i,max} \Rightarrow \begin{cases} P^{DW,i}{}_{(t,e)=0} \\ X^{DW,i}{}_{(t,e)=0} \end{cases} \tag{89}$$

$$\square^{DW,i}(t,e) = \pi^{DW,i}(t,e) \times P^{DW,i}(t,e) \tag{90}$$

$$0 \le \pi^{DW,i}(t,e) \le \lambda^{MCP}(t,e) \tag{91}$$

where Eqs.(90) and (91) respectively show the cost resulting from buying power by the DW and the price bid interval for buying power.

HHW:

$$\begin{cases} \text{if } T^{HHW,i,min} \le T^{HHW,i}(t,h) \le T^{HHW,i,max} & X^{HHW,i}(t,h)=0 \\ \text{Otherwise} & X^{HHW}(t,h)=1 \end{cases} \tag{92}$$

$$X^{HHW,i}(t,h) = 1 \Rightarrow \begin{cases} P^{HHW,i}(t,e) = P^{HHW,i,max} \\ T^{HHW,i}(t) = T^{HHW,i}(t-1,h) + T^{INC,i} \end{cases} \tag{93}$$

$$X^{HHW,i}(t,h) = 0 \Rightarrow \begin{cases} P^{HHW,i}(t,h) = 0 \\ T^{HHW,i}(t,h) = T^{HHW,i}(t-1,h) - T^{INC,i} \end{cases} \tag{94}$$

$$\square^{HHW,i}(t,h) = \pi^{HHW,i}(t,h) \times P^{HHW,i}(t,h) \tag{95}$$

$$0 \le \pi^{HHW,i}(t,h) \le \max(\pi^{TES\text{-},i}(t,h), \pi^{CHP,i}(t,h), \pi^{GB,i}(t,h), \pi^{TSP,i}(t,h)) \tag{96}$$

4.4.Summary

Within the scope of this section, an energy training and matching framework was designed to control the optimal operation of green buildings in a neighbourhood system. This framework is a two-stage optimization process. In the first stage, each green building estimates its own load and determines the shortage or surplus of power at each time interval. In the second stage, power exchanges between green buildings and the upstream grid was considered where green buildings sell their excess energy or buy energy from the upstream grid or other green buildings. The designing of this two-stage optimization process allows for the maximal usage of renewable generation units, for optimal charging and discharging of energy storages, for operational cost decreases and also enhances the reliability of this framework especially for emergency situations.

Chapter 5: Results and discussion

5.1. Introduction

The proposed optimization methods are evaluated using a case study which contains three green buildings (GBs) in Barcelona with a diverse sort of DER technology and consumer units. For this study, both GB 1 and GB 2 have been designed with WT (1*8.2kW), ES (1*2kWh), PV (1*6.3kW), MT (1*12kW), and a responsive/non-responsive load demand. Non-dispatchable DERs and a non-responsive stack request profile within GBs are extricated from (Marzband et al. (2018)). The details of the DER resources, the characteristic of each GB and the load demand profile were presented in Chapter 2. Mathematical framework presented in Chapter 4 will be evaluated in the following.

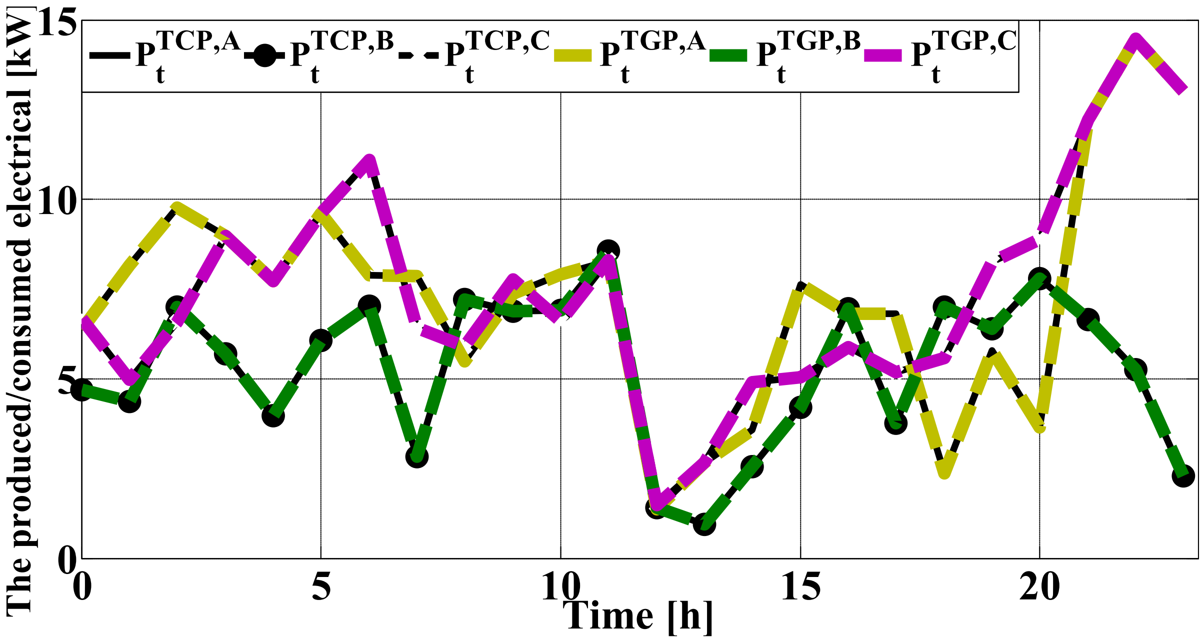
5.2. Evaluation of the algorithm using Barcelona case study

This section presents the evaluation results for the algorithm considering energy matching and trading in GBNSs. These test cases have been undertaken in three GBs in Barcelona. The evaluation was conducted for two use cases:

1. Use case 1: Energy matching in single building
2. Use case 2: Energy trading among multi building

5.2.1. Evaluated energy trading algorithm

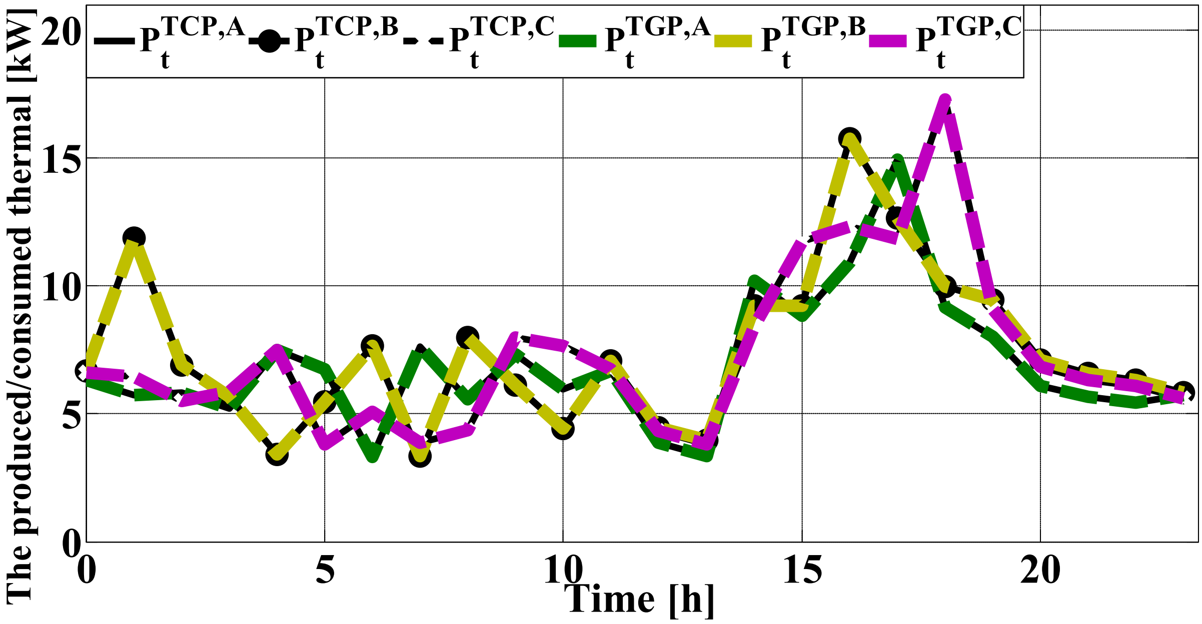
The generated and consumed electrical/thermal energy matching in each GB when they cooperate with each other in a neighbourhood performance, is shown in Figures 31 and 32. As seen in these figures the generated electrical and thermal power in each GB completely match with each other in the neighbourhood grid and also the power equilibrium constraint has also been satisfied.



$P_{t,e}^{TCP,A}$, $P_{t,e}^{TCP,B}$, $P_{t,e}^{TCP,C}$	**The total consumed electrical power in GBs A, B and C, respectively.**

$P_{t,e}^{TGP,A}$, $P_{t,e}^{TGP,B}$, $P_{t,e}^{TGP,C}$	**The total generated electrical power in GBs A, B and C, respectively.**

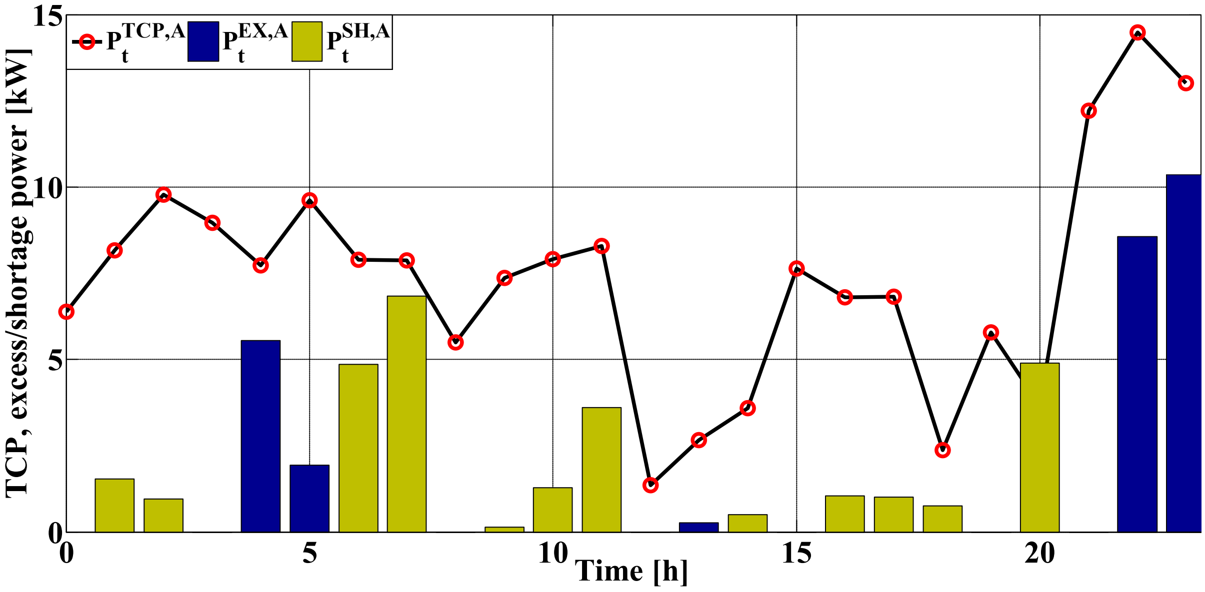
Figure 31: The total value of the consumed and generated electrical power in each GB



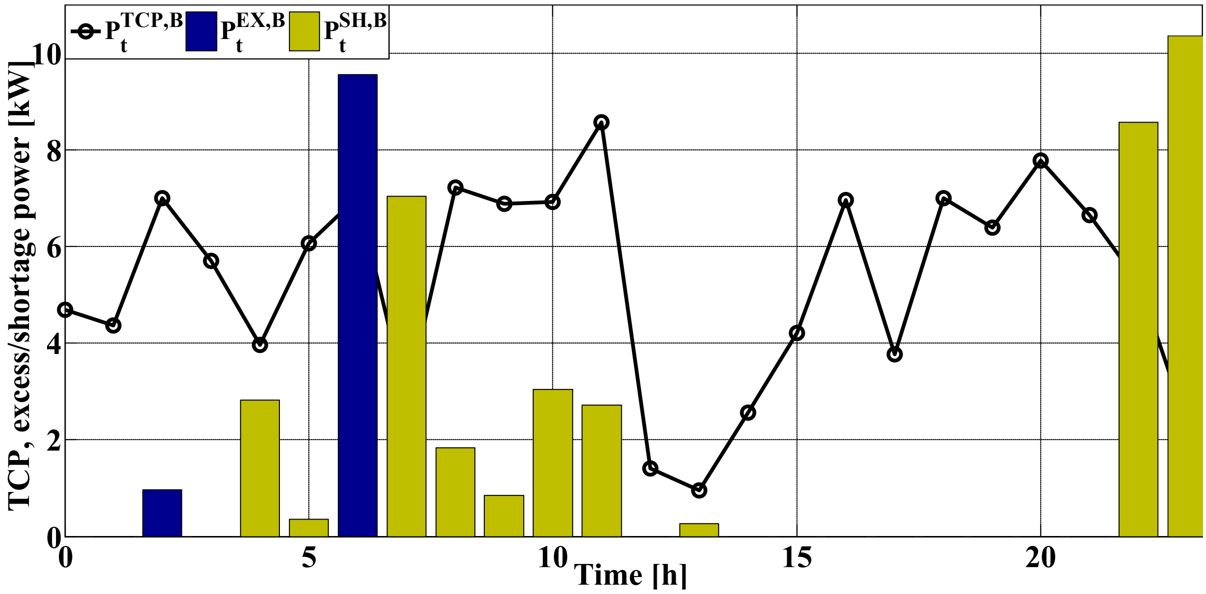
$P_{t,h}^{TCP,A}$, $P_{t,h}^{TCP,B}$, $P_{t,h}^{TCP,C}$	**The total consumed thermal power in GBs A, B and C, respectively.**
$P_{t,h}^{TGP,A}$, $P_{t,h}^{TGP,B}$, $P_{t,h}^{TGP,C}$	**The total generated thermal power in GBs A, B and C, respectively.**

Figure 32: the total value of the consumed and generated thermal power in each GB

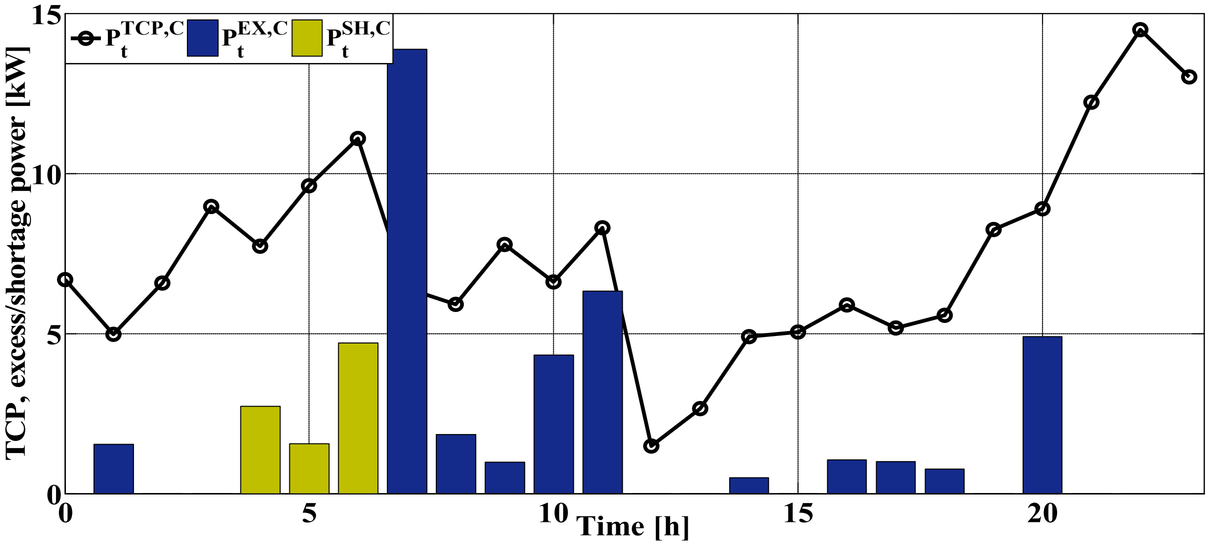
In Figure 33 the total value of the electrical power consumed by the consuming resources and also the electrical power shortage and the excess in each time interval in the GBs is shown. As seen in Figure 33(a), in GB A in no time interval does excess electrical power exist and altogether about 27% electrical power shortage exists in this GB which must be supplied through the upstream grid or be bought from the neighbourhood grid. In the time interval 07-08a.m. excess electrical power exists only in the GB C and also this power has a significant share in supplying a small part of GB A's consumed load. The rest of GB A's required load has been supplied through buying from the upstream grid. In time intervals where the amount of consumed load and the electricity price are low (11am-15pm), the algorithm has intelligently supplied its consumed load power through buying from the upstream grid, so in this way it leads to an increasing profit in each GB.



a) GB A



b) GB B

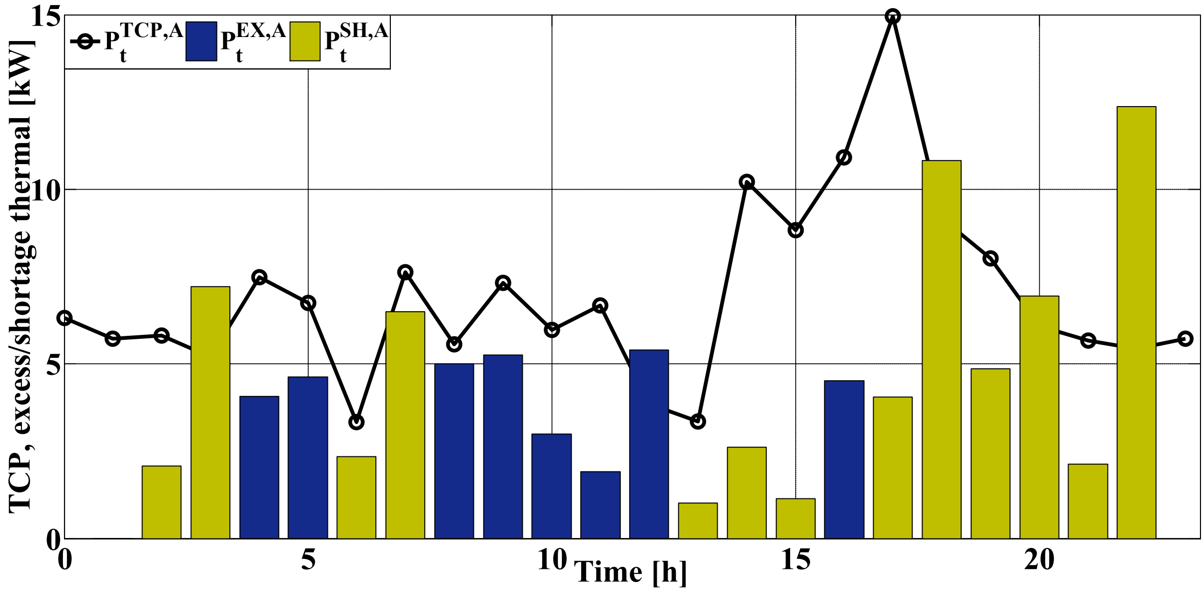


c) GB C

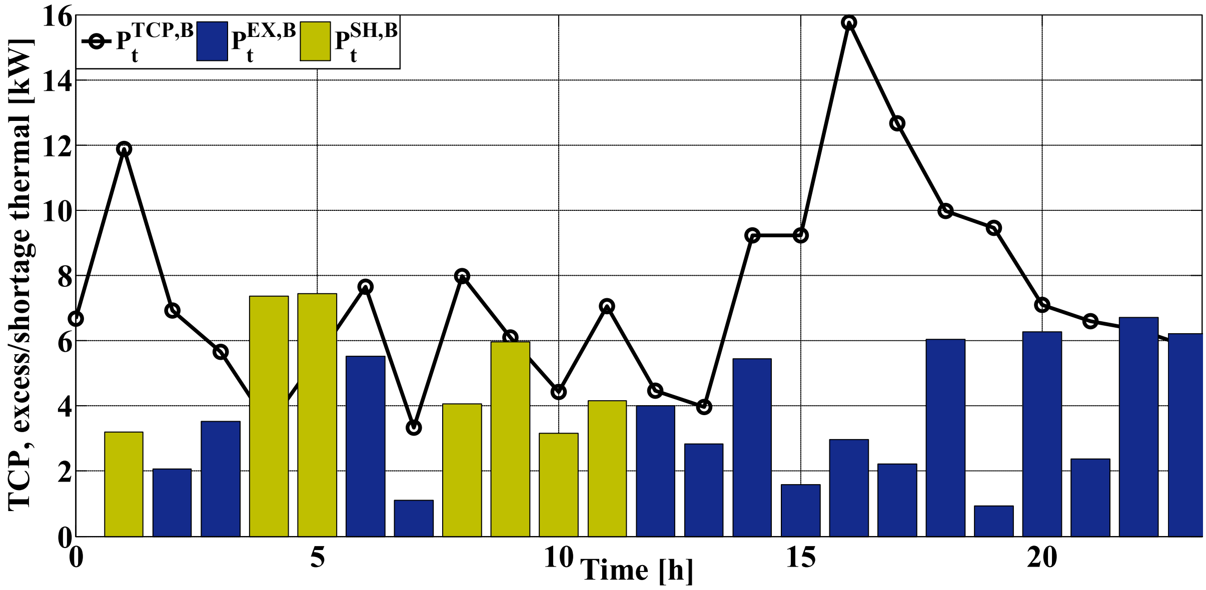
$P_{t,e}^{EX,A}$, $P_{t,e}^{EX,B}$, $P_{t,e}^{EX,C}$	**The excess electrical power in GBs A, B and C, respectively.**
$P_{t,e}^{SH,A}$, $P_{t,e}^{SH,B}$, $P_{t,e}^{SH,C}$	**The shortage electrical power in GBs A, B and C, respectively.**

Figure 33: the value of the total consumed power, the excess power generated and the electrical power shortage in the GBs of A-C

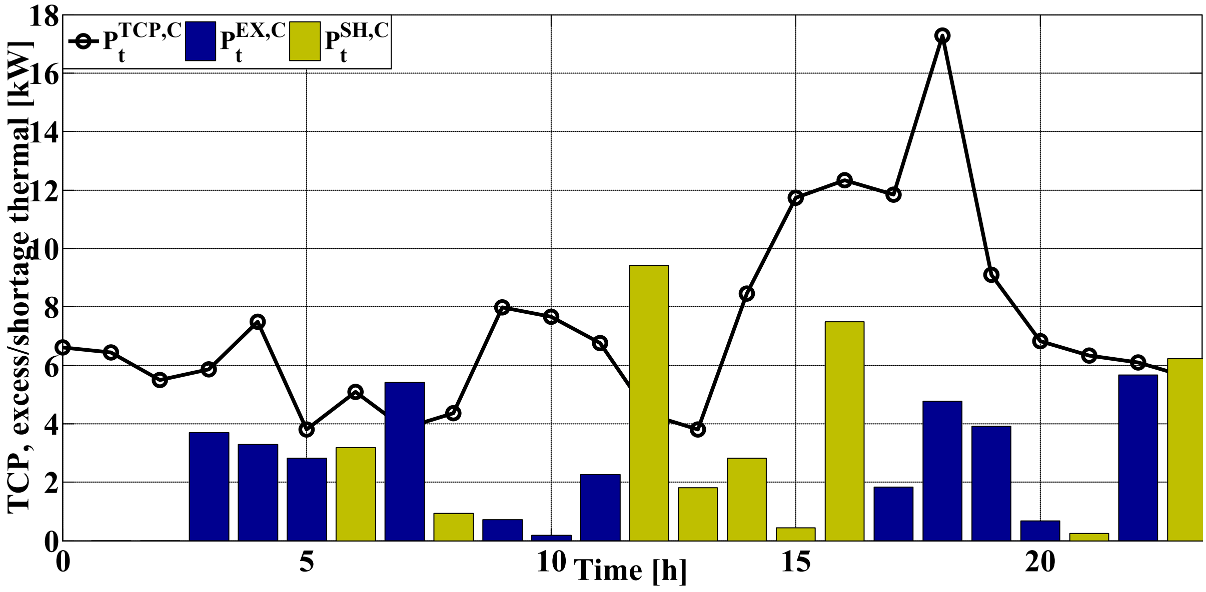
In Figure 34, in the individual case the total value of the thermal power consumed by each GB at each time interval is presented. Despite the existence of an electrical power shortage in most of the GBs, the thermal power generated by the CHP in these GBs has been spent supplying the thermal loads existing in these GBs. The thermal power shortage exists in GB can be supplied by another GB depending on the amount of profit that can be gained.



a) GB A



b) GB B



c) GB C

$P_{t,h}^{EX,A}$, $P_{t,h}^{EX,B}$, $P_{t,h}^{EX,C}$	**The excess thermal power in GBs A, B and C, respectively.**
$P_{t,h}^{SH,A}$, $P_{t,h}^{SH,B}$, $P_{t,h}^{SH,C}$	**The shortage thermal power in GBs A, B and C, respectively.**

Figure 34: the total value of the consumed thermal power, the excess generated thermal power and the thermal power shortage in the GBs of A-C.

The data used in producing the bargraph are presented in Tables 8 and 9. A GB with power shortage can buy the cheapest accessible energy from other GBs. Each condition of shortage and excess electrical/thermal power in each GB is recognized while the retailers (upstream grid) and the interoperability of the GBs can be taken into account. The shortage/excess energy of each GB is calculated while considering the retailer's interest in arranging to advance neighbourhood energy generation and utilization.

5.2.2. Evaluated energy matching algorithm

As mentioned in Section 3, the extreme objective of energy matching is to minimize the mismatch between the feed power by GBs and the load demand as well as to maximize the utilization of the accessible power produced by the GBs based on cheapest cost. The proposed energy matching and trading is utilized on a case study which contains three GBs with different sorts of producers, consumers and prosumers as has appeared in Figure 16. In this structure, the whole load demand in each GB can be provided by all the producers inside them taking into consideration the objective function characterized in the NSO. The GBs' consumed load profile has been created from measurements from several existing buildings in Barcelona city. The city's climatic conditions have been used for measuring the power produced by renewable resources. As shown in Table 8, the value of the total electrical power consumed and generated in all the GBs match with each other. In each

GB when the consumed power is much less than the produced power there exists a possibility for trading. In such a case the income resulting from selling power to other GBs has also resulted in significant reduction. This subject is analyzed in the following paragraphs. The consumer, producer and prosumer profiles of the thermal demand are shown in Table 12. In this table, energy matching in each one of the GBs has been shown in the case study in which they work independently from each other. In the case of the GBs' independent performance the generated thermal power can be less than cooperative operation the case. As a result, the income resulting from the thermal power exchange in cooperative operation will become more than that in independent operation. The following paragraphs present in detail an analysis of this.

Table 8: electrical load demand and producer profiles in energy matching in GBs A-C

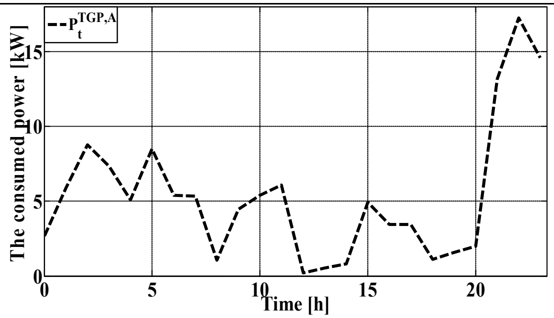
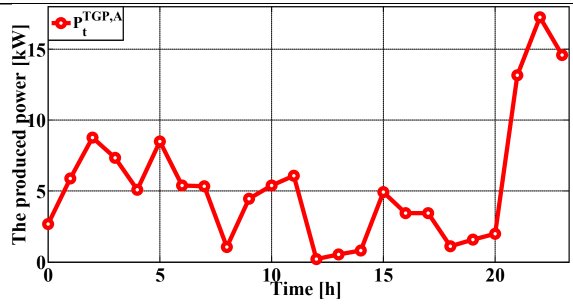
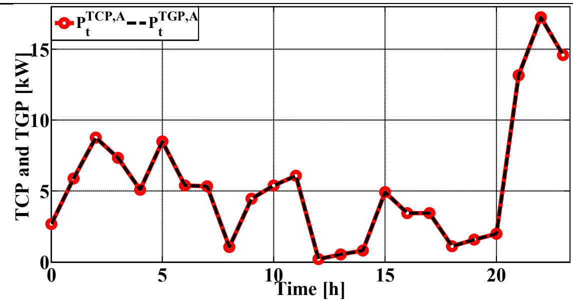
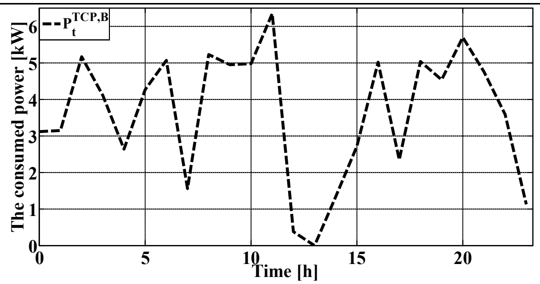
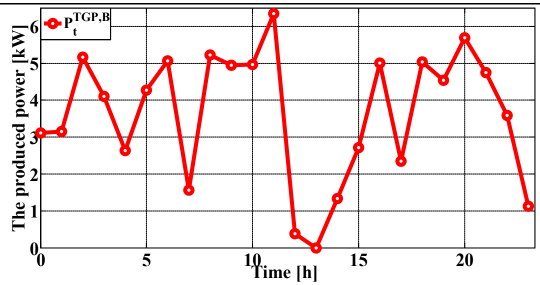
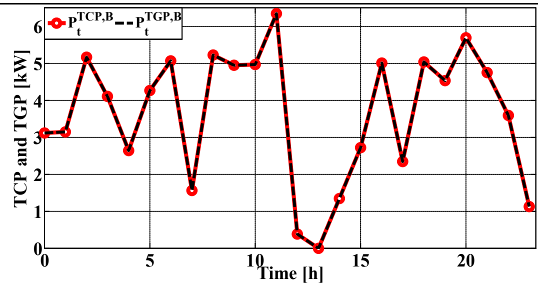
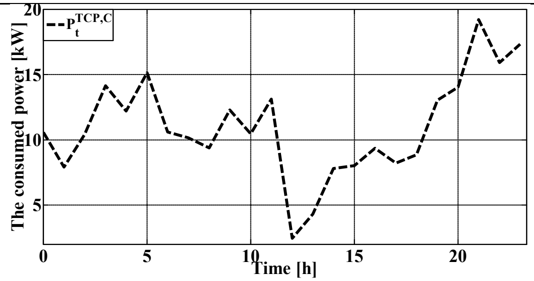
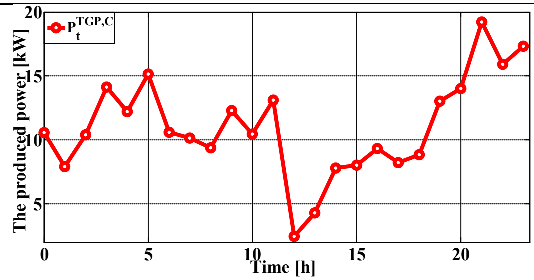
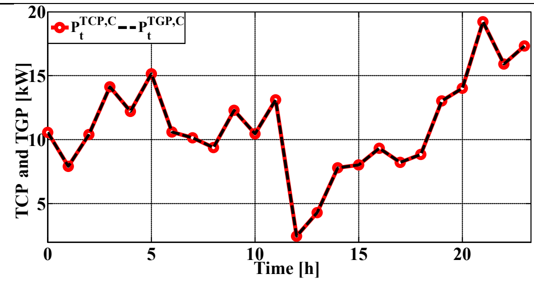
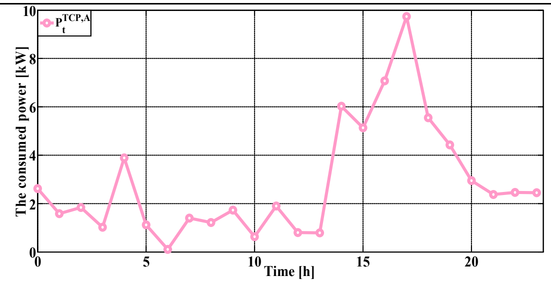
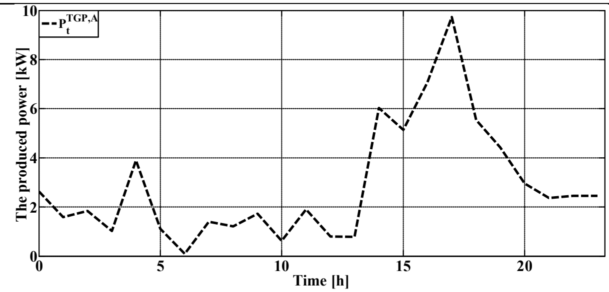
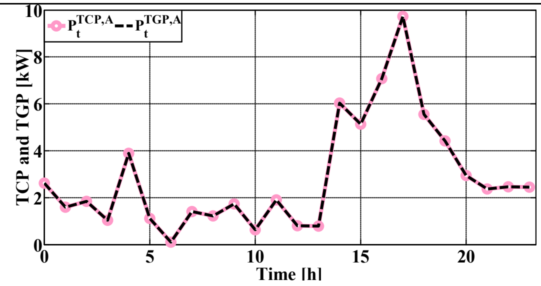
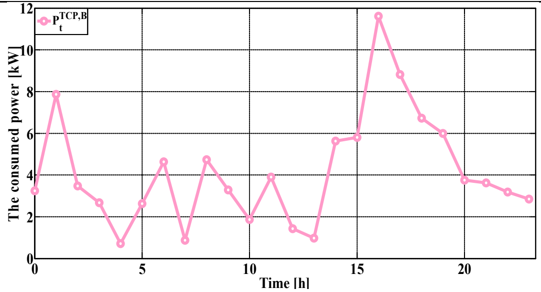
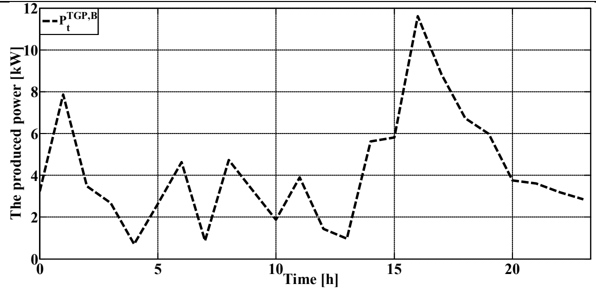
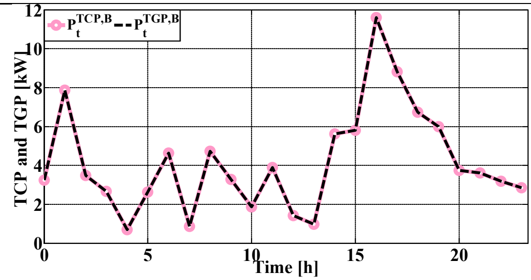
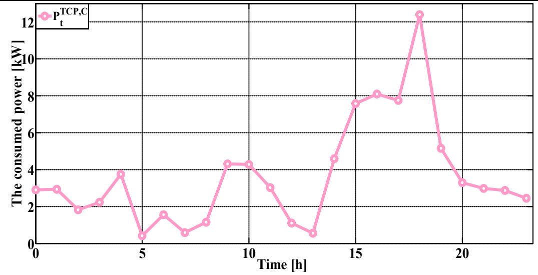
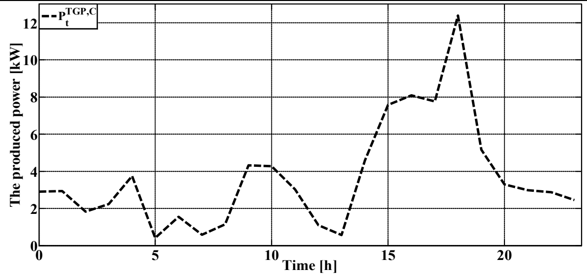
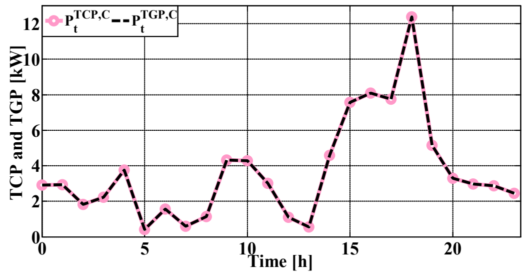
<table>
<tr><th>GB</th><th>consumers</th><th>producers</th><th>results</th></tr>
<tr><td>A</td><td></td><td></td><td></td></tr>
<tr><td>B</td><td></td><td></td><td></td></tr>
<tr><td>C</td><td></td><td></td><td></td></tr>
</table>

Table 9: thermal load demand and producer profiles in energy matching in GBs A-C

GB	consumers	producers	results
A			
B			
C			

In the following paragraphs the results obtained from the suggested algorithms that shows the increase in the profit of each GB and the reduction in the amount of the electricity and heat generation costs (which will lead to the satisfaction of the consumers while the GBs in the neighbourhood grid are operating) are presented. As can be seen in Table 10, the profit value and cost of GB A respectively increases 41% and reduces by 24% when the proposed optimization algorithm has been used. A similar trend has been observed for the GBs of B and C. The largest profit difference created by GB C has been obtained by using the proposed algorithm which is about 51%. However, the largest cost difference achieved belongs to GB A which is about 24%. Regarding the exchange of thermal load among the GBs, a similar improvement is evident through the proposed optimization algorithm. However, the amount of obtained profit has a lower value compared to exchanging electricity.

Table 10: the daily profit obtained from generating electrical and thermal power in each GB with energy trading

	GB	GB A		GB B		GB C	
	Method	With optimization	Without optimization	With optimization	Without optimization	With optimization	Without optimization
Electrical	Profit (£)	46.8	27.5	37.4	18.5	28.6	13.9
	Cost (£)	12.6	15.6	10.4	12.5	8.9	10.3
Thermal	Profit (£)	38.9	28.4	32.8	16.9	27.5	12.8
	Cost (£)	12.3	17.5	10.3	16.4	8.6	13.4

In the following paragraphs the results obtained from the proposed algorithm's proper performance in increasing the profit of each GB and also in reducing the amount of electricity and heat generation costs (which leads to the satisfaction of the consumers) while the GBs are working independently are shown. As is shown in Table 11, the profit value and cost of GB A have respectively reduced 11% and increased about 5.5% respectively. When the proposed optimization calculation has not been utilized, a comparable trend for the GBs of B and C has been observed with this distinction: that the foremost benefit contrast coming about from using the proposed algorithm within the GBs' single performance has been obtained by GB C which is around 30%. While the largest cost difference among the results obtained from using the proposed algorithm belongs to the GB A single performance which is about 5.5%. With regard to the thermal load exchange among the GBs a similar analysis exists with this difference: that the amount of profit obtained compared to the time when the GBs can share the amount of their thermal value with other GBs, has lower value.

Table 11: the profit obtained by each GB without energy trading

	GB	GB A		GB B		GB C	
	Method	With optimization	Without optimization	With optimization	Without optimization	With optimization	Without optimization
Electrical	Profit (£)	41.4	20.5	30.1	12.5	20.3	10.9

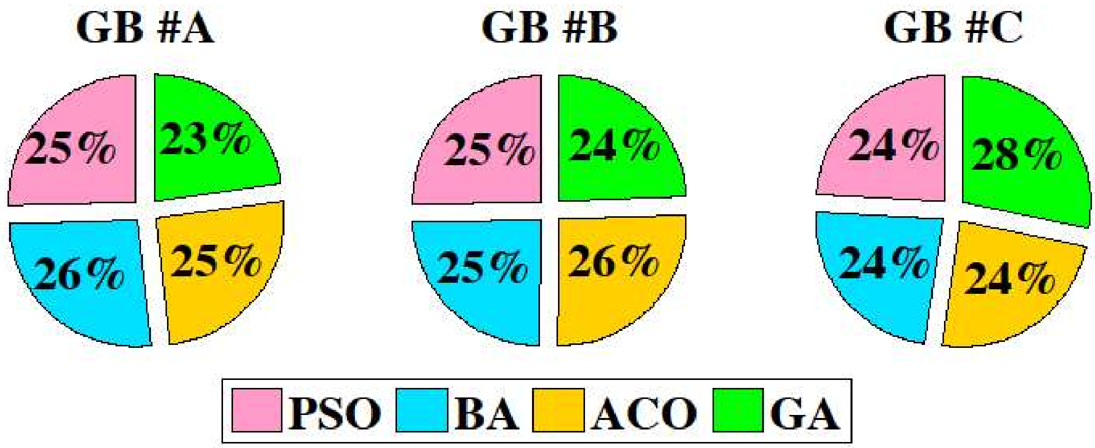
	Cost (£)	13.3	18.6	9.4	17.3	8.1	14.3
Thermal	Profit (£)	38.9	28.4	25.2	11.4	21.2	9.8
	Cost (£)	12.3	17.5	16.6	22.7	14.4	18.7

5.3. Comparison of different optimization algorithm

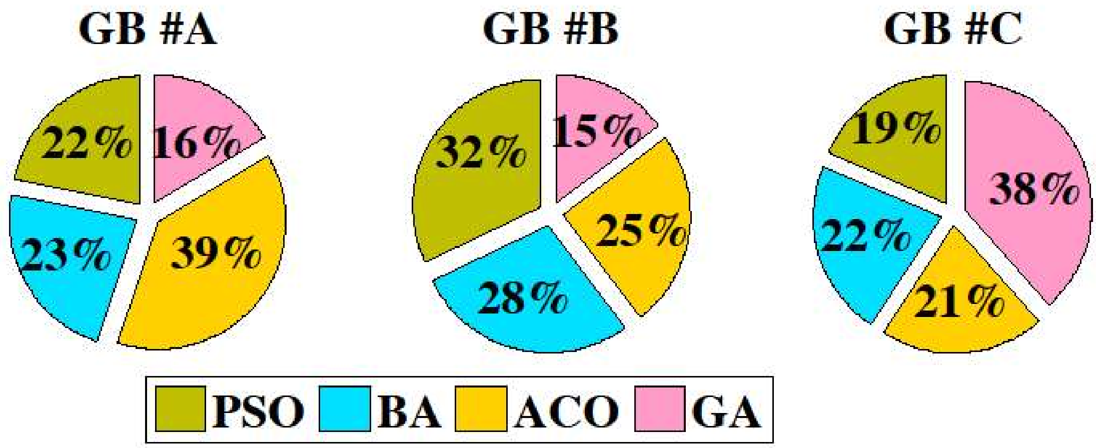
In the following section, three different optimization algorithms are discussed including the partial swarm optimization (PSO) algorithm, Bat algorithm (BA), ant colony optimization (ACO) and genetic algorithm (GA). The simulation has been executed on a computer with Intel CoreTM: 7-5500U CPU@2.5GHz and 8: 00GB RAM was performed by MATLAB software for a 24-hour operating time. In this section, the results of simulating the implementation of four optimization algorithms, PSO, BA, ACO and GA, are presented.

The study system has three GBs A, B, and C which incorporate a variety of generation units and consumer resources. In Figure 35, the total power generated and consumed by each of the electrical and thermal DERs in each GB (as well as the total amount of electrical/thermal power sold/purchased/sold to the retailer by using the optimization algorithms) are shown. In GB A, the highest production was related to the PSO method. In this way, the algorithm attempts to raise sales to the other GBs to earn more money by increasing its production. In this GB, the BA has sold most. This algorithm prefers to earn profits by selling a significant amount of power to the retailer. In GB B, the production rate of the PSO and BA methods is the same, and the highest production is related to the ACO method (which is mainly related to the CHP). In this GB, the PSO has been the largest seller to retail outlets. Given that the best performance in reducing MCP has been observed in the PSO method, it can be concluded that consumers at GB B have received less power from retail sales. In the GB B, the highest-selling retailer and the lowest-selling retailer has the PSO method to assist it to respond to more loads. In GB C, GA method has highest and other methods have the same production rate. In this GB, the largest purchase of retailers has occurred through the GA method. This is despite the fact that most retailers sell by the GA method in this GB. Depending on the amount of electrical MCP in the PSO method, it can be concluded that the PSO chooses to sell power to the retailer to achieve high incomes.

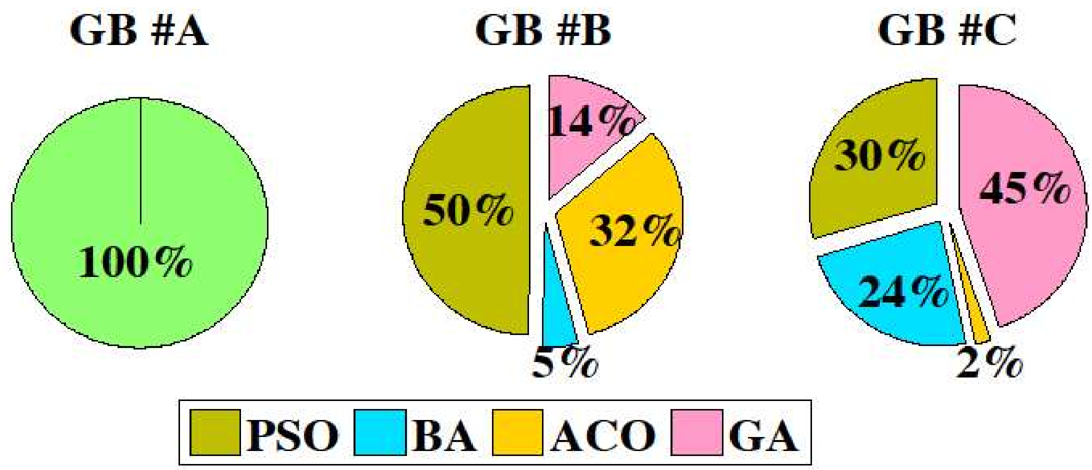
The total amount of thermal power generated by each thermal producer is shown in Figure 355 (d). As can be seen, GB A had the highest production rates for the BA method. In GB B and C, the highest heat output was related to BA method. Considering that in the BA method, the amount of MCP in the mid-day hours was at its maximum, and the BA method at these intervals was successful in reducing the MCP. The fact that BA is cleverly produced with less production while responding to all the thermal loads has brought the most benefit to GB owners. The PSO approach has been similar to the ACO approach, but the BA has had the highest performance in terms of thermal power and has not had a decent performance in reducing MCP compared to other methods, thus the cost to GBs owners has increased.



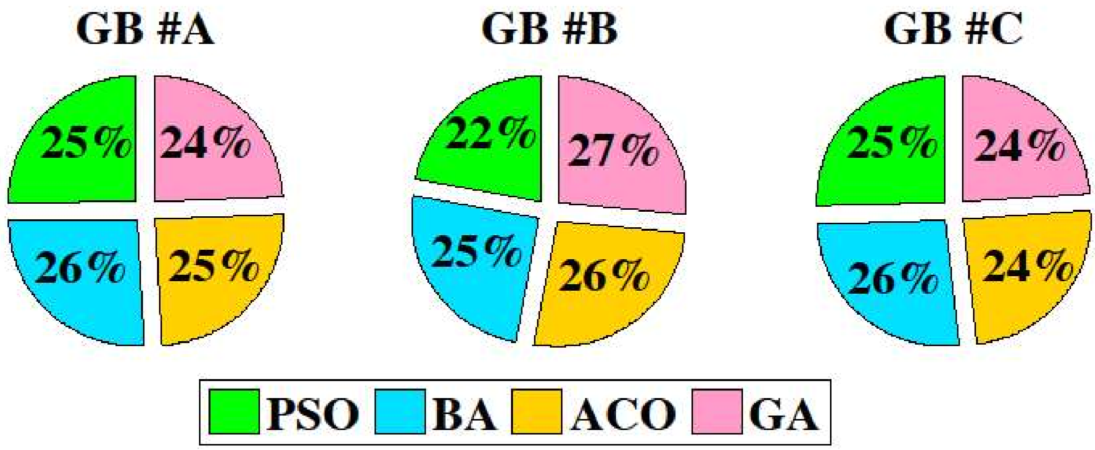
a) The total amount of electrical power generated in GB



b) The total amount of electrical power sold to the retailer



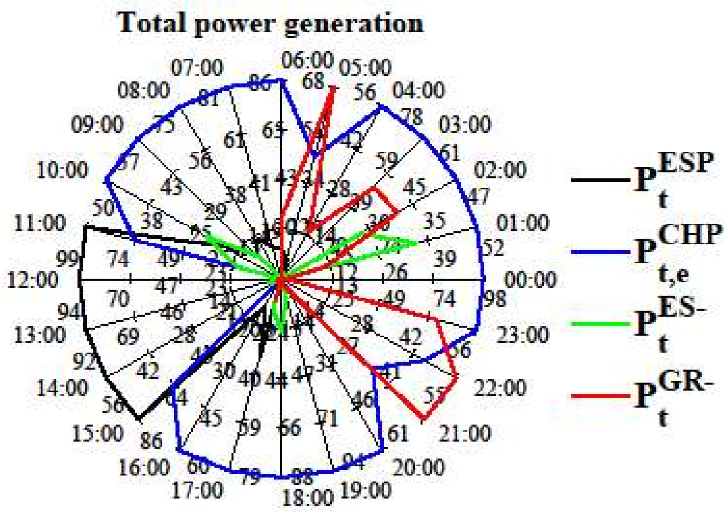
c) The total amount of electrical power purchased from the retailer



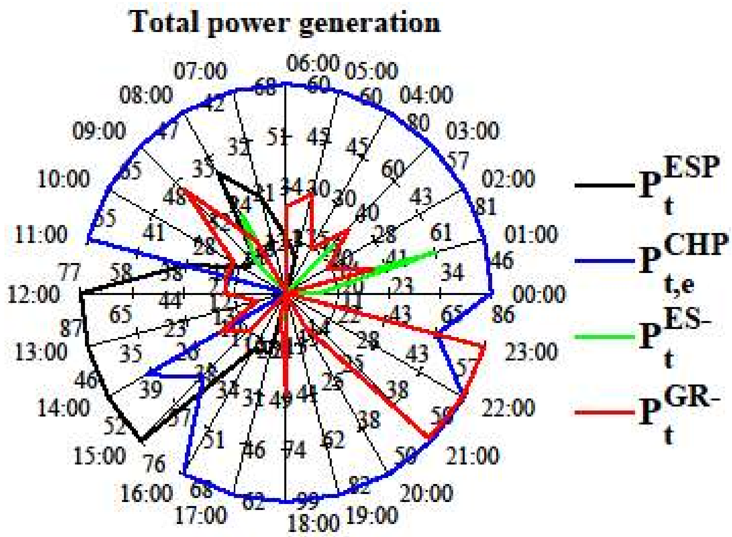
d) Total amount of thermal generated in GB

Figure 35: The total amount of electrical/thermal power consumed by each GB using different optimization methods

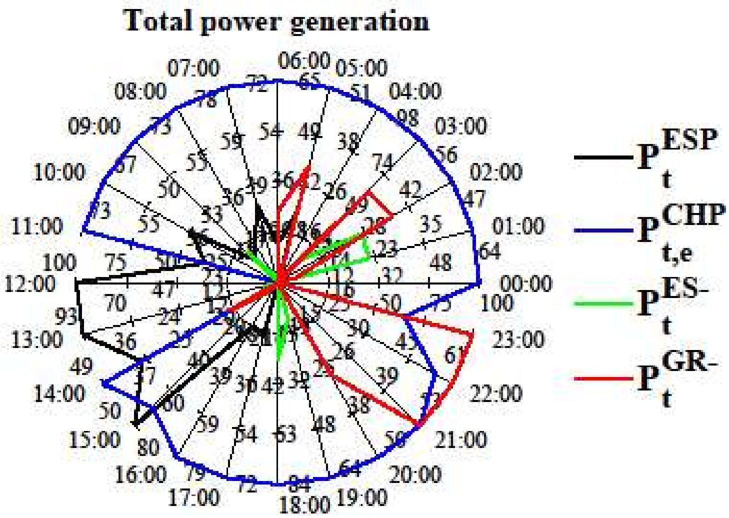
The percentage of participation for each of the electrical/thermal power generation devices by each of the optimization algorithms is shown in Figure 36 and Figure 37. The power produced by each generation unit at each time interval is shown in each optimization algorithm. It should be noted that the amount of production should be equal to the amount of consumption at any time interval. In this case, each optimization algorithm can operate each generation units based on the availability of them. As shown in Figure 36, the algorithms use the maximum energy produced in the hours of the day when sunlight is available and then respond in other ways to the demanded power. But, as can be seen, the largest amount of production has been from the CHP units. The CHP, in addition to its significant coverage of power requirements, has increased system reliability as well as the energy independence in every GB. On the other hand, the algorithms have also benefited from the ES and the retailers in their optimization process. As can be seen, retailers and the ES, as two reliable backup systems, have been able to cover the lack of power satisfactorily and balance the power of each GB. In the photovoltaic intervals, the presence of bulky coloured retailers was a sign of the importance of using photovoltaics for the optimization algorithms.



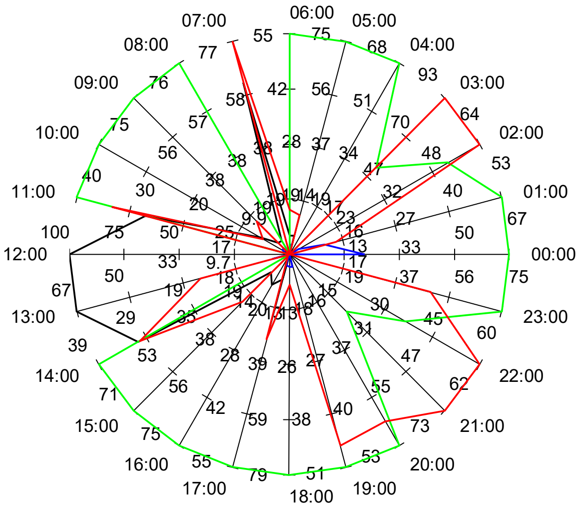
a) The electrical power produced by each of the units in the PSO method



b) The electrical power generated by each of the units in the BA method



d) The electrical power generated by each of the units in the ACO method

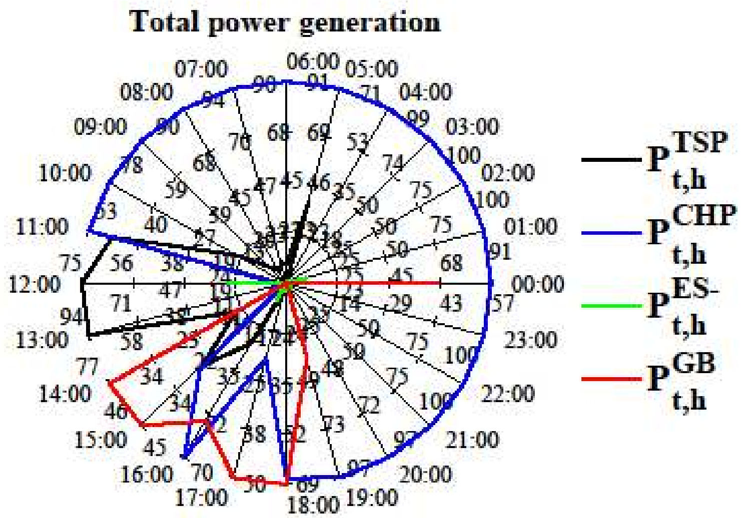


e) The electrical power generated by each of the units in the GA method

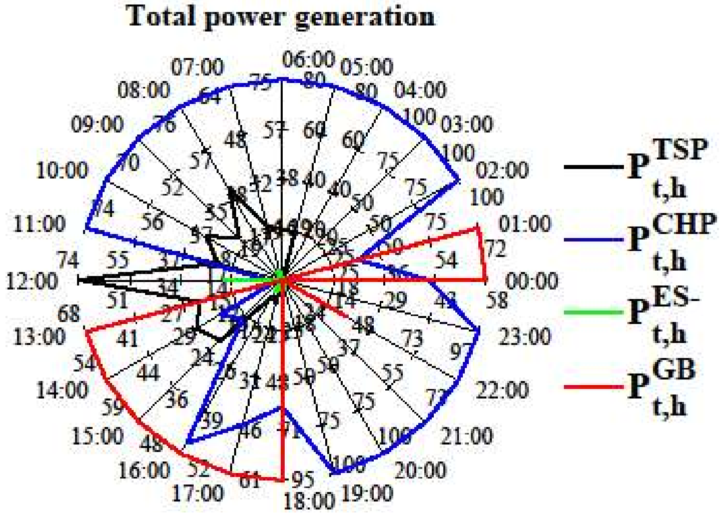
P_t^{ESP}	The electrical power produced by electrical solar panel (kW)
P_t^{CHP}	The electrical power produced by combined heat and power (kW)
P_t^{ES-}	The electrical power produced by energy storage during discharging mode (kW)
P_t^{GR-}	The electrical power bought from upstream grid (kW)

Figure 36: The batch production of each of the electrical manufacturers in different optimization methods

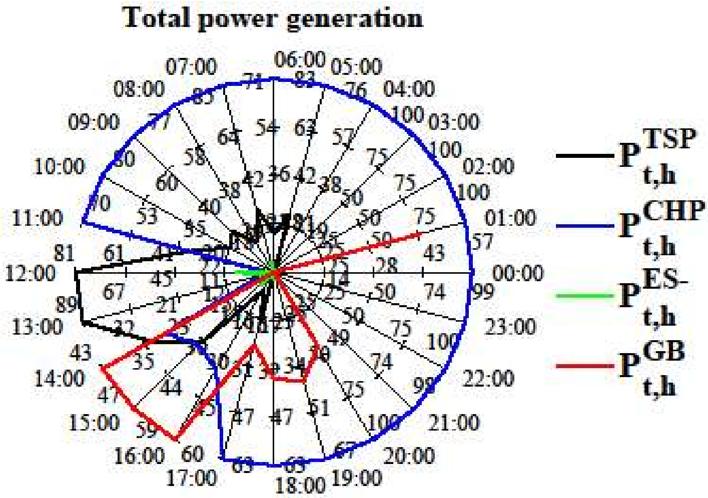
The degree of participation by the thermal producer is shown in Figure 377. As can be seen, in this section, the role of the CHP has been remarkable. The CHP has been able to respond to a significant percentage of the thermal load and reduce demand. The combination of the CHP and that TSP has been able to postpone roughly the orbit of BG, which has reduced emissions and costs.



a) The thermal power generated by each of the units in the BA method



b) The thermal power produced by each of the units in the ACO method



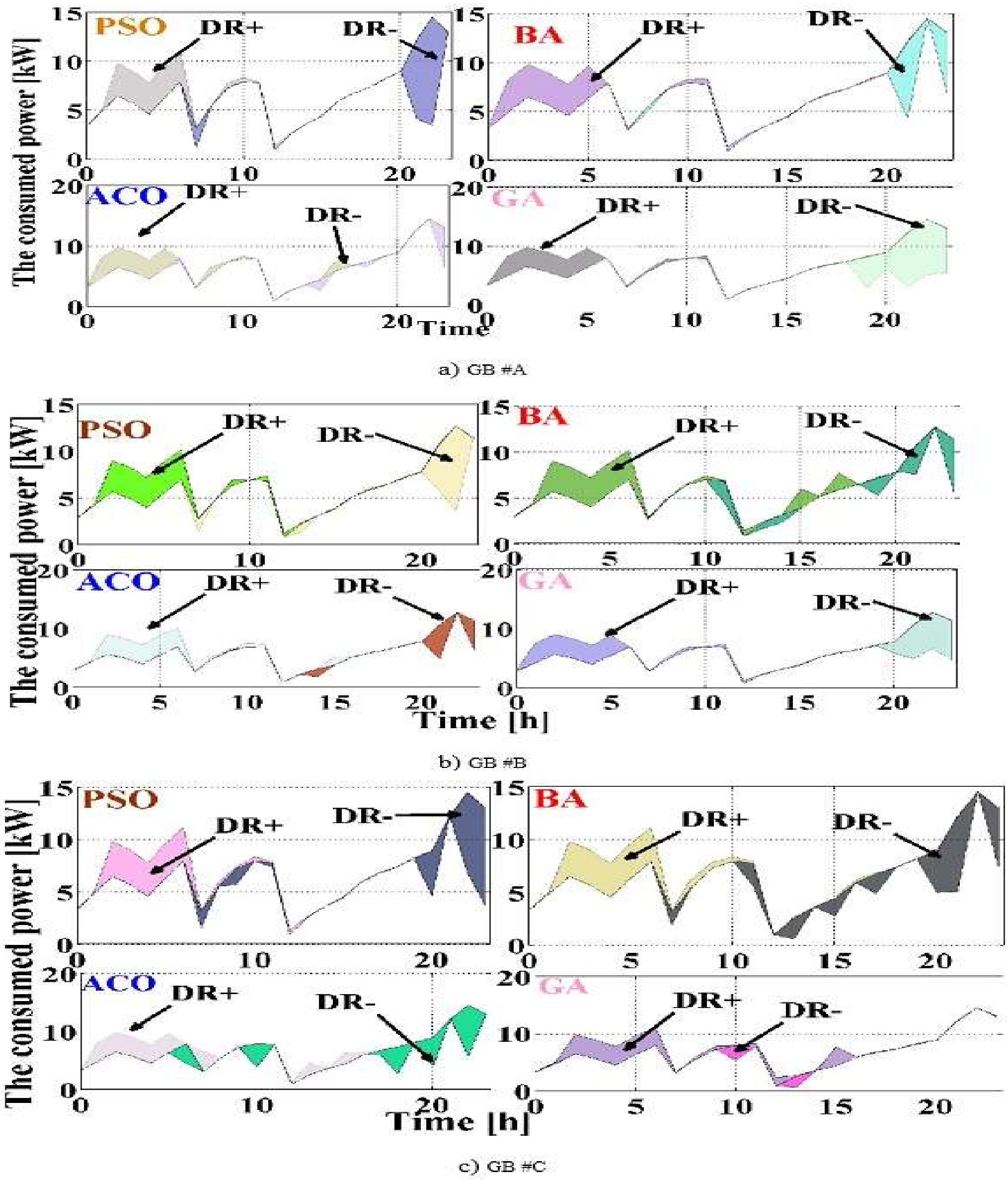
c) The thermal power produced by each of the units in the PSO method

$P_{t,h}^{TSP}$	The thermal power produced by thermal solar panel (kW)
$P_{t,h}^{CHP}$	The thermal power produced by combined heat and power (kW)
$P_{t,h}^{TES-}$	The thermal power produced by thermal energy storage during discharging mode (kW)
$P_{t,h}^{GB}$	The thermal power produced by gas boiler (kW)

Figure 37: the production batch produced by each electrical manufacturer in different optimization methods

Figure 38(a) shows the DR+ and the DR-values in GB A. In this GB, the PSO method was most likely to shift power. The PSO approach in comparison to the BA, ACO and GA, was 13% and 12% better in the demand shifts, respectively. However, in response to shift loads, the PSO has been able to respond to almost 70% of the best response in the area of responsiveness. In contrast, the weakest response was received from the GA method.

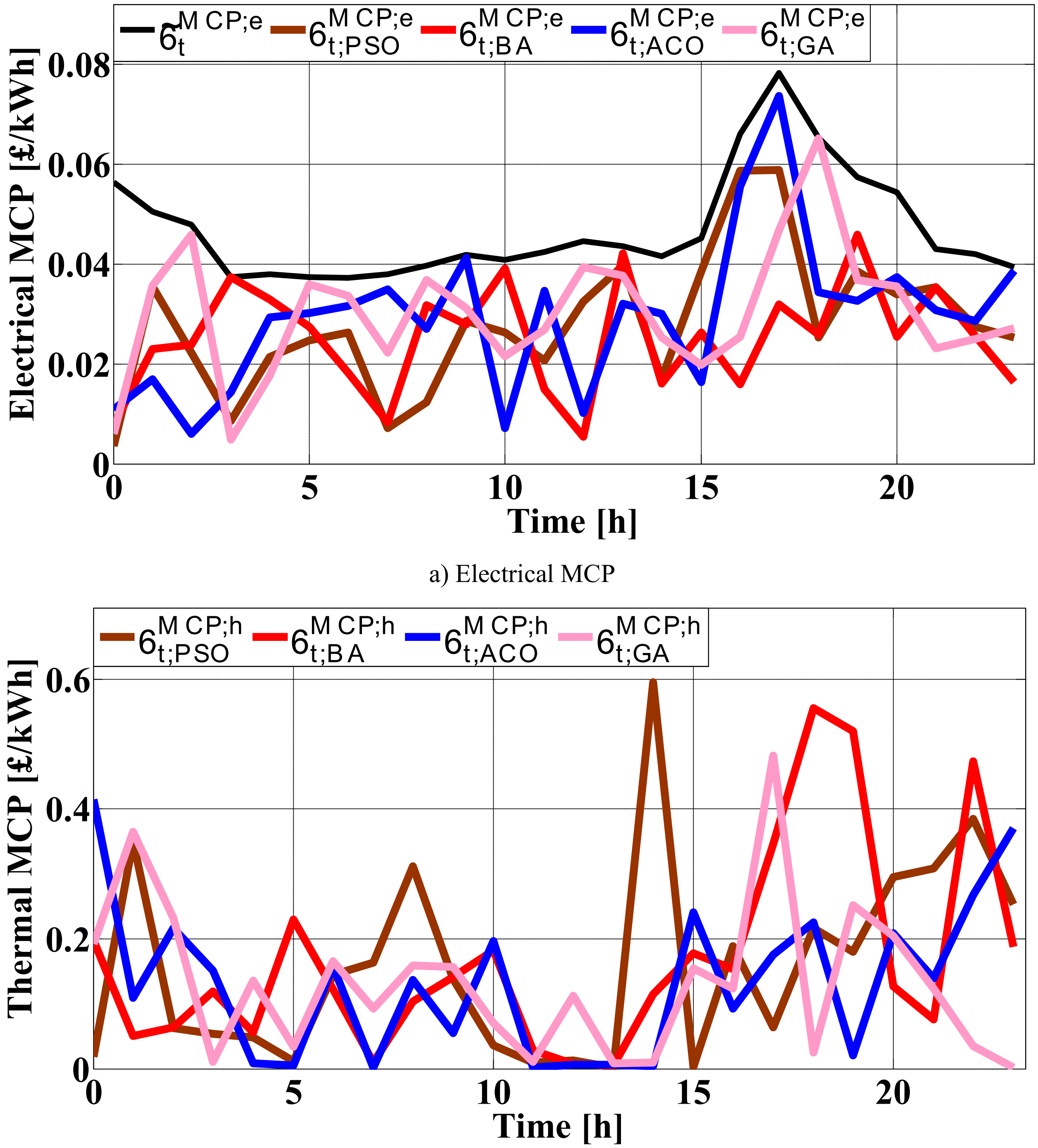
The DR+ and the DR- barge in GB B is shown in Figure 38 (b). In this section, the performance of the PSO and BA methods is the same, but the ACO method has had 12% of the power demand shift compared to other methods. On the other hand, the PSO method is better than the BA and ACO, 32% and 13%, respectively, in response to shifted power. Figure 388(c) refers to DR+ and DR-GB C. In this GB, (as in the GB A), the PSO algorithm has had the best performance in the demand shift. The PSO has been able to display 10%, 11% and 9% better than the BA, ACO and GA, respectively. On the other hand, in response to the PSO, it still had the highest response rate, with the BA, ACO and GA responding 15%, 16% and 13%, respectively.



DR+	**The amount of execs that can be used to fulfil load from another time t (kW)**
DR−	**The amount of responsive load demand that needs to be shifted to other time period (kW)**

Figure 38: load demand profile in GBs

Figure 39 shows the electrical and thermal MCP values under different methods. As shown in Figure 39(a), all the optimization methods have been successful in reducing the 100% MCP in all successful periods. For a more precise and in-depth evaluation, the 24-hour time interval is divided into several intervals. In the first time slot (00:00 - 05:00 hours), the best performance in the reduction of the MCP was from the PSO method. The PSO has shown a 38% reduction compared to the expected MCP. In this interval, the PSO method has a relative advantage over the BA and ACO, which is 5% and 3%, respectively. In the second time slot (06:00 - 12:00 hours), the PSO has been able to maintain its superiority over other methods. The PSO has been able to perform better than the MCP with a 45% prediction, and the ACO and GA methods were better with 2% and 11%, respectively. In the third time period (12:00-18:00 hours), the PSO method has the best performance; the BA with 55%, and then the ACO and GA with 49% and 26% reduced MCP in comparison with the predicted one. In the last time slot (18:00-24:00 hours), the PSO with 36% was the best performance, followed by the BA and ACO with 35% and 28% (meaning that they have been able to play their role well). As can be seen, for the total 24-hour operating range, the PSO algorithm has had a decent performance compared to other methods and has been able to achieve the highest MCP reduction in most of the intervals. Figure 39(b) shows the MCP thermal performance barge by each of the optimization methods. In the first time period (00:00-06:00 hours), the best performance related to the PSO algorithm which was able to perform better than the BA, ACO and GA methods by 28%, 11% and 12%, respectively. In the second time period (06:00-12:00 hours), the PSO method had the best returns, with a superiority of 7% and 9%, respectively, compared to the BA and ACO. In the third time period (12:00-18:00 hours), the pre-PSO range was 24%, 40% and 30% higher than the BA, ACO and GA, respectively. In the last time period (18:00-24:00 hours), the PSO provided the best performance. The PSO has been able to perform better than the BA, ACO and GA with 6%, 24% and 12%, respectively.



a) Electrical MCP

b) Thermal MCP

Figure 39 Electrical and thermal MCP

5.3.1. Evaluate of the algorithm on Manchester case study

In this case study, the supplying of electrical and thermal loads has been investigated within a case-study consisting of five smart GBs as shown in Figure 40. In this case study, other type of technology (e.g. EV, CHP, GB, etc) has been included with the view to evaluating the algorithm with a broad range of technologies. The date for this case study has been extracted from (Marzband, M. et al.). The first assumption is that the whole system is modelled as a single ownership structure. Each one of these smart GBs has separate electrical and thermal energy generation units and different energy storage (ES) assets. The function of the equipment inside each one of the GBs has been considered differently; as a result it covers different load consumption patterns and the implemented algorithm can provide different management relative to the different patterns. In this thesis, hourly day ahead scheduling has been taken into account and a 24 hours' time duration has been considered with one hour time interval.

The electrical and thermal power produced by electrical solar panels (ESP) and thermal solar panels (TSP) have been presented based on radiation during 24 hours, see Table 12 and Table 13 respectively. This solar radiation information is related to the city of Manchester in the UK.

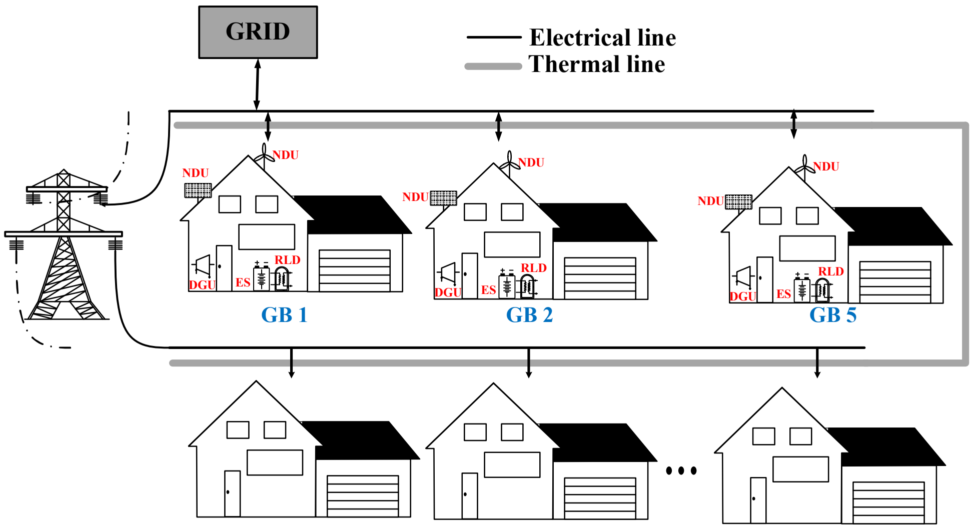


Figure 40: schematic of the case study

Table 12: the amount of electrical power produced by ESP in each GB based on solar radiation

Hour	Radiation amount	GB 1 (kW)	GB 2 (kW)	GB 3 (kW)	GB 4 (kW)	GB 5 (kW)
7	35.45	0.038	0.045	0.057	0.068	0.076
8	211.95	0.233	0.279	0.349	0.419	0.466
9	411.23	0.452	0.542	0.678	0.813	0.904
10	575.92	0.634	0.76	0.951	1.141	1.268
11	745.66	0.82	0.984	1.23	1.464	1.642
12	878.79	0.966	1.157	1.449	1.738	1.932
13	909.9	1	1.2	1.5	1.8	2
14	770.3	0.848	1.017	1.227	1.526	1.696
15	567.93	0.625	0.75	0.937	1.125	1.25
16	359.03	0.395	0.474	0.592	0.711	0.79
17	235.18	0.258	0.309	0.387	0.464	0.516
18	101.57	0.111	0.133	0.166	0.199	0.222
19	27.92	0.03	0.036	0.045	0.054	0.06

Table 13: the amount of the thermal power generated by TSP in each GB

Hour	Radiation amount	TSP in GB 1 (kW)	TSP in GB 2 (kW)	TSP in GB 3 (kW)	TSP in GB 4 (kW)	TSP in GB 5 (kW)

7	35.45	0.031	0.037	0.047	0.056	0.067
8	211.95	0.186	0.223	0.279	0.334	0.372
9	411.23	0.362	0.434	0.543	0.651	0.724
10	575.92	0.572	0.608	0.760	0.912	1.014
11	745.66	0.656	0.787	0.984	1.18	1.312
12	878.08	0.733	0.927	1.159	1.391	1.546
13	907.9	0.8	1	1.2	1.4	1.6
14	770.9	0.678	0.813	1.017	1.22	1.356
15	567.93	0.5	0.6	0.75	0.9	1
16	359.3	0.316	0.379	0.474	0.568	0.79
17	235.18	0.207	0.248	0.31	0.372	0.414
18	101.25	0.089	0.106	0.133	0.162	0.178
19	27.92	0.024	0.028	0.036	0.043	0.048

As seen in Table 12, the ESP systems in each GB are considered completely differently from each other and, to show the capability of the presented algorithm, the capacity of each one of these ESPs has been considered differently. Also, because during some hours of a full day and night solar radiation does not exist in these times electrical energy generation will also become zero. The priority of a smart GB system is using the electricity generated by an ESP because no cost will be paid for in terms of its generation and its excess generation can be sold to the grid. As seen in Table 13, the powers produced by TSPs in each GB are different from each other and each one's capacity has also been considered differently. Additionally, because solar radiation does not exist during some hours of the day and night, so the produced thermal power by TSP will become zero. The priority of a smart GB is to use the power produced by TSP for warming water in the hot water, because no cost is paid for its generation. In addition, the excess thermal power can be exchanged in the neighbourhood system.

The power generated by CHPs in each one of the GBs is presented in Table 14. The electrical efficiency of CHPs is equal to 35% and for thermal efficiency has been assumed to be 45%. The gas boiler (GBo) capacity has been assumed equal to 3kW for all the GBs and its efficiency has been assumed equal to 85%.

Table 14: the capacity of CHP in smart GBs

GB	CHP capacity (kW)
1	50
2	40
3	30
4	60
5	30

The nominal powers of other distributed energy resources (DERs) installed in GBs are presented in Table 17.

Table 15: Nominal power of DERs

DER name	ES	TES	Discharging machine	Refrigerator	EV battery	TSP

Nominal power of DER (kW)	10	10	1	1	3	10

Table 15 and Table 16 present the information relating to the electrical and thermal load demands, respectively.

Table 16: the integrated electrical loads in GBs

Time intervals	GB 1 (kW)	GB 2 (kW)	GB 3 (kW)	GB 4 (kW)	GB 5 (kW)
1	4.063	3.567	3.251	2.844	2.434
2	6.063	5.547	4.851	4.244	3.638
3	8.063	7.257	6.451	5.644	4.838
4	7.063	6.357	5.651	4.944	40.238
5	9.663	5.097	4.531	3.964	3.398
6	7.863	7.077	6.291	5.504	4.718
7	9.863	8.877	7.891	6.904	5.918
8	3.863	3.477	3.091	2.704	2.318
9	6.863	6.177	5.491	4.804	4.118
10	9.063	8.157	7.251	6.344	5.438
11	9.878	8.89	7.902	6.915	5.927
12	9.6778	8.71	7.742	6.775	5.807
13	1.173	1.055	0.938	0.821	0.704
14	3.173	2.855	2.538	2.221	1.904
15	4.482	4.033	3.585	3.137	2.689
16	5.482	4.933	4.385	3.837	3.289
17	7.363	6.626	5.89	5.154	4.417
18	8.363	7.526	6.69	5.854	5.017
19	9.162	8.246	7.329	6.413	5.497
20	10.161	9.146	8.129	7.113	6.097
21	11.117	10	8.894	7.782	60.671
22	15.117	13.6	12.1	10.58	9.071
23	18.105	16.3	14.49	12.68	10.86
24	16.105	14.5	12.89	11.27	9.633

Table 17: the integrated thermal loads in GBs

Time intervals	GB 1 (kW)	GB 2 (kW)	GB 3 (kW)	GB 4 (kW)	GB 5 (kW)
1	2.846	2.562	2.278	1.993	1.708
2	2.846	2.562	2.278	1.993	1.708
3	1.152	1.037	0.922	0.807	0.692
4	1.152	1.037	20.922	0.807	0.692
5	1.336	1.203	1.069	0.935	0.802
6	1.336	1.203	1.069	0.935	0.802
7	1.539	1.385	1.231	1.077	0.923
8	1.539	1.385	1.231	1.077	0.923
9	1.704	1.534	1.364	1.193	1.023
10	1.704	1.534	0.364	1.193	1.023
11	1.805	1.625	1.444	1.264	1.083
12	1.805	1.625	1.444	1.264	1.083
13	1.825	1.643	1.461	1.278	1.095
14	1.825	1.643	1.461	1.278	1.095
15	3.811	3.431	3.05	2.668	2.287
16	3.811	3.431	3.05	2.668	2.287
17	5.672	5.105	4.538	30.971	3.403
18	5.672	5.105	4.538	3.971	3.403
19	4.361	3.926	3.49	3.053	2.617
20	4.361	3.926	3.49	3.053	2.617

21	3.034	2.731	2.428	2.124	1.821
22	3.034	2.731	2.428	2.124	1.821
23	2.685	2.417	2.148	1.88	1.611
24	2.685	2.417	2.148	1.88	1.611

Table 18 shows the electricity price purchased from the upstream grid. These prices are for the city of Manchester and are presented as £/kW in Table 18.

Table 18: electricity market clearing price

Hour	Electricity price (£/kW)
1	0/0563
2	0/0504
3	0/0478
4	0/0374
5	0/0379
6	0/0373
7	0/0372
8	0/0380
9	0/0396
10	0/0418
11	0/0408
12	0/0424
13	0/0445
14	0/0436
15	0/0416
16	0/0452
17	0/0660
18	0/0783
19	0/0653
20	0/0574
21	0/0544
22	0/0430
23	0/0419
24	0/0394

In this section, the simulation results have been presented for a neighbourhood smart system based on objective function and the data discussed in chapter 3. In this section, the obtained results for GBs from both independent operation and in collaboration with other GBs can be compared and the scheduling of the generation units and consumers in GBs are discussed in detail. The GAMS software has been specified and designed to solve linear and non-linear optimization problems. In this thesis, the SBB solver has been used for working out the presented model.

Objective function

In this thesis, the objective is to minimize energy cost by managing the optimum performance of the DERs by considering the limitations and the personal practices of the customer. A neighbourhood smart system can cause flexibility in a building energy optimum management program, such that it causes cost reduction. Without considering the neighbourhood smart system and selling to the grid, an objective function value is obtained which is equal to £33.2/day, whereas by considering a neighbourhood smart system and by selling to the upstream grid, the value of the objective function is equal to £29.6/day, which shows about an 11% reduction of the daily costs, equivalent to £3.6. This amount of reduction during one month will be equal to £108 which is a significant value. Therefore, using this neighbourhood smart system along with the selling system means that the total cost can be reduced for consumers.

Scheduling of DERs and their performance

The neighbourhood smart system model has been simulated by considering sales. Its objective is to minimize the sum of the energy cost for the time duration of 24 hours and with a time interval of one hour.

A) Refrigerator (REF)

In Figure 41, the refrigerator function hours have been presented based on an allowable limit for refrigerator temperature between -10 and -25°C. By considering the refrigerator insulation material and noting this point that in each hour 15 degrees are added to the temperature inside the refrigerator, it is obvious that the motor of the refrigerator must function once every 2 hours. The refrigerator is one of the loads which cannot have much effect on performance so in this type of load, and for similar loads, the aim is supplying the energy required by the refrigerator at the cheapest possible price.

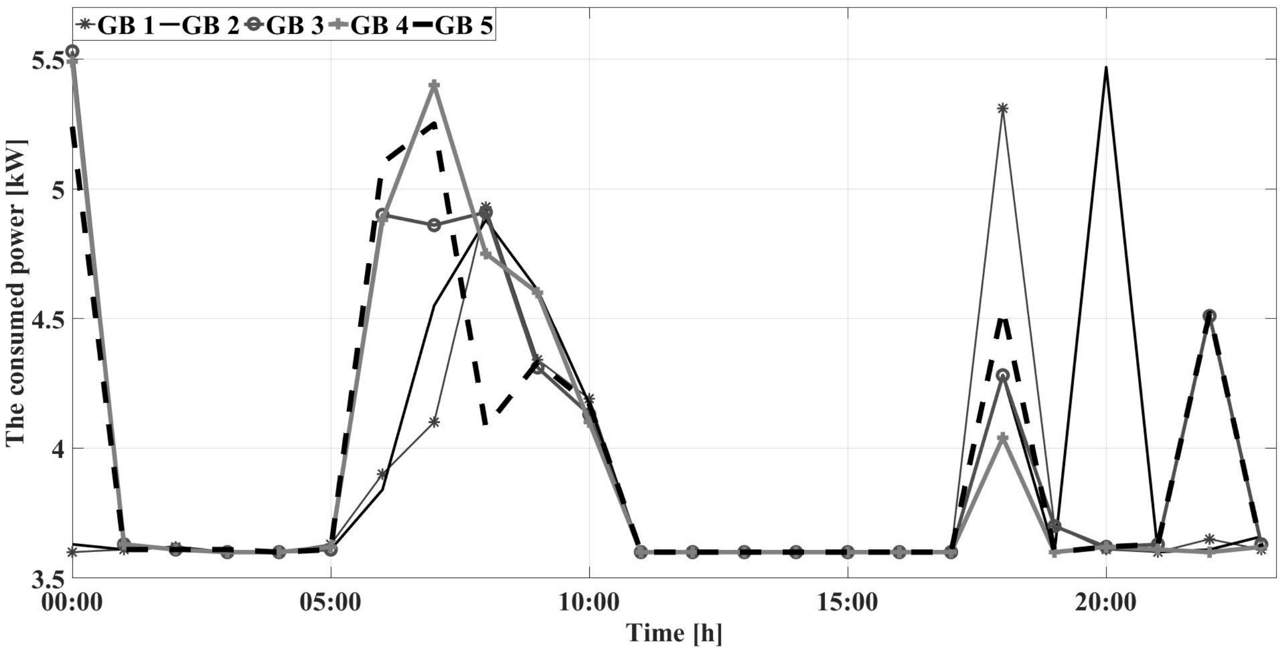


Figure 41: the power consumed by refrigerators in GBs

B) Dishwashing machine (DW)

Table 19 shows the dishwashing machine performance time scheduling by considering the performance time interval defined by the consumers. The required performance time for a dishwashing machine has been assumed to be 1 hour.

Table 19: program proposed hours for dishwashing machine performance

GB	The time interval for device operation	Proposed hour for device operation by the algorithm
1	9-13	10
2	7-11	9

3	13-17	16
4	17-21	20
5	19-23	23

By comparing the optimum management system proposed hours for dishwashing machine performance (which has been presented in Table 19) with the grid electricity price this result is obtained: that the system has selected hours for dishwashing machine performance which, relative to other possible hours, have less cost or the amount of generation in those hours is more than required.

C) ES battery

Figure 42 shows the amount of battery charge and discharge during 24 hours. The presented model tries to maximize the amount of battery discharge to supply the electrical energy required by the consumed loads and also for selling to the upstream grid. Figure 43 shows the SOC of the GBs' batteries separately.

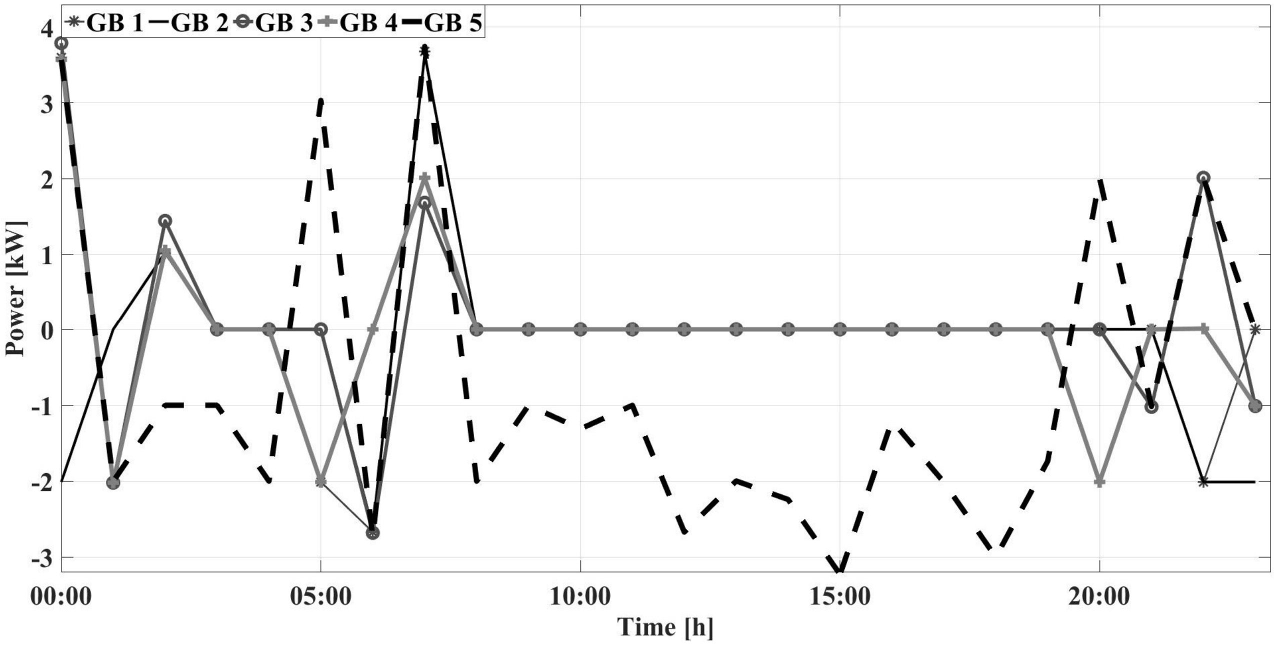


Figure 42: GBs' battery charge and discharge amount

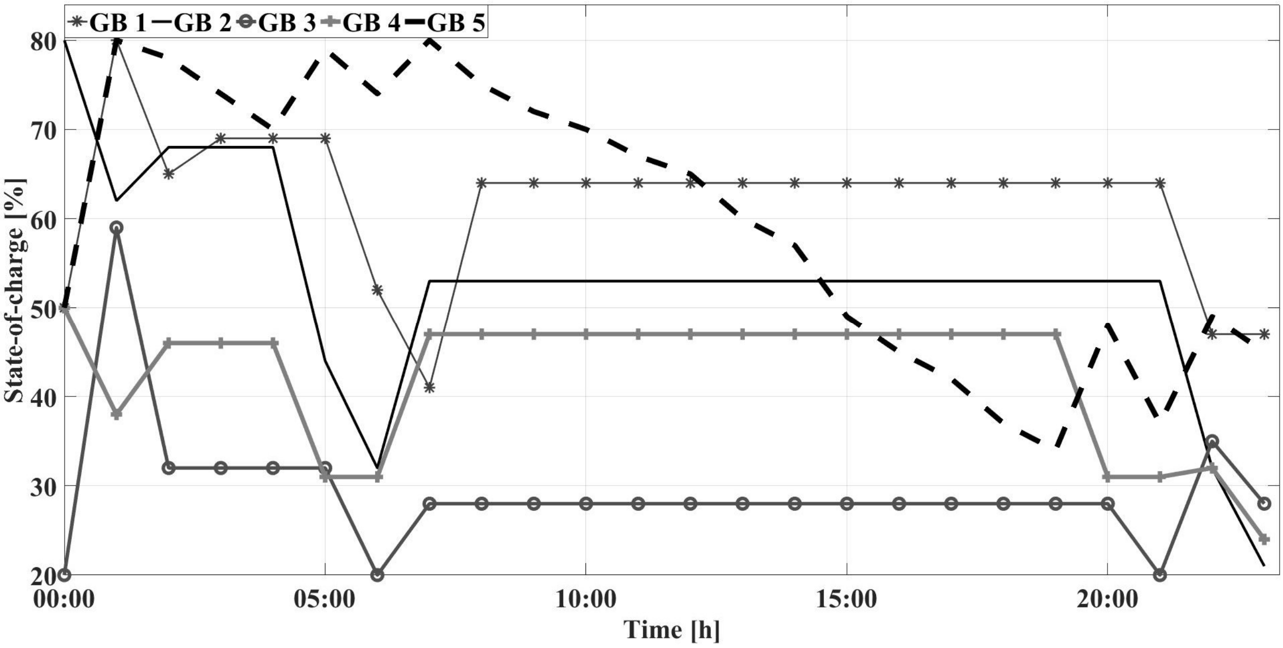


Figure 43: GBs' battery charge percentage

As seen in Figure 43, the battery is charged during the day by CHP, PV and the grid and during the day's final hours when consumption is high, it is discharged.

D) Electrical vehicle (EV)

In this scenario, an electrical vehicle has been considered as a load and the aim is to charge the vehicle from 1.00am to 6.00am up to the level of at least 70%. Figure 44 shows the method and amount of charging the vehicle of each GB during the determined hours.

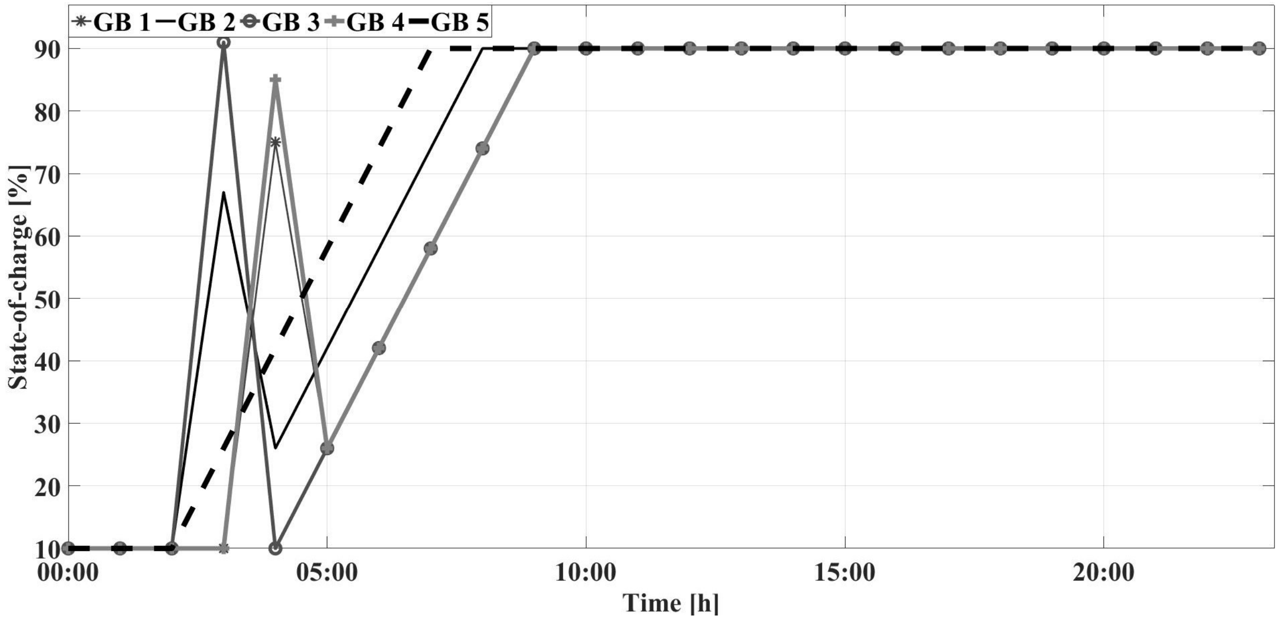


Figure 44: electrical vehicle battery charge percentage

E) CHP

Figure 45 shows the generated electrical power and Figure 46 shows the thermal power generated by CHP during 24 hours.

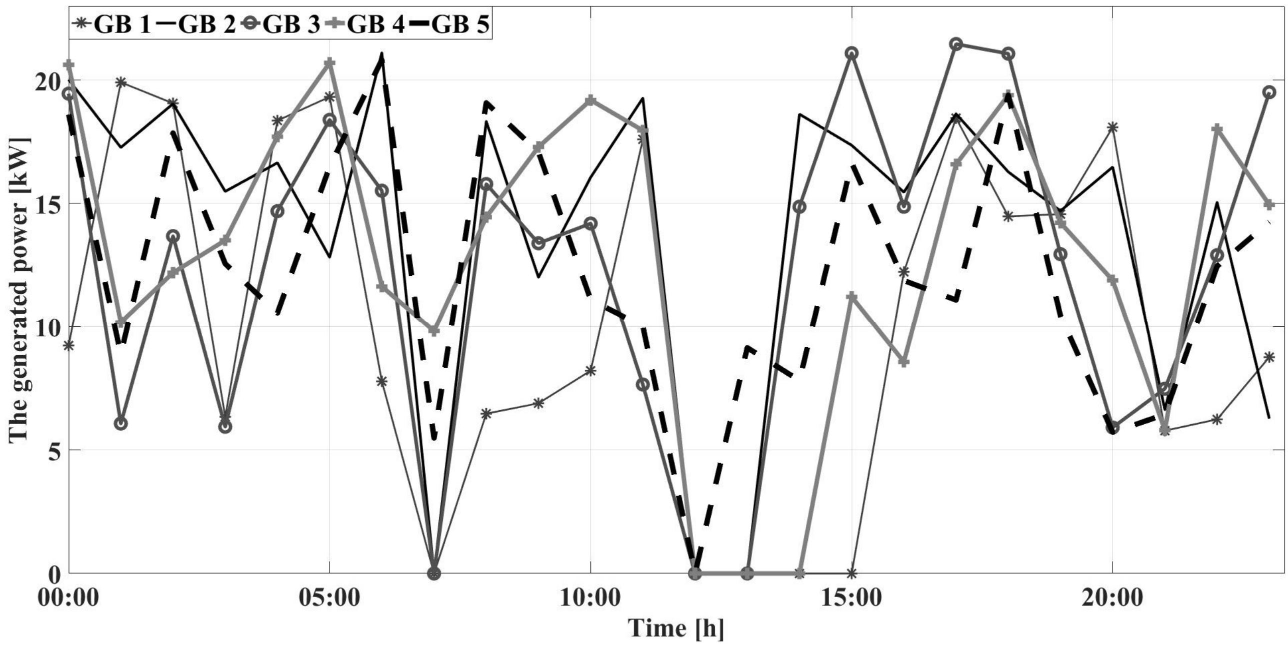


Figure 45: electrical power generated by CHP

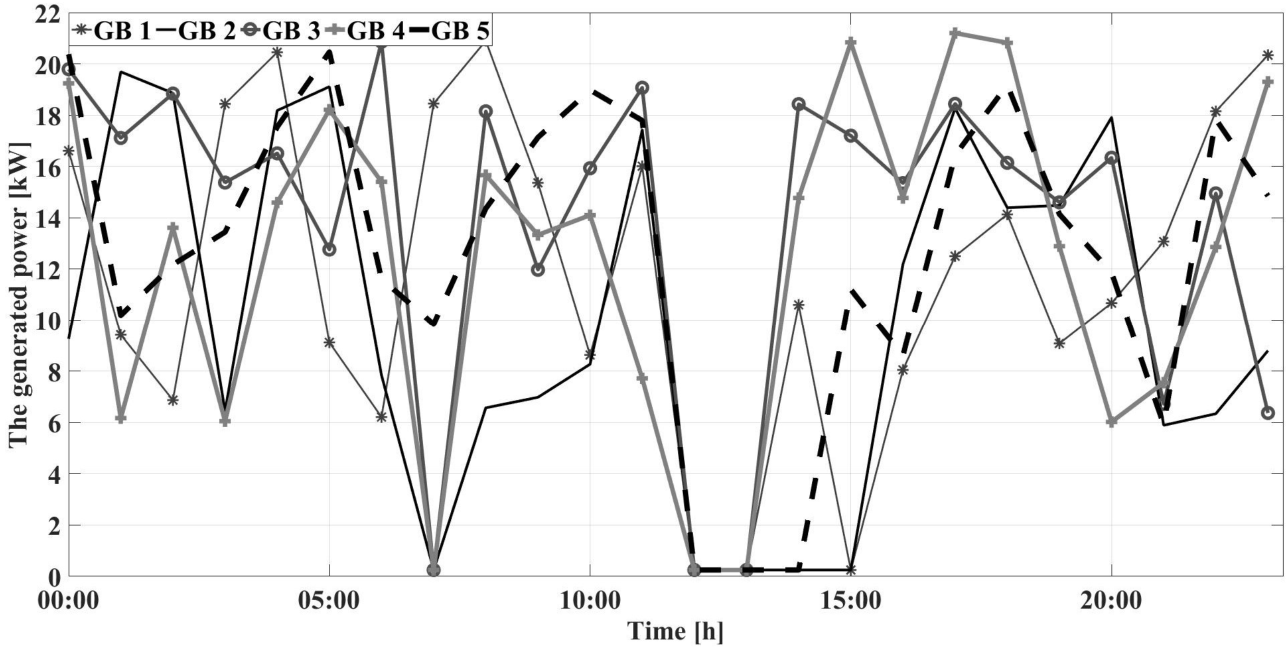


Figure 46: thermal power generated by CHP

As seen in these figures, because gas price is low, relative to electrical energy bought from the grid, the program tries to maximize the use of CHP power. Also, the energy management system by maximizing the use of generated electrical power by CHP and by selling it to the grid tries to reduce the total system costs. By comparing the electrical power selling graph (Figure 47) with the generated electrical power graph (Figure 48) it can be observed that during the hours 13, 14, 15, 17, 18 and 19, because the GBs consumed load is low and the CHP function is at maximum capacity, the amount sold to the grid is more relative to other hours.

F) Electrical heat boiler (EHB)

Figure 47 presents the amount of thermal power generated by a heat boiler. It is obvious that the boiler enters the circuit during the hours when thermal energy generated by CHP and the solar thermal cell does not satisfy the required thermal load.

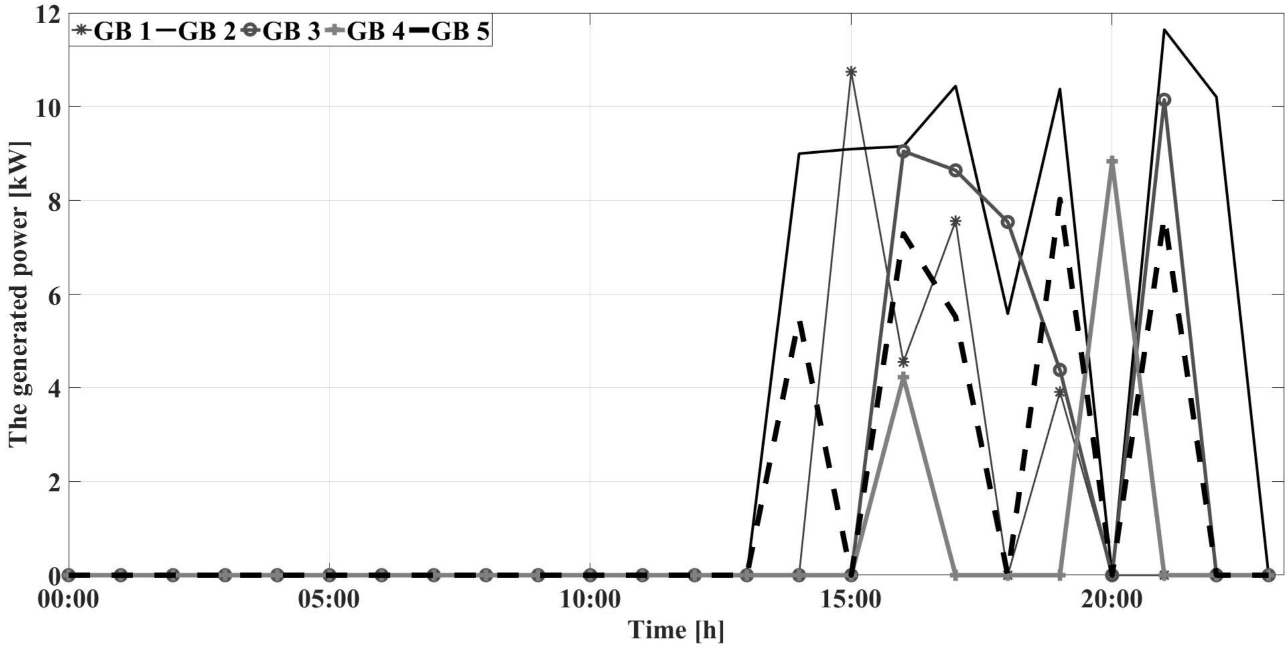


Figure 47: thermal power generated by heat boiler

G) Thermal energy storage (TES)

Figure 48 shows the charging and discharging of the thermal energy storage during 24 hours. The presented model tries to maximize the thermal energy storage discharge amount to supply the thermal energy required by the consumed loads. Figure 49 shows the GBs' thermal energy storages separately.

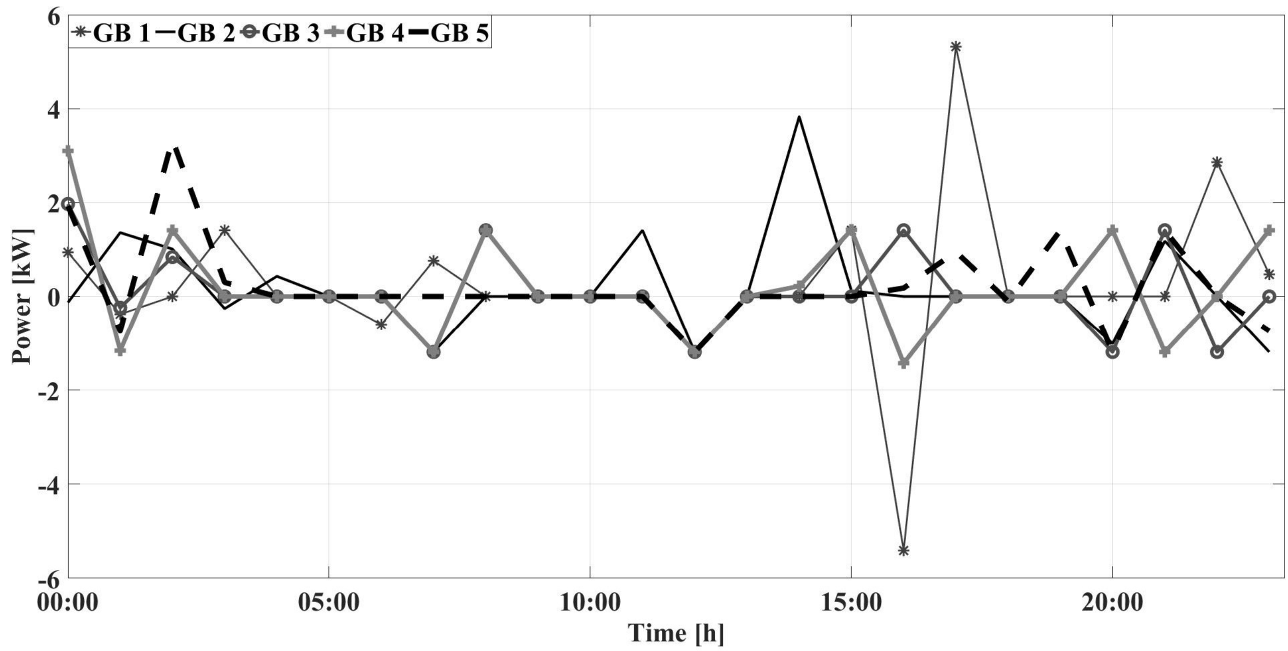


Figure 48: thermal energy storage charge and discharge amount

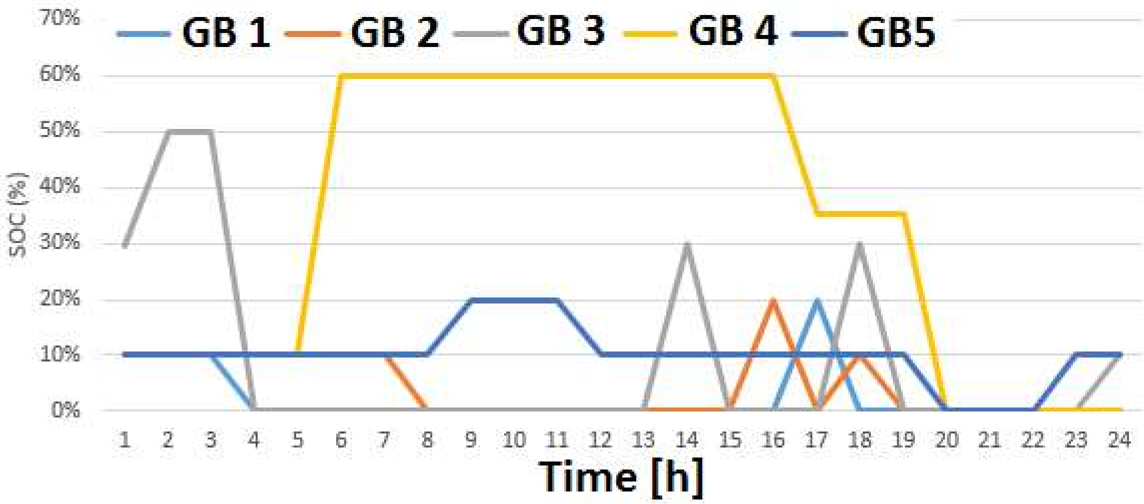


Figure 49: GBs' thermal energy storage charge percent

As seen in Figure 49, thermal energy storage is charged during the day by CHP, solar thermal cells and the heat boiler and is discharged during the hours of the day when the generation does not satisfy consumption.

Neighborhood system

Table 20 shows the amount of electrical energy exchanged among the GBs according to the program for supplying the consumed load shortage at a certain hour. Additionally, Table 21 shows the amount of exchanged thermal energy according to the program decision at a certain hour. This exchange occurs when each GB does not have the ability to supply its consumed load, and exchange in a neighbourhood system is more economical than buying power from the grid.

Table 20: exchanged electrical energy (kWh)

	GB 1	GB 2	GB 3	GB 4	GB 5
GB 1		0	0	0	0
GB 2	0		5.7	9.9	0
GB 3	0	5.7		0	0
GB 4	0	9.9	0		0
GB 5	0	0	0	0	

Table 21: exchanged thermal energy (kWh)

	GB 1	GB 2	GB 3	GB 4	GB 5
GB 1		0	0	0	0
GB 2	0		0	0	0
GB 3	0	0		13.4	0
GB 4	0	0	13.4		11.6
GB 5	0	0	0	11.6	

Selling power to the grid

Figure 50 shows the total amount of the electrical energy generated by GBs, and the total selling power to the upstream grid. As seen, in some generation hours the system cannot supply the consumed load so it will have to buy electrical power from the upstream grid, and in some hours generation is more than required thus the system sells it to the grid with a price close to the grid price. The amount of sold power is obtained from the difference between generated power and the amount of load consumed in each hour. As seen, most of the power generated is related to CHP technology during 4, 23, 21 and 24 time intervals because the consumed load is high. In this time intervals, PV system does not exist as a results, the system has to buy power from the upstream grid. Figure 51 presents the total power which can be sold to the grid, and shows the share of each one of the GBs separately. Figure 52 shows the system proposed price for selling electrical energy to the grid. As observed, the system has almost been able to be based on a pricing system with elasticity variable with time and thus can propose prices close to the grid price so the profits obtained from the sales can be at a maximum.

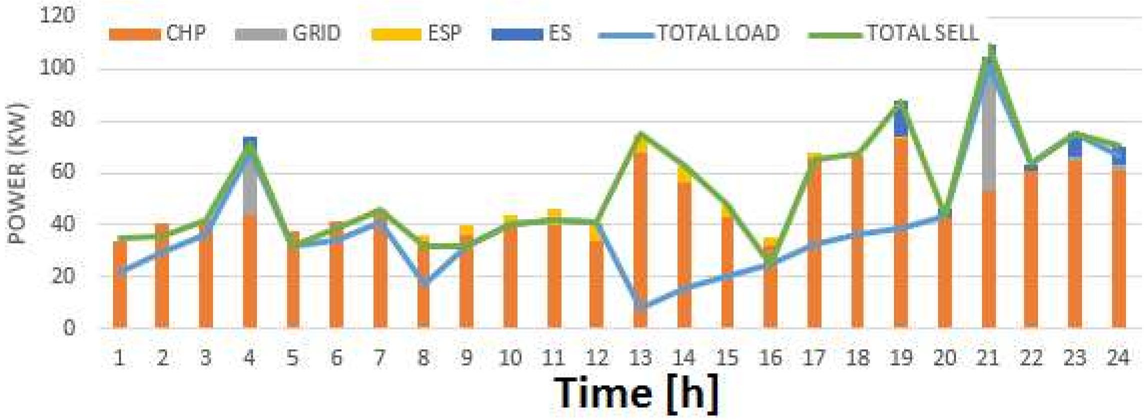


Figure 50: production amount, consumed load and total sales comparative graph

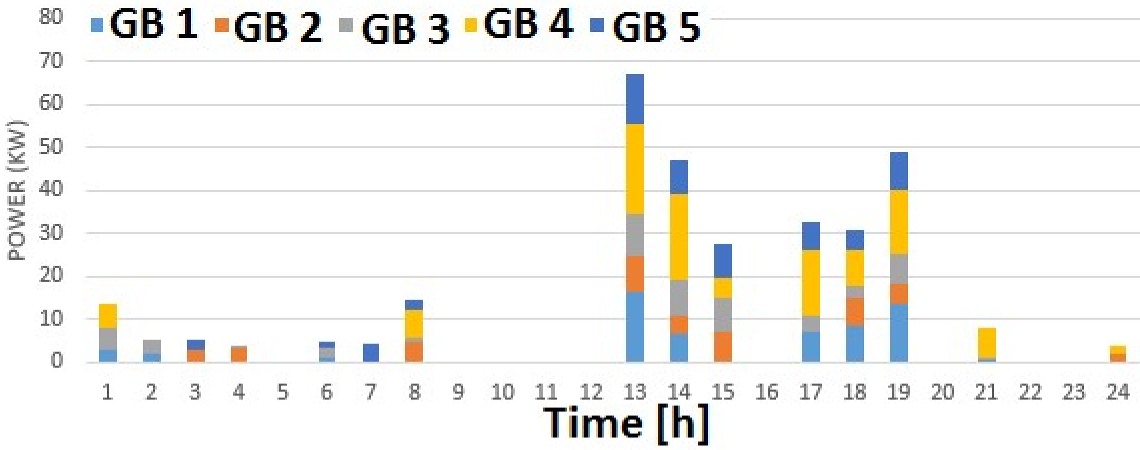


Figure 51: the amount of power sold separately to generation resources

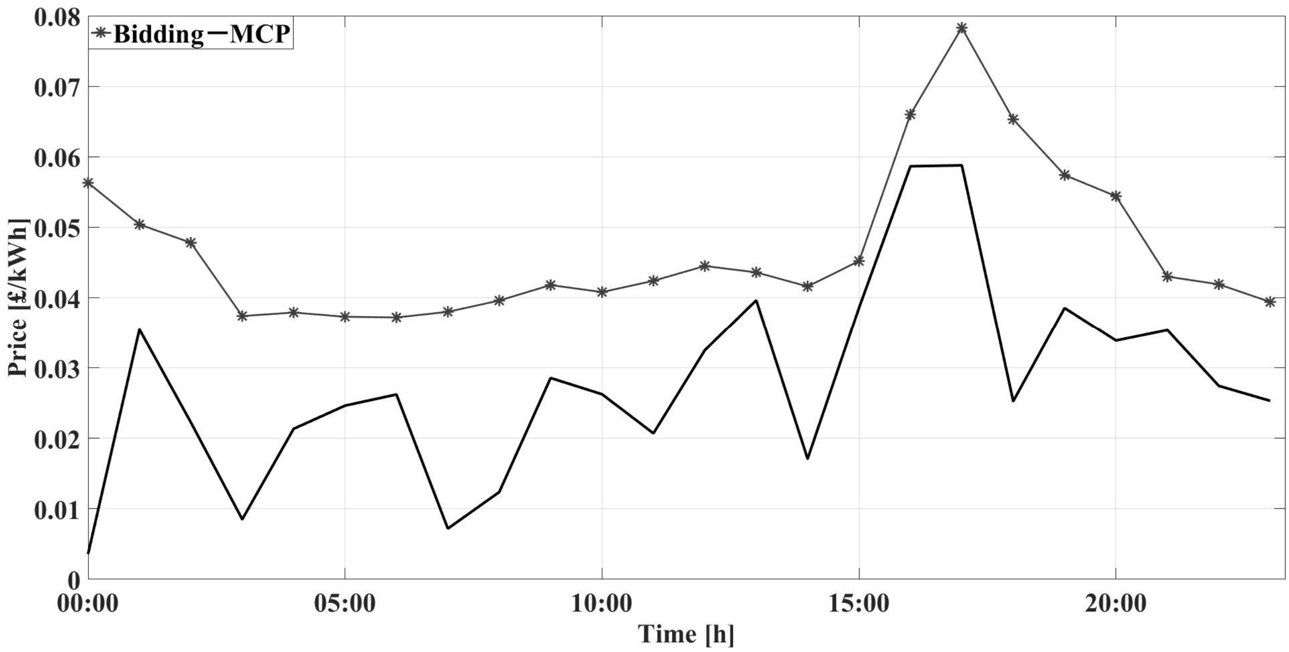


Figure 52: comparing system selling price to grid price

Looking at Figure 50, Figure 51 and Figure 52, it can be concluded that the system has used the concept of the transferred energy that is within the GBs as much as possible, that it sends less information (such as on shortage or excess of electrical or thermal power) and sends price bids for selling electrical power on behalf of the controller. During the 24 hours' time interval in which their performance has been investigated, the only information which the GBs need to share with the upstream grid is the information containing the amount of shortage of electrical power or excess of electrical power and the proposed price for selling the excess of electrical power.

5.4. Summary

Since renewable resources have intermittent characteristics, approaches to analyzing the energy matching and trading in green buildings would be heuristic rather than deterministic. To take the uncertainties into account, a scenario generation method is implemented. A decision making model based on the stochastic algorithm is presented for energy matching and trading within residential buildings. The principal benefits of the proposed algorithm can be summarized as follows:

1- Maximization of the usage of non-dispatchable generation resources based on renewable generation;
2- Prioritization for the charging/discharging of the ES devices in the interior of a green building as a result of reliability enhancement;
3- To better manage, leverage and utilize energy resources and sustained economic growth.

This model also has the ability to add a new generation resource which can usually be installed in various hybrid systems.

Moreover, it can distinguish the conceivable capability within a distributed economic dispatch strategy, where a numerous green buildings with an independent NSO can be connected in the neighbourhood system, taking into consideration that the load sharing function can be extended without an accordant adjustment in the design/requirement model. The obtained simulation results show a significant reduction in the total of electrical/thermal losses and a significant improvement in the ES operation in each time interval. Furthermore, the proposed model can also be applied to a real-time energy matching and trading online application.

In this thesis, several optimization algorithms for the optimum use of existing electrical/thermal assets existing within GBs have been proposed. For each GB, the proposed structure has given an optimum timing for power trading among the GBs while fulfilling objective functions and technical constraints. The proposed method, by establishing collaboration among the GBs, incorporates demand side management, power balancing between generation and consumption, reduction in the market clearing price, profit increases from the generation, and consumers and prosumers taking part in the electricity market. The optimums of the presented results and the capacity of the proposed structure to alter input parameters have been compared with each other utilizing a few strategies. Furthermore, by including technical and economic constraints together, the scheduling of appliances inside green buildings has been considered. The optimum control of the demand response and the ES resources has also caused a reduction in the exploitation costs of each GB and a profit increase. The proposed algorithm can be exploited by various GBNS types under different objective functions and a variety of generation and consumption devices.

A cooperative optimum control concept for reducing energy demand costs with regard to GB energy systems through utilizing optimization methods and also the game theory concept, based on MAS, has been explored in this thesis. Previous studies have primarily centered on the minimization of costs relating to single GBs. This approach can be considered as optimizing a singular performance in which each GB is a completely independent unit in which the energy or pollution cost must be minimized.

It has been shown that how the distributed energy management based on optimization methods can be performed better while considering demand side management combined with ES scheduling.

On the other hand, while the optimum price is less than in the traditional system, the GB profit is assured in the singular and coalitional performance conditions. The presented economic strategy has been investigated in this thesis in order to minimize the total combined operational cost of the thermal and electrical system in one group of GBs using the combined performance of ES and DR in each GB and in a coalitional structure. Instead of looking just at minimizing the cost of the energy demand of one GB, a cooperative optimization method (with the objective of minimizing the total electrical energy costs of the GBs) has been considered. In each time step, a cooperative strategy is applied with adequate programming for activating suitable DERs in each GB. With the participation of the consumers in the DR program, it is designated that each GB has a suitable amount of electrical and thermal energy for placing the GB in the correct limit to provide for the welfare of the consumers. Additionally, programming for minimizing the sum of the GBs' operational costs and with the aim of reducing pollution has also been considered.

In this case study, the optimum control of three GBs connected to an upstream grid under different scenarios has been investigated. By the research which was carried out, it was determined that by using the proposed optimization algorithm, daily load consumed power has been transferred to time intervals with lower prices. However, when cooperative optimization was applied, different patterns of energy exchange among the GBs arose which were investigated. Using a cooperative and coalitional strategy, the controller acts in such a way that for the GBs that have more generation capacity for a short time when energy price is low, the ES in the GBs with lower capacity acts in charging mode. For the small GBs, the consumption pattern is regulated through controlling the DR during on peak hours. The results indicate that by using a cooperative approach, the costs of each GB with high capacity will have a significant reduction (of approximately 15%) compared to optimization in a singular performance. However, almost no increase in cost was observed in the cooperative case relative to the singular performance case. In fact, the results of the simulation and the practical implementation showed that under an hourly dynamic pricing program, cooperative optimization will have a significant cost reduction in comparison to the singular performance case. The proposed algorithm can present a promising implementation of the demand response method in the field of controlling the amount of load demand with the aim of reducing the amount of pollution and generation cost in GBs. The presented framework in this thesis for a group of GBs can easily be developed for the optimization of smart cities.

Chapter 6- Conclusion and future work

6.1. Conclusion

This research set out to develop a mathematical framework to support optimal energy matching and energy trading within a green building neighborhood system (GBNS). The purpose of the proposed algorithms is to manage the amount of energy generation/consumption, as well as purchase/sale of each GBNS. The performance of the proposed algorithm is based on price modification of the energy surplus between GBs, and thereby leading to exchanging power at the lowest possible price. Determining the best scenario of GBs requires the investigation of the information received from energy storage (ES) system, dispatchable/non-dispatchable energy generation resources, plus other local GBs. These algorithms have been implemented in the MATLAB and GAMS software environment with the view to evaluating its effectiveness and the performance. The simulation results indicate the effectiveness of the proposed algorithms, and show a decrease in the total energy cost/bill of the consumers (GB owners), and an increase in the total profit of the GB owners in the proposed structure. This research shows the amount of success concerning the proposed strategy in reaching the determined objectives including selling power by GBs with different bid prices, consumers' cost reduction, and also achieving the collective profit for all stakeholders. Furthermore, the performance of the proposed mathematical framework is not affected by the number of GBs. Due to this reason, it is considered as a practical tool for both electricity companies as well as for GB owners to manage electricity and consumption in neighborhood grids and for controlling the peak upstream grid consumption. This was achieved by initially establishing mathematical models to represent the behavior of various agents such as producers, consumers and prosumers which is necessary for modelling of energy matching and energy trading (Section 4.3.4) and then implementing a comprehensive algorithm that can support energy matching, both within a single and networked GBs, as well as energy trading within a green building neighborhood environment (Chapter 4). The overall framework is capable of supporting different ownership structures (single and multi-ownership) that demand different optimization objectives.

When developing the GBNS concept, the thesis has proposed a flexible structure for managing energy efficiency in GBs. The overall GBNS has been designed and implemented as a multi-cooperation system with a structure with two control layers for managing GBs' energy with multiple ownerships. The proposed energy management system within the GBNS helps to determine the optimum power generation and the consumption. Additionally, in order to estimate the quality of participation of generation and consumption units for reducing MCP, a local energy market approach has been considered in the overall design and implementation. A two-stage optimization process has been considered to allow for the maximum usage of renewable generation units, optimal charging and discharging of energy storages, operational cost reduction and to enhance the reliability of this framework especially during emergency situations. The proposed optimization algorithms are capable of finding an optimum response, compared to other optimization methods, offering considerable economic outcome with higher reliability. In the proposed algorithm, a set of optimum solutions have been considered, such that it fully satisfies the conditions inserted as technical constraints. These solutions present different choices to the operators according to the desired economic outcomes within existing technical constraints, and for selecting a suitable power distribution plan.

The testing of the overall mathematical framework has been conducted using several case studies from Manchester and Barcelona cities.

6.1.1. One isolated GB in Barcelona (Case study 1)

Using this case study, demand side management has been evaluated by applying a demand response based on load shifting. The proposed structure provides a new concept for determining resources' optimum usage and DR simultaneously leading to the reduction of the total generation cost in an isolated GB. Furthermore, by exploiting the local energy market unit, the effect of interruptible loads has been observed on reducing the market-clearing price. The simulation results show that an adequate and on time control of DR leads to 30% reductions in operating costs compared to the conventional method.

6.1.2. Grid connected GBs in Barcelona (Case study 2)

In this case study, the optimization algorithm has been tested for its ability to estimate the optimum performance of one GB in both cases (isolated and grid-connected) with regard to load demand management within the constraints relating to renewable and non-renewable energy resources. As for the analysis of the results obtained from the simulation it is obvious that the optimization trend has performed well and it can determine the generation resources' optimum power value after considering the cost function of each one of them by minimizing the total cost of electricity generation. Because of the nature of variation within the time of load demand, the change of battery state of charge, the necessary time for turning on or off reserve resources and the power slope of these resources, the central control system requires steady exploitation changing conditions. The results obtained from the proposed algorithm has been compared to the energy management algorithm based on PSO optimization method, and the obtained results show a further reduction of total electricity generation cost about 18% by the proposed algorithm.

6.1.3. Multiple GBs in the neighborhood system in Manchester (Case study 3)

In this case study, managing multiple GBs in the neighborhood systems has been evaluated in both operating modes (grid connected and isolated operating modes). It utilized a two-level control plan including a primary control and a secondary control based on the optimization method. To this end, the optimum values of the decision variables were searched in either hourly or real-time to find the best possible solutions based on the minimum generation cost or the maximum profit. The results obtained from this case study show the ability of the algorithms to offer the following:

1. Exploitation of renewable resources with the aim of reducing environmental pollution, and electricity price for the consumers;
2. Maximisation of the energy stored in the ES and keeping SOC in allowable range concurrently, hence improving reliability of the system;
3. Exchange of optimum power with the upstream grid during an excess generation condition to obtain more profit for the GB operator;
4. Application of DR programing to reduce operating cost

The simulation results show the efficiency of the algorithm proposed for energy distribution in GB systems. The main advantage of the proposed structure is to have very fast convergence time. It can help to develop this structure in real-time energy management planning. The proposed algorithm can be used for energy management in regional small power plants which can exploit renewable energy resources.

6.2.Future work

With the movement of developed countries and developing countries towards change in electricity generation (structure renewal, competitive markets and use of distributed energy resources), finding solutions for accomplishing such changes by maintaining existing micro-structures is essential. Also, this solution must lead to further exploitation of renewable energy resources for future energy generations by optimum energy distribution in response to increasing consumptions. The unprecedented growth in energy consumption means that without correct management and correct planning, there will be a further increase in energy carries, unnecessary waste of natural resources and an increase in the pollution of the environment. One of the most important practical solutions for preventing the above problems is unifying the concept of energy, in other words, attention must be paid to optimizing a uniform energy system in different planning arenas and to its management.

Efforts that can be made to supply energy in future includes renovating the electricity grid, increasing power quality and reliability relating to supplying energy, and preventing the crisis of environmental effects resulting from greenhouse gases. GB is a logical choice for achieving these goals. However, for the proper exploitation of GBs, methods and optimum energy management initiatives need to be implemented. This way, there will not only be quality solutions but also the speed of reaching a practical solution will be high. The GBNS systems implemented using innovative optimization algorithm similar to the once presented in this thesis can lead to improving reliability and better performance during demand peak times while the consumers paying the least possible cost. The proposals presented for future works are as follows:

1- Investigate the effects of DR on the dynamic performance of GB systems particularly on the load frequency control problem;
2- Examine central DR in real-time for the initial regulation of frequency with the aim of reducing load manipulation in smart systems;
3- Investigate environmental modelling and optimizing systems having several generation resources (electricity, gas and thermal);
4- Study the dynamic pricing of the distributed resources existing in a GB with the aim of increasing system profit and a mechanism for driving the profit obtained among these resources;
5- Investigate a multi-purpose system for maximizing the profit from generation resources and reducing the consumed electricity price for the consumers;
6- Investigate renewable resources' uncertainty, load demand and their proposed offers in multi energy systems.
7- Develop a double side auction structure by considering the offer prices of consumers and producers simultaneously;
8- Consider the uncertainty of the renewable generation resources and the load demand (using methods such as the Monte Carlo, the Markov chain, two points' estimation, etc.);
9- Consider real time programming for the more exact modelling of generation and load;
10- Consider voltage fluctuations and reactive power in the grid and investigating such problems in a multi-ownership structure;
11- Add combined heat and power units and thermal loads and, considering multi-energy carriers or integrated energy systems;
12- Define several objective functions by considering a maximization of GBs' owners and the profit of the national grid;
13- Include the effect of MCP on economic dispatch by using the definition of a new constraint in the optimization program;
14- Prepare algorithms for creating competition among the producers in order to increase profit;
15- Allocate profit among the players participating in the proposed local markets;
16- Define more cost functions, such as increasing social welfare and reducing the fuel consumption costs. As a result, help to reduce the pollution resulting from the consumption of fossil fuel and achieve increased revenue, etc.

17- Consider more retailers for supplying the GBs' electrical energy storage and also consider variable pricing based on the retailers' requirements.

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A real-time evaluation of energy management systems for smart hybrid home Microgrids

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ABSTRACT

Real-time energy management within the concepts of home Microgrids (H-MG) systems is crucial for H-MG operational reliability and safe functionality, regardless of simultaneously emanated variations in generation and load demand transients. In this paper, an experimental design and validation of a real-time mutli-period artificial bee colony (MABC) topology type central energy management system (CEMS) for H-MGs in islanding mode is proposed to maximize operational efficiency and minimize operational cost of the H-MG with full degree of freedom in automatically adapt the management problem under variations in the generation and storage resources in real-time as well, suitable for different size and types of generation resources and storage devices with plug-and-play structure, is presented. A self-adapting CEMS offers a control box capability of adapting and optimally operating with any H-MGs structure and integrated types of generation and storage technologies, using a two-way communication between each asset, being a unique inherent feature. This CEMS framework utilizes feature like day-ahead scheduling (DAS) integrated with real-time scheduling (RTS) units, and local energy market (LEM) structure based on Single Side Auction (SSA) to regulate the price of energy in real-time. The proposed system operates based on the data parameterization such as: the available power from renewable energy resources, the amount of non-responsive load demand, and the wholesale offers from generation units and time-wise scheduling for a range of integrated generation and demand units. Experimental validation shows the effectiveness of our proposed EMS with minimum cost margins and plug-and-play capabilities for a H-MG in real-time islanding mode that can be envisioned for hybrid multi-functional smart grid supply chain energy systems with a revolutionary architectures. The better performance of the proposed algorithm is shown in comparison with the mixed integer non-linear programming (MINLP) algorithm, and its effectiveness is experimentally validated over a microgrid test bed. The obtained results show convergence speed increase and the remarkable improvement of efficiency and accuracy under different condition.

1. Introduction

While smart grids are known as the future of power systems, home Microgrids (H-MGs) are known as the vital technology to deliver the functional blocks of smart grid on a local scale [1,2]. Although the idea of H-MGs seems to be similar to the various areas of operation in the traditional power system, they are different in which they have to be fully capable of autonomous operation in islanded mode [3,4]. In addition, H-MGs could be formed in a small-scale like a commercial building to as large as a town area. Since high level integration and control of renewable energy and storage devices are expected in H-MGs, their safe operation and control (traditionally known as ancillary services in the power system) is an important issue for the future smart power system. For an islanded H-MG, shortage in generation or excess available generation will often happen during a day because of the variation of weather data like solar irradiation and wind speed variations. In addition, generation shortage might occur when some of the micro sources are out of service for scheduled maintenance or unexpected event or

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Nomenclature

ABC	artificial bee colony
BES	battery energy storage
BIO	biomass
CAE	compressed air energy storage
CCU	central controller unit
COE	cost of energy
CTU	combustion turbines unit
DAC	data acquisition
DER	distributed energy resources
DGN	diesel generator
DSA	double side auction
ECS	electrochemical system
EGP	excess generated power
ESS	energy storage system
FCE	fuel cells
FLY	flywheels
GEO	geothermal
GEN	gas engine
GTD	gas turbine devices
IREC	institut de recerca en energia de catalunya
LEM	local energy market
MABC	multi-period ABC
MCF	molten carbonate fuel cell
MTG	microturbine generator
NRL	non-responsive load
PSS	pumped storage system
PAF	phosphoric acid fuel cell
PEM	proton exchange membrane
PV	photovoltaic
RR	renewable resources
REN	reciprocating engine
RLD	responsive load demand
RTD	real time dispatching
RTEMS	real-time energy management system
SHT	small hydro-turbines
SME	superconducting magnetic energy storage
SOF	solid oxide fuel cell
SSA	Single Side Auction
STS	solar thermal system
TCP	total consumed power
TGP	total generated power
UP	undelivered power
WTG	wind turbine generator

sudden load increase. In this regard, a top-level supervisory control and management system is critical for H-MGs to operate the system with minimum cost and emission within a safe condition. Since it is likely to have shortage or excess in power generation anytime during the daily operation of an islanded H-MG, the energy management system (EMS) design should consider this specification. It is also desired for the EMS design to adapt and compensate itself in real-time to any changes in the types and capacity of the generation and storage assets quickly, without any modification in the EMS, in addition, maximizing the operational efficiency (equivalently minimizing the cost of operation), minimizing the emission [5], maximizing the lifetime of assets [6–9], increasing the reliability of inter-operatability [10,11] or a combination of the above for a multi-objective type EMS [12–15]. The proposed supervisory controllers for the safe and optimal H-MGs operation are categorized as: central energy management system (CEMS) and distributed energy management system (DEMS), where certain advantages and drawbacks have been comparatively reviewed in [12,16]. These algorithms are only developed and implemented in the simulation software with specific H-MG structure [8].

In [17], the design of an CEMS is developed in order to obtain the best purchasing price in day-ahead market, as well as to maximize the utilization of existing DER and study the system stability is reported. However, no optimization approach was used in that work. Furthermore, the research work presented in this paper is a continuation of the work by the authors [14], where a framework for considering non-deterministic polynomial-hard (NP-hard) problem with the cheaper version of the software is needed. Moreover, the global optimal solution in the fastest possible time which is an important issue in real-time application development is achieved in comparison with [14]. In this study, a general CEMS framework with a plug-and-play structure is proposed to minimize the operation cost of H-MG. The allows a degree of freedom in the H-MGs operation to automatically adapt the management problem under any changes in the generation and storage resources in real-time to achieve optimal operation, expanding its capabilities from the first-time operation of the H-MG after implementation, to existing real-time H-MG operation. As a result, the proposed CEMS can be considered as a control box, capable of adapting and optimally operating itself with any H-MGs of a given size and integrated types of generation and storage devices by minimizing the cost of operation. For real-time applications, an extensive database of all available generation and storage technologies for H-MG operation (to the best of authors′ knowledge) are considered with their mathematical cost functions and operational constraints. Assuming a two-way communication between each asset in the H-MG with the CEMS (inherent feature of H-MG management system), each device can inform the CEMS with its type and capacity at the beginning of connection, and concurrent changes. Furthermore, the proposed CEMS framework consists of a CCU processor unit which includes day-ahead scheduling (DAS) integrated with real-time scheduling (RTS) units, and LEM units based on Single Side Auction (SSA) to clear the price of energy in real-time. The methodology is structured as follows:

1. a real-time flexible CEMS for all types of H-MG;
2. a plug-and-play operational demonstration in real-time and comprehensive mathematical modeling of different generation and storage assets in NRL and responsive load demand (RLD) loads;
3. a comprehensive local electricity market matrix for any islanded H-MG;
4. a general cost function optimization matrix in real-time based on MABC.

2. The proposed CEMS

For optimal operation of H-MGs, regardless of the EMS being central or distributed architecture, H-MG system developer should be able to make optimal decisions in a short amount of time in real-time operation. Primarily EMS should be able to satisfy plug-and-play operation particularly in larger H-MGs with different players, as such to the EMS should adapt itself to real-time changes in the type and capacity of generation and storage assets. In this study, a comprehensive CEMS is proposed to overcome the problems discussed above where the plug-and-play operation is provided with a database access feature in the CCU (as shown in Fig. 1). The database contains cost function and technical constraints of generation resources, storage devices, and consumers' loads, commonly utilized in H-MGs (to the best of the authors' knowledge), being the core feature of the plug-and-play concept where each plugged-in device informs the CCU with its type. The CCU thereby, modifies the overall cost function and

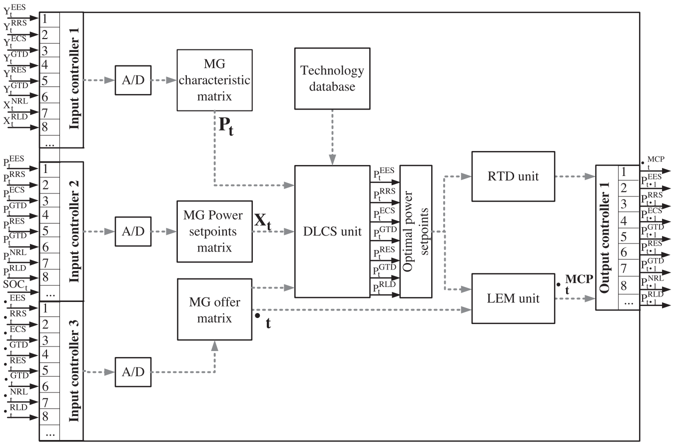


Fig. 1. Block-diagram representation of the proposed CEMS.

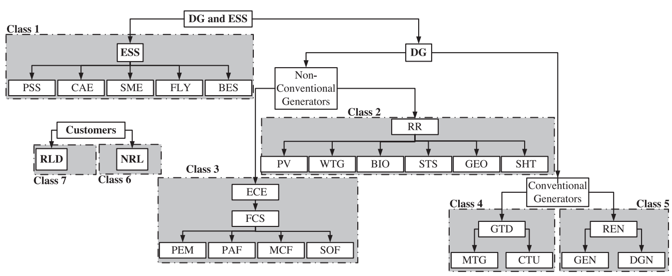


Fig. 2. Generation and storage technology database of the proposed plug-and-play structure.

technical constraints with the new available technology. The communication link between different devices with the CEMS is also a major feature required for the future smart grids integration, as considered in this study. Although advancements in generation, storage devices, and communications technologies are the primary motivation for H-MG implementation, cost optimization of H-MGs with single- and multi-ownership is also critical [14,17]. In this study, single ownership is considered to simplify the market structure and optimization analysis with features like, e.g., plug-and-play type real-time optimal operation. Nevertheless, the LEM can be implemented for multi-ownership H-MGs.

Another effective feature of the proposed CEMS architecture is that all theoretical considerations for a given MG topology can be easily integrated. For instance, in our case, the main contribution is the experimental validation and implementation of this architecture into a real MG. Various concepts have been considered, such as the digital communication protocols of IEC 61850 application for our MG topology, to emulate each of micro-sources using digital signal processing (DSP), as well as, coordination of transmitted signals from central controller to the DSP and so on, was also achieved. The software packages have been developed in the C environment to perform each of these actions individually and other tools have also been validated to highlight the effectiveness of the proposed architecture. A detailed description for the proposed EMS-MABC structure is also presented, that extends the advantages of this algorithm topology compared to previous works.

A comprehensive database of all available technologies, different types of DERs and storage devices is categorized into different classes and sub-section unit details are as follows:

2.1. Technology database

This is formed with seven different classes of technologies as shown in Fig. 2, that includes all generation resources, storage

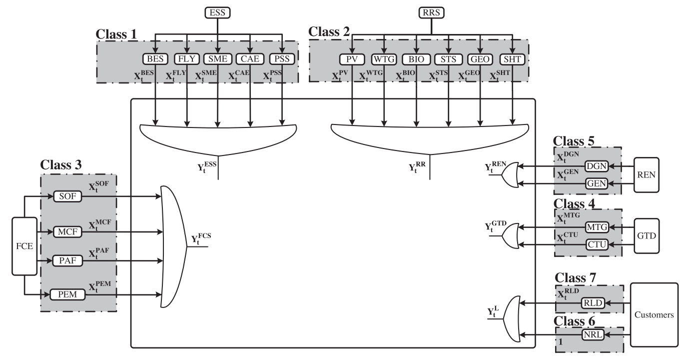


Fig. 3. Block-diagram representation of H-MG characteristic matrix.

devices, and consumers' load demand, which are commonly utilized in H-MGs. In each class, similar technologies (only generation and storage) in terms of same type of operational cost and technical constraints recognized for all technologies available in that class are considered. As an illustrative example in Fig. 2, accommodates conventional rotating generation resources with the same operational structure of minimum on and off time, and ramp-up and ramp-down limits. Consumers' loads are also considered in two different categories based on their availability for management: non-responsive load (NRL) and responsive load demand (RLD). The first class includes a part of consumers' critical loads which always must be satisfied regardless of the H-MG situation (e.g., the electricity price, on-peak load hours and so on). The second class, however, contains consumers' responsive loads which are available for demand response (DR) and can participate in the market with their offer price to respond to the utility command to move their power consumption from on-peak to off-peak hours changing the electricity price. HVAC load, Electric Water Heaters (EWHs), and heat pumps are good examples of this category. The price offer of the same class members might be different with others in the same class in the market.

2.2. H-MG characteristic matrix

The proposed plug-and play H-MG characteristic matrix structure contains a specific and unique binary (on/off) variable for each class (Y_t^i, $i=1, \ldots, 7$) and individual members of each class (X_t^i, i = members of class), as shown in Fig. 3. This approach is similar for all generation resources, storage devices, and consumers' loads available in the technology database and is given as follows:

$$\begin{aligned} X_t = \; & [\overbrace{X_t^{PV}, X_t^{WTG}, X_t^{BIO}, X_t^{STS}, X_t^{GEO}, X_t^{SHT}, \ldots}^{Y_t^{RR}} \\ & \overbrace{X_t^{BES}, X_t^{FLY}, X_t^{SME}, X_t^{CAE}, X_t^{PSS}, \ldots}^{Y_t^{ESS}} \\ & \overbrace{X_t^{SOF}, X_t^{MCF}, X_t^{PAF}, X_t^{PEM}, \ldots}^{Y_t^{ECS}} \\ & \overbrace{X_t^{DGN}, X_t^{GEN}, \ldots}^{Y_t^{REN}} \\ & \overbrace{X_t^{MTG}, X_t^{CTU}, \ldots}^{Y_t^{GTD}} \\ & X_t^{RLD}] \end{aligned} \tag{1}$$

As evident from Eq. (1), the proposed plug-and play structure with the H-MG characteristic matrix can be easily expanded to include any new technology type.

2.3. H-MG power set-points matrix

Based on the characteristic matrix in Eq. (1), the scheduled power for each device can be represented by another matrix as follows:

$$
\begin{aligned}
P_t = \; & [\overbrace{P_t^{\mathrm{PV}}, P_t^{\mathrm{WTG}}, P_t^{\mathrm{BIO}}, P_t^{\mathrm{STS}}, P_t^{\mathrm{GEO}}, P_t^{\mathrm{SHT}}, \ldots}^{P_t^{\mathrm{RR}}} \\
& \overbrace{P_t^{\mathrm{BES}}, P_t^{\mathrm{FLY}}, P_t^{\mathrm{SME}}, P_t^{\mathrm{CAE}}, P_t^{\mathrm{PSS}}, \ldots}^{P_t^{\mathrm{ESS}}} \\
& \overbrace{P_t^{\mathrm{SOF}}, P_t^{\mathrm{MCF}}, P_t^{\mathrm{PAF}}, P_t^{\mathrm{PEM}}, \ldots}^{P_t^{\mathrm{ECS}}} \\
& \overbrace{P_t^{\mathrm{DGN}}, P_t^{\mathrm{GEN}}, \ldots}^{P_t^{\mathrm{REN}}} \\
& \overbrace{P_t^{\mathrm{MTG}}, P_t^{\mathrm{CTU}}, \ldots}^{P_t^{\mathrm{GTD}}} \\
& \overbrace{P_t^{\mathrm{NRL}}, P_t^{\mathrm{RLD}}}^{P_t^{L}}]
\end{aligned} \tag{2}
$$

2.4. H-MG offer matrix

In order to develop overall objective function based on operation cost, it is essential to get the offer price from different technologies available in the H-MG. Therefore, a H-MG offer (bid) matrix is defined, where each technology can have its own offer price. The offers from different generation, storage assets and DR is received by the CEMS unit at each time interval, which is then integrated in the same pre-defined H-MG characteristic matrix as follows:

$$
\begin{aligned}
rl\pi_t = \; & [\overbrace{\pi_t^{\mathrm{PV}}, \pi_t^{\mathrm{WTG}}, \pi_t^{\mathrm{BIO}}, \pi_t^{\mathrm{STS}}, \pi_t^{\mathrm{GEO}}, \pi_t^{\mathrm{SHT}}, \ldots}^{\pi_t^{\mathrm{RR}}} \\
& \overbrace{\pi_t^{\mathrm{BES}-}, \pi_t^{\mathrm{FLY}-}, \pi_t^{\mathrm{SME}-}, \pi_t^{\mathrm{CAE}-}, \pi_t^{\mathrm{PSS}-}, \ldots}^{\pi_t^{\mathrm{ESS}-}} \\
& \overbrace{\pi_t^{\mathrm{SOF}}, \pi_t^{\mathrm{MCF}}, \pi_t^{\mathrm{PAF}}, \pi_t^{\mathrm{PEM}}, \ldots}^{\pi_t^{\mathrm{ECS}}} \\
& \overbrace{\pi_t^{\mathrm{DGN}}, \pi_t^{\mathrm{GEN}}, \ldots}^{\pi_t^{\mathrm{REN}}} \\
& \overbrace{\pi_t^{\mathrm{MTG}}, \pi_t^{\mathrm{CTU}}, \ldots}^{\pi_t^{\mathrm{GTD}}} \\
& \overbrace{\pi_t^{\mathrm{BES}+}, \pi_t^{\mathrm{FLY}+}, \pi_t^{\mathrm{SME}+}, \pi_t^{\mathrm{CAE}+}, \pi_t^{\mathrm{PSS}+}, \ldots}^{\pi_t^{\mathrm{ESS}+}} \\
& \pi_t^{\mathrm{RLD}}]
\end{aligned} \tag{3}
$$

2.5. LEM unit

In this section, a LEM is presented to calculate the cost of energy (COE) for the consumers, as represented in Fig. 4. Once the optimization unit performs at each time interval, the LEM unit calculates the market clearing price (MCP) for the consumers, that might be used to calculate the consumers' electricity cost. It is also utilized in this study to show the effectiveness of the proposed CEMS to reduce the MCP. The LEM structure could be formed as single- or double-sided auction model [14,17], SSA and DSA, respectively. A SSA model is a mechanism in which every player only can be buyer or seller, not both simultaneously, and the auction goes to the lowest bidders to cover the electricity demand. In this paper, the SSA-based proposed LEM structure is formed for simple interpretation. The key input features for LEM unit are robust modification to adapt to any market structure without changing the CEMS with optimal setpoints for H-MG offer matrix.

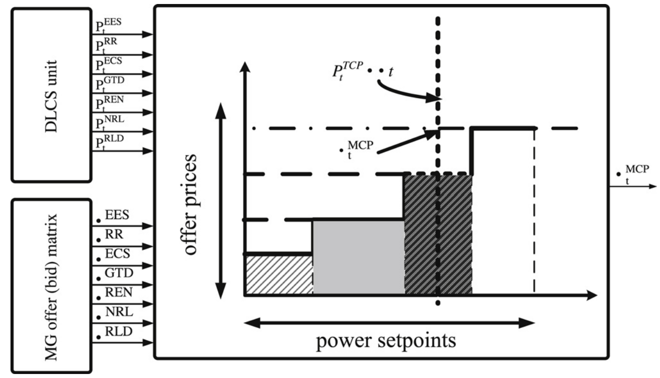


Fig. 4. The LEM unit block-diagram representation.

2.6. RTD unit

This unit is responsible for transmitting optimal operation setpoints data from the CEMS unit to the H-MG testbed unit, where transmission speed and data package lost are parameters of optimization [17,14]. For optimization by each specific device (emulator), confidential signals are designed between the RTD unit and each individual device in the H-MG testbed. The details on dispatch power set-points from CCU to emulators is discussed elsewhere [17].

2.7. Double layer control scheme (DLCS) unit

Conventionally, the ABC algorithm is also similar to the algorithms based on the innovative methods of a recursive process that starts with an initial population that includes acceptable responses that fulfill consumers requirements). Each input source shows a possible response for solving the problem. So, the initial population of the responses is made up of N_p number of random D-dimensional vectors, with real values in which each response is defined as the vector $X_t^i = \{X_t^{i,1}, X_t^{i,2}, \cdots, X_t^{i,D}\}$. This vector determines the position of the ith input source in the generated population. The parameters that must be given initial value in the MABC optimization technique for each response are the D number of the variables of the problem, the number of initial food sources (N_p), the maximum number of cycles in which the optimum finding algorithm must be repeated and the limit that shows the maximum number of times for which a response is investigated. If the response is not optimized during a repetition limit, it is considered as left response.

A double layer control scheme (DLCS) including primary and secondary control based on MABC algorithm is implemented to ensure optimum planning to hourly, and real-time operations as shown in Fig. 5 and illustrated by a Pseudo-code in Algorithm 1. The control levels as follows:

Algorithm 1 MABC UNIT

Require: PV, WTG and H-MG load demand profile, the initial SOC of ES and the characteristic of system [18–20].
Initialize *control parameters/ the problem specific parameters*
for $t = 0 : m$ **do** ▷ m: the number of time periods
  Generate the initial population by
$$X_t^{i,j} = \underline{x}^j + \rho \times (\overline{x}^j - \underline{x}^j) \quad (4)$$
▷ $X_t^{i,j}$: j^{th} variable from the i^{th} response at time t, $i \in 1, 2, \cdots, N_P$, $j \in 1, 2, \cdots, D$ ▷ $\overline{x}^j$ and $\underline{x}^j$: upper and lower of component x ▷ ρ: random number in $[0, 1]$ interval
  Evaluate (Eq.(7))
  cycle =1
  while cycle <MCN **do** ▷ MCN: maximum cycle number
    Employed bee **Generates** $x_t'^{i,j}$ by
$$x_t'^{i,j} = x_t^{i,j} + \rho' \times (x_t^{i,j} - x_t^{k,j}) \quad (5)$$
▷ $k \in 1, 2, \cdots, N_P$, $k \notin i$ ▷ $x_t'^{i,j}$: new input source in the neighborhood of $x_t^{i,j}$ position
    Evaluate and **apply** the greedy selection process
    Onlookers **Calculate** P_t^i for $x_t^{i,j}$ by
$$P_t^i = \frac{fit_t^i}{\sum_{j=1}^{N_P} fit_t^j} \quad (6)$$
▷ fit_t^j: fitness value of i^{th} response at t
    Generates $x_t'^{i,j}$ based on P_t^i
    Evaluate and **apply** the greedy process
    Scout **Determine** the abandoned $x_t^{i,j}$ if exist
    Update it by Eq.(7)
    Update the best solution acquired so far
  end while
  Return optimal power set-points
end for

2.7.1. Primary control

A general optimization structure is devised to determine the H-MG technologies set-points at each time interval with minimum cost of operation. The optimization unit includes a general cost-based objective function which is updated in real-time by the H-MG characteristic matrix. Similar to the technology database which contains all available technologies in the H-MG, the optimization unit is required to have cost function and technical constraints of all available technologies too. As mentioned in Section 2.1, technologies in the same class have similar operational constraints; so seven set of operational constraints can be recognized as a part of the technology database, as an example case.

The ESS class participates with two different offers: charging offer (π_t^{ESS-}) and discharging offer (π_t^{ESS+}). In this study, the H-MG offer matrix is constant throughout a day of operation. The overall objective function of the H-MG optimization problem is defined as follows:

$$\min \quad [\sum_{\forall t} \left(\begin{array}{c} \sum_{i=1}^{5}\sum_{j=1}^{n_i} X_t^{i,j} \times P_t^{i,j} \times \pi_t^{i,j} \\ -\sum_{i=6}^{7}\sum_{j=1}^{n_i} X_t^{i,j} \times P_t^{i,j} \times \pi_t^{i,j} \\ +P_t^{UP} \times \pi_t^{UP} \end{array} \right) \times \Delta t] \quad (7)$$

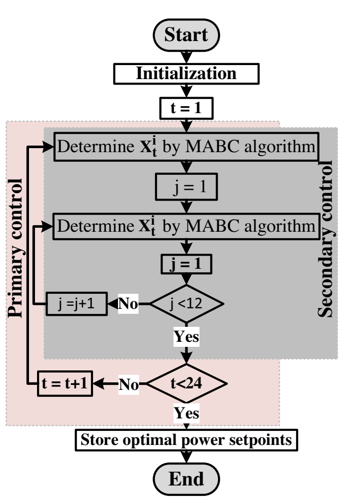


Fig. 5. Block-diagram runtime representation of the proposed MABC optimization structure.

As mentioned earlier, the overall objective function is dynamic, since the H-MG characteristic matrix will be updated in real-time. Similar to the H-MG offer matrix, different offers for charging and discharging are considered for the ESS class. P_t^{UP} and π_t^{UP} are the amount of undelivered power (the unsatisfied part of NRL) at time t and its cost, respectively, as inclusion of this in the objective function serves as a penalty cost for the H-MG operator to avoid undelivered power to the NRL. Objective function is also minimized at each interval (every 5 min) for a day to determine the optimal operation setpoints of the H-MG characteristic matrix, which is fixed and used for the rest of the day. This minimization is done for the current time interval and the rest of the day, not the previous intervals. In addition, it is this variable generation and load demand forecast is always used in the objective function for the rest of the day, uniquely.

In (7), linear cost function is considered for each class because the optimization unit receives offer from each technology, as its owner is responsible to calculate the cost of electricity in that unit, where the cost function might be linear or nonlinear; however, the H-MG operator's decision is based on the load demand, available power, and their offers, irrespectively.

To satisfy the H-MG and technologies safe operation, several constraints should be included in the optimization unit. Generation and demand balance is a key operational constraint in a power system, which is given as:

$$\sum_{i=1}^{5}\sum_{j=1}^{n_i} X_t^{i,j} \times P_t^{i,j} = P_t^{NRL} - P_t^{UP} \quad (8)$$

In (8), available power from generation resources and storage devices in discharging mode are given in the right-hand side, while load demand (NRL and RLD) and storage devices in charging mode are on the other side, profound terms of interest. P_t^{EGP} might be positive (more load is added to utilize excess available generation) or negative (in power shortage), all based on the initial system condition. Therefore, the excess available generation is stored in the RLD and/or ESS in the charging mode. Different constraints for efficient operation of ESS and restrictive optimization constraints of RLD are defined in already as standards [14].

In (9), the scheduled power from classes 2 to 5 between the minimum and maximum forecasted power or their rated capacity can be limited.

- Generation limit for the micro-sources in classes 2–5

$$X_t \times (\underline{P}_t \le P_t \le \bar{P}_t) \quad (9)$$

The generation upper and lower limits can be updated in real-time similar to the H-MG characteristic matrix for variable generation technologies, based on updated forecasts from each unit. Similarly, Technologies available in the GTD class have extra capacity to regulate operational constraints such as; start-up time, ramp-up and -down. These requirements are given in (10)–(13).

- Maximum and minimum operating times in the GTD class

$$[Y_t^{\mathrm{GTD}} - \bar{T}^{i,\mathrm{GTD}}] \cdot [I_{t-1}^{i,\mathrm{GTD}} - I_{t-1}^{i,\mathrm{GTD}}] \geq 0 \tag{10}$$

$$[-Y_{t-1}^{\mathrm{GTD}} - \underline{T}^{i,\mathrm{GTD}}] \cdot [I_t^{i,\mathrm{GTD}} - I_{t-1}^{i,\mathrm{GTD}}] \geq 0 \tag{11}$$

- Ramp-up and ramp-down limits in the GTD class

$$[P_t^{i,\mathrm{GTD}} - P_{t-1}^{i,\mathrm{GTD}}] \leq \bar{R}^{i,\mathrm{GTD}} \tag{12}$$

$$[P_{t-1}^{i,\mathrm{GTD}} - P_t^{i,\mathrm{GTD}}] \leq \underline{R}^{i,\mathrm{GTD}} \tag{13}$$

where $\bar{T}^{i,\mathrm{GTD}}$ and $\underline{T}^{i,\mathrm{GTD}}$ are maximum and minimum up and down time of unit i in the GTD class (min), respectively, $\bar{R}^{\mathrm{GTD}}$ and $\underline{R}^{\mathrm{GTD}}$ are ramp up and down of unit i in the GTD class (kW/min), and $I_t^{i,\mathrm{GTD}}$ is the operating status of unit i in the GTD class (i.e., $I_t^{i,\mathrm{GTD}} = 1$ when the unit is on, and $I_t^{i,\mathrm{GTD}} = 0$ when it is in off state). t is the current time interval.

At each time interval, new operation settings can be decided with respect to the changes in the H-MG for the proposed CEMS. The restructured CEMS is able to generate the optimal operation set-points for the H-MG based on all available generation, storage, demand and their associated prices. The components of vector X_t^i in the primary control are determined for each time interval during daily system operation, considering the technical constraints, followed by processing by the secondary control.

2.7.2. Secondary control

In the secondary control, real time optimization is performed by including the hourly optimum values derived from the primary control, load values, maximum output power of non-dispatchable generation resources. The load values and the output power of non-dispatchable resources are generated randomly for real time 5 min intervals by using the values of hourly forecasting, and by applying designated distribution functions. Each variable of interest is determined by noting the inputs, objective function and the constraints defined in the primary control, considering real-time operation. In addition to the constraints in the primary control, extra constraints are also proposed in the secondary control as follows:

1. Improving the condition of charge ES [21]
   SOC at the last 5 min time interval related to each hour of optimization is always greater than 60% Of its initial value (i.e. $\mathrm{SOC}_F \geq 60\%$).
2. Exchanging power with grid

$$\sum_{j \in J} (P_j^{\mathrm{GRID}-} - P_j^{\mathrm{GRID}+}) \leq \left|J\right| (\bar{P}_t^{\mathrm{GRID}-}) \pm 5\% \tag{14}$$

3. Power balance
   Power balance between generation and consumption must always be kept at real-time period, as responsive load demand (RLD) is constant for 1 h, as same as the value obtained from primary control.

$$P_j^{\mathrm{WTG}} + P_j^{\mathrm{PV}} + P_j^{\mathrm{MT}} + P_j^{\mathrm{BES}-} + P_j^{\mathrm{GRID}-} + P_j^{\mathrm{PU}} = P_j^{n} + P_t^{\mathrm{RLD}} + P_j^{\mathrm{ES}+} + P_t^{\mathrm{GRID}+} \tag{15}$$

4. Objective function
   Objective function calculation is based on minimizing the total generation cost in reall-time, raising the share of generating H-MG power and reducing the power required from the grid and increasing the efficiency of BES.

$$\min \sum_{\forall t} \begin{bmatrix} P_j^{\mathrm{WTG}} \times \pi^{\mathrm{WTG}} + P_j^{\mathrm{PV}} \times \pi^{\mathrm{PV}} + P_j^{\mathrm{MT}} \times \pi^{\mathrm{MT}} \\ +P_j^{\mathrm{BES}-} \times \pi^{\mathrm{BES}-} + P_j^{\mathrm{GRID}-} \times \pi^{\mathrm{GRID}-} \\ -P_j^{\mathrm{DR}} \times \pi^{\mathrm{DR}} - P_j^{\mathrm{EWH}} \times \pi^{\mathrm{EWH}} - \\ P_j^{\mathrm{BES}+} \times \pi^{\mathrm{BES}+} - P_j^{\mathrm{GRID}+} \times \pi^{\mathrm{GRID}+} \\ +P_j^{\mathrm{UP}} \times \pi^{\mathrm{UP}} \end{bmatrix} + \mathbb{C}_t^{\mathrm{PB}} + \mathbb{C}_t^{\mathrm{SOC}} + \mathbb{C}_t^{\mathrm{GB}} + \mathbb{C}_t \tag{16}$$

where $\mathbb{C}_t^{\mathrm{PB}}$ represent the cost due to unbalance between the generated and consumed power (mismatch power cost), calculated as:

$$\mathbb{C}_t^{\mathrm{PB}} = \pi^{\mathrm{PB}} \times P_t^{D} \tag{17}$$

where the coefficient π^{PB} is considered a great value for preventing unbalance between generation and consumption. P_t^D can also be calculated as:

$$P_t^D = (P_j^{\mathrm{WTG}} + P_j^{\mathrm{PV}} + P_j^{\mathrm{MT}} + P_j^{\mathrm{BES}-} + P_j^{\mathrm{GRID}-}) - (P_t^{\mathrm{DR}} + P_t^{\mathrm{EWH}} + P_j^{\mathrm{ES}+} + P_t^{\mathrm{GRID}+}) \tag{18}$$

where $\mathbb{C}_t^{\mathrm{SOC}}$ is the cost resulting from not fulfilling the SOC achievement condition by the proposed algorithm calculated as:

$$\mathbb{C}_t^{\mathrm{SOC}} = \beta \times X_t^{\mathrm{SOC}} \tag{19}$$

where β is a very large penalty coefficient. X_t^{SOC} is also a binary variable and can satisfy the following relation:

$$X_t^{\mathrm{SOC}} = \begin{Bmatrix} 0 & \text{if} \quad \mathrm{SOC}_t \geq 60\%; \\ 1 & \text{otherwise.} \end{Bmatrix} \tag{20}$$

where $\mathbb{C}_t^{\mathrm{GB}}$ shows the cost resulting from not achieving power exchange condition with the grid and Can be calculated from the following relation:

$$\mathbb{C}_t^{\mathrm{GB}} = \gamma \times X_t^{\mathrm{GB}} \tag{21}$$

where X_t^{GB} is a binary variable which should be employed by:

$$X_t^{\mathrm{GB}} = \begin{Bmatrix} 0 & \text{if} \quad \hat{P}_t \geq \hat{P}'_t; \\ 1 & \text{if} \quad \hat{P}_t < \hat{P}'_t. \end{Bmatrix} \tag{22}$$

where $\hat{P}_t$ is the difference between the power purchased and sold in each hour in optimizing real time. $\hat{P}'_t$ is also the difference between the purchased power and sold power in each time interval in hourly optimization. $\mathbb{C}_t$ also shows the difference between the costs obtained from real-time and hourly optimization, as the proposed algorithm numerically minimizes the value of this variable:

$$\mathbb{C}_t = \delta \times X_t \tag{23}$$

where δ is a very large penalty coefficient. X_t can satisfy the following condition:

$$X_t = \begin{Bmatrix} 0 & \text{if} \quad \mathrm{Cost}^h \geq \mathrm{Cost}^{\mathrm{rt}}; \\ \mathrm{Cost}^{\mathrm{rt}} - \mathrm{Cost}^h & \text{if} \quad \mathrm{Cost}^h < \mathrm{Cost}^{\mathrm{rt}}. \end{Bmatrix} \tag{24}$$

where $\mathrm{Cost}^{\mathrm{rt}}$ and Cost^h are respectively equal to the costs resulting from exploitation in real-time and hourly time optimizing. The above shows that any appropriate heuristic and deterministic algorithms can be used to solve the optimization problem based on CEMS as long as the optimization algorithm should be

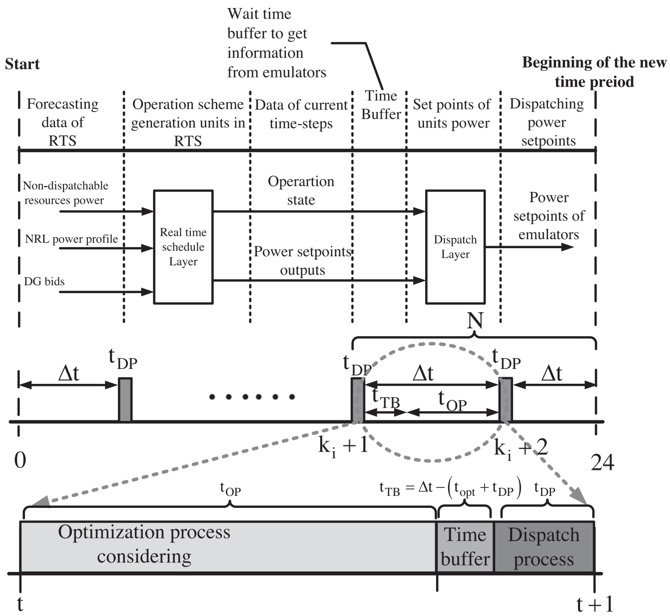


Fig. 6. Block-diagram routine representation of the proposed real-time optimization operation for optimal generation and demand forecasts.

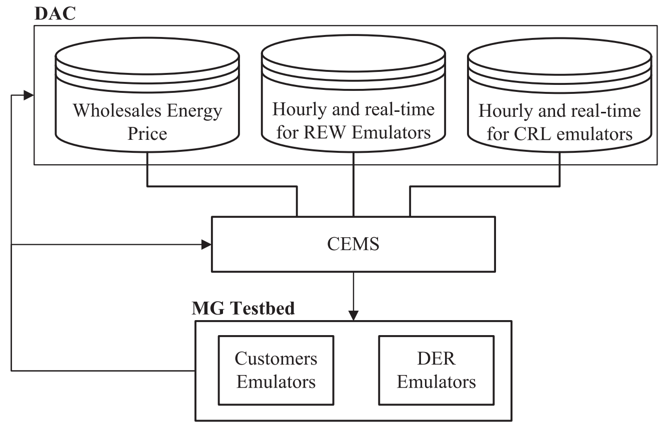


Fig. 7. Block-diagram representation of the proposed RTO.

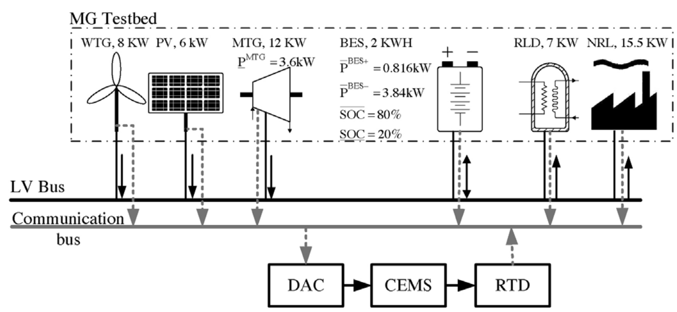


Fig. 8. Schematic diagram of the IREC's H-MG testbed.

fast enough to solve the problem with optimal or near optimal solutions, as in our case in less than 5 min (including communication delays between the CEMS and individual devices). This feature is facilitated by the multi-period artificial bee colony (MABC) used for DLCS unit to solve the H-MG optimization problem due to the population-based search capability, the simplicity of implementation, adequate convergence speed and robustness [22]. In addition, EMS based on mixed-integer non-linear programming (MINLP) (called hereafter EMS-MINLP) is utilized in the optimization unit [14] and the results obtained are compared with those obtained from EMS-MABC algorithm. MINLP refers to mathematical programming with continuous and discrete variables and nonlinearities in the objective function and constraints, similar to the objective function and constraints in this paper. The use of MINLP is a natural approach of formulating problems where it is necessary to simultaneously optimize the system structure (discrete) and parameters (continuous).

Where the proposed optimization approach minimizes cost of real-time operation in the H-MG, it is also desired to guarantee the daily optimum operational routine, not only for the current intervals. Indeed, the proposed MABC algorithm considers the future predictability of information in real-time (i.e., forecasted generation and demand) at each interval for cost minimization. This is advantageous in optimization of time-dependent system since it considers the possible condition of the H-MG in the predicted future (e.g., variation of RES class and the SOC of the ESS). Since the consumers' demand pattern repeats each day, optimization horizon is considered as 24 h daily cycle. This concept is depicted in Fig. 6. Finally, the optimal set-points will be passed to the LEM unit to calculate the MCP for the consumers, also will be sent to the RTD unit to be dispatched to different devices in the H-MG testbed.

3. The proposed real time operation (RTO) architecture

In order to evaluate the performance of the proposed CEMS, real-time emulator environment is adapted with real communication links and delays as illustrated in proposed RTO of Fig. 7. The method is to model each technology and consumers' load using an emulator in the testbed. The proposed RTO structure includes four main units, namely DAC, CEMS, RTD, and H-MG testbed.

3.1. DAC unit

This unit is responsible for receiving and storing data from different devices in the H-MG, finally it is sent to the CEMS for executing optimal solution of the H-MG operation.

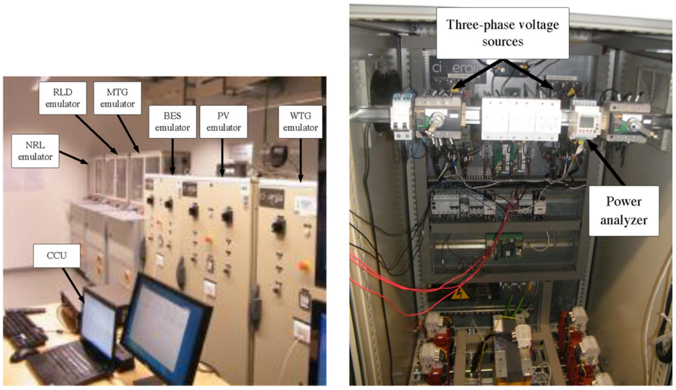
3.2. CEMS unit

This unit contains DLCS unit, technology database, and LEM unit which are explained in details in Section 2.

3.3. The H-MG testbed

The different generation resources and consumers' load with battery storage are considered in the H-MG testbed, as shown in Fig. 8. PV, WTG, and MTG are considered as the generation resources in the H-MG. BES is also considered in the H-MG testbed as storage device. The consumers' load is divided to NRL and RLD. Fig. 9 illustrates the experimental H-MG testbed in the laboratory setup. The designed structure is modular, such as standard experimental practices [17,14] which more emulators for extra generation and storage devices can be added to the system without any further modifications in the running software. Actual real-time operation is performed using WTG, PV, and load demand data [17,14], where the data is sampled every 5 min of the same day, where key features are:

1. Sending and receiving data from/to the devices (i.e., emulators) takes 1.5–3 s, with best performance under 3 s delay. In addition, the optimization unit spends 3 min in average to find the optimal solutions
2. The measured data does not show any meaningful variation in 5 min interval



(a) IREC′s H-MG (b) Cabinet inside details

Fig. 9. System configuration of IREC's H-MG testbed.

Table 1
The offers suggested by the micro-sources and the consumers have been presented [€/kWh].

π^{WTG}	π^{PV}	π^{MTG}	$\pi^{\text{BES}-}$	$\pi^{\text{BES}+}$	π^{UP}	π^{RLD}
0.083	0.1	0.15	0.145	0.125	1.5	0.105

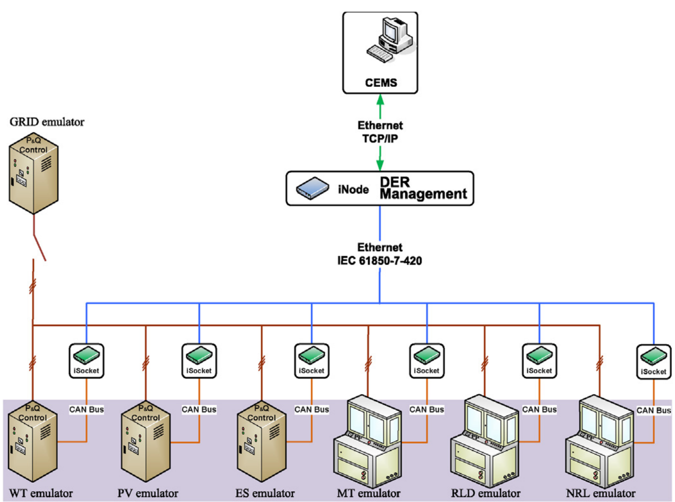


Fig. 10. Single line diagram of the system under study.

In Table 1, the constant offer prices used for different devices are reported.

3.4. The IREC's H-MG system configuration

The schematic of the system under study has been shown in Fig. 10.

4. Results and discussion

Experimental evaluation over the islanded IREC's H-MG is carried out to verify the EMS operation under different scenarios. The scenarios bellow have been considered for testing the performance and efficiency of the suggested algorithm:

- Scenario ♯1: Normal operation (In this scenario, the system is in normal operation mode and the optimum power and the proper timing of each one of the present microsources in the system will be obtained by the suggested algorithm)

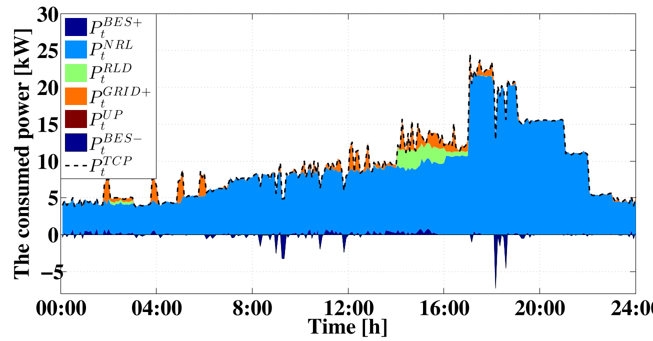


Fig. 11. TCP and consumed power by the consumers.

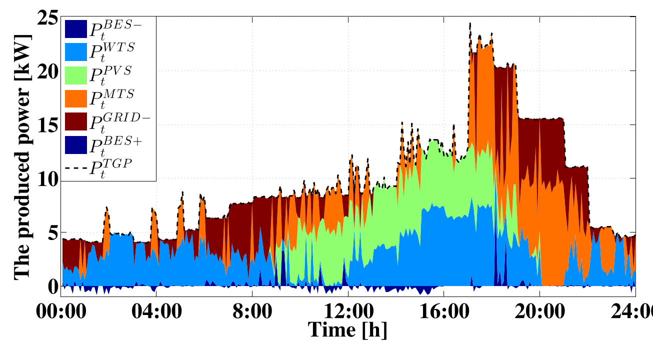


Fig. 12. TGP and power generated by the generation resources.

- Scenario ♯2: Sudden load increase (Sudden load increase is occurred during 17:00–17:30 and 18:00:18:30 periods.)
- Scenario ♯3: Plug and play ability (The system plug and play ability can be investigated by this scenario. WTG has shutdown during 19:30–21:00 periods. Also, PV has shutdown during 19:30–20:00 periods.)

The total consumed power (TCP) by the consumers and the power consumed by each of them are shown in Fig. 11. As it is observed, mainly the RLD load is supplied by proposed algorithm during the periods 00:00–06:00 and 12:00–18:00, where the secondary control tries to fulfil power balance in real-time optimizing performance, where the consumption peak is low and BES has its maximum SOC. During the period 12:00–18:00 after discharging BES and SOC reaching a lower value than the value defined in one of the constraints, the proposed algorithm in the secondary control charges BES, such that it fulfils the defined constraints. For daily operation the proposed algorithm frequently tries to sell the excess generated power to the grid. The process circumvents and adjusts any constraints for supplying power between the grid and H-MG in secondary control.

The value of the total generated power (TGP) is shown in Fig. 12. As before PVS unit entering service begins (coming into operation), the power shortage is mainly supplied by purchasing power from the grid. As soon as PVS comes into operation, a major part of power shortage is supplied by MTS. During the period in which the power generated by PVS is increasing, the proposed algorithm tries to store excess power in BES, so that remainder of the time-wise SOC condition needs for secondary control can be fulfilled. After the occurrence of Scenario ♯2 and ♯3, MTS comes into operation with maximum capacity and the rest of the required power is supplied by the grid, such that, while maintaining the power balance constraints in the grid, the power exchange between the grid and H-MG, are also regulated.

Table 2
Average calculation time for the system under study.

	MINLP	MABC
Execution time (s)	8.23	1.14

4.1. The convergence specifications/comparison for EMS-MABC and EMS-MINLP algorithms

The proposed algorithm has been implemented for solving the energy management system-EMS problem in the C programming environment and has been tested by using a computer with the specifications CPU 2.6 GHz and RAM 4GB. For comparison, the execution time of the proposed algorithm and the absolute value of CPU time have been mentioned in Table 2 for both algorithms. The obtained results show that in addition CPU can allocate less time for executing EMS-MABC algorithm compared with EMS-MINLP, the following cases from the viewpoint of practical implementation must be considered:

- For the real-time implementation of EMS system in the MG the execution time of the algorithm has significant importance. Real-time in different papers have been reported between 3 min to 5 min. Also, its reason is that this time is less than the adjustment time for protective relay reactions such as under-/over-voltage relay. In addition, atmospheric variations usually need more than 5 s for affecting PV systems and wind turbines. The system under study has a connection network by using IEC 61850 standard between central computer and emulators which have been used for simulating the performance of distributed generation sources. The required time for sending data (the optimum power of all the DER sources and the amount of RLD from the central computer to the simulators) is between 1.5 and 3 s. Furthermore, the necessary time for exchanging data among intelligent sockets present inside the emulators which have been connected to each other by using connection link under CAN protocol and operate as local controller is also less than 3 s. So, the sum of the required time for executing the algorithm and the required time for sending data and information exchange has become much less than 3 min in both of the algorithms.
- Other point which can be stated is that the problems related to unit commitment in the MGs are mainly large-scale with a large number of variables; non-convex, non-linear and belonging to non-deterministic polynomial time hard (NP-hard). With the increase of the number of variables, the algorithm execution time will increase in exponential progression. So, using heuristic algorithms which give close to optimal point can be considered as a solution for such problems. Finally, the proposed algorithm is not only just for the system under study with a number of low variables but in fact the main purpose of presenting it, is for solving networks with greater scale.
- Another point is about the convergence specification of the implemented algorithm. The proposed algorithm convergence specification for a time interval has been shown in Fig. 13. Maximum iteration is set to 100. As it is observed in the Figure, the algorithm has become convergent after 68 iterations. For showing the quality of the presented solution by the EMS-MABC algorithm for the system under study, the efficiency of the algorithm for 100 iterations has been presented in Table 3 with the results obtained

Table 3
Comparison of solution quality for the system under study.

Standard deviation	Average cost	Minimum cost	Algorithm name
0.0066	0.2279	0.22	EMS-MABC
0.0425	0.2745	0.23	EMS-MINLP

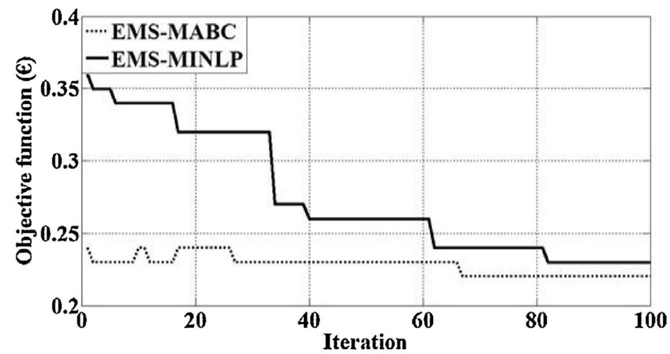


Fig. 13. The characteristic of the convergence of the proposed algorithm for the system under study during a time interval.

from the realistic algorithm (MINLP) (presented in [14]) under cases such as average cost, minimum cost and standard deviation. As it is observed in Fig. 13, it is obvious that the EMS-MABC algorithm has reached its minimum cost after 68 iterations. While the EMS-MINLP algorithm has reached its minimum value after 83 iterations. As it is observed in Table 3, the average value in the EMS-MABC algorithm is very close to the value of minimum cost and standard deviation is also much less than the other algorithm.

The H-MG operated by using the EMS-MABC algorithm has been able to perform optimum, robust, safe and stable function based on the following features:

1. A higher overall system input stream by taking into consideration the DG bids that accounts for the total consumed power by loads, as well, the total generated power by renewable sources;
2. A maximum satisfaction load rate by minimizing the operation cost in islanded mode;
3. An intelligent management of renewable units for long-term period intermittent durations and real-time forecasting by using real time schedule layer;
4. A precise adjustment of the set-point related to production units in real time schedule layer for the optimization of power distribution;
5. A fast precision-based algorithm reaction time and decision making by considering real-time forecast data for unwanted incidents resulting from the exit/entrance and/or increased/reduced capacity of non-dispatchable sources, as well, an increased demand for NRL.

5. Conclusions

An intelligent EMS architecture and experimental evaluation has been successfully demonstrated for optimizing the power generation balance under DER electrical systems. The EMS-MABC energy management algorithm demonstrates the time-wise scheduling practical capability for a range of integrated power devices and demand loads. A significant reduction, being one of the primary feature, in the total electricity cost can be obtained. The priority of entering/exiting service of power generation sources and feeding responsive loads, based on the emulated objective function, demonstrates the inclusiveness of all the known constraints in DER. Comparison of experimental and simulation results shows the capability of the proposed algorithm to tolerate adequately the encounter with unwanted transients/incidents for the whole cycle of power generation to distribution operation.

The results highlights the effectiveness of the proposed EMS-MINLP algorithm under very high convergence time, an incentive for the smart grids energy management and distribution for H-MG applications in real-time. The demonstrated our H-MG topology seems a logical choice for achieving these goals, and our adaptive and recursive EMS-MABC algorithm devises our initiatives to show for optimum energy management that can certainly be envisioned for future hybrid multi-functional smart grid supply chain energy systems with a revolutionary architectures. The real-time energy management capability of a H-MG is shown to inter-operate at both; a connected to the grid and an independent from the grid, where the optimization algorithm based on ABC-method using a double layer control scheme, including a dedicated primary and secondary control. The optimum controllable set-points related to each of the variables can be obtained in hourly and real-time intervals by control schemes as follows:

- Adequate exploitation of non-dispatchable resources with the aim of increasing utilization with maximum capacity as a result of significant reduction of environmental population and also reduction of consumed electricity;
- Maximizing the energy stored in the BES and maintaining SOC at acceptable level for increasing BES system reliability and life cycle.
- Exchanging adequate power with the grid and efficient demand side management by applying DR and stable load feed with a reduced operational cost.
- The demonstrated results show the effectiveness of the proposed EMS-MINLP algorithm under very high convergence time, overall that can offer an incentive of smart real-time energy management, planning and distribution in power systems for H-MG applications.

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Optimal energy management system based on stochastic approach for a home Microgrid with integrated responsive load demand and energy storage

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ABSTRACT

In recent years, increasing interest in developing small-scale fully integrated energy resources in distributed power networks and their production has led to the emergence of smart Microgrids (MG), in particular for distributed renewable energy resources integrated with wind turbine, photovoltaic and energy storage assets. In this paper, a sustainable day-ahead scheduling of the grid-connected home-type Microgrids (H-MG) with the integration of non-dispatchable/dispatchable distributed energy resources and responsive load demand is co-investigated, in particular to study the simultaneously existed uncontrollable and controllable production resources despite the existence of responsive and non-responding loads. An efficient energy management system (EMS) optimization algorithm based on mixed-integer linear programming (MILP) (termed as EMS-MILP) using the GAMS implementation for producing power optimization with minimum hourly power system operational cost and sustainable electricity generation of within a H-MG. The day-ahead scheduling feature of electric power and energy systems shared with renewable resources as a MILP problem characteristic for solving the hourly economic dispatch-constraint unit commitment is also modelled to demonstrate the ability of an EMS-MILP algorithm for a H-MG under realistic technical constraints connected to the upstream grid. Numerical simulations highlight the effectiveness of the proposed algorithmic optimization capabilities for sustainable operations of smart H-MGs connected to a variety of global loads and resources to postulate best power economization. Results demonstrate the effectiveness of the proposed algorithm and show a reduction in the generated power cost by almost 21% in comparison with conventional EMS.

1. Introduction

Future smart buildings will incorporate an increasing non-dispatchable/dispatchable generation units and energy storage (ES) devices coupled with responsive load demand (RLD) switching from conventional routines of consumptions to distributions and regulation counterparts (Chandrasekaran & Simon, 2013). In specific RLD loads are of interest because of their interruptible nature, in contrast with NRLD counterparts of non-interruptible nature, and being not part of the sensible loads that have the ability to flexibly respond to the Microgrid's customer financial encouraging contractual implementations, with respect to minimizing consumers lead costs while maximizing operational efficiency by shifting from peak time loading to non-peak periods. With continuous increase in the growth rate of home Microgrid (H-MG) and renewable resource penetrations for more than a decade unregulated load demand together with intermittent renewable generation are posing additional challenges on supply-demand balancing conditions in smart H-MG (Ogunjuyigbe, Monyei, & Ayodele,

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Nomenclature

Acronyms

DER	distributed energy resources
ES	energy storage
EMS	energy management systems
UG+, UG−	buying/selling power from/to H-MG/the upstream grid
H-MG	home microgrid
MILP	mixed integer linear programming
MT	micro-turbine
MCP	market clearing price
NRL	non-responsive load
PV	photovoltaic
ES+, ES−	ES during charging/discharging mode
RLD	responsive load demand
RLD+, RLD−	amount of demand that goes/come from/to other time period to/from t
SOC	state-of-charge
TCP	total consumed power
TGP	total generated Power
WT	wind turbine

Parameters

P^n_t	the predicted consumed electrical load demand at time t (kW)
P^A_t A $\in$ {WT, PV}	available power of A (kW)

Constants

ζ^B_e	electrical efficiency of the thermal B$^{\text{th}}$ DER in H-MG (%)
π^{ng}	natural fuel price offer (£/kWh)
$\overline{P}^B$, $\underline{P}^B$	maximum/minimum electrical power generated by B (kW)
$\overline{\text{SOC}}$, $\underline{\text{SOC}}$	the lower/upper limit of SOC (%)
SOC_{INI}	initial SOC (%)
$E^{\text{ES}}_{\text{Tot}}$	total capacity of ES (kWh)
$T^{\text{MT}}_{\text{ON}}$, $T^{\text{MT}}_{\text{OFF}}$	turn on/off time (min)
R^{MT}_l, R^{MT}_u	ramp down/up limit (kW)
η	a part of excess/shortage power required by H-MG
ζ^{MT}	MT efficiency (%)
π^B	the supply bids by B (€/kWh) B $\in$ {MT, ES −, ES +, RLD +, RLD −, UG +, [[*amp*]]UG − }
Δt	time step (h)

Decision variables

P^B_t	available power of B (kW)
X^B_t	binary variable of B
FU^{MT}_t	fuel consumption rate
SOC_t	ES SOC (%)
λ^1_t-λ^8_t	MCP at each time t in the following algorithms, respectively:
λ^1_t	EMS-MILP algorithm
λ^2_t	EMS unit
λ^3_t	imperialist competitive algorithm
λ^4_t	NikaidoIsoda/relaxation algorithm
λ^5_t	multi-artificial bee colony
λ^6_t	multi-ant colony optimization
λ^7_t	multi-gravitational search algorithm
λ^8_t	mixed integer non-linear programming

2015). H-MG represents a vision for non-dispatchable/dispatchable distributed generations and consumptions, enhancing the robustness and stability of power grids and explores new ways of utilizing sustainable energy resources in terms of new generation of renewable integrated energy systems (Marzband, Azarinejadian, Savaghebi, & Guerrero, 2015; Marzband, Ghadimi, Sumper, & Domínguez-García, 2014; Marzband, Parhizi, & Adabi, 2015; Ogunjuyigbe et al., 2015). Facilitated by recent advances in RLD and renewable generation, systems are managed adaptively in response to variations of renewable power supply and load demand, simultaneously. (Parra, Walker, & Gillott, 2014). These adaptive features combined with the objective of reducing the overall operational cost of the whole H-MG system, the RLD can play a critical role as in to offer a fully integrated platform to be collaboratively perform features like peak shaving and load shedding with all considerations of physical, financial, and environmental constrains (Lamedica, Teodori, Carbone, & Santini, 2015; Montuori, Alcázar-Ortega, Álvarez-Bel, & Domijan, 2014).

In H-MG, the issue of supply-demand mismatch with renewable energy generation can be made if energy generation sources are not sufficient enough to supply the load demand and no proper energy management system (EMS) is employed. A proper EMS is one which makes effective use of available distributed energy resources (DERs) optimally, while ensuring efficient resources usage and the sustainability of the supply. However, these EMSs have constrictive bounds to their operational limits and may also fail to supply the load demand if total demand is more than the maximum capacity of the generation resources. Under such scenarios, employing backup systems, such as energy storage (ES), and/or applying RLD options helps reduce electricity supply-demand unbalance (Hamad & El-Saadany, 2016; Marzband, Parhizi, Savaghebi, & Guerrero, 2016; Mazidi, Zakariazadeh, Jadid, & Siano, 2014; Mohan, Singh, Ongsakul, & Suresh, 2016). RLD is a mechanism to enable customers to participate in the electricity market in order to reduce the peak demand by scheduling both power consumption and operation time for power-shiftable appliances and time-shiftable appliances. One of the key objectives of EMS with RLD availability is to reduce power consumption in peak hours and shifting demand to off-peak hours when cheaper, cleaner electricity is available (Marzband, Sumper, Chindriş, & Tomoiagă, 2012; Marzband, Sumper, Domínguez-García, & Gumara-Ferret, 2013; Marzband, Sumper, Ruiz-Álvarez, Domínguez-García, & Tomoiagă, 2013).

In this paper, an intelligent EMS based on mixed integer linear programming (MILP) (EMS-MILP) is designed to easily accommodate a wide range of ES and RLD in the grid-connected H-MG. as to demonstrate smart grid implementation and optimization, presented as an energy management system. For all purpose H-MGs, the optimum performance of each one of the production resources requires optimized management of load demand under different conditions, as also considered in this study. Since the model considered for the H-MGs is non-linear, the optimization algorithms for finding the best solution for the efficient and intelligent power distribution, in particular for H-MGs connected to the upstream grid, where load demand fluctuations can lead to frequency variations and reactive power can also be considered in this study (Marzband, Moghaddam, Akorede, & Khomeyrani, 2016; Marzband, Sumper, Gomis-Bellmunt, Pezzini, & Chindris, 2011).

The proposed EMS-MILP offers an intelligent maintenance, regulation and unit scheduling framework for grid-integrated H-MG that can be utilized for real-time optimization considering all achieved smart energy generation units with improved performance/energy monitoring and reduced energy cost. In addition, where DERs have a positive effect over electricity market efficiency and reliability of supplying power by using revolving reserves, our optimum algorithm incorporates the contribution of power for revolving reserves, energy storage resources and DERs, all integrated to emulate conditions for uncontrollable resources and uninterruptable loads, measured in real-time from upstream grid by using central controlling unit. The optimum scheduling in this integrated structure including generation and DER resources combined together also addresses scenarios of maximizing performance and minimizing system cost. Moreover, a generalized framework model that can adopt for all global consumers to participate in RLD program is proposed. The main contributions of the work are as follows:

- Presenting a stochastic bidding strategy for H-MG participating in local energy market in consideration of uncertainties of load demand and available output power of wind turbine (WT) and photovoltaic (PV) resources;
- Presenting RLD programming combined with ES is investigated under the presence of variable renewable generated power to demonstrate its ability for DER generation to reduce the market clearing price.

2. Application to test grid

The schematic diagram of a grid-connected H-MG which is main focus of this paper is illustrated in Fig. 1. In this configuration, dispatchable/non-dispatchable DERs and ES devices and associated RLD are configured in H-MG. To begin, EMS-MILP receives data including the generated power by non-dispatchable DERs and the non-responsive load (NRL) demand, the general properties of each DERs (such as maximum/minimum power generated by them, the turning on and turning off time of non-dispatchable DER as presented in Table 1), ES SOC. Then, all the optimal power set-points of each DERs and RLD will be dispatched to them at each time interval based on the proposed EMS. Simulation evaluations are performed for a grid-connected H-MG including wind turbine (WT), photovoltaic (PV), microturbine (MT), and energy storage (ES). The real life experimental data carried out from (Marzband, Sumper, Ruiz-Álvarez, et al., 2013) are also used to simulate WT, PV and NRL demand. The WT, PV, and NRL demand profiles are shown in Fig. 2.

For investigating the proposed algorithm performance correctness in encountering different incidents, three scenarios have been implemented over the grid-connected H-MG under study: (the SOC initial value (i.e. SOC_{INI}) in all the scenarios has been set equal to 50%).

Scenario #1: normal operation.
Scenario #2: sudden increase in load demand.
Scenario #3: emergency shut-down at non-dispatchable resources.

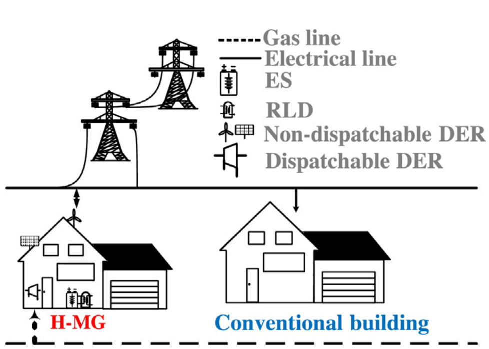

Fig. 1. Comparison between a conventional building and H-MG with the integration of non-dispatchable/dispatchable distributed energy resources and responsive load demand.

Table 1
Configuration parameters for each non-dispatchable/dispatchable DER and ES resources.

Parameter	Symbol	Value
ES system		
Voltage (V)	V_t^{ES}	24
Nominal Ah capacity at +25°C	N^{ES}	84
Fully Charged voltage (V)	$\overline{V}^{ES}$	26
Cut-Off discharge voltage (V)	$\underline{V}^{ES}$	21
Maximum continuous charge current (A)	$\overline{I}^{ES+}$	34
Maximum continuous discharge current (A)	$\overline{I}^{ES-}$	160
Maximum battery power during charging Mode (kW)	$\overline{P}^{ES+}$	0.816
Maximum battery power during discharging Mode (kW)	$\overline{P}^{ES-}$	3.84
Maximum delivered power by converter (kW)	$\overline{P}^{ES}$	4
Initial SOC (%)	SOC_{INI}	50
Maximum SOC (%)	$\overline{SOC}$	80
Minimum SOC (%)	$\underline{SOC}$	20
Initial stored energy in battery (kWh)	E^{ES}_{INI}	1
Maximum stored energy in ES (kWh)	$\overline{E}^{ES}$	1.6
Minimum stored energy in ES (kWh)	$\underline{E}^{ES}$	0.403
Total capacity of ES (kWh)	E^{ES}_{Tot}	2
Charge efficiency factor (%)	η_c	96
PV system		
Maximum instantaneous power for PV(kW)	$\overline{P}^{PV}$	6
Minimum instantaneous power for PV (kW)	$\underline{P}^{PV}$	0
WT system		
Maximum instantaneous power for WT (kW)	$\overline{P}^{WT}$	8
Minimum instantaneous power for WT (kW)	$\underline{P}^{WT}$	0.45
MT system		
Maximum instantaneous power (kW)	$\overline{P}^{MT}$	12
Minimum instantaneous power (kW)	$\underline{P}^{MT}$	3.6
Turn on time (min)	T^{MT}_{ON}	6
Turn off time (min)	T^{MT}_{OFF}	6
Ramp down limit (kW)	R^{MT}_{l}	6
Ramp up limit (kW)	R^{MT}_{u}	6

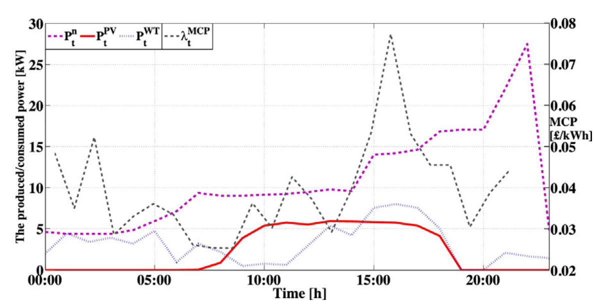

Fig. 2. NRL load demand profile comparison for power produced by PV, WT resources and the predicted MCP profile based on the hourly experimental data adapted from (Marzband, 2013; Marzband, Sumper, Ruiz-Álvarez, et al., 2013).

3. Problem formulation

3.1. Objective function

Our first attempt considers defining the objective function as a problem structure that includes profit negative values that requires minimization via EMS optimization. Although, the above function can be fully extended to integrate other variables, constraints and balancing conditions to include other technical and environmental aspects for a given H-MG. values that requires minimization via EMS optimization. Although, the above function can be fully extended to integrate other variables, constraints and balancing conditions to include other technical and environmental aspects for a given H-MG. Profit negative is equal to the overall cost of generating electricity by the H-MG without the H-MG incomes stream.

The defined objective function for a grid-connected H-MG thereby can be expressed as follows.

$$Z=\mathbf{min}[\sum_{t=1}^{24}\left(\begin{array}{l}(FU_t^{MT}\times\pi_t^{ng}+P_t^{ES+}\times\pi_t^{ES+}\\+P_t^{RLD+}\times\pi_t^{RLD+}+P_t^{UG-}\times\pi_t^{UG-})\\-(P_t^{WT}\times\pi_t^{WT}+P_t^{PV}\times\pi_t^{PV}\\+P_t^{ES-}\times\pi_t^{ES-}+P_t^{MT}\times\pi_t^{MT}\\+P_t^{UG+}\times\pi_t^{UG+}+P_t^{RLD-}\times\pi_t^{RLD-})\end{array}\right)\times\Delta t] \quad (1)$$

Subject to:

- **power balance**

$$P_t^{WT}+P_t^{PV}+P_t^{ES-}+P_t^{MT}+P_t^{UG-}\times\left(1-X_t^{UG}\right)$$
$$=P_t^{n}+P_t^{ES+}+P_t^{RLD+}\times(1-X_t^{RLD})-P_t^{RLD-}\times X_t^{RLD}+P_t^{UG+}\times X_t^{UG} \quad (2)$$

- **Supply/consumer bids**

$$\underline{\pi}^B\le\pi_t^B\le\overline{\pi}^B \quad (3)$$

where $\underline{\pi}^B$ and $\overline{\pi}^B$ are respectively the minimum and maximum offer of the electrical price in the Bth DER. $\overline{\pi}^B$ can be considered the equivalent of the value of predicting electrical MCP of the day before implementing uncertainty. $\underline{\pi}^B$ can be considered zero for non-dispatchable DER generation resources and for resources which consume fuel can be estimated by calculating electrical marginal cost (MC_e) value of the desired resource. MC_e for fuel consuming resource is calculated from the following relation:

$$MC_t^B=\frac{P_t^B}{\zeta_e^B}\times\pi^{ng} \quad (4)$$

- **non-dispatchable resources (WT and PV in this study)** (Marzband, Sumper, Ruiz-Álvarez, et al., 2013; Marzband, Yousefnejad, Sumper, & Domínguez-García, 2016; Moafi, Marzband, Savaghebi, & Guerrero, 2016)

$$\underline{P}^{PV}\le P_t^{PV}\le\overline{P}^{PV} \quad (5)$$

$$\underline{P}^{WT}\le P_t^{WT}\le\overline{P}^{WT} \quad (6)$$

- **dispatchable resources (MT in this study)**
  - turn on/turn off limit

$$X_t^{MT}-X_{t-1}^{MT}-e_t^{MT}+a_t^{MT}=0 \quad (7)$$

$$a_t^{MT}+\sum_{k=t}^{\delta_{t1}}e_k^{MT}\le 1,\quad \delta_{t1}=\min\{t+T_{ON}^{MT},T\} \quad (8)$$

$$e_t^{MT}+\sum_{k=t}^{\delta_{t2}}a_k^{MT}\le 1,\quad \delta_{t2}=\min\{t+T_{OFF}^{MT},T\} \quad (9)$$

X_t^{MT} is a binary variable which shows the off or on condition of unit MT at time t, when the unit is on. It allocates the one value to itself and otherwise its value is zero. a_t^{MT} and e_t^{MT} are also binary variables which their condition regarding the unit exploitation conditions change. If X_{t-1}^{MT}=1 (a_t^{MT}=1 will become one and when e_t^{MT}=1 if X_{t-1}^{MT}=0 and X_t^{MT} when a_t^{MT}=e_t^{MT}=0 if X_t^{MT}=1 and X_{t-1}^{MT}=0)

  - ramp up and down limit (Chabaud, Eynard, & Grieu, 2015; Marzband, Javadi, Domínguez-García, & Moghaddam, 2016)

$$R_l^{MT}\le(P_t^{MT}-P_{t-1}^{MT})\le R_u^{MT} \quad (10)$$

  - MT generation limit

$$X_t^{MT}\cdot\underline{P}^{MT}\le P_t^{MT}\le X_t^{MT}\cdot\overline{P}^{MT},\quad X_t^{MT}\in\{0,1\} \quad (11)$$

  - fuel consumption rate

$$FU_t^{MT}=P_t^{MT}/\zeta^{MT} \quad (12)$$

- **ES constraints** (Marzband, Sumper, Domínguez-García, et al., 2013; Marzband, Yousefnejad, et al., 2016)
  - maximum discharge limit

$$P_t^{ES-}\le\overline{P}^{ES-}\times X^{ES},\quad X^{ES}\in\{0,1\},\quad P_t^{ES-}\ge 0 \quad (13)$$

  - maximum charge limit

$$P_t^{ES+}\le\overline{P}^{ES+}\times(1-X^{ES}),\quad P_t^{ES+}\ge 0 \quad (14)$$

  - maximum discharge limit considering the stored energy

$$(P_t^{ES-}\times\Delta t)\le E_{t-1}^{ES} \quad (15)$$

  - Maximum charge limit considering the stored energy

$$((P_t^{ES+}\times\Delta t)+E_{t-1}^{ES})\le\overline{E}^{ES} \quad (16)$$

  - energy balance

$$E_t^{ES}=E_{t-1}^{ES}+(P_{t-1}^{ES+}-P_{t-1}^{ES-})\times\Delta t \quad (17)$$

  - ES SOC

$$SOC_t=\frac{E_t^{ES}}{E_{Tot}^{ES}} \quad (18)$$

  - energy stored limit

$$\underline{E}^{ES}\le E_t^{ES}\le\overline{E}^{ES} \quad (19)$$

- **RLD constraints**

On the other hand, the amount of power allocated for the RLD can be specified by EMS-MILP incorporates the technical and economic constraints. After determining the optimum set-point powers of each DERs and the value of surplus and shortage powers, this information will be spontaneously sent to the RLD unit. For the first time, our novel EMS-MILP implementation incorporates all constraints for RLD/DER where household consumed loads for a H-MG are classified as both interruptible loads (i.e. RLD) and no interruptible loads (i.e. NRLD), respectively. For generated power in H-MG, the generation resources are more than the consumption amount by the consumers (i.e. at the beginning of the day) thereby excess generation is created, and the proposed EMS algorithm during operational times decides to supply RLD+ loads:

$$P_t^{TCP}=P_t^{n}+P_t^{ES+}+P_t^{RLD+}+P_t^{UG+} \quad (20)$$

Also, when power shortage exists in the H-MG (i.e. at the end of the day) and the amount of generation resources is less than the amount of consumed power, the proposed EMS transfers interruptible loads from this time interval to other time intervals for helping system stability:

$$P_t^{TGP}=P_t^{WT}+P_t^{PV}+P_t^{MT}+P_t^{ES-}+P_t^{RLD-}+P_t^{UG-} \quad (21)$$

$$P_t^{RLD-}\le(P_t^{TCP}-P_t^{TGP})\times X_t^{RLD} \quad (22)$$

$$\sum_{t=1}^{24}(P_t^{RLD+}\times(1-X_t^{RLD}))=\sum_{t=1}^{24}(P_t^{RLD-}\times X_t^{RLD}) \quad (23)$$

- **upstream grid constraints**

$$\overline{P}^{UG}\le\eta\times(P_t^{WT}+P_t^{PV}+P_t^{MT}+P_t^{ES-}) \quad (24)$$

$$P_t^{UG-}\le\overline{P}^{UG}\times(1-X_t^{UG}) \quad (25)$$

$$P_t^{UG+} \leq \overline{P}^{UG} \times X_t^{UG} \quad (26)$$

The above implementation signifies the functional ability of GAMS/EMS-MILP objective function to study the increase of energy generation shared under renewable resources, where a co-optimization of maximizing profit and/or minimizing cost considered with all technical constraints of load supply for all resources in the H-MG. In addition, where simultaneous use of renewable energy generation resources and energy storing/battery resources along with responsive loads creates complexities for multiscale H-MG energy management, the proposed algorithm also successfully adapts to the above structure. Determining that what amount of load demand can be shifted/supplied to/from a time interval to another is one of key roles of the RLD unit.

3.2. Mixed-integer linear programming optimization

A mixed-integer linear program optimization is applied to the above objective function as; problem with:

- For linear objective function of $f^T x$, where f is a column vector of constants, and x is the column vector of unknowns.
- All bounds are considered as linear constraints, and no nonlinear constraints have been defined.
- The restrictions on some components of x to have integer values is also applied.

In mathematical terms, given vectors f, lb, and ub, matrices A and Aeq, corresponding vectors b and beq, and a set of indices intcon are defined to compute a vector x to solve:

$$\mathbf{min}_x \;\; f^T x \;\; \text{subject to} = \begin{cases} \text{x is integers} \\ A.x \leq b \\ Aeq.x = beq \\ lb \leq x \leq ub \\ \end{cases} \quad (27)$$

where integer variables must take an integer value (0, 1, 2, ...). A unique integer variables is a binary variables that can only take the value 0 or 1, where a maximum of 1 and implicitly a minimum of 0 on each variable are constrictive bounds at all times. If all variables are integer then it is a pure integer model, else it is a mixed-integer model, sometimes denoted as MIP (Mixed Integer Programming).

4. The proposed EMS-MILP

The EMS-MILP proposed in this paper is depicted in Fig. 3. This algorithm is encompassed from two part namely EMS-MILP and conventional EMS. EMS-MILP will be executed if switches of S1 and S2 have the status of ON and OFF, respectively. Conventional EMS is based on method without optimization algorithm. It comprises different units, i.e. economic dispatch (ED) unit, RLD unit, Taguchi's orthogonal array testing (TOAT) unit and market clearing price (MCP) unit. The relationship between these four units is shown in this figure. As observed, information such as the technical constraints of the devices involved in the H-MG, prediction of the NRL demand and the non-dispatchable generation resources and offers of each existing resources in the H-MG are sent to the TOAT unit. TOAT is used to represent the probability distribution of the intermittent supply from non-dispatchable DERs, NRL and MCP profiles as addressed in literature (Marzband, Parhizi, et al., 2016). After applying uncertainty over the inputs, the total consumed power (TCP) and the total generated power (TGP) can be determined in ED unit by solving minimization problem based on an objective function subject to the constraints described in Section 3. After

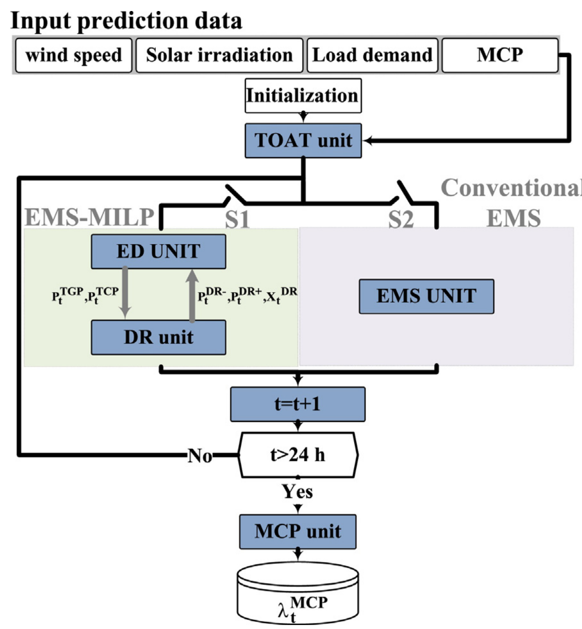

Fig. 3. Proposed EMS-MILP algorithm implementation consisting of load response RLD and economic distribution ED units.

selecting the H-MG operation mode (islanded or grid-connected) and by introducing a binary variable (i.e. X_t^{UG}), ED unit is computed and executed completely independent, irrespective of the optimum power values of the existing dispatchable and non-dispatchable DERs and NRL demands. Since the H-MG under consideration is operated in an islanded mode, there will be no power trade-off between/with the upstream grid. On the other hand, the grid connected H-MG can also make it possible to exchange information on power generation and consumption between H-MG and upstream grid. Noting the objective function and offers of the existing DERs in the H-MG, the excess power generation can be supplied to the upstream grid. RLD is also considered to be an alternative energy resource to keep this power in the H-MG instead of release it to the upstream grid. It can often help reduce the amount of power the corporation has to generate from expensive fossil fuels by dispatchable DER. EMS-MILP specifies based on the minimization of objective function (e.g. profit negative or operation cost), decides whether power exchange with the outside is beneficial for the MG owner or not. On the other hand, the amount of power allocated for the RLD can be specified by EMS-MILP incorporates the technical and economic constraints. After determining the optimum set-point powers of each DERs and the value of surplus and shortage powers, this information will be spontaneously sent to the RLD unit. For the first time, our novel EMS-MILP implementation incorporates all constraints for DR/DER where household consumed loads for a H-MG are classified as both interruptible loads (i.e. RLD) and noninterruptible loads (i.e. NRLD), respectively. For generated power in H-MG, the generation resources are more than the consumption amount by the consumers (i.e. at the beginning of the day) thereby excess generation is created, and the proposed EMS algorithm during operational times decides to supply RLD+ loads.

Also, when power shortage exists in the H-MG (i.e. at the end of the day) and the amount of generation resources is less than the amount of consumed power, the proposed EMS transfers interruptible loads from this time interval to other time intervals for helping system stability.

Determining that what amount of load demand can be shifted/supplied to/from a time interval to another is one of key roles of the RLD unit. The exchange of information between RLD and ED units performs the optimum scheduling via minimizing production cost and using both controllable and non-dispatchable resources, the variables transferred between these units are illustrated in Fig. 3. EMS unit receives power production information from different production and energy storage units during each time period followed by the performance optimization for MGs. ED unit determines the MG production units optimum level with the least exploitation cost considering technical and economic constraints. RLD unit performs equilibrium between the supply and demand for active load-defined reduction in MG production units to supply load demand, when load demand shift for different times cannot be provided directly. Controllable loads (i.e. RLD) also require power supply when excess production exists in the system, which is also facilitated by RLD. Overall integration successfully delivers optimum power balance conditions for a diverse nature of resources connected to the microrgid. After obtaining all power set-points and supply/consumer bids by using ED unit, all information must be dispatched to MCP unit. This unit makes the determination of MCP value possible that is the participation optimum powers in the market which are obtained through the ED unit. The process of this unit is implemented as shown in Fig. 4. In this flowchart, N_g and N_c are the equal to the number of generating and consuming agents in the electricity market, respectively. The proposed EMS-MILP algorithm is illustrated by a Pseudo-code in Algorithm 1.

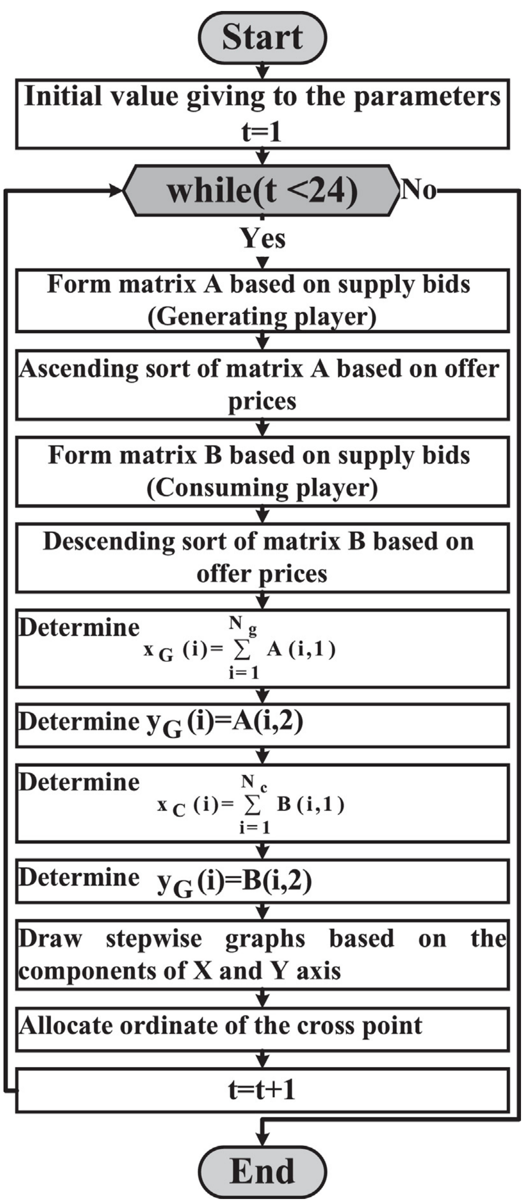

Fig. 4. Proposed MCP unit algorithm.

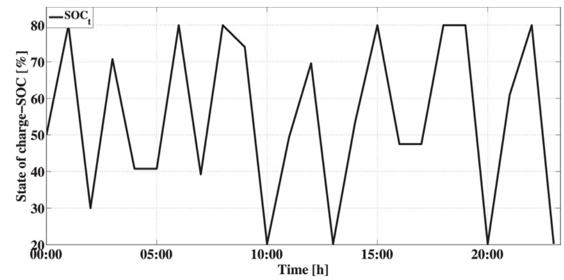

Fig. 5. SOC condition during the system 24 h performance.

Algorithm 1. EMS-MILP ALGORITHM

Require: Initialization ▷ Hourly prediction data of MG, $\overline{SOC}$, $\underline{SOC}$, $\overline{P}^{MT}$ and $\underline{P}^{MT}$.
while t $\leqslant$ 24 **do** ▷ EMS-MILP
1. **TOAT unit**
Generate power scenarios randomly for WT, PV and NRL with the probability of occurrence.
2. $P_t^{TGP}=P_t^{WT}+P_t^{PV}$ and $P_t^{TCP}=P_t^{n}$;
3. **if** $P_t^{TGP}= P_t^{TCP}$ **then**
The generated power will be spent supplying the main load by WT and PV.
4. **else if** $P_t^{TGP} \geqslant P_t^{TCP}$ **then**
$P_t^{EGP}= P_t^{TGP}- P_t^{TCP}$ ▷ **EGP: Excess generated power**
5. **if** $SOC_t \leqslant \overline{SOC}$ **then**
6. **if** $P_t^{EGP} \leqslant \overline{P}^{ES+}$ **then**
7. Isolated mode: Charging ES (P_t^{ES+}), supplying RLD ($P_t^{RLD+}= P_t^{EGP} -P_t^{ES+}$)
8. Grid connected: Charging ES (P_t^{ES+}), supplying RLD (P_t^{RLD+}), Selling to upstream grid ($P_t^{UG+}= P_t^{EGP}- P_t^{ES+}-P_t^{RLD+}$)
9. **else**
10. Isolated mode: Charging ES ($P_t^{ES+}= \overline{P}_t^{ES}$), supplying RLD ($P_t^{RLD+}= P_t^{EGP} -P_t^{ES+}$)
11. Grid connected: Charging ES ($\overline{P}_t^{ES}=P_t^{ES+}$), supplying RLD ($P_t^{RLD+}$), Selling to upstream grid ($P_t^{UG+}= P_t^{EGP}- P_t^{ES+}-P_t^{RLD+}$)
12. **end if**
13. **else** ▷ **Fully charged mode**
14. Isolated mode: supplying RLD ($P_t^{RLD+}= P_t^{EGP}$)
15. Grid connected: supplying RLD (P_t^{RLD+}), Selling to upstream grid ($P_t^{UG+}= P_t^{EGP}- P_t^{RLD+}$)
16. **end if**
17. **else if** $P_t^{TGP} \leqslant P_t^{TCP}$ **then**
$P_t^{TCP}- P_t^{TGP}= P_t^{SGP}$; ▷ **SGP: Shortage generated power**
18. **if** $P_t^{SGP} \leqslant \underline{P}^{MT}$ **then**
19. Turning on MT with with $P_t^{MT} = \underline{P}^{MT}$ and $P_t^{ES+} = P_t^{MT} - P_t^{SGP}$
20. **else if** $P_t^{SGP} \leqslant \overline{P}^{MT}$ **then**
21. $P_t^{MT}= P_t^{SGP}$
22. **else if** $SOC_t \leqslant \underline{SOC}$ **then** ▷ **Fully discharged mode**
23. $P_t^{MT} = \overline{P}^{MT}$ and $P_t^{RLD-}= P_t^{SGP}- P_t^{MT}$.
24. **else if** $\overline{P}^{ES-} + \overline{P}^{MT} \geqslant P_t^{SGP}$ **then**
25. Supplying generation shortage by using MT and ES.
26. **else**
27. $P_t^{ES-} = \overline{P}^{ES-}$, $P_t^{MT} = \overline{P}^{MT}$ and $P_t^{RLD-}= P_t^{SGP}- (P_t^{MT} + P_t^{ES-})$
28. **end if**
29. **end if**
end while
return Return determine the optimum capacity and profit of the all players.

5. Results and discussion

The proposed structure is validated over a case study which contains a grid-connected H-MG with different type of generation and consumer units. For this study, an H-MG has been configured by one PV (6 kW), one WT (8 kW), one MT (12 kW), one ES (2 kWh), and responsive/non-responsive load demand.

Fig. 5 shows state-of-charge (SOC) in the charge and discharge modes for the proposed algorithm. As demonstrated in this figure, during the time interval 00:00–06:00 the SOC value has not changed that much, at the beginning of interval because ES has acted in the charge mode the value of SOC has acted in the charge mode the value of SOC has reached to $\overline{\text{SOC}}$, and then by discharging and charging ES in the next hours, the SOC value at the end of this interval has approximately approached its initial value. As it is observed during the time interval 06:00–12:00, the increasing load demand and reduction in renewable generation (compared to the previous time intervals), the EMS decided to partially use ES to supply the shortage in power. The value of SOC in this time interval fluctuates. Such that at the beginning of this interval the SOC value has its maximum value (i.e. $\overline{\text{SOC}}$), then because EMS decides to use ES, the value of SOC at 10:00 o′clock has reached to $\underline{\text{SOC}}$. Generally in this interval, ES in 50% of the times is in the charging state and in 50% of the times operate in the discharging mode. At the beginning of this interval 12:00–18:00, because of not using MT for supplying load demand, EMS has used ES for helping to supply demand and as a result is in discharging mode and SOC value at 13:00 has reached to $\underline{\text{SOC}}$. Because of the suitable climate conditions for producing renewable resources the EMS has decided to use these resources with high capacity, not only satisfying NRL and ES charging consumption but also causing the generation of excess power, so EMS has spent the excess generated power supplying RLD. At the beginning of hour 15:00, the battery SOC reaches to its maximum limit. As a result, MT shut down is requested by the EMS while renewable resources are generating at the maximum available rates. During hour 15:00 and 16:00, scenario #2 is observed where the ES is utilized to supply load demand while MT is shut down. The battery SOC at the end of this interval will be reduced which is reasonable.

In the time interval 18:00–24:00, because of the occurrence of scenario #3, the proposed EMS at 19:00 has decided to use ES, so out of necessity the battery has discharged such that the value of SOC at 20:00 o′clock has reached to $\underline{\text{SOC}}$. Scenario #3 occurred during 18:00–24:00 time interval when load demand is at peak. In this case, MT is producing at the rated power ($\overline{P}^{\text{MT}}$). However, it is not enough to satisfy the total load demand. As a result, the ES is commanded by the EMS to cover the rest of the load demand. This way, battery SOC reaches to $\underline{\text{SOC}}$ at the end of the day. It is mentionable in this time interval, the value of SOC in 50% of the times has reached to $\overline{\text{SOC}}$ which shows the adequate performance of the proposed algorithm in managing the energy stored in ES. Generally during the total 24 h time interval, as for the highness of ES price bid in the discharge mode relation to MT, about 42% of the times ES has been used for supplying the consumed load (discharge mode), about 12% of the times idle (nor in the charging mode nor in the discharging mode) and about 46% of the times ES has been in the charging mode; so more charge has remained in it for essential times. As illustrated in this figure, more than 50% of the times during the system 24 hours performance, the value of SOC has been more than 50% which this fact shows the good support of load demand by ES in the proposed algorithm. It must be noted initialization conditions are based on a balanced SOC consideration be equal to $\sim$ 50%, under the maximum and minimum SOC bounds of 80% and 20% because E^{ES}_{Tot} and E^{ES}_{I} are respectively considered equal to 2 and 1 kWh, thereby initial $\text{SOC}_t = \frac{E^{\text{ES}}_t}{E^{\text{ES}}_{\text{Tot}}}$ equals to $\sim$ 50%. As SOC_t is the energy storage state-of-charge and $E^{\text{ES}}_{\text{Tot}}$ is the total energy stored in ES (battery system our case), the presented model has no baring on ES overall capacity, and/or SOC initialization conditions on the final simulated results. In Fig. 6, the bar-graph related to power generated by generation resources has been shown. As it is obvious during the interval 00:00–06:00, MT has been in service during all this time interval always with its minimum power ($\underline{P}^{\text{MT}}$) and EMS in addition to supplying the NRL consumed load demand and charging ES, has spent excess power supplying RLD. As it is observable from the figure, wind turbine is always in service in this time interval and photovoltaic because of lack of sunshine has been out of service.

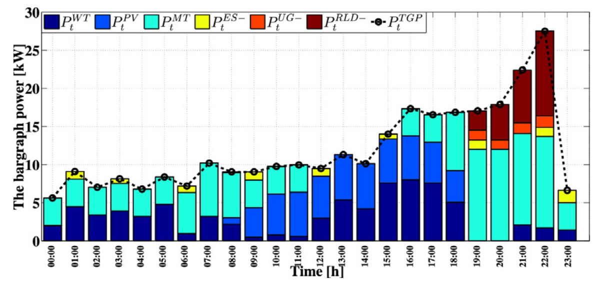

Fig. 6. Barograph related to the power produced by generation resources.

During the time interval 06:00-12:00, MT is always in service and during the first half of this interval (06:00–09:00), because the NRL load demand has increased relative to the previous interval and renewable resources operate with their low production capacity, EMS for supplying the NRL required power has to use more MT production capacity, but in the end half of this interval because PV resource power has increased, MT operates in service with its minimum power. Generally MT has always been in service in this time interval and EMS in addition to supplying the NRL required power and charging ES, has spent excess generated power supplying RLD power. During the time interval 12:00–18:00 scenario #2 has occurred. As for the suitable climatic conditions for generating renewable generation resources, these resources have been put to service with their high capacity and because of the lower price bid of renewable resources relative to MT, the proposed EMS has made a correct decision for turning off MT about 67% of the times which causes the system total cost reduction.

As for the occurrence of scenario #2 in this time interval, it is observable that the proposed algorithm has supplied the power required by NRL and power required by ES for charging and has spent the excess power created supplying RLD power which shows the good algorithm performance for optimum use of production resources and satisfying the consumers demand with the objective of minimizing the total cost of H-MG. Also ES in this interval has operated in the discharging mode about 34% of the times. During the interval 18:00–24:00, scenario #3 has occurred. MT despite higher price bid relative to renewable resources has been in service 67% of the time with its maximum capacity ($\overline{P}^{\text{MT}}$), to supply load. Because of the increase of load demand in this time interval, EMS cannot satisfy the total consumption demand. As a result the EMS has attempted to buy power from the upstream grid ($P_t^{\text{UG}-}$) and shift consumption load ($P_t^{\text{RLD}-}$) to other hours. Generally during the total 24% time interval, about 83% of the times the designed EMS has attempted to use MT. Also, regarding renewable generation resources, WT has been in service about 92% of the times and PV has been in service about 46% of the time. So the proposed EMS has tried all its effort for supplying the consumed load by using these resources, because producing these resources has no cost for the H-MG, as a result supplying the consumed load with these resources will bring more profit for the H-MG.

In Fig. 7, the bar-graph of the power consumed by consuming resources has been shown in each time interval. In the time interval 00:00–06:00 the value of NRL load relative to other time intervals is much less and the proposed EMS in addition to supplying the NRL total demand and charging ES, has supplied the RLD power. About 11% of NRL total load demand and about 65% of total RLD power participation share is located in this time interval. During the time interval 06:00–12:00 the amount of NRL load demand has reduced relative to the previous time interval and the proposed EMS has spent a small amount of the excess power supplying RLD power. In addition to supplying total NRL demand, at 07:00, 10:00 and 11:00 o′clock, the EMS has supplied the ES charging consumption.

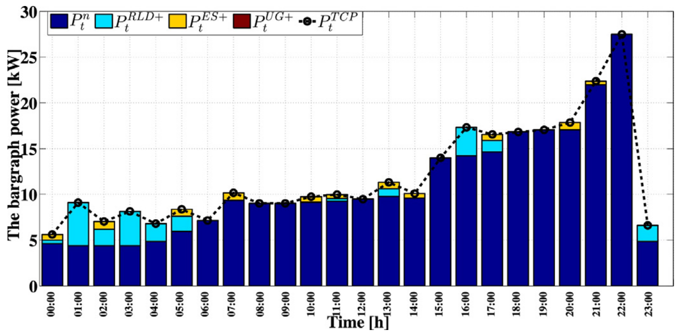

Fig. 7. Bargraph related to the consumed power by consumers.

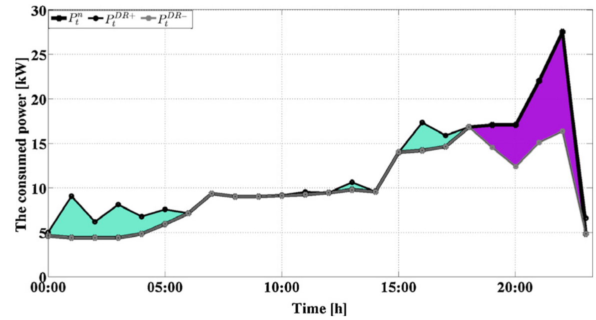

Fig. 9. Electrical MCPs in the different optimization algorithms.

About 20% of total NRL demand is in the time interval 12:00–18:00. In this time interval, despite the occurrence of scenario #2 and the increase of consumption demand relative to previous intervals, and although only about 9% of total generated power in this time interval is related to MT (about 67% of the time MT is out of service), but because of suitable climate conditions for producing renewable resources with high capacity, excess production has been created. In addition to supplying total NRL demand and charging ES, the EMS has spent excess power supplying RLD. This shows the adequate performance of proposed algorithm in the occurrence of scenario #2. During the time interval 18:00–24:00, scenario #3 has occurred, as has the system load demand peak has occurred and about 40% of the total NRL power demand. But because production resources cannot supply the total load demand in this interval, EMS is forced to shift consumed load ($P^{\text{RLD}-}_t$) to the other hours of the day and to buy power from the upstream grid ($P^{\text{UG}-}_t$). At the end of this time interval, because of the reduction of consumption demand, excess generated power has been allocated to supplying RLD power.

It is notable that about 25 kW of created excess consumption has been shifted to other hours and about 5 kW has been estimated through buying power from the upstream grid ($P^{\text{UG}-}_t$). Also, as can be observed, the H-MG under study has not allocated excess power for selling to the upstream grid, that is it has spent all the excess generated power supplying RLD and charging ES. Fig. 8 is related to RLD+ and RLD- curves and NRL load demand during the system 24 h performance. From this figure it is observable that in the final hours of the day the amount of load demand is much more than other times; as a result the EMS has attempted to shift consumed load to other hours of the day, so that about 17% of the times during the total system 24 h interval the EMS has attempted to shift consumed load to other hours, namely 19:00, 20:00, 21:00 and 22:00 in which the system load peak has occurred. As shown in this figure, proposed EMS at the early hours of the day and during sunset has allocated a power for RLD. Generally during the total 24 h interval,

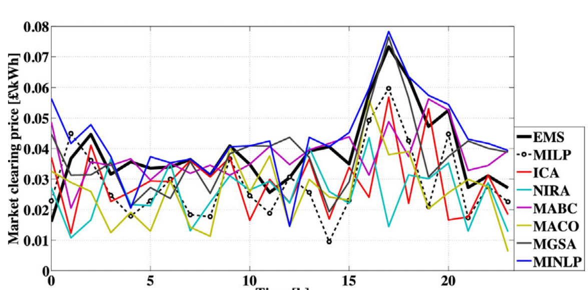

Fig. 8. RLD+ and RLD-load demand profile comparison for EMS system over 24 h performance benchmark.

EMS successfully supplies 50% of the times the responsive loads, being the primary allocated power fraction for supplying responsive load for the initial time interval 00:00–06:00. The excess power is generated when RLD+ occurs at the beginning of the day since NRLD load demand is low, and this power is already spent supplying RLD+. In comparison, RLD− occurs when excess consumption is proposed and the system cannot supply load consumption from other production resources. In specific, RLD- ensues at the end of the day relative to other times since for that period the load demand increases for the proposed EMS algorithm that shifts the excess consumption to other times for maintaining overall system stability under balancing conditions. After performing scheduling using the RLD constraints of Eq. (23), the sum of shifted power from all intervals to other time intervals (RLD−) equals to the sum of the value of RLD+ supplied to load. EMS supplies 50% of times the responsive loads, where allocated power for supplying responsive load is related to the time interval 00:00–06:00. The excess power is generated under RLD+ only at the beginning of the day, since NRLD load demand is low, and this power is spent supplying RLD+. Although, RLD− occurs when excess consumption is proposed and system cannot supply load consumption from other production resources, generally at the end of the day because load demand increases for the proposed algorithm shifts for excess consumption to other times for maintaining system stability.

The values of MCP obtained by EMS-MILP algorithm (λ^1_t), without optimization algorithm (EMS unit) (λ^2_t), imperialist competitive algorithm (ICA) (λ^3_t) (Marzband, Parhizi, et al., 2016), NikaidoIsoda/relaxation algorithm (NIRA) (λ^4_t) (Marzband, Javadi, et al., 2016), multi-artificial bee colony (MABC) (λ^5_t) (Marzband, Azarinejadian, et al., 2015), multi-ant colony optimization (MACO) (λ^6_t) (Marzband, Yousefnejad, et al., 2016), multi-gravitational search algorithm (MGSA) (λ^7_t) (Marzband et al., 2014), mixed integer non-linear programming (MINLP) (λ^8_t) (Marzband, Sumper, Domínguez-García, et al., 2013) is shown in Fig. 9. As depicted in this figure, demand side strategy applied in EMS-MILP algorithm has had a significant effect in reducing the MCP value in almost all of the time intervals. MCP values obtained from EMS unit are higher than those from EMS-MILP algorithm in all of time intervals when H-MGs operate by the proposed algorithm. In particular, the difference between λ^1_t, λ^2_t and λ^3_t has respectively reached 79% and 92% of time intervals; considering that it has undergone even more intense reduction under λ^4_t up to 33% of time intervals than any other algorithms. It is worthful to mention here that the maximum and minimum values of MCPs have had significant reduction in all the possible scenarios as seen in Fig. 9. This is while the maximum value of λ^1_t is reached by 4–28% in comparison with MCP under different algorithm. In addition, the minimum value of $\lambda^1_{t,e}$ has shown more reduction (between 17% and 96%) relative to MCP in all the implemented algorithm. The proposed demand side management among H-MGs undoubtedly had considerable effect in lowering the maximum values of MCP especially with respect to case that H-MGs are allowed to work more independently. This is while the maximum value of MCP is negligibly increased under λ_t^8, but its minimum value is significantly reduced under λ_t^1. By comparing the values of λ_t^1 and λ_t^2 shown in Fig. 9, when MCP has its maximum value under all time interval, EMS-MILP algorithm has tried to motivate the customers shift their demand to off-peak period when MCP is lower and when it is more convenient for the H-MG to produce electricity. Regarding the minimum value of λ_t^1, it is relevant to mention that it has occurred at the early hours of the day in all the possible condition in which a significant reduction in the value of λ_t^1 is observed at the end of the day.

6. Conclusions

An intelligent energy management system using mixed-integer linear programming EMS-MILP for smart form sustainable power generation and delivery optimization for an H-MG structure is demonstrated. The stochastic optimization algorithm devised for H-MG outperforms its conventional counterpart under different load patterns, wide ranges of non-dispatchable/dispatchable DER installation capacity and electricity economization. In specific, using fast computational timesteps of about ∼30 s, accuracy to produce higher accuracy, compatibility, extendibility and flexibility, for both offline and online power and energy distribution in H-MG applications. The optimization reduces energy costs due to non-dispatchable DER installation, and decreases the systems′ dependence on traditional centralized generations. Also, where a combination of proposed ES and RLD integrated structure help not only to reduce the operational cost of the H-MG, but also to prevent unwanted events to effect system performance. The above concept signifies how an increase in the number of H-MGs in a multiple electrically/thermal coupled global grid system reduces the operational cost and/or maximizing profit at initial stages before dynamic variability's, cost starts to increase. In addition, the optimization highlights full control agility of generation and consumption trends to maintain maximize/minimize its economical profit/operational cost by making an intelligent power balance and exchange for H-MGs with upstream global grids at all times. Numerical simulations show the effectiveness of EMS-MILP algorithm in optimizing a moderate correlation between ES and RLD integrated H-MGs. In specific, this is advantageous to, stationary ES to store excess power generated in economically expensive Microgrids, where effective and cost reduction functionality can be achieved by this optimization strategy by integrating a RLD schedule in real-time. The stochastic optimization algorithm also offers ability for power system administrators to further enhance operational efficiencies for grid-connected integrated H-MG structures with different non-dispatchable /dispatchable DER resources. In summary, the proposed methodology can be fully incorporated for all global H-MGs with integrated multivariate renewable energy generation, distribution resources and loads under optimal real-time better management, performance and scheduling, adaptable versatile industrial standards and compliances.

Acknowledgments

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Energy matching and trading within green building neighborhoods based on stochastic approach considering uncertainty

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ABSTRACT: Non-dispatchable generation resources can be installed as small scale generation units that environmentally and economically could be competitive with conventional power generation. To reach this aim, a hybrid system including several types of non-dispatchable generation, dispatchable generation resources incorporated with energy storage assets can provide a sustainable necessary electricity/thermal/water pumping power during a green building's daily operation. The objective of this paper is to model a dynamic system for a single green building considering several generation resources for feeding of some electrical and thermal specific load demands needed in a sustainable way. The proposed model based on a dynamic decision process is implemented to manage and monitor a complex hybrid system encompassing several generation resources and load demands by considering various uncertainties. In order to handle the uncertainties, scenario generation approach is utilized. The model is developed in The General Algebraic Modeling System (GAMS) environment in order to determine the optimal solution with scheduling resources by setting up the optimal power set-points for them. The optimization model is applied to a case study where the produced power is also used to supply water pumping for domestic consumption. Furthermore, other capabilities such as extendibility, reliability, and flexibility are examined about the proposed approach.

Keyword: Green buildings, energy management system, mixed integer linear programming, distributed energy resources.

I. INTRODUCTION

A continuous and optimal supply of energy demand throughout a day in green building is an incredibly complex issue which could be addressed by future research. Due to the intermittency nature of the renewable energy resources and the load demand, some alternative cooling/heating systems with integrated energy storage are poised for success. To accomplish this, some strategies can be also profitably used to manage the energy storage. It can be adjusted to improve efficiency, to maintaining stability under increasingly environment robustness. The most important feature of this may be its ability to reduce carbon dioxide emissions as well as to provide an optimal mode scheduling in hybrid systems which will be installed on a green building [1]–[3]. Under this direction, renewable energy technologies that utilize renewable energy resources such as the sun, the wind, biomass, geothermal, water, and so on can be used in the green buildings [4]. These energy generation resources are naturally available and environmental friendly. Since the energy supplied by the renewables is unpredictable and intermittent, uncertainty analysis is essential tool to obtain a robust representation of model predictions consistent with the state-of-knowledge [5]. Furthermore, energy storage (ES) devices integrated with these generation resources based on renewable energy sources can be a great way to increase power reliability, improve power quality, decrease electricity bills, reduce carbon footprint, or even realize energy autonomy [3]. During daily operation in these systems, the power exchange between household and upstream grid can be treated if there is insufficiency or excess generations in either side. It can help to verify the possibility of a power sharing optimization between these parties. In this regard, a proper energy management system (EMS) is crucial to avoid any mismatch in power [5]. Moreover, EMS in the top-level management should be able to supply all load demands including large residential/ commercial buildings and industrial consumers without any interruption [4]. It means that if the total generated power by renewable resources at each time interval in the green building is bigger than the load demand, this excess generation can be applied to supply ES, to feed responsive load demand as well as to sell to the upstream grid. In addition, it is possible that this green building may have a generation shortage during daily operation system. All these cases, and others, can be controlled and monitored by the developed EMS.

The contributions of this paper are as follows:

1-To propose a comprehensive model based on mixed integer non-linear programing (MINLP) within a green building toward scheduling for the day-ahead operation plan of a grid-connected green building. In this context, a comprehensive model is presented and illustrated that it is flexible and could be used for different configurations of green building systems;

2-To formulate an uncertainty mechanism based on scenario analysis approach.

II. Problem statement

A green building connected to the upstream grid with several energy generation facilities and energy storage technology and load demand is depicted in Figure. **1**. The proposed system is developed for a household where electrical, thermal and water pumping is needed at the same time by the consumers, so that the distributed energy resources (DER) have to be the optimal choice to determine the supply and load demand. The important goal of this structure is the maximum use of renewable and existing resources in green buildings and also optimum management of existing loads in it while satisfying pay-off function for both sides. In the proposed structure, the decision making variables are the quantities (the production and consumption resources offers). The performance of green building is studied in a typical day on an hourly basis, under the assumption that a similar operation could be done for each day. The proposed problem in this paper is multi-period and thought to be applied for planning and scheduling hourly day-ahead purposes of green building and DER, that is, not in real time. However, it can be easily expanded and adopted to the real-time applications. As seen in this figure, the system has several DERs which can easily deliver the desired output power within a board range of operating parameters and some given constraints.

III. EMS-MINLP architecture

The proposed framework in this paper to develop an optimal decision support system is shown in Figure. 2. This framework for energy management system based on mixed integer non-linear programing (termed EMS-MINLP herein) is composed to two sub-units, namely scenario generation unit, and energy management system (EMS) unit. As seen in this figure, first, the predicted values of electrical/thermal and water pumping load demand, wind power generation and solar irradiation should be sent to scenario generation unit in order to integrate uncertainties inherent to the evaluations. The relevant scenarios of each parameter with the related probabilities can be generated in this unit. This unit is modelled using the scenario decision tree method. After calculation of weighted values of each uncertainty parameters in scenario generation unit, these values will be sent to EMS unit. In this unit makes decisions, for each period, about the quantities to electricity and thermal generate and related procedures for electricity supply, to buy/sell from/to the upstream grid, considering technical and economic constraints.

The EMS unit assign priority to overcome the shortage of electricity/thermal, offer to decrease production or increase consumption in situations when there is a surplus of electricity in the system based on offer prices associated with generation units or the defined objective function. In addition, it can choice best possible energy alternative to trade energy between green building and upstream grid aiming to optimize a certain objective function.

The optimization problem proposed in EMS-MINLP unit is a non-linear programming in the general case and a linear programming in some particular cases. This optimization problem consists of an objective function and a set of constraints. A general description of this optimization problem is provided in what follows, and they will be described in detail in the problem formulation section.

IV. Problem formulation

The system under study is considered a grid-connected green building including non-dispatchable generation resources (wind turbine- WT, photovoltaic-PV and flat plate collector- FPC) and dispatchable generation resources (biomass- BIO) and energy storage-ES supplying some non-responsive load demand (electrical, thermal and water pumping). The aim of the proposed EMS is to minimize thermal and electrical losses, to maximize the energy sold to the upstream grid, to increase the energy stored in the ES or to improve state-of-charge (SOC). The optimization problem is defined as the following objective function:

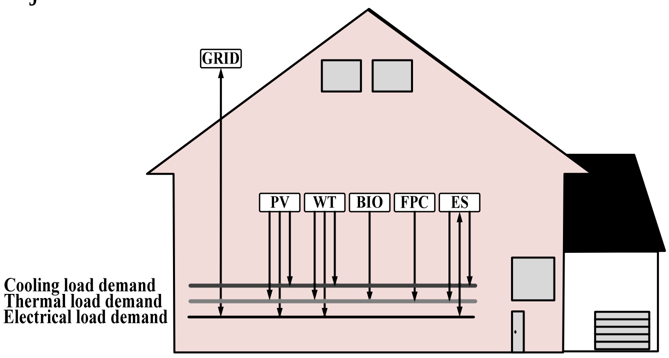

Figure. 1. Energy flows between the hybrid system and the green household

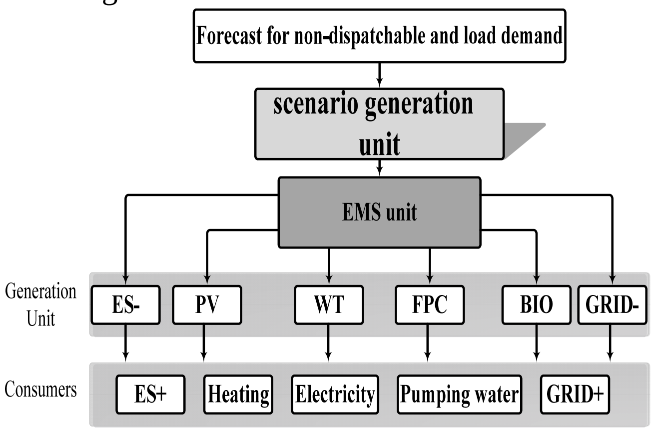

Figure. 2. EMS-MINLP architecture

$$Z=\sum_{t=1}^{T}\left(\begin{array}{l}\alpha\cdot\left(\begin{array}{l}E_{(t,s)}^{WT,th}+E_{(t,s)}^{\mathrm{PV},th}+E_{(t,s)}^{\mathrm{FPC},th}+\\E_{(t,s)}^{\mathrm{BIO},th}+E_{(t,s)}^{GRID,th}+\\E_{(t,s)}^{ES,th}-E_{(t,s)}^{\mathrm{D},th}\end{array}\right)^{2}+\\\beta\cdot\left(\begin{array}{l}E_{(t,s)}^{WT,\mathrm{ele}}+E_{(t,s)}^{\mathrm{PV,ele}}+\\E_{(t,s)}^{GRID,\mathrm{ele}}+E_{(t,s)}^{ES,\mathrm{ele}}-E_{(t,s)}^{\mathrm{D,ele}}\end{array}\right)^{2}+\\\gamma\cdot\left(\begin{array}{l}\dfrac{E_{(t,s)}^{WT,\mathrm{ele}}+E_{(t,s)}^{\mathrm{PV,ele}}+E_{(t,s)}^{GRID,\mathrm{ele}}+E_{(t,s)}^{ES,\mathrm{ele}}}{\rho gh}\cdot\eta_{ps}-\\E_{(t,s)}^{D,wp}\end{array}\right)^{2}+\\\varphi\cdot E_{(t,s)}^{GRID,ele}+\gamma\cdot E_{(t,s)}^{ES,\mathrm{ele}}-\rho\cdot SOC_{(t,s)}^{ES}\end{array}\right)\quad(1)$$

$$\forall\, t\in\{0,\ldots,T\}$$

where T is the number of simulation periods in time interval t. The objective function in (1) allows autonomous or grid connected decision making to determine the hourly optimal dispatch of generators depending on system technical and economic constraints. The three first six items in (1) represent the energy losses due to the transport of electrical/thermal and water pumping power energy, related to the characteristics of the distribution system, the supplied demand and types of equipment in use. The forth item is the net electricity power between upstream grid and green building. The two last items are included in the objective function to improve ES performance in order to supply the load demand as economically as possible within pre-defined continuity, quality and security patterns. $\alpha,\beta,\varphi,\gamma$ and ρ are weighting factors. $E_{(t,s)}^{A,th}$ is the generated energy by A resources which can be estimated by

$$E_{(t,s)}^{A,th}=P_{(t,s)}^{A,th},\quad \forall A\in\left\{\begin{array}{l}WT,PV,FPC,BIO,GRID+,\\GRID-,ES+,ES-\end{array}\right\}\quad(2)$$

The decision variables of the optimization problem are the power produced by generation resources and the consumed power by consumers, and SOC. The minimization of the objective function is subject to the following constraints.

A. *Wind turbine (WT)*

The following model is used to simulate the electrical power generated by WT [6]:

$$P_{(t,s)}^{WT}=\begin{cases}0 & V_{(t,s)}\le V_{ci}\\ P_r^{WT}\times\dfrac{\left(V_{(t,s)}\right)^2-V_{ci}^2}{V_r^2-V_{ci}^2} & V_{ci}\le V_{(t,s)}\le V_r\\ P_r^{WT} & V_r\le V_{(t,s)}\le V_{co}\\ 0 & V_{(t,s)}>V_{co}\end{cases}\quad(3)$$

where $V_{(t,s)}$ is the wind speed in time interval t under scenario s (m/s). It is worth to mention that the wind speed is predicted by some meteorological model and hence these predictions are retained as realistic ones. P_r^{WT} represent the rated electrical power, V_{ci}, V_{co} and V_r are the cut in, the cut off and the rated wind speed, respectively. In general, the wind speed measurements are given at a height different than the hub height of the wind turbine which can be expressed by

$$V_{(t,s)}=\tilde{V}_t\times\frac{\ln(H_{hub}/z)}{\ln(H_{meas}/z)},\quad \forall\, t\quad(4)$$

where H_{hub} and H_{meas} are the hub height and the height of the measurement, respectively. z is the surface roughness length and $\tilde{V}_t$ is the forecasted wind speed at the height of the measurement.

B. Photovoltaic (PV) [7]

The power generated from PV modules can be calculated using the following formula [8]:

$$P^{PV}_{(t,s)} = S^{PV} \times \eta^{PV} \times p^{f} \times \eta^{PV} \times G_{(t,s)} \quad (5)$$

where S^{PV} is the solar cell array area, η^{PV} is the module reference efficiency, p^{f} is the packing factor, η^{PV} is the power conditioning efficiency and $G_{(t,s)}$ is the forecasted hourly irradiation.

C. Flat plate collector (FPC)

The useful thermal energy extracted from the water collector depends on the instantaneous incident solar irradiation, the plate area, and its efficiency [9]. It can be formulated as:

$$E^{FPC}_{(t,s)} = \eta^{FPC} \times A^{FPC} \times G_{(t,s)} \times \Delta t \quad (6)$$

where η^{FPC}, A^{FPC} and $G_{(t,s)}$ are the efficiency of the solar FPC, the area and the forecasted hourly irradiation, respectively. Δt is the energy management time step. During summer period when normal heat supply to the district heating is required less, water for heating passing through the FPC may be stopped. This constraint can be formulized as follows:

$$E^{FPC}_{(t,s)} \geq E^{FPC,th}_{(t,s)} \quad (7)$$

D. Biomass (BIO)

Energy provided by the biomass heating plant depends on the used biomass quantity $u_{(t,s)}$, the biomass volumetric mass (VM) (i.e. the ratio between the dry mass and the volume), the lower heating value (LHV).

The LHV assumes that the latent heat of vaporization of water in the fuel and the reaction products is not recovered. Then, it can be calculated once higher heating value (HHV) and moisture content (MC) are known. The HHV is the total energy release in the combustion with all of the products at 273 K in their natural state when water has released its latent heat of condensation. In the present work, the HHV is evaluated from the basic data analysis of biomass. The biomass MC represents the water amount present in the biomass and it can be expressed as a percentage of the dry weight. As regards production plant, the plant is supposed to operate at the maximum productivity level. The following equation provides the plant developed energy [10]:

$$E^{BIO}_{(t,s)} = f \times \eta^{BIO} \times LHV \times u_{(t,s)} \times VM \quad (8)$$

Biomass may not be used (especially during summer, heating is not necessary and cannot be sent to the network), as a result this constraint can be defined as follows:

$$E^{BIO}_{(t,s)} \geq E^{BIO,th}_{(t,s)} \quad (9)$$

E. Energy storage (ES) [3], [11]–[13]

$$SOC^{ES}_{(t,s)} \leq C^{ES}_{\mathrm{Tot},(t,s)} \quad (10)$$

$$E^{ES}_{(t,s)} = E^{ES,\mathrm{ele}}_{(t,s)} + E^{ES,th}_{(t,s)} + E^{ES,\mathrm{wp}}_{(t,s)} \quad (11)$$

$$E^{ES}_{(t+1,s)} = E^{ES}_{(t,s)} + E^{WT,ele}_{(t+1,s)} + E^{PV,ele}_{(t+1,s)} + E^{GRID,ele}_{(t+1,s)} \quad (12)$$

F. Upstream grid (GRID)

$$E^{GRID,ele}_{(t,s)} \leq E^{WT,ele}_{(t,s)} + E^{PV,ele}_{(t,s)} \quad (13)$$

G. Equations

$$E^{th}_{(t,s)} = \begin{bmatrix} E^{WT,th}_{(t,s)} + E^{PV,th}_{(t,s)} + E^{FPC,th}_{(t,s)} \\ + E^{BIO,th}_{(t,s)} + E^{GRID,th}_{(t,s)} + E^{ES,th}_{(t,s)} \end{bmatrix} \quad (14)$$

$$E^{ele}_{(t,s)} = E^{WT,ele}_{(t,s)} + E^{PV,ele}_{(t,s)} + E^{GRID,ele}_{(t,s)} + E^{ES,ele}_{(t,s)} \quad (15)$$

$$E^{wp}_{(t,s)} = E^{WT,wp}_{(t,s)} + E^{PV,wp}_{(t,s)} + E^{GRID,wp}_{(t,s)} + E^{ES,\mathrm{wp}}_{(t,s)} \quad (16)$$

The amount of pumped water is proportional to the energy used for this purpose, that is: [10]

$$Q^{wp}_{(t,s)} = \frac{E^{wp}_{(t,s)}}{\rho g h} \times \eta_{ps} \quad (17)$$

V. RESULT AND DISCUSSION

The operation of the case study is optimized based on available day-ahead hourly non-dispatchable and dispatchable generation resources for given electrical, thermal and water pumping demands. The uncertainty parameters are the electricity and thermal load demand in green building, wind speed, solar radiation. The input of optimization model can be classified as follows:

1-Electrical/thermal and water pumping demands by the consumers;

2-Data about locally available energy resources including solar irradiation data (w/m^2) and wind speed (m/s) as shown in Figure. 3;

3-Technical and economic performance of non-dispatchable and dispatchable DERs. These characteristic include, for example, rated power for PV, power curve for WT, the capacity of ES and the initial value of SOC.

To begin, EMS-MINLP algorithm receives data including the generated power by non-dispatchable DERs and load demands provided by the scenario generation unit, the ES SOC. Then, all the optimal power set-points of other generation resources will be dispatched to them at each time interval based on the EMS algorithm in this unit. The electrical/thermal and water pumping load demand profiles are shown in Figure. 4. The real life experimental data carried out from [3], [10] are used to simulate WT, PV and load demand profiles.

The power generated by non-dispatchable and dispachable DER resources (BIO, ES during discharging operating mode, FPC, PV, and WT) and the electricity bought from upstream grid are presented in Figure. 5. The obtained results, indicated in Figure. 5, show that the most of the necessary power for supplying the water pumping and electricity load demands (around 85% and 93%, respectively) is provided by electricity purchased from the upstream grid and the rest of power is supplied by the ES if it is possible according to the present value of SOC and WT generation unit (about 14.5% and 3.5%, respectively). This is while all generated power by PV is only used to supply ES during charging mode. Upstream grid has still a significant role to play for supplying the thermal demand (almost 47%). FPC, BIO and ES are available generation resources that are identified to produce the rest of thermal power (28%, 9.5%, 16%, respectively).

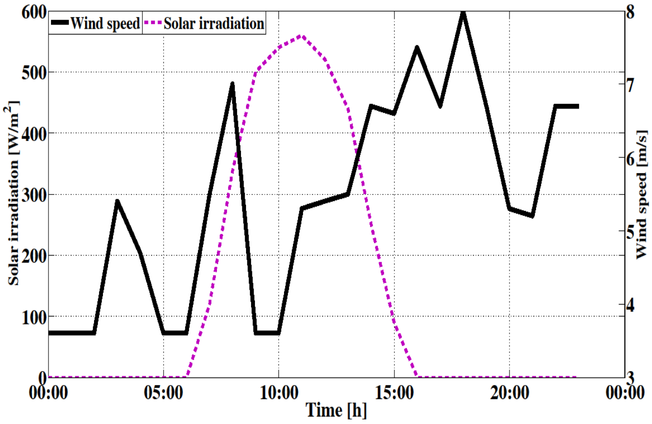

Figure. 3. input wind speed and solar irradiation as used in the model

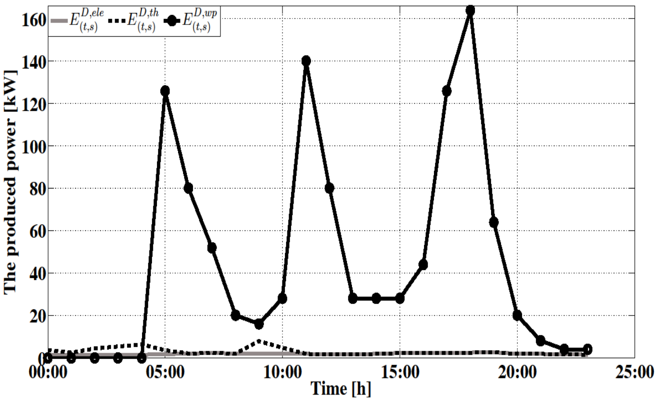

Figure. 4. Electrical/thermal and water pump load demand profiles

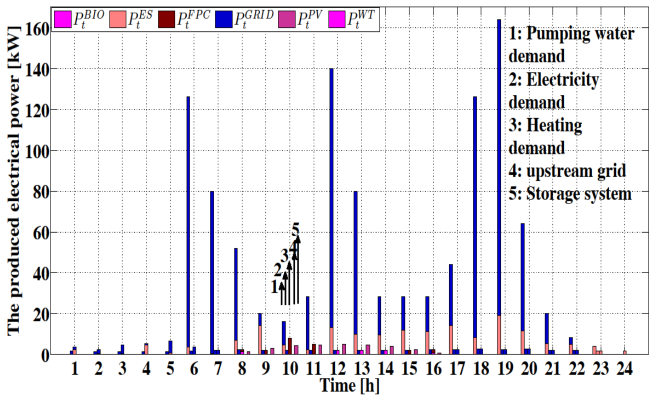

Figure. 5. The bar-graph related to the DER resources during system performance

VI. Conclusion

Since renewable resources have intermittent characteristics, approaches to analyse the energy management in green buildings would be stochastic rather than deterministic. To take the uncertainties into account, scenario generation method is implemented. Decision making model base on stochastic algorithm is presented for energy management within the residential buildings. The principal benefits of the proposed algorithm can be summarized as follows:

1-maximize usage of non-dispatchable based on renewable generation;

2-prioritization for the charging/discharging of the ES devices inside green building as a result reliability enhancement;

3-To better manage, leverage and utilize energy resources and sustained economic growth.

This model also has ability to add a new generation resource which can be usually utilized to install in various hybrid systems. Furthermore, it can identify possible capability in the distributed economic dispatch strategy, where multiple green building with independent EMS taking into account load sharing function can be exploited without accordant modification in design/requirement model. The obtained simulation results show the significant reduction of the total electrical/thermal loses (about 10%) and the significant improvement in ES operation in each time interval. Furthermore, the proposed model can also be applied for the real-time energy management online application.

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NOMENCLATURE

The main notation used throughout the report is stated below for quick reference. Other symbols are defined as required.

Acronyms

BIO	Biomass.
DER	distributed energy resources.
ES	energy storage.
ES+, ES- modes.	ES during charging/discharging
FPC	Flat plate collector.
MINLP	Mixed-integer nonlinear programming.
PV	Photovoltaic.
GRID	Upstream grid.
SOC	State-of-charge.
WT	Wind turbine.

Variables

$E^{A,th/ele}_{(t,s)}$: the produced electrical/thermal energy by A at each time t under scenario s (kWh)

$E^{D,th/ele}_{(t,s)}$: the electrical/thermal load demand during time interval t under scenario s (kWh)

$E^{D,wp}_{(t,s)}$: the amount of load demand for water pumping (kWh)

$A \in$ {WT, PV, FPC, BIO, GRID+, GRID-, ES+, ES-}

$Q^{WP}_{(t,s)}$: the amount of pumped water in time t under scenario s (m^3/h)

η_{ps}: pumping water efficiency (%)

ρgh: density of pumping water (kW/m^3)