ALGORITHMS FOR ENERGY MANAGEMENT IN MICRO-GRIDS

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Declaration

بسم الله الرحمن الرحيم

I hereby declare that except where specific reference is made to the work of others, the contents of this Ph.D thesis are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University. This thesis is the result of my work and includes nothing which is the outcome of work done in collaboration, except where explicitly indicated in the text. Parts of this thesis appeared in the following refereed papers in which by own work was that of a full pro-rata contributor.

1. M. Arikiez, P. Gatens, F. Grasso, and M. Zito. Smart domestic renewable energy management using knapsack. In *2013 4th IEEE/PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, pages 1–5, Copenhagen Oct 2013.
2. M. Arikiez, F. Grasso, and M. Zito. Heuristics algorithm for coordinating smart houses in microgrid. In *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 49–54, Miami Nov 2015.
3. M. Arikiez, F. Grasso, and M. Zito. Heuristics for the cost-effective management of a temperature controlled environment. In *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, pages 1–6, Bangkok Nov 2015.
4. M. Arikiez, F. Grasso, D. Kowalski, and M. Zito. Heuristic Algorithm for Minimizing the Electricity Cost of Air Conditioners on a Smart Grid. In *2016 IEEE International Energy Conference and Exhibition (ENERGYCON)*, pages 1–6, Leuven April 2016.
5. M. Arikiez, F. Grasso, and M. Zito. Minimizing the electricity cost of coordinating houses on microgrids. In *2016 4th IEEE/PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, pages 1–6, Ljubljana Oct. 2016.
6. M. Arikiez, F. Grasso, and M. Zito. Heuristic Algorithm for Minimizing the Electricity Cost of Smart House. *Submitted to Journal of Energy and Power Engineering*, 2016.

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Abstract

Population explosion is one of the primary causes for concern in the power sector nowadays because residential buildings consume a high percentage of available electricity in the market. Also, the majority of current power plants use fossil fuel to generate electricity which makes the situation even worse due to the high price of fossil fuel. Consequently, electricity bills have soared dramatically in the last decade. If that was not enough, many countries have a shortage of electricity because they cannot increase their generation capacity to cover electricity demand. Many solutions have been introduced to improve the efficiency of the power grid and reduce electricity price for the users. For instance, Demand Side Management and Demand Response, domestic top-roof renewable micro-plants, and distributed renewable plants are introduced as a part of the solution to improve the situation. However, users are still paying a high percentage of their monthly income to electricity companies, that is because the surplus renewable power is not well utilized. The primary problem here is to find an efficient way to minimize the electricity cost and maximize the utilization of renewable power without using storage systems (batteries). Another issue is to solve the massive power allocation optimization problem in polynomial time. In this thesis, heuristic optimization algorithms are proposed to cope with the complexity of the problem as these kinds of problems are NP-hard. Furthermore, a set of different power allocation problems has been addressed in this thesis. The first one uses an online algorithm to solve power allocation problem that is modeled as a Knapsack problem. Additionally, the thesis has coped with the computational issue of a massive LP-based optimization problem of large buildings. Finally, an MILP-based heuristic algorithm has been used to solve power allocation problem in micro-grids (a set of houses shares renewable power for particulate rate). The empirical experiments and evaluations, in general, show promising results. The findings depict how an appropriate knapsack formulation can be used to address a significant dynamic energy allocation problem in a straightforward and flexible way and how good our heuristic algorithms can solve enormous power optimization problem in polynomial time. Finally, the results prove that our micro-grid model can reduce power bills by using the principle of renewable power sharing for a fair price.

To my parents.

اهداء الى والدي

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I would like to start by thanking Allah Almighty for giving me the patience, inspiration, time, and strength to finish this work. With Allah's will and mercy, I have been able to achieve this framework. Also, I would like to extend my respect to Prophet Mohammed, peace be upon him and all other Prophets. I also would like to thank my country, Libya, for giving me this chance and supporting me financially to study for a Ph.D. degree.

It is a great pleasure to thank the people who supported me during my Ph.D. Words will never be enough to express my gratitude to them. When looking back on the path leading to this milestone in my academic and personal life, there are many people without whose support this would not have been possible. Foremost, I would like to thank my supervisors, Dr. Michele Zito, and Dr. Floriana Grasso, for challenging me into taking up my Ph.D studies in the first place. Also, for setting up a unique environment granting me the opportunity to develop and pursue an excellent vision encompassing many of my ideas and interests over all those years. I would, also, like to thank those who lead me to this path by their pieces of advice, in particular, my advisers (Dr. Terry Payne, Dr. Irina Biktasheva, and Dr. Lin Jiang). Additionally, I would like to thank the Computer Science Department, in particular, the Algorithms and Optimization Research Group, I think that all of you are special persons. Furthermore, I would like to thank the internal and external examiners, Dr. Irina Biktasheva, and Dr. Maysam Abbod, respectively. Finally, I'm in great gratitude to all those people supporting me in my private life throughout those years. Especially, My mother for her constant support, my father for his encouragement, my wife for her patient and help, and my friends in the department. Without you, this would not have been possible.

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Nomenclature

Abbreviations

AC	Air Conditioner.
CHP	Combined Heat and Power.
CRLP	Cumulative Round Linear Programming.
CRLP-V	CRLP that violates temperature constraints.
DG	Diesel generators.
DR	Demand Response.
DSM	Demand-Side Management.
EM	Energy Manager.
FIT	Feed-In Tariff.
HVAC	Heating, Ventilation, and Air Conditioning.
ILP	Integer Linear Programming.
LP	Linear Programming.
MDR	Minimum Deviation Rounding.
MDR-V	MDR algorithm that violates temperature constraints.
MILP	Mixed Integer Linear Programming.
MILP-H	MILP-based Heurstic algorithm.
MOOP	Multi Objective Optimization Problem.
NEG	National Electricity Grid.
PHEV	Plug-in Hybrid Electric Vehicle.

PV	Photovoltaic.
RTP	Real Time Pricing.
SOOP	Single Objective Optimization Problem.
TOU	Time of Use.

Mathematical Symbols

α	Nominal power of a household appliance.
$\alpha_{i,j}$	The nominal power of the i^{th} AC unit when it works in j level in cooling mode.
$\bar{P}(t)$	The maximum amount of power that can be consumed by a set of AC units from electricity grid (NEG) at time t.
$\bar{P}_s$	The generation capacity or the maximum output of PV array.
$\beta_{i,j}$	The nominal power of the i^{th} AC unit when it works in j level in heating mode.
$\delta_i^h(t)$	auxiliary binary variable.
Δ_i	Number of phases of appliance i.
Δ_i^h	Number of virutal appliances in appliance i in house h.
Δ_{min}	Length of clusches of virutal appliances.
$\dot{M}$	The air flow rate from AC to the room/house.
η_c	The efficiency of the power conditioning devices.
η_d	The degradation factor of PV array.
η_e	The efficiency of solar cells of PV array.
η_w	The wiring efficiency of the PV array system.
Γ	Set of all permissible allocated power to AC unit in case of cooling or heating.
$\gamma_h^r(t)$	The cost of renewable power generated by micro-plant r and consumed by house h.
$\grave{P}_s$	The total solar energy generated in specified time interval.

$\grave{P}_w$	The total wind energy generated between t_0 and t_T.
$\lambda_h(t)$	Electricity cost for house h.
$\mathscr{A}_{AC}^{h,r}$	Set of AC units in house h.
$\mathscr{A}_h$	Set of appliances in house h.
$\mathscr{A}_m$	Set of AC units in the whole building.
$\mathscr{H}$	Set of houses in a micro-grid.
$\mathscr{I}_i^h$	Set of virual appliances belongs to appliance i in house h.
$\mathscr{M}$	Set of rooms in the building.
$\mathscr{M}_h$	Set of rooms in house h.
$\mathscr{R}$	Set of micro-plants in a micro-grid.
$\mathscr{R}_h$	Set of micro-plants in house h.
μ	The mean of consumed power (the mean of nominal power).
Ω	The discomfort factor for whole building.
$\overline{\Theta_i^h}$	The final state of charge of i^{th} PHEV in house h.
Φ	The profit function of residential building.
$\pi_{h,i}$	Charging efficiency of i^{th} PHEV in house h.
Ψ	The cost function of whole building.
Ψ_h	The cost function of a house h connected to a micro-grid.
ρ	The air density.
σ	The standard deviation of consumed power (the mean of nominal power).
τ	Length of a time slot.
$\underline{\Theta_i^h}$	The initial state of charge of i^{th} PHEV in house h.
Υ^r	The discomfort factor or function of room r.
$\vartheta_i^h(t)$	The state of charge of i^{th} PHEV of house h.
$\widetilde{\Psi_h}$	The cost function of a house h considered as isolated unit.

$\widetilde{\Xi}_r$ The cost function of a micro-plant r considered as isolated unit.

Ξ_r The cost function of a micro-plant r working in a micro-grid.

A_s The surface area of PV array.

A_w The swept area of wind turbine.

B The capacity of knapsack (the available renewable power).

b_r Number of comfortable period of room r.

c_w The power coefficient of the wind turbine.

$E(t)$ The amount of surplus renewable power exported to NEG.

$E_g^r(t)$ The amount of energy produced by micro-plant r and sold to the NEG.

$G_r^h(t)$ The amount of energy generated from plant r and used by house h.

$I_T(t)$ The solar radiation at time t.

k_c Number of working levels of AC unit in case of cooling (if k_c =2, working levels are On/ OFF).

k_h Number of working levels of AC unit in case of heating (if k_h =2, working levels are On/ OFF).

$L_g^h(t)$ The amount of energy from the NEG used by house h.

$L_g(t)$ The amount of NEG energy consumed by all the appliances in the whole building.

$L_r(t)$ The amount of renewable power used in the whole building.

M Number of rooms in the building.

M_{air} The mass of air inside the room/house.

N The number of appliances.

N^h Number of appliances in house h.

n_m^h Number of AC units in room m.

n_i The number of times that appliance i must be used.

n_m Number of AC units in apartment or room m.

$P(t)$ The power allocated to AC unit.

$P_h(t)$	The quantity of heat at time t.
$P_i^m(t)$	The total allocated power to AC unit i in room m at time slot t.
P_j	The profit.
$P_m(t)$	The total allocated power to a set of AC units in room m.
$P_s(t)$	The solar power generated by PV array at time t.
$P_w(t)$	The output power of wind turbine.
P_{rate}	The maximum output power of wind turbine.
$P_{ren}(t)$	The predicted renewable power (solar or wind) at time slot t.
P_{s_T}	The total amount of generated solar power during specific time interval.
R_{eq}	The equivalent thermal resistance of the house.
$t_{end}^{h,i}$	The prefered finish time for appliance i in house h.
$t_{start}^{h,i}$	The prefered start time for appliance i in house h.
$T_{min}^{m,j}$	The minimum inside room temperature of room m and comfortable period j.
t_T	The total time.
$T_{in}^m(t)$	The inside temperature for m^{th} room at time t.
$T_{max}^{m,j}$	The maximum inside room temperature of room m and comfortable period j.
T_{opt}^m	The prefered optimal temperature by user in room m.
$v(t)$	The wind speed at time t.
v_r	The required wind speed to operate wind turbine at maximum capacity.
$v_{c_{in}}$	The wind speed at which the turbine first starts to rotate and generate power.
$v_{c_{out}}$	The wind speed where braking system must be used to bring the rotor to a standstill.
v_j	The value of appliance j
w_h	The weight of cost function Ψ_h.

w_i The weight of cost function i.

w_r The weight of cost function Ξ_r.

$x_j^{h,i}(t)$ Binary decision variable when AC unit in cooling mode in room i using power level j in house h at time slot t.

$x_{i,j}(t)$ Binary decision variable when AC unit in cooling mode for room i, and power level j at time slot t.

$y_j^{h,i}(t)$ Binary decision variable when AC unit in heating mode in room i using power level j in house h at time slot t.

$y_{i,j}(t)$ Binary decision variable when AC unit in heating mode for room i and power level j at time slot t.

Part I

Preliminaries and Foundations

Chapter 1

Introduction

"Without knowledge action is useless and knowledge without action is futile."

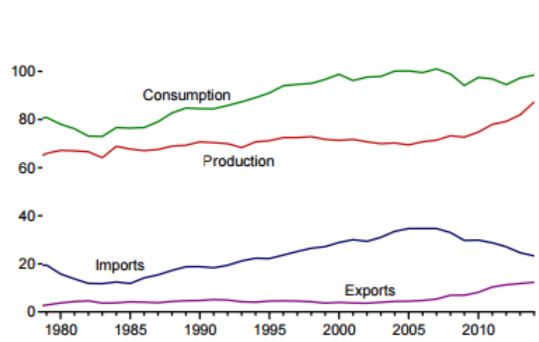
Abu Bakr As-Siddiq

The introductory chapter illustrates the primary motivation for the research in Section 1.1. Section 1.2 explains the research question together with the associated issues to be addressed and the adopted research method. In addition, the chapter presents the objectives of the research and the research contributions in Section 1.3. Also, Section 1.4 gives a summary of the publications. The scope of this thesis and assumptions is determined in Section 1.5. Finally, thesis outline is illustrated in Section 1.6.

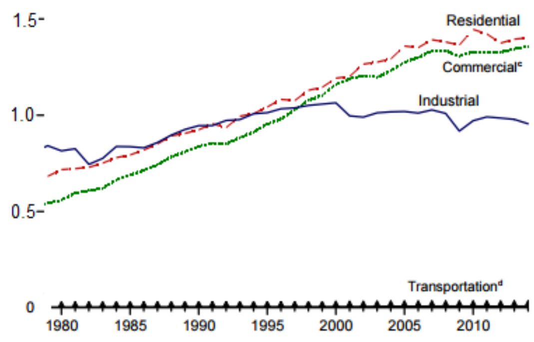
1.1 Motivation

Population explosion is one of the leading cause of concerns to power sector; the world population reached 7 billion in 2011 with a growth rate of 1.4% per year, and it would hit at least 11 billion by 2050 if the increase rate stayed at this rate. This remarkable increase in world population has caused a serious problem in the power sector because the relationship between global population and energy demand is positive, which means that the energy demand would increase at least at a rate of around 1.4% a year as well. In reality, the electricity demand rate exceeded the population growth rate. The electricity energy consumption in 1980 was around 9 TW, whereas it was about 15.2 TW in 2008 with 1.9% growth rate a year. Therefore, the predicted energy demand in 2030 would hit something around 22 TW [2]. Residential buildings consume around 40% of the electricity in the USA, 68% in the European Union [7], and about 50-70% in the Arabian Peninsula states (53% in Saudi Arabia) [8]. Also, Figure 1.1a illustrates the energy production and consumption in the United States of

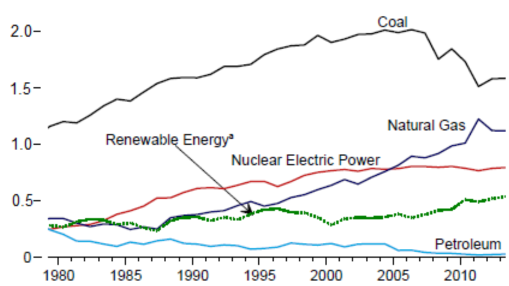
America, whereas Figure 1.1b demonstrates electricity consumption by sector over 30 years in the USA. Furthermore, these two figures depict that there is a significant increase in energy demand in general. In addition, Figure 1.1c explains the resources of electricity power in the USA. Figure 1.1d shows the electricity price in the USA over more than 30 years [9]. Obviously, increasing the generation capacity with this rate may not be applicable in near future [10]. Furthermore, the situation is more complicated in highly populated countries, such as India, Nigeria, and Egypt. These countries are already suffering from a lack of electricity production (electricity demand is much higher than their production capacities). Therefore, they control the demand by cutting electricity on some towns to maintain the stability of the electricity grid.



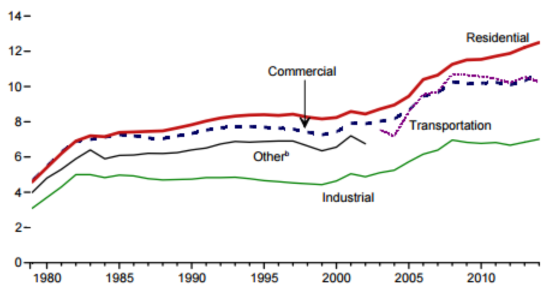
(a) The electricity energy production and consumption in the United States of America in Quadrillion Btu over 30 years [9].



(b) The electricity energy consumption in the United States of America by sector over 30 years [9].



(c) Electricity Net Generation in Billion kilowatt-hour in the United States of America over 30 years[9].



(d) The average of electricity price in cent/kilowatt-hour in the United States of America over 30 years [9].

Figure 1.1: Energy situation in the United States of America in the last 30 years

According to the U.S. Energy Information Administration (EIA) report [9], fossil fuels have been the primary energy source that has been used over the globe in the last century. For example, fossil fuels made up at least 80% of the USA fuel since 1900 [9]. By contrast, more than 98% of electricity is generated by gas and oil in Libya because these resources are widely available in the country [11]. These kind of energy sources are not renewable resources (it is running out every day), environmentally friendly (it causes air pollution by increasing the carbon dioxide), or cheap fuel (fossil fuel price soars dramatically in the last decade).

Renewable energy is an excellent alternative for fossil energy. The total renewable electricity generation capacity in the world has risen from 2.9 trillion kilowatt-hours in 2002 to 4.7 trillion kilowatt-hours in 2012 [9]. Although the capacity has increased to double in 10 years, more renewable power can be generated. Currently, 22% of electricity in the globe is produced by renewable resources [12]. However, many countries produce all their electricity from fossil fuels. The available solar energy on earth can provide the world with 14,000 times the current electricity demand [13]. Generating 100% of electricity demand from renewable is not an impossible mission nowadays. Norway, for instance, comes first concerning renewable power generation capacity, in the last decade, between 95% and 99% of their electricity consumption came from renewable resources, a vital portion of this percentage comes from hydro-power [14]. Denmark is considered as one of the leading countries in wind power, 43% of their electricity comes from wind energy. Additionally, Denmark has a plan of increasing this percentage to 50% by 2020 and to hit 100% by 2050 [15]. It is difficult to say how realistic this plan is, it would be a significant success if they can reach their target. In addition, Germany's renewable energy sector is one of the most successful renewable models in Europe. It provided the country with 30% of its demand in 2014. Also, Germany comes first regarding Photovoltaic arrays (PV arrays) with installed capacity of 33 Giga Watt-hours in 2012 [16]. The European Union has a plan that each state should generate 20% renewable power of its energy consumption by 2020. Some countries have already achieved this goal, whereas the others have to work seriously toward this goal. Although, some countries are working toward generating 100% of their electricity demand from renewable resources, there are many countries which have not started using renewable resources yet. In particular, countries that have fossil fuel resources and the developing countries. Although renewable power is sustainable, cheap, and environmentally friendly, it could be unreliable (it is from intermittent resources). Hence, much work needs to be done in the area of energy management in residential buildings in micro-grids. For example, improve the storage system and increase it, maximizing the utilization of renewable energy by using load shifting technique and allow power sharing between residential buildings.

1.2 Problem Statement and Rationale

Electricity price has soared dramatically in the last two decades. For instance, in the United Kingdom, the average spent on electricity bills was £106 ($150) per month in 2012, whereas it was £69 ($99) in 2002 with increasing rate of 55% [17]. If that was not enough, the power bills are going to keep growing in future at an even higher rate. Consequently, this considerable increase in electricity price affects our monthly income because it takes a substantial portion of it. Therefore, minimizing the cost of electricity is crucial, and it benefits almost everybody.

Many ways can be used to improve the situation. Firstly, residents can improve their house insulation by using foam insulation, blanket insulation, double glazing, etc. Nevertheless, building insulation is outside the scope of this thesis. Secondly, users could install domestic renewable resources (rooftop PV array, rooftop wind turbine, etc.). Thirdly, home automation techniques (motion sensors, thermostated appliances, etc.) could be used to reduce power consumption in the residential or commercial buildings. Finally, end users may use power management and optimization system to find an optimal schedule for their activities that guarantees the minimum cost (using Demand-Side Management (DSM) and Demand Response (DR)[1]).

Renewable resources are intermittent. For example, PV array system has maximum potential output at midday when most of the inhabitants are at work or schools (outside the residential building), which mean that the utilization of PV array will be minuscule. On the other hand, PV array does not generate any electricity at night. Therefore, few solutions have been introduced in the past to tackle this issue. Firstly, using energy storage systems such as batteries to accommodate the surplus renewable power and use it at night. However, the storage system has many disadvantages such as high capital cost, safety issues, efficiency issues, space taken, etc. The second way is to sell the surplus renewable energy to national electricity grid using Feed-In Tariff agreement or contract. Though these contracts are usually unfair for residents, and the users will get nothing for their surplus power in some countries. Thirdly, the end user could exploit their surplus energy for heating water or running some other appliances. Finally, users can use a control system to schedule their house activities (cleaning, washing, heating, etc.). Nevertheless, there is a computational problem with this method such as runtime as these kinds of problems are NP-hard. All previous methods have improved the utilization of renewable power and decreased the electricity bills. However, local renewable use can be further improved. The load shifting concept is used to maximize the utilization of domestic renewable power (using different optimization algorithms to schedule household appliance demand, more detail in the next chapter). There are many pieces of research have been done in this area, see Section 2.8. For example, using reactive control system in the residential building to maximize the utilization of renewable power, where local renewable energy is allocated immediately to household appliances using the online algorithm, or using predictive control system in the residential building where the household activities (load) can be scheduled based on renewable power forecasting. However, the complexity of the problem is still the primary cause for concern especially to large or huge problems such as building with a

[1] Demand Side Management (DSM) is a strategy that has been designed to encourage the customer to be more energy efficient. Demand Response (DR) is the action that has been taken by the end user to cut down the amount of electricity at the specific time.

broad range of appliances, or micro-grid with many houses.

There have been countless studies in this field that tried to come up with perfect model and method that minimizes the cost of electricity for the user and maximizes the profit of electricity companies. However, it is tough to achieve this goal for many reasons (e.g. it is a very complex problem, uncertainty, etc.). Finding an optimal solution for a single house with few household appliances could be feasible. Nevertheless, finding an optimal solution for power allocation problem to large buildings, with a wide range of household appliances, or micro-grid with many houses, is not an easy task. It could be even impossible to find an optimal solution to these kinds of problems. Therefore, a trade-off between cost and run-time is required and the sub-optimal solution, in such complex problems, is not a choice but a must. In this thesis, a number of mathematical models and heuristic algorithms have been designed to give sub-optimal solutions for power management problems. The research gap in this field is that finding an optimal solution of massive problems could be infeasible[2]. Some frameworks have tackled the computational issue with a heuristic algorithm to find a sub-optimal solution, see Section 2.8. However, the proposed method will be different from these studies (more detail later). Furthermore, all studies in literature review have not tackled the computation time seriously (run-time) especially for massive problems. Furthermore, they have not considered more than one AC unit works in the same room, which adds much complexity to the problem, such algorithms will not cope with such massive problems. On the other hand, they have not used local power sharing between residents efficiently. Also, the run-time of their algorithms was not considered seriously.

1.3 Objectives and Contributions

The primary objective of this thesis is to develop a comprehensive mathematical model for a set of residential buildings, commercial buildings (e.g. offices buildings), and renewable plants working in a micro-grid setting as a single controllable load. Moreover, designing a heuristic algorithm for the proposed model is another objective. The thesis will also discuss an appropriate way to convert the complex multi-objective optimization problem of allocating power to a set of houses in a micro-grid into a single objective optimization problem in a way that nobody will lose in micro-setting.

Therefore, based on the aforementioned objectives of this thesis, the main contributions of the research (with respect to both computer science and electrical engineering) can be itemized as follows:

* **A comprehensive mathematical model for a micro-grid**. The thesis has pro-

[2] Infeasible solution if there exists no solution that satisfies all of the constraints.

posed a micro-grid model that consists of a set of houses and renewable plants working collaboratively. It also provides detail about the implementation and the evaluation of the model, more detail in Chapter 3.

* **A way to convert a multi-objective optimization problem to a single optimization problem.** The thesis has proposed a way (hybrid method of ε-constraint technique and scalarizing technique) to convert a multi-objective optimization problem (MOOP) into a single objective optimization problem (SOOP). The main goal of this hybrid method is to improve the fairness issue in the micro-grids. The thesis also provides full detail of the implementation and the evaluation, more detail in Chapter 5.
* **A way to improve fairness issue in micro-grids.** The thesis has provided a set of constraints with hybrid method to guarantee that nobody will lose in micro-grid settings, more detail in Chapter 5.
* **Propose a fair pricing rate for sharing local power in a micro-grid:** the thesis has proposed a pricing rate for houses and plants in micro-grids, more detail in Chapter 5.
* **Using LP relaxation and rounding techniques:** the thesis has used LP relaxation and a set of rounding techniques.
  - **Cumulative Rounding LP (CRLP) strategy.** LP relaxation technique has been used to reduce the complexity of our optimization problem presented in Section 4.2. Additionally, the thesis has shown a design for a heuristic algorithm, an MILP formulation of the problem, and an empirical evaluation of the proposed algorithm. The proposed algorithm uses rounding method (CRLP) to convert the LP-relaxed solution to a practical solution for the residential building. Finally, CRLP is intended for AC units only, more detail in Chapter 6.
  - **Minimum Deviation Rounding (MDR) strategy.** Another rounding technique (MDR) has been designed and tested to improve the performance of the previous algorithm (uses CRLP). The main difference between CRLP and the new rounding method (MDR) is that CRLP rounds the allocated power for the AC unit without considering the room temperature, whereas MDR rounds the LP-relaxed solution based on the room temperature, more detail in Chapter 6. The MDR is designed for AC units only.
  - **Minimum Cost Rounding (MCS) strategy.** This technique is designed to adjust the relaxed allocated power[3] to uni-phase interruptible appliances (discussed in Section 3.4.2).

[3] The power allocated to household appliances after using LP relaxation may not be practical and it needs to be rounded to either zero or nominal power.

* **A mathematical model of air conditioning system.** The thesis has provided a mathematical model for air conditioning system. Also, it has considered a model for a set of AC units or heaters working in the same room, more detail in Chapters 3, 5 and 6.

* **A reactive control system of a smart house.** The thesis has suggested an energy manager for a single stand-alone house. The energy manager can maximize the utilization of renewable resources based on user preferences, more detail in Chapter 7.

1.4 Publications

In this section, an annotated list of publications to date that have arisen from the work described in this thesis is presented. Total of six papers (three papers have been already published, two have been accepted and are waiting to be published, and one is submitted to Journal of Energy and Power Engineering) have emerged out of the research presented in this thesis, and these are listed and summarized in this section:

1. **M. Arikiez, P. Gatens, F. Grasso, and M. Zito. Smart domestic renewable energy management using knapsack. In *2013 4th IEEE/PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, pages 1–5, Oct 2013**. It describes how a variant of the knapsack optimization problem can be applied to the solution of an allocation problem arising in the management of the renewable energy generated by a micro-generation plant. The study used an online optimization algorithm to maximize the utilization of domestic renewable power based on user preferences. Theoretical and empirical analysis show that the proposal is viable, it results in significant energy savings, and can be adapted to a number of different usage patterns.

2. **M. Arikiez, F. Grasso, and M. Zito. Heuristics algorithm for coordinating smart houses in microgrid. In *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 49–54, Nov 2015**. This work presents a framework for efficiently managing the energy needs of a set of houses connected in a micro-grid configuration. The micro-grid consists of houses and local renewable plants, each seen as independent agents with their specific goals. In particular, houses have the option to buy energy from the national grid or the local renewable plants. The authors have discussed a practical heuristic that leads to power allocation schedules that are cost-effective for the individual houses and profitable for the local plants. The authors present experiments describing the benefits of their proposal. The results illustrate that houses and micro-plants

can make a considerable saving when they work in micro-grid compared with working alone.

3. **M. Arikiez, F. Grasso, and M. Zito. Heuristics for the cost-effective management of a temperature controlled environment. In *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, pages 1–6, Nov 2015**. This study investigates the use of linear programming based heuristics for solving particular energy allocation problems. The primary objective is to minimize the cost of using a collection of air conditioning units in a residential or commercial building and keep the inside temperature within pre-set comfort levels. Further, optimal methods do not scale up well when the number of appliances or the system time granularity grows past a certain threshold. Therefore, the authors have proposed a heuristic algorithm that uses LP relaxation and rounding to offer a good trade-off between cost and computation time.

4. **M. Arikiez, F. Grasso, D. Kowalski, and M. Zito. Heuristic Algorithm for Minimizing the Electricity Cost of Air Conditioners on a Smart Grid. In *2016 IEEE International Energy Conference and Exhibition (ENERGYCON)*, pages 1–6, April 2016**. This paper has investigated using heuristic algorithms to solve Multi-Objective Optimization Problem (MOOP). The primary goal is to minimize the electricity cost for a set of air conditioners in residential or commercial buildings. The second objective is to minimize the discomfort factor. The proposed algorithm also enhances the utilization of local renewable power. This allocation problem can be formulated using a static technique such as Mixed Integer Linear Programming (MILP). Nevertheless, solving MILP-based MOOP could be impracticable in massive problems due to the hardness of the problem. Accordingly, a trade-off between cost and run-time is required. Our algorithm uses an MILP-based heuristic optimization algorithm and LP relaxation and an innovative rounding technique called Minimum Deviation Rounding (MDR) to get a sub-optimal solution. The result reveals that our algorithm can solve a massive problem in few seconds and gives a superb sub-optimal solution.

5. **M. Arikiez, F. Grasso, and M. Zito. Minimizing the electricity cost of coordinating houses on microgrids. In *2016 4th IEEE/PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, pages 1–6, Oct. 2016**. This manuscript presents a comprehensive mathematical model for multi-objective optimization problem of the micro-grid. The micro-grid consists of houses and local plants, each seen as independent agents with their specific goals. We also propose a heuristic algorithm for optimizing the electricity cost by using the concept of load shifting and renewable power sharing between houses in the mi-

crogrid for a particular price. Also, the algorithm minimizes the loss of energy by prioritizing power exchange between close houses and minimize discomfort factor. The findings have shown that houses and micro plants working in a micro-grid setting can make a significant saving. The results have illustrated that our algorithm guarantee nobody will lose in the micro-grid.

Furthermore, the work described in this Ph.D. thesis has led to a follow-up investigation results of which are not reported in this thesis, though the follow up paper is listed here for completeness:

1. **M. Arikiez, F. Grasso, and M. Zito. Heuristic Algorithm for Minimizing the Electricity Cost of Smart House.** ***Submitted to Journal of Energy and Power Engineering***. This framework proposes a heuristic algorithm based on Linear Programming (LP) for optimizing the electricity cost in large residential buildings, in a smart grid environment. Our heuristic algorithms tackle large multi-objective energy allocation problem (a large number of appliances and high time resolution). The primary goal is to reduce the electricity bills, and discomfort factor. Also, increase the utilization of domestic renewable energy, and reduce the running time of the optimization algorithm. Our heuristic algorithm uses linear programming (LP) relaxation, and two rounding strategies. The first technique, called Cumulative Rounding (CR), is designed for thermostatic appliances such as air conditioner and electric heater, and the second approach, called Minimum Cost Rounding (MCR), is designed for other interruptible appliances. The results show that our heuristic algorithm can be used to solve large Mixed Integer Linear Programming (MILP) problems and gives a decent sub-optimal solution in polynomial time.

1.5 Scope of Thesis and Assumptions

This thesis has tackled two control systems, reactive and predictive. The reactive system uses an on-line algorithm to solve an optimization problem based on real time instant inputs, whereas predictive system uses an off-line algorithm to solve an optimization problem based on predicted input data. In the predictive system, our solution depends mainly on prediction (e.g. PV array depends on weather forecasting). Furthermore, error in prediction is beyond the scope of this thesis. This research is not dedicated to a particular geographical area or country. However, the performance of our model changes considerably from area to another. For example, it performs much better in the Mediterranean countries than in north Europe because the weather prediction in the Mediterranean countries is relatively accurate compared with the weather forecasting in north Europe.

Some assumptions have been made to reduce the complexity of this problem. Firstly, it is assumed in this thesis that all appliances are powered by electricity. Secondly, the proposed models in this thesis have used an equation that models the relationship between outside temperature of the building, inside temperature, and consumed power; this equation is not linear. Therefore, the author had to do some approximation on the model to convert it to a linear system, more detail will be given in Chapter 3. Moreover, it is assumed in this thesis that the states of all doors and windows in the buildings are closed. Additionally, the number of inhabitants in the building (residents affect the inside temperature) was neglected. It is also assumed that the output of PV array and wind turbine are constant over one hour that is because all weather forecasting station gives data with one-hour time resolution. In addition, a model for the battery of PHEV has been used, the relationship between consumed power and state of charge is not linear. Therefore, the author had to approximate some variables related to charging and discharging mode. Also, we have converted the continuous problem to discrete one, and the time horizon is split into a set of time slots.

1.6 Organization of the Thesis

The rest of the thesis is organized as follows:

Chapter 2 illustrates a general background of the power system, electricity pricing, electricity bills, and smart grids. It, also, provides a literature review of the previous work that is of relevance with respect to the work presented in this thesis.

Chapter 3 provides a comprehensive model of micro-grid and its components. The chapter starts with modeling renewable resources (wind turbine and solar PV array). Then, it models household appliances.

Chapter 4 defines the computational problems of optimizing the electricity cost of a set of houses in micro-grids. Additionally, it illustrates the special cases of the power allocation problems in micro-grids, and gives a mathematical formulation of these problems.

Chapter 5 presents MILP formulation of the proposed micro-grid model. The chapter proposes a predictive control system for a micro-grid. Further, it proposes a heuristic algorithm to solve the optimization problem. Finally, the findings are presented and discussed.

Chapter 6 demonstrates MILP formulation of the proposed micro-grid model. The chapter suggests predictive control system for a set of AC units in a large building. It also proposes a set of heuristic algorithms to tackle the problem of power management in large buildings.

Chapter 7 illustrates ILP formulation of the proposed micro-grid model. It also introduces a reactive control system for knapsack problem in a smart house.

Chapter 8 presents conclusions and future work.

Chapter 2

Background and Literature Review

"There is no knowledge and science like pondering and thought, and there is no prosperity and advancement like knowledge and science"

Ali Ibn Abi Talib

This chapter presents a background review of the main concepts relevant to the research of energy management in micro-grids in Sections 2.1, and 2.2. Furthermore, the chapter discusses electricity prices and Demand-Side Management (DSM) strategies that are available in the electricity market in Sections 2.3 and 2.4. This chapter also defines most of the basic concepts in smart grids and micro-grids in Sections 2.5, and 2.6. Further, smart house is defined in Section 2.7. The related works will be discussed in Section 2.8. Finally, Section 2.9 summarizes the chapter.

2.1 Electricity Systems

An electricity system consists of four parts: i) generation, ii) transmission, iii) distribution, and iv) consumption. Generation is the process of producing electricity from natural resources (fossil resources, or renewable resources) [2]. The transmission process is responsible for transferring the electricity from power plants to distribution stations over high voltage power lines. In the distribution process, the high-voltage electricity is converted to low voltage electricity using step-down transformers so that customers can use the energy, as shown in Figure 2.1 for more detail [2]. Grid reliability is crucial in the electricity grid, so the main challenges for electricity companies are to maintain reliability and efficient operation of the grid. Also, electricity companies should ensure that there is enough generation capacity for the future. Other challenges which affect the operation of current resources are: i) increasing fuel cost, ii) potential for supply disruptions, iii) technological advances, and iv) additional cost imposed by climate changes [1].

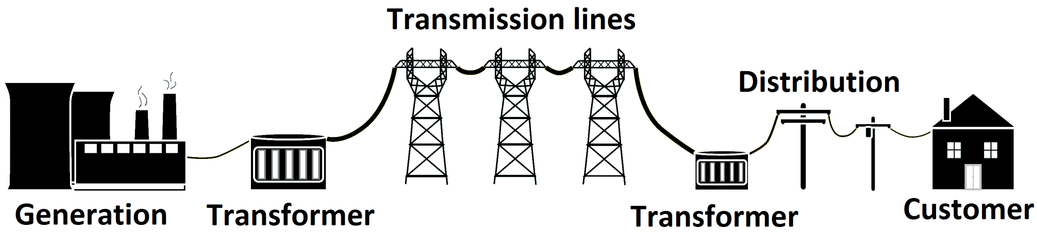


Figure 2.1: Power system diagram

2.2 Electricity Bills

This section gives a review of the ways that have been used before to reduce electricity bills. According to report in [1], there are four ways that customers can consider to reduce their electricity bills:

* Energy conservation: it is one of the cleanest and most affordable methods to decrease electricity bills and lessen the gap between the electricity demand and electricity supply. For example, a customer could switch off some unneeded household appliances (lights, or heaters, air conditioner, etc.) to save electricity and as a result save money. Usually, it is not easy to convince people to reduce their electricity consumption and change their living style, especially at peak hours, for many reasons. For instance, people, who have high monthly income, would not bother saving some money from switching some of their household appliances off. Besides, it could be impractical to switch some appliances off at a particular time because it may damage the appliance itself or corrupt the task or the job that is being done by the appliance [1].
* Energy efficiency: consuming less energy to reach the same goal by using efficient household appliances (e.g. consider using two different washing machine A, and B for the same job (clothes washing) at the same time. Washing machine A consumed 3 kWh to finish the job properly, and washing machine B consumed 3.3 kWh). Furthermore, most of the modern appliances are categorized in different levels (usually from A to G) based on their power efficiency, where a household appliance designed with level A is the most efficient appliance regarding electricity consumption, and appliance with level G is the worst energy efficient appliance. Energy efficient household appliances are usually expensive and not everybody can afford to buy these appliances, which means efficient appliances can help to reduce the demand for electricity, but this reduction would not be considerable [1].

* Smart appliances usability: There are many appliances nowadays which have many working levels or programmed for different tasks, so that they consume a different amount of electricity energy each time. For instance, an electric cooker could have a number of working programs (rice, meat, pasta, etc.), or washing machine could have a number of working levels (heavy load, light load, white clothes, colored clothes, etc.). Therefore, it is important to choose the correct working mode to save electricity energy. By contrast, lack of knowledge about how to operate these smart appliances could make them consume more than what they need to finish the task properly. Therefore, the saving of electricity depends on the user knowledge (elderly people may find it difficult to use such smart appliances) [1].
* Load Management: it is, also, known as demand side management, it is the process of changing the electricity load (demand) rather than changing the output of electricity power plants to balance the demand and supply. Demand-Side Management (DSM) is action or tools that encourage end users to consume electricity energy at different times of the day. For example, the electricity demand during peak hours could be lessened by using a dynamic pricing scheme, home automation system, and/or power management control system. Similarly, the action of electricity provider is called demand side management, whereas the action of the end user is called the Demand Response (DR). The main disadvantage of this approach is that it may reduce the comfort level. Also, it may need automatic control systems and more advanced hardware which are usually more expensive. The complexity of the system is also an issue [1, 18]. For more detail about demand-side management and demand response see Section 2.4 .

The thesis will consider just the last two ways to minimize the electricity cost, namely smart appliances and load management, whereas energy conservation and energy efficiency are outside the scope of this thesis. Next, electricity pricing strategies in the market are reviewed in detail.

2.3 Electricity Pricing Strategies

Electricity cost is the important part of the energy market. The price of electricity is a function of four main factors which are : i) customer services, ii) distribution services, iii) transmission services, and iv) generation services. Further, electricity bills take a considerable amount of consumer's monthly income. Although energy companies have offered different kinds of electricity pricing in the last 30 years to help customers to save some money, many consumers still face an inefficient fixed price option. There are many electricity pricing strategies all over the world [1]. In the forthcoming sections, a review of the most important of electricity pricing strategies is introduced.

2.3.1 Hourly Pricing Strategies

The retail electricity prices vary hourly to control the demand. Suppliers usually notify their customers a day ahead or an hour ahead [1]. The following listed types explain some versions of hourly pricing in the market:

* Basic hourly pricing: This pricing model can be attractive for large consumers. End users who consume a large amount of energy (e.g. manufacturers, hospitals, or universities, etc.), are usually interested in the lowest price offered by competitive suppliers regardless of the risk of varying electricity price, Figure 2.2 [1].

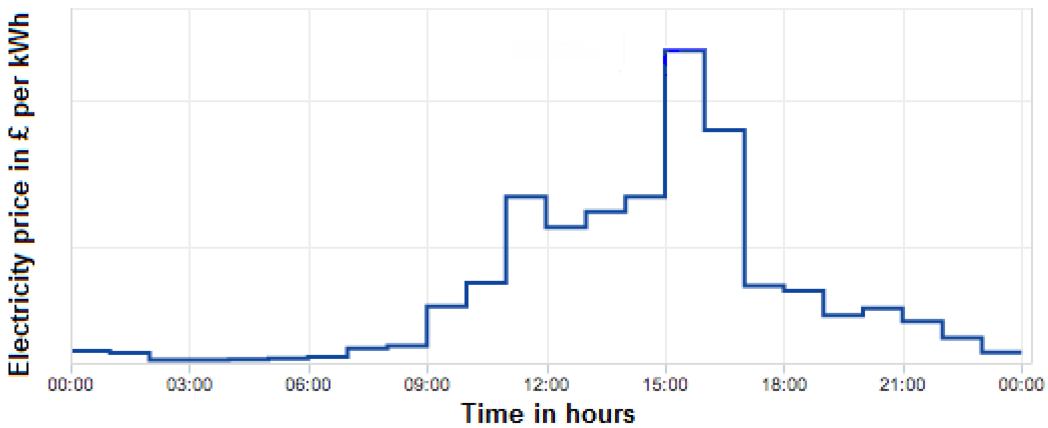


Figure 2.2: Basic hourly pricing [1]

* Block and index pricing offered by competitive retail providers: Although, the customers, in these kinds of combined contracts, pay a fixed price for a fixed amount of energy, they pay prices indexed to the relevant market, locational marginal pricing (LMP), every hour for any extra demand above the threshold. The customers who do not care about price certainty during their contract, and have a high-risk tolerance may be interested in this strategy. On the other hand, if electricity prices fall, the customers have to pay at the rate specified in the contract, which means the customer will pay a higher rate than the current market rate, see Figure 2.3 [19].

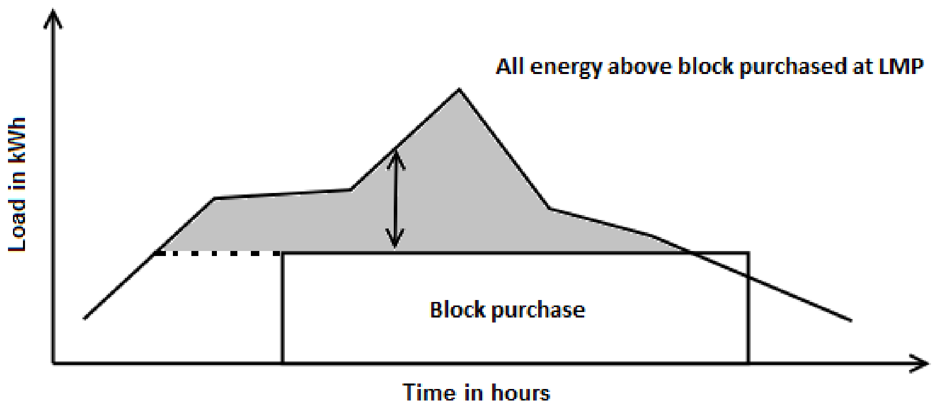


Figure 2.3: Block and index pricing, the consumed power above block purchase (gray area) will be more expensive at LMP [1]

* Two-part real-time pricing at regulated utilities: Under this price strategy, the electricity bills are divided into two sections. The first section is that the customer pays a standard tariff for a particular amount of energy, called Customer Baseline Load (CBL), calculated using their historical consumption, usually for one year before joining real time pricing. The second section is that the clients pay an hourly price, Real Time Price(RTP), for any amount of power above CBL, see Figure 2.4 [1].

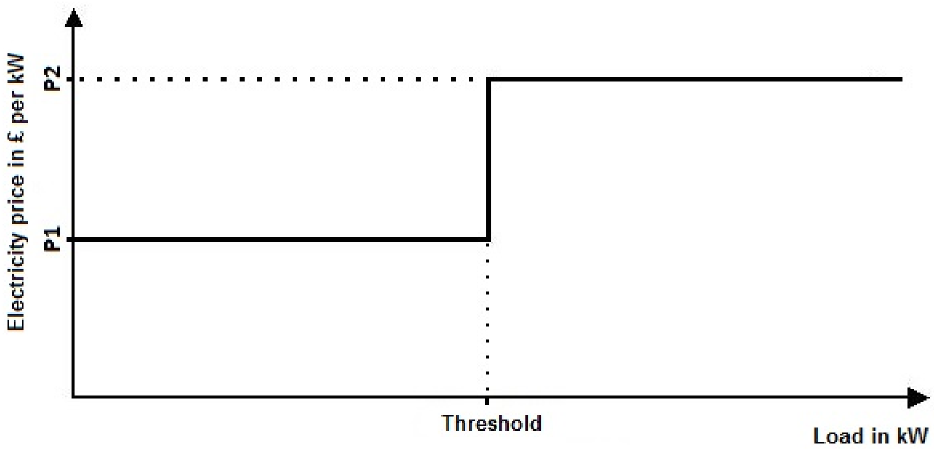


Figure 2.4: Two-part RTP [1]

* Unbundled real-time pricing with self-selected baseline load: electricity tariffs usually consist of a set of the components for a generation, transmission, and distribution cost. In this tariff, utility companies unbundle the total cost and add hourly pricing to the generation component only [1].

2.3.2 Daily Pricing Strategies

In daily pricing, suppliers sell electricity for a fixed price over blocks of time, but the price of these blocks may vary daily. This change in price could be announced on a daily or hourly basis [1]. According to [1], the following pricing schemes present example on daily pricing:

* Day-type Time-Of-Use (TOU) rate: electricity supplier will prepare a set of TOU prices, which are a low rate, medium rate, and high rate to reflect the price at that time, after that suppliers announce one of these pricing structures a day ahead based on the wholesale prices. Tempo residential tariff is one example, and Electricite de France offers it [1].
* Variable peak rate: electricity suppliers fix the price of electricity on off-peak periods, whereas the on-peak price is announced daily to reflect energy market price. ISO-NE proposes this pricing strategy.
* Critical peak pricing: in this critical peak pricing, the price of electricity will be increased significantly if electricity supplier notices emergency conditions in the power system or high market prices [1].
* Variable critical peak pricing: this is a combination of time-of-use and real-time pricing; several critical prices are prepared. Then, the price in peak hours can be varied by the supplier based on market conditions [1].
* Critical peak pricing linked to a standard tariff: utility companies, in this pricing structure, add critical price charge to the standard rate [1].
* Peak-day rebate: the customers, in this pricing structure, can get paid by electricity companies if they reduce their demand below the expected value when there is an emergency condition in the electricity grid. Furthermore, the electricity rate will stay the same during emergency conditions [1].

2.3.3 Fixed Time-of-Use Pricing

The time horizon, in this tariff, is split into a set of time-of-use pricing periods, these periods could be divided based on demand (on the peak, mid peak, and off peak) or days (weekend and weekdays). Moreover, the price is fixed during each period and will not be influenced by any situation in the grid and electricity market [1].

2.3.4 Seasonal Flat Pricing

The electricity price, in this pricing structure, is fixed over the whole season or couple of seasons, and it may be changed between seasons, but not during the season [1].

2.3.5 Other Pricing Strategies

2.3.5.1 Plug-In Hybrid Electricity Vehicle (PHEV) Charging Rates.

To encourage people using PHEV, electricity price should not be more than the traditional fossil fuel. Nowadays, powering PHEV with fossil fuel is cheaper than using electricity power. Some countries give discounted prices for PHEV, but that is unfair to others. More work needs to be done in this area to come up with sufficient rate [1].

2.3.5.2 Rates Related to Distributed Generation (DG)

In this thesis, DG means the micro power plants that belong to the customers. DG can be a wind turbine, PV arrays, CHP, fossil fuel generator, etc. [6, 20, 21]. The following rates for DG are included but not limited to:

* Incentives for economic distributed generation: fixed cost of consumed electricity energy, which is higher than the wholesale price, may encourage many customers to invest in DG (PV array, wind turbine, CHP, etc.) in order to reduce their power bills or even to make some money [1].
* Sell-back rates: this price usually consists of two components which are generation tariff and export tariff [1]. Since 2010, it is known as Feed-In Tariff (FIT) in the UK, and customers get paid for their surplus local generated power that exported to NEG. Also, they get paid for every kWh they generate. FITs are not the same in all countries. For instance, in the UK, they pay £0.032 to £0.045/kWh [22], whereas in Florida in the USA, they pay $0.45/kWh [23]. By contrast, in Libya, you will get nothing for your surplus power because the electricity is very cheap [11].
* Standby rates: In the case of an outage in DG system, customers of DG will have to buy electricity from utility companies which will charge them. Usually, the charge consists of two components; the first one represents the actual energy consumption and the second one present the penalty for customers of DG [1].

It is imperative to review and understand all pricing strategies that have been used in the market before you start modeling and designing optimization algorithm. To the best knowledge of the author, almost all pricing strategies in the market have been reviewed in this section. However, in this thesis, daily pricing (dynamic pricing), fixed time-of-use pricing and fixed pricing will be used because they fit with the proposed model of the micro-grid, the rest of pricing strategies may need a reaction from the electricity providers and end-users which will not be available if the micro-grid works in islanded mode. In the next section, Demand-Side Management and Demand Response will be discussed in detail.

2.4 Demand-Side Management (DSM) and Demand Response (DR)

Stability of the electricity grid is essential [2]. Therefore, electricity suppliers are working hard to keep demand and supply in balance at all time, as in Figure 2.5. Demand side management (DSM) and Demand Response (DR) are designed and implemented to keep balance in the electricity grid and to smooth out peaks and valleys in electricity energy demand [18, 24]. However, there are a lot of challenges facing DSM and DR.

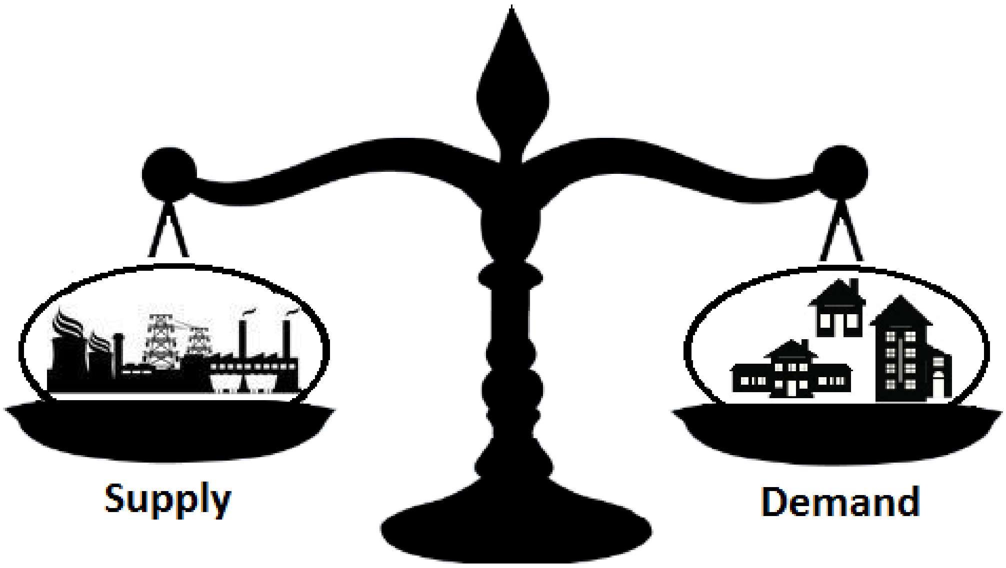


Figure 2.5: Balancing demand and supply in electricity grid

DSM and DR are historically known as load management. The electricity demand over 24 hours is very variable. Consequently, it may affect grid stability. Therefore, variation in electricity demand is one of the primary cause for concern for generation companies. In the early 1980s, DSM was first coined by Clark Gellings (Electric Power Research Institute, USA) [25]. Additionally, monitoring, implementation, and planning of utility activities that are designed to change the end user power profile are known as DSM [24]. The main purpose of DSM programs is to encourage customers to be more energy efficient. On other words, DSM is designed to encourage end users to change their power profile, and usually, aims for long-term reduction [26], whereas DR is the action that is taken by customers to reduce energy consumption in specific time. For example, customers may reduce their electricity consumption during peak hours and increase it during off-peak hours (usually at night). Three things make end users adapt to the DSM or change their power profile based on DSM, these are:

* Dynamic pricing: it is crucial that electricity energy companies design an appropriate dynamic pricing scheme to encourage customers to manage their power

consumption and change the shape of their power demand on electricity by their living style (reduce their demand on peak hours by scheduling their time-flexible activities on off-peak hours).

* The ability of end users to make a change in their power profiles: it is vital that end users are equipped with a control system that allows them to control and monitor their electricity consumption (change their living style). In contrast, there is some load that can not be delayed or shifted to another time, such as TV set, PC, beard trimmer, or lights, etc.
* The ability to measure the profit that made by adopting DSM: it is critical that the customers can see how much they saved by using DSM, so that it encourages them to continue taking part in DSM. Therefore, an appropriate interface is needed. Also, presenting a readable summary of the activities can help a lot, especially for people who does not have any background about how to calculate electricity bills [1].

2.4.1 DSM Strategies

There are many DSM strategies [24, 26, 27], see Figure 2.6, that are used to shape the demand curve including but not limited to:

* Load shifting: the central idea of this strategy is to shift loads from peak hour to off-peak hours. For example, customers may chill/heat water at night (off-peak hours) and use it at morning (peak hours).
* Conservation: it is the oldest and the most known strategy to cut down electricity demand on all time not just in peak hours. For example, energy-efficient appliances can save power at all times.
* Peak clipping: the primary goal of the strategy is to reduce the demand on peak hours (e.g. at 07:00 PM). The reduction can be achieved by controlling interruptible appliances such as AC unit or heater by end users or electricity providers.
* Valley filling: the principal purpose of this strategy is to build up the demand during off-peak hours to smooth out the electricity demand, PHEV is a good example for valley filling where the battery is charged at night.
* Load growth: this strategy is opposite of conservation policy, it consists of growth in overall sales (off-peak and peak hours).
* Flexible load shape: In this strategy the utility company has the right to interrupt loads when required without telling the users. Flexible load shape usually refers to variations in reliability or quantity of service.

Almost all DSM strategies are designed and implemented in order to maximize the use of current power plants. Also, another important aim is to avoid, defer or postpone the need for new power plants (conventional or renewable plants).

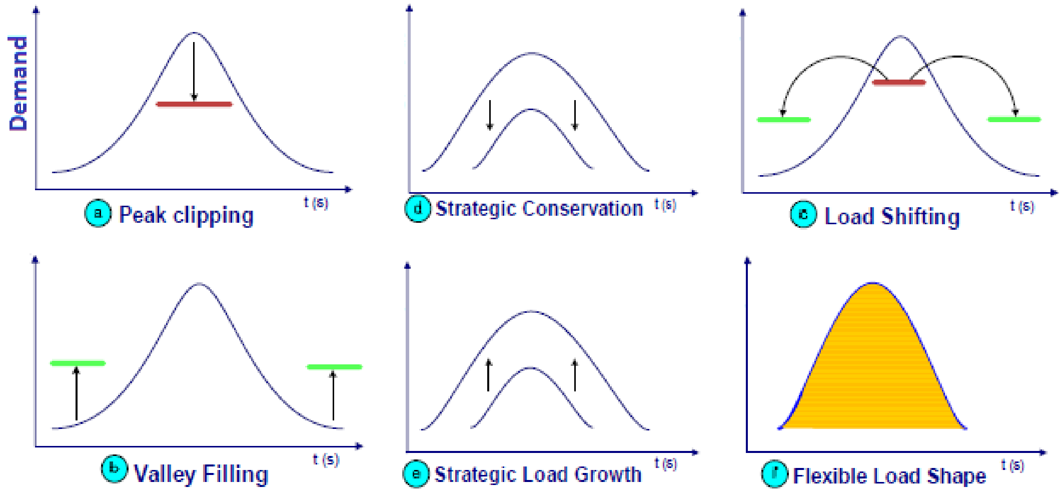


Figure 2.6: Demand-Side Management strategies and objectives

In this thesis, load shifting techniques to minimize the electricity cost will be used. All related work about DSM and DR will be presented in Section 2.8.

2.4.2 Challenges for Demand-Side Management

According to framework [18], there are many challenges for DSM including the following:

Information and Communication Technology

The primary challenge for DSM is that there is a lack of Information and communication technology infrastructure in most of the current electricity grid. Applying DSM technology needs advanced metering infrastructure including advanced meters, two-way communication between customers and suppliers, controllers, sensors, and information technology. Furthermore, adding all of these components to the smart grid will make it an extremely complicated electricity grid [18].

Security and Privacy

One of the primary cause for concern to a researcher is security and privacy issues in the smart electricity grid. Plus, exchanging data in the smart grid could raise a cybersecurity issues. Therefore, many pieces of research are needed to find an efficient system that can not be hacked or, at least, minimize the risk of cyber attacks. Confidentiality is another issue, hackers or even electricity providers may know exactly the type of activity inside the house at any time [18].

Benefit of Demand-Side Management

There is a lack of understanding of the benefits of DSM among customers, which are considered as a principal challenge for a supplier to applying DSM in the smart electricity grid. Additionally, the advantage of DSM is not significant when there is enough generation capacity, whereas the value of DSM is crucial when the demand is higher than or close to the generation capacity [18].

Competitiveness of DSM-based Solutions

Concerning technical, economic and environmental[1], the performance of solutions based on DSM is not competitive with traditional solutions. Therefore, a comprehensive work needs to be done in this area to improve the situation and make DSM in smart grid more preferable than conventional solution [18].

Complexity of DSM-based solutions

The system complexity of DSM-based solutions is much higher than the conventional solutions since DSM needs more modern devices to apply it to the electricity grid. For example, sensors, smart meters, controllers, and communication devices. Also, information system between customers and utility companies needs security system which will add complexity to the DSM-based solutions. Besides, this complexity will affect demand response as well (e.g. tenants of a residential building have a set of household appliances, and they would like to use DSM and DR to minimize the cost of electricity by scheduling the load in off-peak hours) [18].

Unsuitable Market

The current market of electricity structure is not appropriate for DSM because there are many types of customers taking part in DSM, each of them has different preferences, which create a real challenge to suppliers, researchers, and developers of DSM system. In addition, there is a lack of incentives as mentioned above [18].

[1] DSM-based is proposed to reduce electricity consumption and cost. As a result DSM improves the gas emission produced by power plants.

2.5 Smart Grids

The notion of a smart grid is relatively new. It is an enhanced electrical grid in which information and communication technology is used to improve the power system and increase the profit of consumers, distributors and generation companies, see Figure 2.7 [28]. Additionally, smart grid accommodates different types of electricity resources (e.g. conventional plants (such as CHP and diesel generators) or renewable resources (such as PV arrays and wind turbine)) [6]. The essential features of such infrastructure are reliability, flexibility, efficiency, sustainability, peak curtailment, and demand response. It is, also, market enabling, it provides a platform for advanced services, and increases the manageability of resources. To exploit the smart grid in residential buildings, we need new technologies such as integrated communications, sensing and measurements, smart meters, advanced control, advanced components, power generation, and smart appliances [28]. The central parts of the smart grid are integrated two-way communication, advanced component, advanced control methods, sensing technologies, measurement techniques, improved interfaces, improved decision support, and applications of smart grid technology.

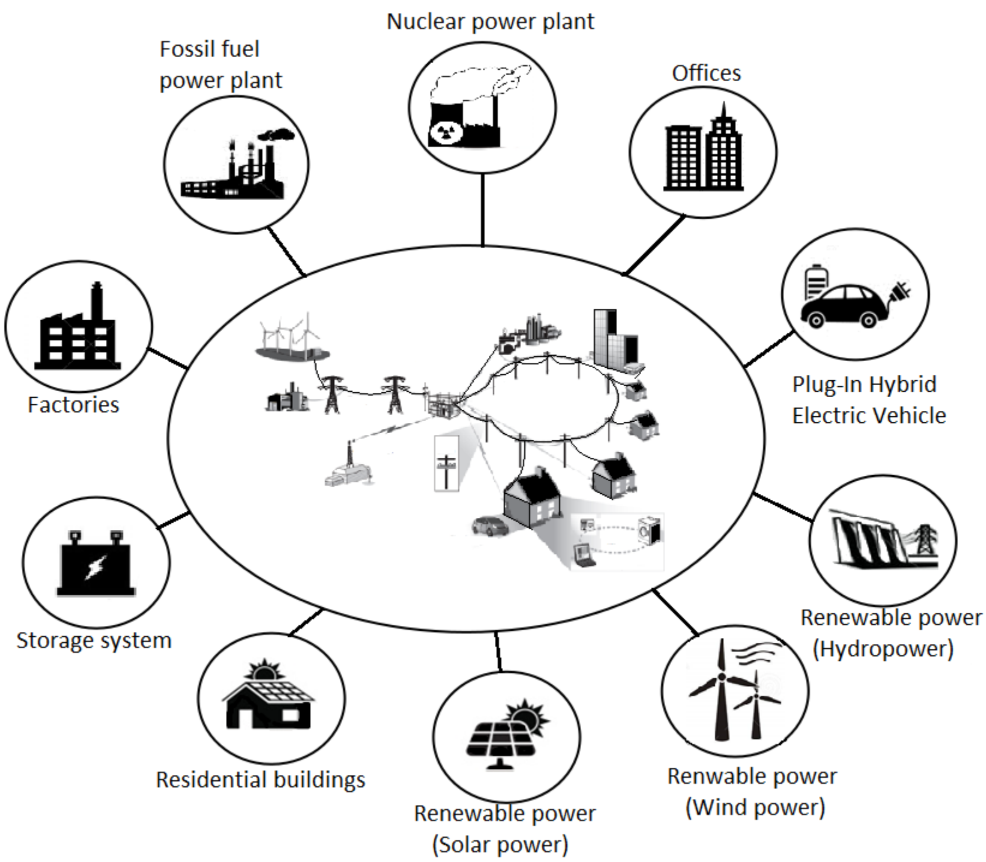


Figure 2.7: Smart grid diagram

Table 2.1 demonstrates summarized comparison between current conventional electricity grid and future electricity smart grid.

Table 2.1: Comparison between conventional grid and smart grid [6].

Electricity Grid (Conventional grid)	Smart Grid
Electromechanical	Digital
One-Way Communication	Two-Way Communication
Centralized Generation	Distributed Generation
Hierarchical	Network
Few Sensors	Sensors Throughout
Blind	Self-Monitoring
Manual Check/Test	Remote Check/Test
Limited Control	Pervasive Control
Few Customer Choices	Many Customer Choices
Failures and Blackout	Adaptive and Islanding
Manual Restoration	Self-Healing

The proposed work fits within the smart grid setting because two-way communication between customers and electricity providers is required which is available only in smart grids. Also, a smart grid is a pervasive, self-monitored, and self-healing. These features are an essential requirement in the proposed model. Finally, the optimization techniques related to this work will be presented in Section 2.8.

2.6 Micro-grids

2.6.1 Basic Concepts of Micro-grids

The power grid consists of a complex fabric of generation plants, substations, transformers, and transmission lines that supply electricity to cities, businesses, and industry. Additionally, there exist smaller power grids, called micro-grids or remote-grids. Micro-grid provides electricity power to island, rural area, and remote operation that have limited or no access to primary grid power. Traditionally, micro-grid uses diesel generators (DG), and diesel pickup system for generating electricity, in some micro-grids. Also, integration of renewable power plants (e.g. wind turbine, geothermal heat pump, ground-coupled heat exchanger, hydro-power turbine, and PV array) are used in combination with diesel generators; storage system is used, as well as to accommodate the surplus renewable power, see Figure 2.8. Furthermore, micro-grid must continually manage fluctuation in demand and generation to maintain 60 Hz frequency (50 Hz in the UK) which is required to maintain electricity grid stability. Moreover, any drop in frequency could create serious issues such as brownout[2] or blackout[3]. The micro-grid, also, can be defined as a set of houses containing loads (appliances) and co-located resources (such as Photovoltaic (PV) arrays, gas turbines, or wind plants) working as a single controllable system, see Figure 2.8 [29]. Micro-grids also offer the possibility to export the surplus of locally generated power to the national grid or neighbors [30]. Additionally, micro-grid can be grid-tied[4] to National Electricity Grid (NEG), or islanded[5] [21]. Moreover, the US Department of Energy gives the following definition to smart micro-grid, "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A micro-grid can connect and disconnect from the grid to enable it to operate in both grid-connected or island mode."[20].

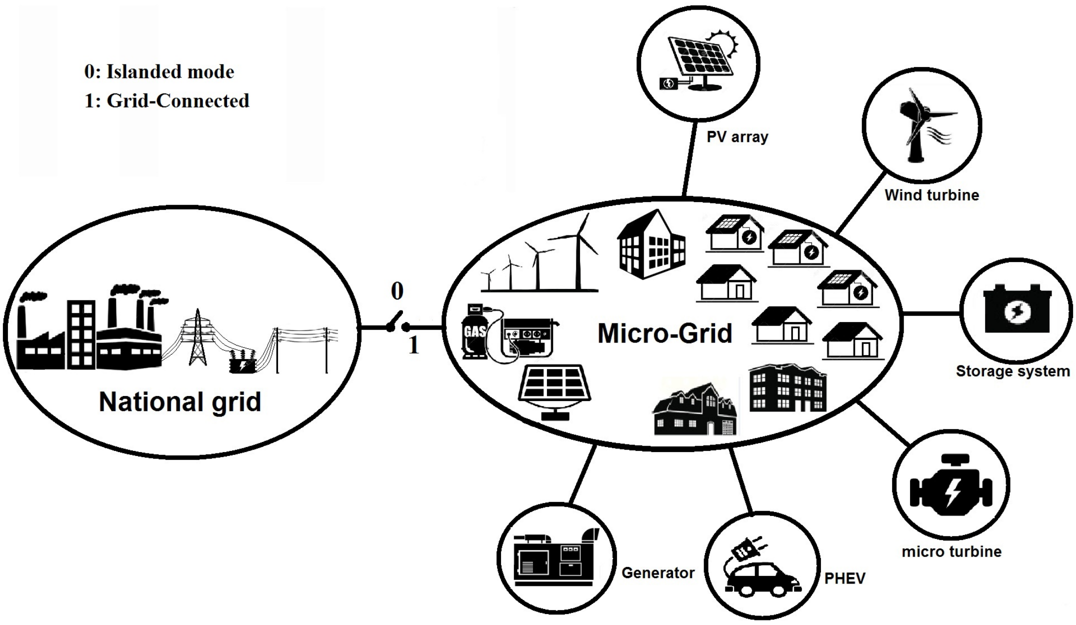


Figure 2.8: Micro-grid diagram

2.6.2 Topology of Micro-grids

As mentioned above, micro-grids work in two modes, grid-tied and islanded [6]. Additionally, it integrates with the following features:

* The micro-grid is equipped with co-generation micro-plants such as wind turbine, PV arrays, Hydro-power micro-plant, or Combined Heat and Power (CHP) unit that generate electricity for local use within the micro-grid. The micro-grid is also able to penetrate any surplus power into the NEG.

2 Brownout is a drop in voltage caused by a state of poor power quality. Intentional brown-out is used to prevent a blackout by reducing the voltage on pockets of customers.
3 Blackout is power failure or cut, it is a loss of electricity for short or long time to an area.
4 Grid-tied means that the micro-grid consumes part of its electricity demand from NEG.
5 Islanded micro-grid means that micro-grid consumes 100% of its demand from local generators.

* The electricity demand in the micro-grid could come from residential, commercial, offices, or industrial building.
* Using renewable resources is one of the useful features of the micro-grid, but one of the primary cause for concern is that renewable power is intermittent. Therefore, the micro-grid must be able to use it's local storage system, such as batteries, to smooth out the fluctuation in renewable power.
* The micro-grid is provided with two-way communication system which consists of smart meters, sensors, etc. Thus, it can use this advanced infrastructure to know the power profile of each customer at any time and react to it if required.
* The micro-grid exploits the communication infrastructure to send and receive information between customers and utility companies over data cable or via wireless communication.
* The micro-grid can communicate with smart appliances and smart component in the end user to control them (On/Off) as requires, or schedule the load of these appliances to decrease the demand for electricity during peak hours [6].

Chapter 3 will introduce research contributions in the micro-grids research area which is a comprehensive mathematical model for micro-grids. Also, Chapter 4 will present MILP-based formulation of micro-grids. The relevant work about micro-grids will be reviewed in Section 2.8. Finally, all related work about micro-grids will be illustrated in Section 2.8.

2.7 Smart Houses

Smart house, Figure 2.9, is a residential building that is designed carefully to assist occupiers to run a particular household function (e.g. cooking, space heating/cooling, etc.) by using an automatic control system. This automatic control system usually deploys information and telecommunication technology. The primary purpose of using such system is to optimize power consumption in the building to reduce electricity and gas bills. Also, increased comfort is one of the advantages of using automation in a domestic setting [31]. Although the idea of the smart house could be applied everywhere, disabled and elderly people are the most interested in such systems in their houses because it facilitates their independent life. The smart house could have local power plants (traditional or renewable), and it can work as a standalone house or as a part of a so-called smart grid. The main challenge for smart homes in smart grid is that the smart house depends on other grid entities (e.g. other houses, renewable micro plants, and utility companies). The smart house usually consists of a set of smart appliances, smart meter, power micro-plant (e.g. PV array, wind turbine, CHP, or diesel generator), control system, and storage system (e.g. PHEV, or batteries) [32].

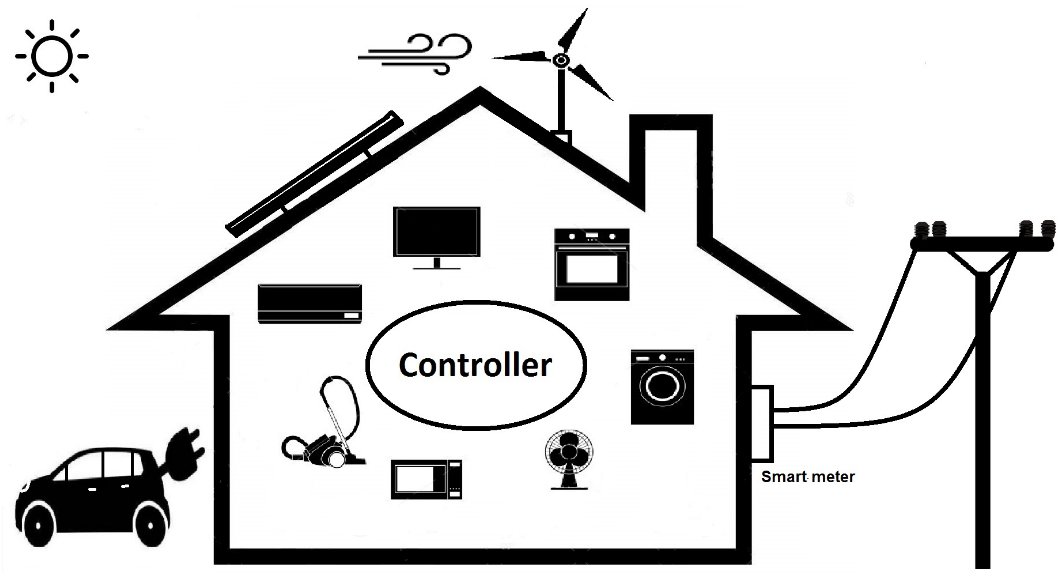


Figure 2.9: Smart house

2.8 Optimization Techniques

Many computational tools and techniques have been used with DSM and DR to minimize the cost of electricity, and to increase the utilization of renewable resources in the residential and commercial buildings [2]. The authors in [2] classified optimization techniques into decision system, static, adaptive dynamic programming, evolutionary programming, and intelligent system. Furthermore, Figure 2.10 gives more detail about optimization tools of each category. This section will review most of the optimization tools that have been used in the area of micro-grids research. In what follows, the most relevant literature to the thesis will be discussed in detail.

2.8.1 Decision Systems

Decision systems are computer software that can analyze a set of data and make decision based on a set of rules [33]. Many studies have investigated using a decision system as an energy optimization tool to minimize the cost of electricity in the residential building, including but not limited to frameworks [34–41]. However, the most important studies that have been used in the area of decision systems will be presented. In study [34], game theory was used to optimize the cost of electricity in the smart grid. The authors introduced an optimal autonomous distributed incentive-based energy consumption scheduling algorithm. The primary objective of this algorithm is to minimize the cost of electricity power for all houses in the smart grid. The authors claim that the main focus of their study was the cooperation between the users (houses), not between end user and electricity provider. Additionally, they minimize the communication between customers into just one message. The framework, also, proposes smart

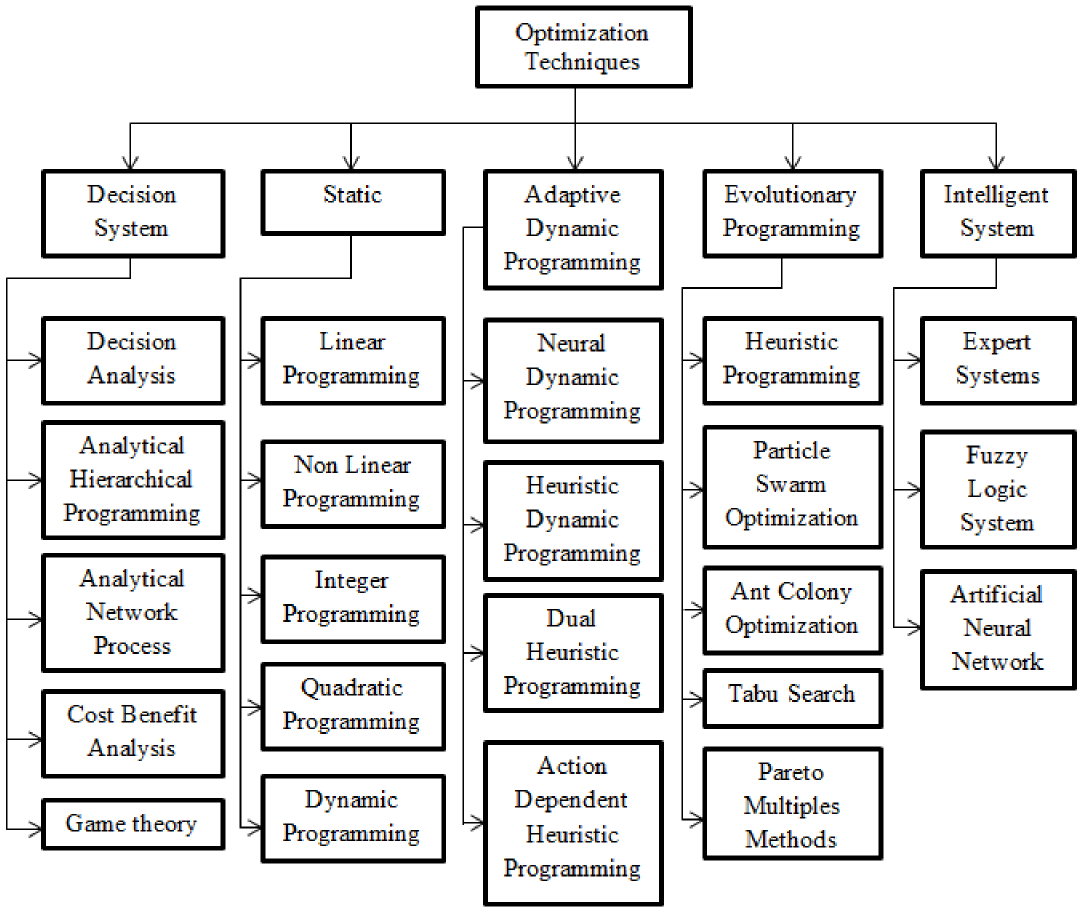


Figure 2.10: Optimization techniques [2]

pricing tariff between users. In addition, framework [35] proposed Demand Response Management system (based on game theory) that considers multiple utility companies, the interaction between electricity providers and end users is modeled as a two-level game. Furthermore, they formulate the competition among electricity providers as a non-cooperative game. By contrast, they modeled the interaction among customers as an evolutionary game. The proposed algorithm is iterative. The authors claim that their simulation results help smart grids to avoid variation of electricity demand and reduce the average peak hour demand.

To conclude, decision systems could be used as an optimization tool for residential buildings. However, if the size of the problem is large, these systems would become very complicated and may fail to provide provable optimal/ suboptimal solution.

2.8.2 Adaptive Dynamic Programming

Adaptive dynamic programming is an approximate dynamic programming optimization tool [42, 43]. The study [44] investigates the use of Action-Dependent Heuristic Dynamic Programming for minimizing the cost of electricity bills. This algorithm invokes two Neural Networks (NN) to manage energy system in the smart home connected to a battery system, photovoltaic system and National Electricity Grid (NEG). The first one works as online sub-algorithm whereas the another works as offline sub-algorithm. Also, they exploit Particle Swarm Optimization in order to pre-train the weights of NNs. Framework [45] has introduced an intelligent self-learning optimization algorithm that can be used for minimizing the energy cost of the residential building. The proposed algorithm has the ability to learn from user demand and the environment. Single critic NN is used in this algorithm to eliminate the iterative training loops between the action and the critic networks. As a result, the training process is considerably simplified. Optimization algorithm based on Action-dependent heuristic dynamic programming for residential energy management is proposed in paper [46], the algorithm controls the load of two houses in real time pricing environment. It allows electricity energy sharing between these houses in order to minimize the electricity cost. The algorithm is based on NN.

Based on the literature review, ADP uses some intelligent systems such as NN to minimize the electricity cost. To the best knowledge of the author, there are very few studies that have using ADP as an optimization tool in micro-grids. Also, the results were not promising regarding the run-time. Therefore, the author has decided not to investigate this method.

2.8.3 Evolutionary Programming

Evolutionary Programming (EP) is heuristic optimization tool. In addition, Particle Swarm Optimization, Ant Colony optimization, Tabu search are an example of EP.

Particle Swarm Optimization (PSO) is an evolutionary programming. In 1995, Dr. Eberhart and Dr. Kennedy introduced PSO. PSO is a stochastic optimization method inspired by social behavior of fish, flocking or bird movement. The central idea of PSO is that it generates random solutions then searches for optimal one by updating the existing solutions. However, there are many common things between PSO and other evolutionary computation techniques such as Genetic Algorithms (GA), PSO does not have evolution operators such as mutation or crossover [47]. Many studies have used PSO in order to minimize the cost of electricity in residential buildings. Framework [48] proposes scheduling algorithm based on PSO to reduce the peak to average ratio in a residential building. The proposed algorithm shifts the load or the demand and reschedules to avoid sharp fluctuation. Also, dynamically distributed resource management in a Demand-Side Management is introduced in the paper [49]. The primary goal of this framework is to minimize the cost of electricity in residential buildings. PSO is used as resource management technique. Study [50] investigate using controller based on Binary PSO to reduce the peak demand on electricity power. The elemental objective of this study is to find the optimal load demand schedule that minimizes the peak demand and maximizes the comfortable level of the users. Study [51] has investigated the use of Binary PSO in demand side management, the principal objects of this framework is to minimize the electricity cost of interruptible appliances, minimize the switching On/Off. The authors simplified this multi-objective optimization problem by using a single aggregate objective function and by dividing the swarm into a set of sub-swarms. The framework [52] has introduced a cost-effective energy management system for a set of houses and micro-generators working in a micro-grid setting. The proposed mathematical model provides renewable power sharing between houses in the micro-grid. Further, the authors have formulated the distributed resources in micro-grid as a nonlinear integer programming problem. As known, Nonlinear integer programming problem is NP-hard. Therefore, authors used PSO.

The Ant colony optimization (ACO) is also one type of evolutionary programming. In 1999, Marco Dorigo introduced ACO in his Ph.D. The behavior of ant colony was what inspired him to introduce this technique [53]. In study [54], the authors use an ACO-based algorithm to predict energy demand. Energy demand model was proposed using ACO as a multi-agent system. The model is developed based on population, gross domestic product (GDP), import and export.

Tabu Search is one kind of evolutionary programming. In 1986, Fred W. Glover created Tabu search, after three years he formalized it [55, 56]. Minimizing the cost of household appliances in residential building is an NP-Hard problem. Therefore, finding the optimal value is not easy. Tabu Search is optimization meta-heuristic method that uses local search to find a heuristic solution to such problems. A study [57] investigate using Tabu Search for optimizing the electricity cost of the residential building. The idea of home automation and power management is achieved in this by using a control system that uses Tabu Search. The authors divided the automation control system into three parts or levels, which are anticipation, reactive and device layers. The primary aim of this algorithm is to maximize comfort level and minimize the electricity cost. Another study [58] uses Tabu Search and Genetic Algorithm (GA) to minimize the electricity cost in a residential building by applying load shifting idea (from peak hours to off-peak hours). They split the algorithm into two main parts. One deals with controllable loads such as dishwasher and washing machine, whereas the second one schedules the resources.

To sum up, the main disadvantages of using Evolutionary programming is that no guarantee for finding optimal solutions in a finite time. Also, it needs a long time for convergence (e.g. it needs a decent size of the population to get good results). Moreover, in GA, mutation rate, crossover parameters, fitness/selection parameters depend on trial and error and it could take tremendous time in huge problems such as micro-grids. Additionally, in PSO, the representation of weights is tough.

2.8.4 Intelligent System

Intelligent systems can be used as optimization tools for minimizing the electricity cost of residential buildings. Expert systems, Fuzzy logic, and Artificial Neural Network are type of intelligent system [2]. Furthermore, expert systems rely on heuristic or rule-driven decision-making [2]. Framework [59] has proposed optimization algorithm for residential building in smart grids based on rule-based decision-making system. Nevertheless, they have not presented solid evaluation about the computation time. Additionally, they have used low time resolution (15 minutes).

Fuzzy logic is an intelligent system. The idea of fuzzy logic was first advanced in the 1960s by Prof. Lotfi Zadeh of the University of California at Berkeley. Dr. Zadeh was working on the problem of computer understanding of natural language. Fuzzy logic is a many-valued logic which means the truth value could be any number between 0 and 1 [60]. Further, James in [2] gives the following definition of Fuzzy logic, "Fuzzy logic is a superset of conventional logic that has been extended to handle the concept of partial truth, which are the truth values between completely true and completely false". Framework [61] used fuzzy logic control for air conditioning system in residential buildings. However, the objective of this study is not minimizing the electricity cost. Additionally, they have not tackled the problem of computational time. Study [62] has used fuzzy logic decision-making algorithm to reduce the load of a HVAC system in a smart residential building. Nevertheless, the authors have not tackled the run-time problem.

In 1943, artificial neuron was introduced by Warren McCulloch and Walter Pits. "Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems." [63]. In addition, Neural Network (NN) is a sort of intelligent system, and it is exploited in [64–66] to minimize the electricity cost of residential building.

2.8.5 Static Optimization Technique

Numerous frameworks have used the static optimization technique to minimize the electricity cost in residential and commercial buildings. The framework [67] has proposed a mathematical model based on MILP for power allocation problem in the residential building. The study used LP solver to solve this optimization problem. The manuscript considered two pricing strategies to find the optimal solution for an apartment building with just two household appliances. The study also has shown the computation time of the algorithm but the authors have not tackled it seriously (they have not tested their algorithm with large number of appliances and high time resolution). Moreover, it does not consider the use of local renewable energy. Additionally, it has not proposed a model for all type of appliances (e.g. AC unit and PHEV). To the best knowledge of the author, the proposed algorithm would not scale up well with a broad range of appliances, especially if we use high time resolution. Also, the algorithm can not tackle large optimization problems such as large building or micro-grid. The authors stated that the algorithm can not provide a feasible solution when the number of appliances is significant (20 appliances) due to the hardness of the problem. To the best knowledge of the author, this depends on time resolution, the proposed algorithm may not be able to find the optimal solution to a house with 5 AC units with time resolution < 2 sec., for instance.

Manuscript [68] has tackled the load uncertainty in smart grids. The authors have designed and implemented an MILP-based mathematical model for residential building in a smart grid. The proposed algorithm is a real-time multi-stage optimization algorithm. The strong aspect of the proposed model is that it considers uncertainty in electricity demand. The proposed control algorithm can update the schedule once new demand information is revealed. In the result, authors claim that their algorithm can benefit end users and utility companies. Nevertheless, the time granularity used in this study is (1 hour, 30 minutes, and 15 minutes) which are very low time resolution. Some appliances may need 10 minutes or less to finish their tasks. Moreover, the study does not consider HVAC system and electric vehicle. Finally, to the best knowledge of the author, this algorithm would not cope with all kind of appliances in residential building. Additionally, it can not take large building with a large number of appliances.

Authors, in paper [27], have proposed an integer linear programming based model for residential building in a smart grid. The mathematical model does not add a lot to the model that has been introduced in study [67]. The model is, in fact, straightforward because it does not consider renewable power and temperature controlled appliances such as AC unit, or heater, etc. Also, authors do not consider appliances that have a battery such as PHEV (PHEV and AC unit add a lot of complexity to the optimization problem). The authors have used low time resolution (1 hour). Also, the results do not show the computation time of the proposed algorithm. As known, this optimization problem is NP-hard. Therefore, the computation time of the algorithm is crucial. The proposed model definitely will not cope with a wide range of appliances and high time resolution especially if the model contains AC units and PHEV(s), these kind of appliances make the problem more complicated as they need more variables to model them.

The authors, in framework [69], have introduced an MILP-based model for energy management problem in a residential building. Moreover, the mathematical model seems relatively comprehensive, compared with the studies that have been mentioned above; the manuscript provides a general model of appliances included AC unit. They have, furthermore, considered use of domestic renewable resources. However, in their evaluation, authors have used time slot of one hour, which is a really low time resolution. The scheduling optimization algorithm can find an optimal solution if the number of appliances in a house is around a handful of appliances. For example, with this setting, each appliance needs just 24 binary decision integer variables, whereas if time resolution is 5 minutes, each appliance needs 12 times 24 integer variables which makes the problem harder to solve. Therefore, the proposed algorithm in this framework can not be used in the large problem. Also, more evaluation is needed to examine the performance of the proposed algorithm properly.

Papers [70, 71] have proposed a comprehensive mathematical model for energy management problem in residential buildings. In the first framework [70], the authors have proposed a new idea to reduce the complexity of the optimization problem of power allocation (by using two sampling strategies, the first one is high sampling resolution, whereas the second one is low sampling resolution). Furthermore, low sampling resolution is designed for uninterruptible appliances such as dishwasher, washing machine, etc., whereas the high sampling resolution is designed for interruptible appliances such as air conditioning unit, electric heater, and water heater, etc. The authors, in their evaluation, have used time resolution of 5 minutes for interruptible appliances and 20 minutes for uninterruptible appliances. However, they have used a time horizon of just 6 hours. Therefore, each uninterruptible appliances needs 6 times 3 binary variables and each interruptible appliance need 6 times 12. In the studies mentioned above, they have used one hour and 30 minutes time slots for 24 hours. So, each appliance 24 times 2 binary variables for both interruptible and uninterruptible variables. So, the improvement is not significant. To the best knowledge of the author, even with using this technique, it is extremely hard to solve the large problem to provable optimality. The study [71] is an improved version of framework [70]. Authors use 24-hour time horizon, but they have not provided accurate evaluation about computation time of the problem.

Authors, in framework [72], have designed and implemented an MILP-based cogeneration model for the energy allocation problem in residential building problem working in a smart grid. The provided algorithm seems to work in the given settings because they have used low time resolution (one hour). The authors, in a study [73], have included battery system to the previous model presented in [72]. They have used decomposition method to reduce the complexity of the problem and improve the performance of the algorithm. Nevertheless, the provided evaluation has not tackled the run-time issue of the proposed optimization algorithm. In the results, authors have used one hour time resolution. Therefore, form the author's point of view, this algorithm will not cope with the same model if high time resolution was used, such as a time slot less than or equal to 5 minutes.

The authors in [74] have proposed a mathematical model for cost optimization of smart appliances in a residential building in smart grids. The study has explicitly modeled the interruptible and uninterruptible household appliances. Also, it has presented clearly all the constraints of each type of appliance. The study used a couple of case studies to evaluate the performance of the suggested algorithm. But it has not tackled the run-time issue of the algorithm. Also, it has not provided a model for an air conditioning system which is the most difficult system to model and the most complicated system to solve.

Many studies, [75–85], have used an MILP-based algorithm to minimize the cost of electricity for residential building in the smart grid by using local renewable power and the concept of load shifting. The primary goal of all these studies was to find the optimal solution. Therefore, they had to sacrifice the accuracy of the model by making a lot of assumptions in their models. Also, the proposed algorithm can be used to find the optimal solution for a single house with a limited number of appliances. However, all of them have not used LP relaxation in this area.

Study [86] has tackled single objective optimization problem of a smart micro-grid. The authors have proposed a mathematical model for a set of houses and micro-plants working in micro-grid settings. Furthermore, the authors claim that their algorithm (MILP-based energy management system) can solve the problem to optimality. The primary objective of this algorithm is to minimize the overall electricity cost of all houses in the micro-grid by using domestic renewable resources and load shifting. However, scalability is the main issue in the proposed algorithm, because this is an NP-hard problem.

The authors in framework [87] has proposed an MILP-based model for a smart residential micro-grid. The primary aim is to minimize the operating cost of a residential micro-grid. The model operates in grid-connected mode. The proposed residential micro-grid, basically, consists of a single house with few appliances (including PHEV), storage system, and few micro plants (including renewable and traditional micro plant such as CHP). Although the authors have used relatively high time resolution (15 minutes), scalability is a serious issue in such NP-hard optimization problem if there is more than one house in the micro-grid. Actually, from the author's point of view, the proposed model is not really for micro-grid but a single home equipped with a set of electricity generators.

Authors in paper [88] have suggested a mathematical programming formulation (MILP-based model) for fair profit distribution among residential buildings in a smart micro-grid. The recommended model allows renewable power sharing between houses. Furthermore, authors have proposed Lexicographic Minimax approach to finding a fair solution. The Pareto-optimal solution of their method depends on predicted data of renewable resources and demand. In the finding, the authors have demonstrated two scenarios (case studies). In the first scenario, they have examined a micro-grid with ten houses, and in the second scenario, they have tested micro-grid with fifty homes. However, the time resolution is not high which means the number of decision variables is small. Moreover, they have not considered household appliances that depend on other variables such as temperature in the case of heaters and AC units or state of charge in case of using Plug-In Hybrid Electric Vehicle (PHEV).

Framework [89] uses MILP-based scheduling algorithm to minimize the electricity cost of a set of residential building equipped with micro CHP unit and solar PV arrays. The study compares the cost of 20 houses working individually and the same houses working in a micro-grid setup. Although this study adds some knowledge to the field, it does not tackle the important issue of computation time. In studies of this type, the time complexity of the particular algorithm increases with the system's granularity or the number of available appliances. The authors are only able to present examples that allocate resources over relatively large time slots.

A study [90] investigates using optimization algorithm for residential building in micro-grid environment. The main objective of this algorithm is to find the optimal cost of electricity for a set of houses. However, the study does not tackle computation time and complexity of the problem well. Authors used just 48-time slots which are not suitable for interruptible appliances such as AC units and heaters. They claim that the MILP solver can solve the problem in a matter of few seconds, but this will not always be the case because this problem is an NP-hard and the computation time would go to infinity if time slot were small (< 5 minutes).

The proposed scheduling algorithm in the paper [91] uses MILP formulation to model micro-grid and solve it using a commercial solver. The authors use a convex piecewise affine function to approximate nonlinear cost function and constraints into linear equations. The main objective of this study is to reduce the peak demand on particular times. The same authors as in [91] have provided a further study in [92], and they have used control-oriented approach for optimizing the cost in micro-grid and MILP combined with Model Predictive Control. However, the authors have not discussed the complexity of the problem well. Regarding the computation time, they mentioned in the first study that the calculation time is around 5 seconds, but from the author's point of view, this is not always the case. In a further study [93], authors extended their previous work and tried to provide more results and discussions. However, there is no considerable contribution about computational time.

A stochastic power management system has been suggested for a micro-grid by authors in framework [94]. The proposed model has considered uncertainties in the renewable energy generated by local resources. They have tackled this problem by using a diesel generator. Further, the optimization problem has been decomposed into central or master MILP-based problem and nonlinear programming (NLP) sub-problem. Additionally, the master problem consists of a 24-hour stochastic energy scheduling problem (MILP solver solves these problems), whereas the sub-problem is an hourly radial micro-grid power flow with a set of variables received from the master problem solution.

The authors in framework [95] has proposed dynamic programming algorithm and simplex method to solve the optimization problem of a micro-grid. However, the micro-grid in this study consists of just a CHP, a PV array, a Wind turbine, a Fuel cell, and heat load (boiler). Also, time resolution is large (one hour). Furthermore, study [96] has suggested a dynamic programming based method for developing optimal micro-grid architectures. Moreover, the authors in paper [97] have proposed a dynamic programming approach for minimizing the cost of a micro-grid and maximizing the efficiency of energy storage system. Nevertheless, the algorithm can not solve large optimization problem as the authors have only managed to use micro-grid with one PV array, one wind turbine, one hydrogen-based fuel cell, batteries and diesel generator.

All literature mentioned above uses a predictive control system. Regarding reactive control system, the idea of trying to effectively allocate electric power using online algorithm is not new. Maximum demand control is an established research area in Electrical Engineering [98]. More recently, several proposals have emerged in the context of renewable energy management [27, 69, 99, 100]. Knapsack models [101] have been used in this area. However, these tend to be “predictive” systems: the power allocation is planned in advance using information about the geography of the place, as well as historical meteorological and usage data. Such systems are bulky and do not cope well with changeable weather conditions. Furthermore, there is little analysis of the quality of the resulting allocation in terms of its efficiency. Perhaps the closest to the proposal reactive system (Presented in Section 4.3 and Chapter 7) are hardware components like EMMA [102] or Solar Switch system [103]. Both of these try to adapt the household energy usage to the amount of available power. However, in both cases, the system’s behaviour is quite limited: the hardware is hooked up to the household water tank and any surplus energy is used to heat up the water. A number of issues had to be addressed. An electric appliance will typically use a variable amount of power, only coarsely bound by the nominal power mentioned in the manufacturer’s information sheet. A natural way to deal with this is to assume that the appliance loads are not fixed numbers but, rather, random quantities. Related to this, the variability of the renewable power source implies that any empirical evaluation will have to resort to both real-life and simulated experiments enabling the investigation of different allocation strategies or different parameter settings under essentially identical conditions. Last but not least, Knapsack is an NP-hard problem [104]. There is a vast literature on the

Knapsack problem, ranging from the study of exact and approximation strategies to the study of many generalizations [105, 106]. In particular several stochastic variants have received significant attention [107, 108]. These are obtained by replacing part of the standard problem definition with a random component. Some authors have studied models in which the item availability is governed by a probabilistic law. Others have looked at the case of random profits [109].

Micro-grid issues are discussed in detail in [110, 111]. Additionally, frameworks [112–123] illustrate extensive literature review about optimization methods and approaches that have been used to minimize the running cost of a set of houses in micro-grids.

2.9 Summary of Literature Review

It can be concluded from the literature review that several mathematical models and optimization algorithms based on various approaches have been proposed for optimizing the electricity cost of the residential building using renewable power resources and load shifting in micro-grid settings and a smart grid environment [27, 67–85, 90, 124–127]. Although there are countless pieces of research which have used static tools as optimization method, the author has decided to work in the same area due to the fact that the proposed methods using other optimization tools are not as good as a static method in this area. Moreover, the LP solvers have become very powerful and can solve relatively large problems, and these solvers can provide heuristic solutions. All the previous frameworks have added decent knowledge to the field. However, there are few issues that have not been tackled seriously. Firstly, the computational time (run-time) of the proposed optimization algorithm has not been addressed seriously. Further, the proposed algorithms can not scale up well with large or huge optimization problems such as micro-grids or a large building with a large number of appliances. Secondly, AC systems have not been considered carefully because solving a problem with k AC units (or any thermostated household appliance such as electric heater) is more complicated than solving the same problem with k Dishwashers, as AC system depends on inside and outside temperature. Also, to the best knowledge of the author, nobody has proposed a model for AC system when there is more than one AC unit working the same room. Therefore, this thesis has introduced a comprehensive mathematical model for AC system (it is assumed that AC unit operates in $k > 2$ modes) and a couple of an MILP-based heuristic optimization algorithm that is able to solve the problem to near-optimal in polynomial time by using LP relaxation and rounding. Regarding frameworks about micro-grid, the proposed algorithm, and model, in [52, 76, 85, 90–93, 113–116, 118–123], have added decent knowledge to the research field. Nevertheless, they have not considered the run-time problem with detail. In other words, they have used low time resolution and a small number of grid entities. Also, the proposed models are not comprehensive, most of the study proposed a single objective model. In this thesis, a comprehensive multi-objective model for the micro-grid has been introduced.

Part II

Model Development

Chapter 3

System Modeling

"Acquire wisdom from the story of those who have already passed"

Uthman Ibn Affan

A comprehensive mathematical model of micro-grids (operating in grid-tied mode) is illustrated in this chapter in Section 3.1. Potential power exchange in the micro-grid is explained in Section 3.2. Furthermore, this chapter presents a detailed model of micro-grid components such as renewable micro generators (e.g. PV arrays and wind turbines) and smart household appliances in Sections 3.3 and 3.4, respectively. Moreover, this chapter proposes a mathematical model for each type of household electric appliance. Additionally, the chapter discusses our approximation technique of the power profile of household appliances and explains the sampling technique in Section 3.5. Finally, Section 3.6 summarizes the chapter.

3.1 The Micro-grid

In this thesis, it is assumed that the micro-grid operates in grid-connected mode to cover the extra demand needed in the micro-grid. Consider a micro-grid consists of a set of smart houses $\mathscr{H}$ and a set of micro-generation power plants $\mathscr{R}$, some of these plants may belong to house h, $\mathscr{R}_h$. Additionally, each house consists of a set of rooms $\mathscr{M}_h$ and each house has a set of electric household appliances $\mathscr{A}_h$. Some houses in the micro-grid (like houses labeled with symbol H4, and H1 in Figure 3.1) may be directly connected to one or more generators, and therefore be able to receive energy from them in a particularly efficient way, and for free, but in general the houses in the system may receive their power from any of the generators in the micro-grid or the National Electricity Grid (NEG). Furthermore, the proposed model will consider each house and micro-plant in the micro-grid as an agent; each agent has its own

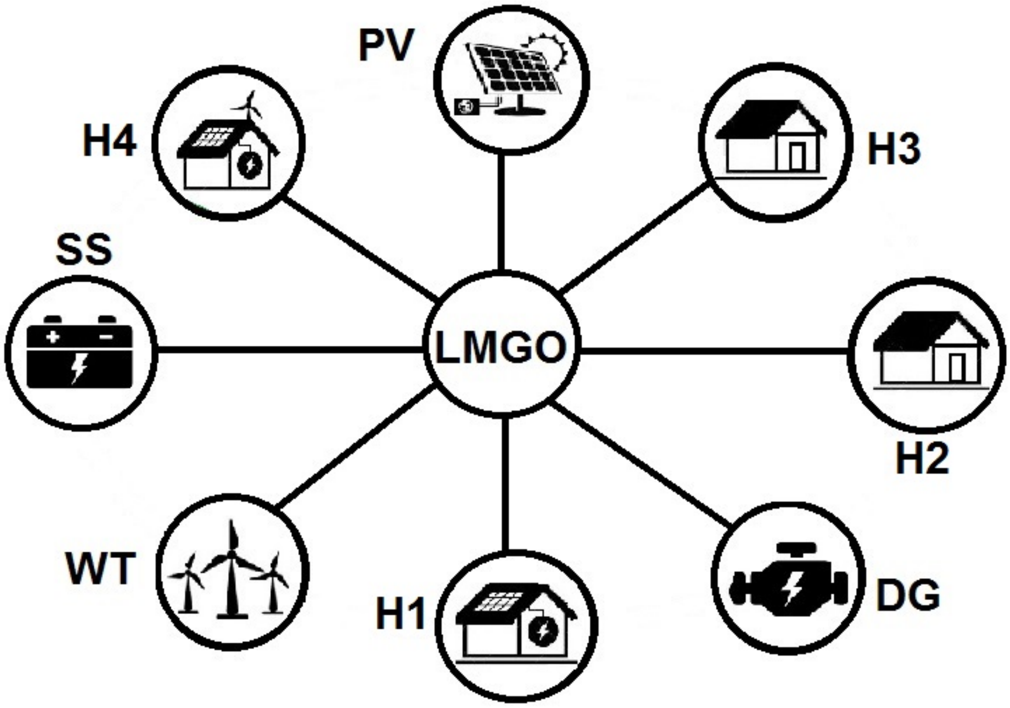


Figure 3.1: Micro-grid (set of houses, storage systems, and micro generators), some houses are equipped with rooftop PV array or wind turbine, and some of them not.

objective. The energy exchange between these agents within a micro-grid is controlled by a central control system called Local Micro-Grid Optimizer (LMGO). The power plants generate energy which can be either used by the houses in the micro-grid or exported to the NEG.

3.2 Power Exchange in Micro-grid

Without considering technical issues regarding power exchange between micro-grid agents, Figure 3.2 describes the possible energy exchanges between a house, a generator, and the NEG. Houses (and their appliances) can only use electricity. The electricity comes into the house either from a generator (internal to the house or external) or the NEG. The labels on the arcs represent the electricity cost that the entity at the end of the arrow will have to pay to the entity at the other end to get electricity from it. In this thesis, it is assumed that the energy produced by a generator $r \in \mathscr{R}$ can be sent to a house $h \in \mathscr{H}$ at a unit cost $\gamma_h^r(t)$ for each kWh, or exported to the NEG at a cost $\zeta_r(t)$ for each kWh. Alternatively, a house can buy energy from the NEG at a cost $\lambda_h(t)$ for each kWh. Additionally, all costs might change over time (hence they depend on the time parameter t). Note that the price of local renewable power, $\gamma_h^r(t)$, is decided by residents and the owner of local generators in a micro-grid, whereas electricity rate, $\zeta_r(t)$ is set by electricity providers. In what follows, the chapter will give detail of the various components of the micro-grid system.

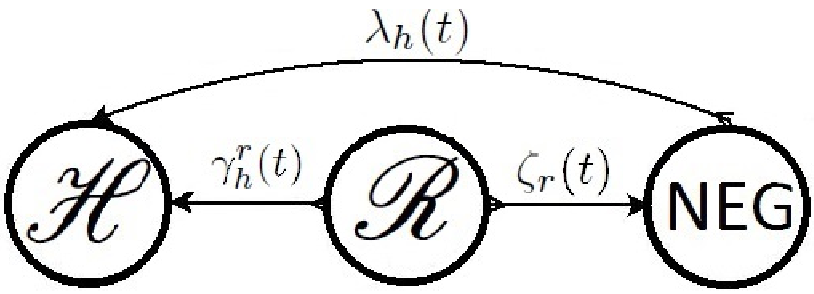


Figure 3.2: Diagram shows local renewable energy exchange between the agents in a micro-grid.

3.3 Micro-generation Plants

This section illustrates renewable power generation. Renewable generation is the process of producing electricity or heat from renewable resources. There are many resources of renewable energy (including but not limited to sunlight, wind, rain, tides, waves, and geothermal heat) that can be used to generate electricity. However, the most common resources that can be employed in the residential building are solar and wind power.

3.3.1 Solar Power and PhotoVoltaic Array

Solar power is a renewable power generated by converting the sunlight into electricity using a Photovoltaic (PV) array. This sort of power is the most common source of energy in the residential building [9]. The main issue with solar power is that the output during the night is zero kWh. Furthermore, the operating time could be only a few hours in countries such as Finland and Sweden during wintertime.

PV cells are joined via tiny electric wires in series or parallel circuits to generate higher voltages, currents and power levels. Moreover, PV arrays are solar energy micro-plants that consist of a set of PV panels. Additionally, each PV Panel consists of a set of PV modules that include a set of PV cells, assembled in series and parallel, and sealed in an environmentally protective laminate, see Figure 3.3 [128].

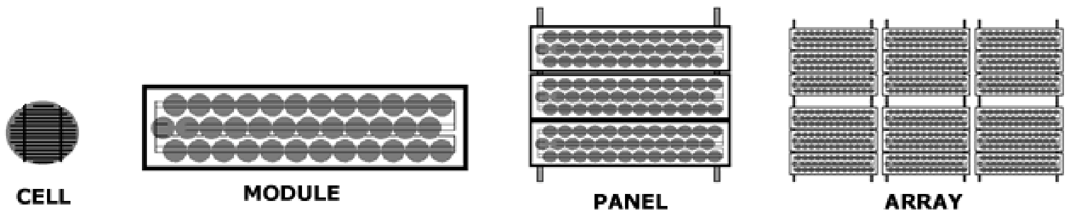


Figure 3.3: PV cells, Module, Panel, and PV array.

The total amount of generated solar power during a distinct time interval, P_{s_T}, is

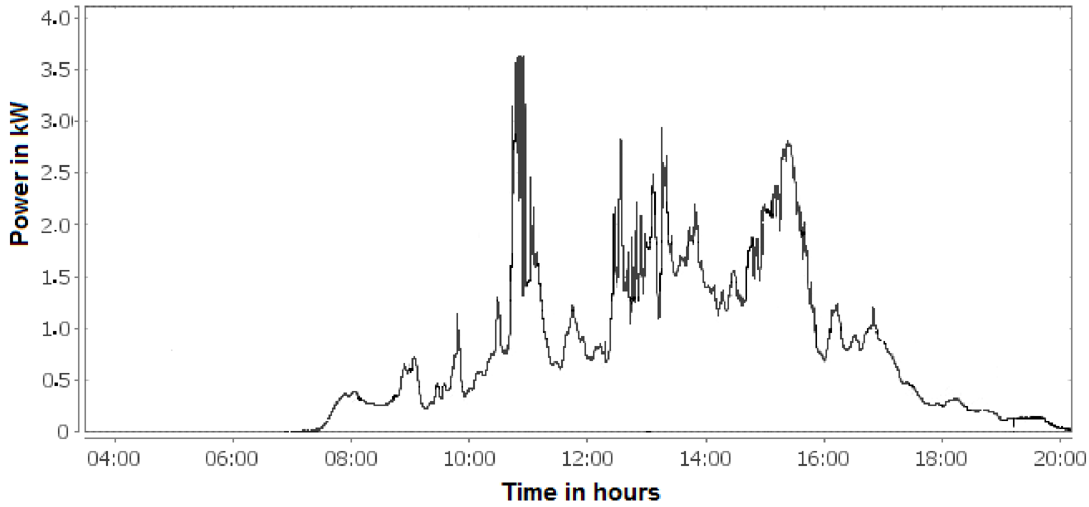


Figure 3.4: The output power of a PV array

presented in the following equation:

$$P_{s_T} = \int P_s(t)\,dt. \qquad 0 \leq P_s(t) \leq \overline{P_s}, \tag{3.1}$$

where $\overline{P_s}$ is the maximum output of PV array, whereas the instance output of PV array at any time can be estimated by using the following equation:

$$P_s(t) = \eta_e \cdot \eta_d \cdot \eta_c \cdot \eta_w \cdot A_s I_T(t), \tag{3.2}$$

where $P_s(t)$ is the solar power at time t, η_e is the efficiency of a solar cell, η_d is the degradation factor of PV array, η_c is the efficiency of the power conditioning devices, and η_w is the wiring efficiency of the PV array system. A_s is the PV array surface area and $I_T(t)$ is the solar radiation in W/m^2 at any time, t [129]. In this thesis, Equation (3.2) is simplified into the following equation:

$$P_s(t) = \eta_T \cdot A_s I_T(t), \tag{3.3}$$

where η_T is the efficient of PV array.

Figure 3.4 depicts real data for the output power of a PV array (maximum capacity of 4.1 kWh in the city of Liverpool, England).

3.3.2 Wind Power and Wind Turbine.

Wind power is renewable power generated by converting kinetic energy (wind power) to electrical energy by using a wind turbine. This sort of renewable is less common than the solar energy in the residential building. The main issue with wind energy is that it is intermittent and very fluctuated. Consequently, it is not a reliable source

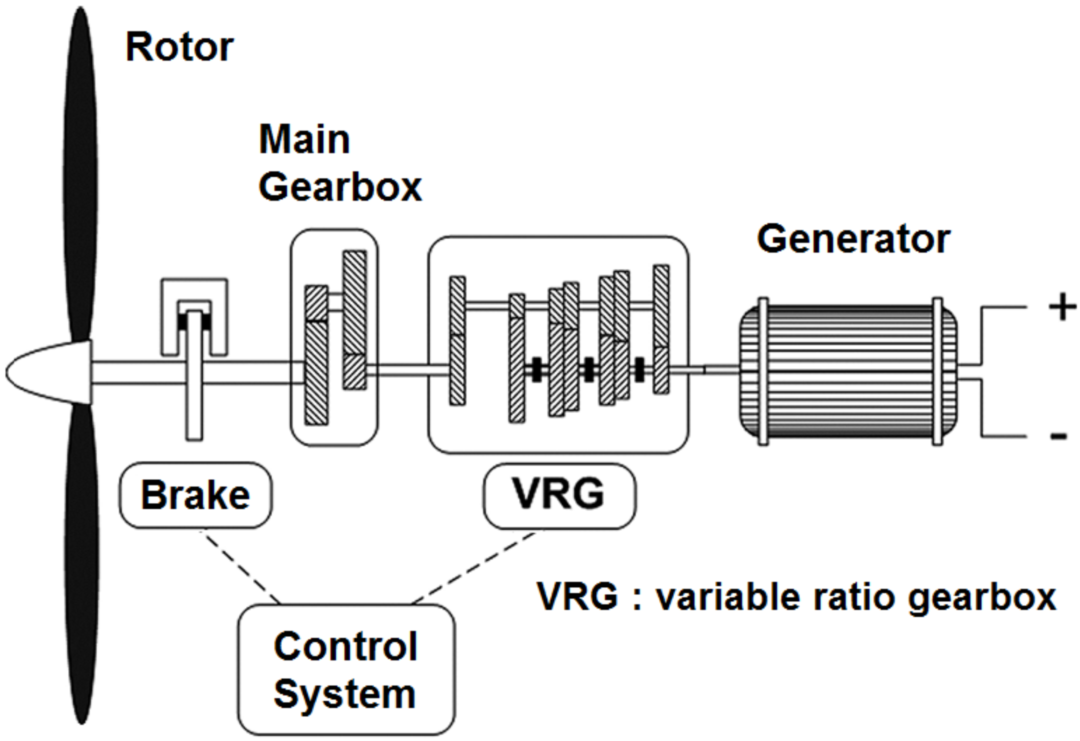


Figure 3.5: Wind turbine component [3]

of energy. Additionally, having rooftop wind turbine in the residential building could cause some safety issues.

The wind turbine is a tool, or electricity plant, used to generate electricity by converting wind power to electrical energy. There are four main parts in wind turbine: a rotor, control system, main gearbox and generator, (see Figure 3.5). It is very hard to estimate the output of wind turbine because it depends on wind speed, wind density, and other weather parameters. The cumulative amount of energy generated by wind turbine during a particular period is presented in the following equation:

$$P_{w_T} = \int P_w(t)\,dt. \qquad 0 \le P_w(t) \le \overline{P_w}, \tag{3.4}$$

where $\overline{P_w}$ is the maximum output of wind turbine. In addition, the instance output of wind turbine can be estimated by using the following equation:

$$P_w(t) = \begin{cases} 0 & v_{C_{out}} < v(t) \le v_{C_{in}} \\ \frac{1}{2} \cdot c_w \cdot \rho \cdot A_w \cdot v^3(t) & v_{C_{in}} < v(t) \le v_r \\ P_{rate} & v_r < v(t) \le v_{C_{out}} \end{cases} \tag{3.5}$$

where $P_w(t)$ is the output power of wind turbine, c_w is the power coefficient of the wind turbine, $A_w = \pi \cdot r^2$ is the swept area of a wind turbine, ρ is the air density, $v(t)$ is the wind speed at time t, and P_{rate} is the maximum output power. In order to use this

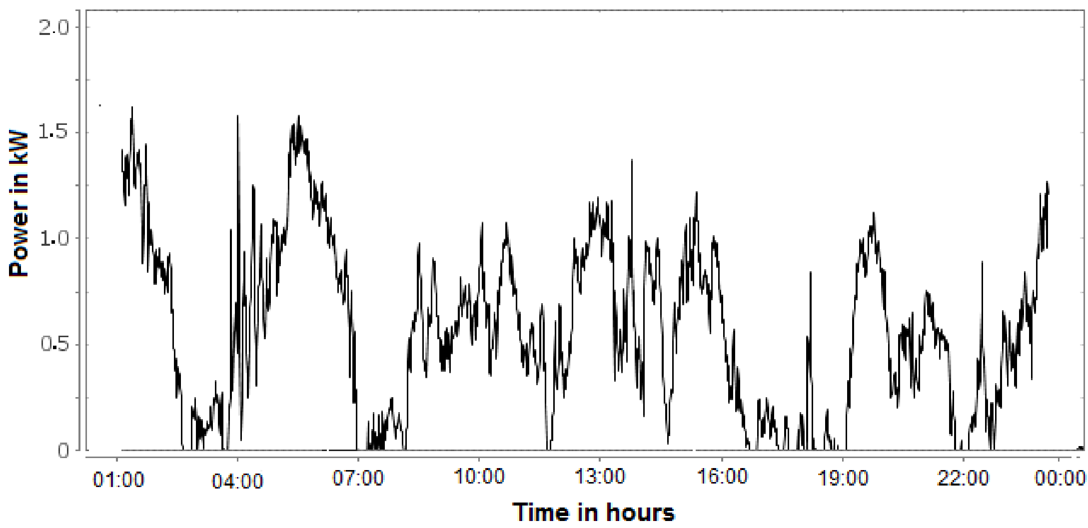


Figure 3.6: The output of wind turbine (real data) [4]

formula, some approximation and assumption must be made. For instance, ρ depends on weather variant parameters and it is very difficult to measure them or get them from meteorological stations [3].

Figure 3.6 depicts the output power (real data) of wind turbine (maximum capacity of 1.78 kWh in the city of Liverpool, England) [4].

3.3.3 Renewable Power Approximation

Figure 3.7 demonstrates real data of solar power, measured every 5 seconds. The data was generated in the city of Liverpool (North West England, UK) in June in 2012. In this thesis, recorded data (heuristic data) for solar radiation and wind speed have been used in the experiments to estimate the output of the renewable micro-plants (PV array and wind turbine, respectively) at each hour. To deploy the proposed model, predicted data of wind speed and solar radiation must be provided to the model. Unfortunately, to the best of our knowledge, there is no weather forecasting station which provides a predicted wind speed and solar radiation with high time resolution such as every 5 seconds or even higher. However, they are able to provide hourly (average) predicted data for solar radiation or wind speed with time resolutions of one hour. Therefore, hourly (average) wind speed and solar radiation have been used as input to the proposed models of wind turbine and PV array to estimate the predicted output renewable energy of these micro-plants over time horizon (24 hours say).

3.3.4 Renewable Power Pricing

As mentioned in Section 2.3.5.2, there are many tariffs in the market nowadays. These tariffs are very different from one country to another. In this thesis, an exchange rate

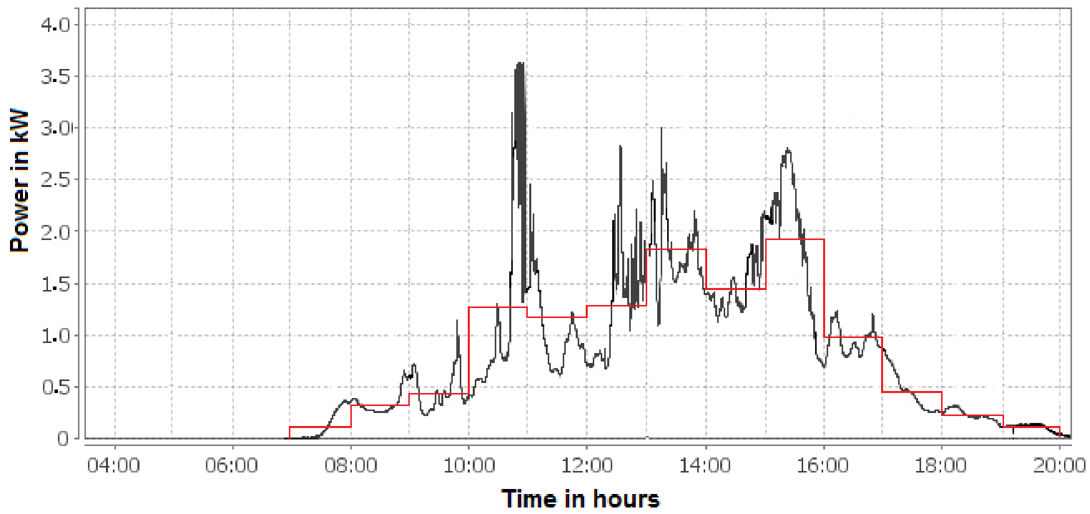


Figure 3.7: The output solar power of PV array (Capacity is 4.1 kWh), the data was generated in Liverpool, Merseyside, North West England (53°24´N 2°59´W)

for the surplus renewable power generated by local micro-plants in micro-grids has been proposed. The key idea is that the local power should be sold to residents for any amount of money between the NEG electricity rate and the NEG export tariff, in other words, it should be cheaper than NEG price and higher than the export rate to the NEG.

3.4 Appliances Modeling

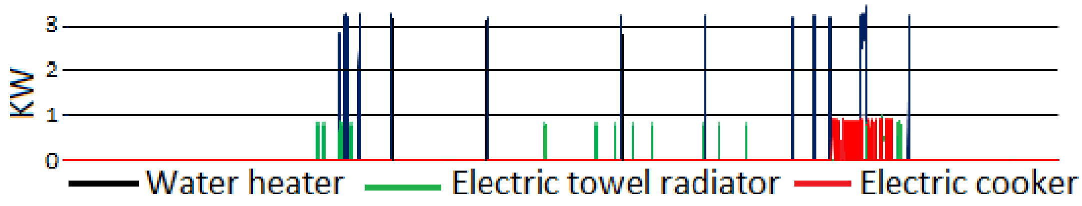
This section presents a model of household electric appliances in detail.

3.4.1 Definition of Household Appliance

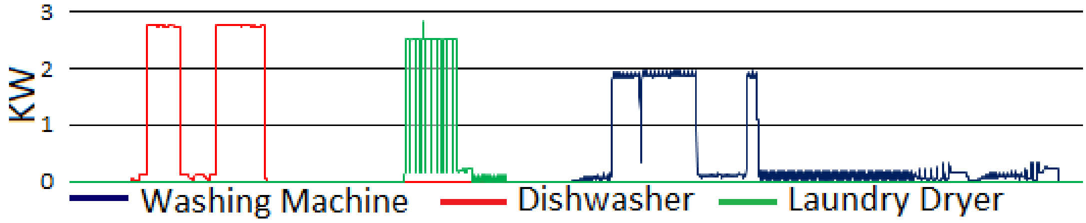
Household appliances are machines that are used to perform a particular household function, (e.g. washing, cleaning, cooking or heating). Within this thesis, only electric appliances have been considered.

3.4.2 Appliances Classification

To model household appliances, the power profile of each appliance must be analyzed and understood. Further, Figure 3.8 shows recorded real data of energy consumption of various appliances. Figure 3.8a demonstrates that some of the household appliances consume almost the same electricity over their operating time, these type of appliances are called uni-phase appliances. Moreover, some of these appliances are interruptible (Electric towel radiator in green, and water heater in black). These kinds of appliances can be switched on or off during their operating time without any techni-



(a) Interruptible uni-phase appliances



(b) Uninterruptible multiphase appliances

Figure 3.8: Uniphase vs Multiphase appliances [5]

cal issue and without affecting its performance (e.g. air conditioner, heater, or PHEV). By contrast, there are some appliances that have uninterruptible power profile such as Electric cooker (in red). On the other hand, Figure 3.8b illustrates power profile of three uninterruptible household appliances (washing machine in navy blue, laundry dryer in green, and dishwasher in red). These appliances are called multiphase appliances because their power consumption varies over their operating time. For instance, washing machine performs a sequence of cycles, and each cycle consumes a particular amount of energy (e.g. wash cycle, rinse cycle, and spin cycle). To the best of our knowledge, all multiphase appliances are uninterruptible appliances, which means that these appliances cannot be interrupted during their operating time (e.g. washing machine, dishwasher, or laundry dryer) because it may harm the appliance or it may affect the performance of the appliance. Finally, some smart appliances, called grid-friendly appliances, are provided with computer microchip, this component can sense high electricity demand by measuring electricity frequency[1]. Then it acts to this high demand by switching itself off [2, 67, 75, 130].

The total amount of energy consumed by any household appliance $i \in \mathscr{A}$, over specific time, can be calculated using the following equation:

$$P_i = \int P(t)dt. \tag{3.6}$$

where P_i is the total amount of energy, in kWh, that is consumed by appliance i to finish its task, $P(t)$ is the instance consumed power at any time, t, in kW.

There are some appliances where its job or task depends on other variables such as

[1] The electricity frequency, called line frequency in the USA (60 Hz) and mains frequency in the UK (60 Hz), is the frequency of the oscillations of alternating current (AC) in an electric power grid transmitted from a power plant to the end-user.

AC unit and PHEV (they depend on temperature and state of charge, respectively).

3.4.2.1 Heating, Ventilation, and Air Conditioning System

One of the most complicated system to model is Heating, Ventilation, and Air Conditioning system (HVAC) because it is a function of many variables, such as outside temperature, insulation, state of the door and windows (Open/Close), etc. AC unit is uni-phase and interruptible appliance. So, it can be switched ON/OFF at any time without affecting its efficiency and without any technical issues. The mathematical model for AC system (presented in frameworks [71, 75]) is used in this thesis. The thermodynamic system modeled by Equations (3.7), (3.8), and (3.9) presents heat/cool exchange, in the room, among room temperature, AC system and outside temperature.

$$\frac{dT_{in}(t)}{dt} = \frac{1}{M_{air}.c}\left\{\left(\frac{dQ(t)}{dt}\right)_{HVAC} - \left(\frac{dQ(t)}{dt}\right)_{losses}\right\}, \tag{3.7}$$

$$\left(\frac{dQ(t)}{dt}\right)_{HVAC} = \dot{M}.c \times (T_h(t) - T_{in}(t)), \tag{3.8}$$

$$\left(\frac{dQ(t)}{dt}\right)_{losses} = \frac{T_{in}(t) - T_{out}(t)}{R_{eq}}, \tag{3.9}$$

where $T_{in}(t)$ is the room temperature, $T_{out}(t)$ is external temperature, $T_h(t)$ is the air temperature, M_{air} is the mass of air inside the room, c is the heat capacity of air inside the room at constant pressure, $\dot{M}$ is the air flow rate from the air conditioner to the room, R_{eq} is the equivalent thermal resistance of the house, $({}^{dQ}/_{dt})_{losses}$ is the quantity of heat exchanged between room temperature and outside temperature, and $({}^{dQ}/_{dt})_{HVAC}$ is the quantity of heat exchange between room and air conditioner unit [71].

Assume that the time horizon T is split into a set of time slots, each of which is with length τ, and $\tau \ll T$. It is also assumed in this thesis that $T_{out}(t)$ is constant over τ. For simplicity, the quantity of heat $({}^{dQ}/_{dt})_{HVA}$ is assumed to be constant over time τ and equal to $P_h(t)$. Equation (3.10) is produced by using these assumptions in Equation (3.7):

$$\frac{dT_{in}(t)}{dt} + \frac{T_{in}(t)}{M_{air} \times c \times R_{eq}} = \frac{P_h(t)}{M_{air} \times c} + \frac{T_{out}(t)}{M_{air} \times c \times R_{eq}} \tag{3.10}$$

By solving the differential Equation (3.10) for $T_{in}(t)$, assuming that the time being taken at the beginning of time slot t.

$$T_{in}(t) = \left(T_{in}^{0}(t) - R_{eq} - T_{out}(t)\right) \times \exp\left(\frac{-t}{M_{air} \times c \times R_{eq}}\right) + R_{eq} \times P_h(t) - T_{out}(t) \tag{3.11}$$

For simplicity, we need to convert our continuous function to discrete function. $T_{in}(t)$

is a continuous function. Therefore, $T_{in}(t) = T_{in}^0(t+1)$, where $T_{in}^0(t)$ is the temperature at the beginning of each time slot t. For simplicity, we assume that $T_{in}(t) = T_{in}^0(t+1)$. Also, we assume that $\varepsilon = \exp\left(\frac{-t}{M_{air} \times c \times R_{eq}}\right)$.

$$\varepsilon \times T_{in}^0(t) - T_{in}^0(t+1) + (1-\varepsilon) \times R_{eq} \times P_h(t) = (\varepsilon - 1) \times T_{out}(t), \tag{3.12}$$

$$T_{in}(t+1) = \varepsilon \times T_{in}(t) + (1-\varepsilon)\left[R_{eq} \times P_h(t) + T_{out}(t)\right]. \tag{3.13}$$

The relationship between $T_{in}(t)$, $T_{out}(t)$, and $P(t)$ is presented in the following equation [71]:

$$T_{in}(t+1) = \varepsilon \times T_{in}(t) + (1-\varepsilon)\left[T_{out}(t) + \frac{\eta}{\kappa} \times P(t)\right]. \tag{3.14}$$

Note, we used the following approximation

$$R_{eq} \times P_h(t) = \frac{\eta}{\kappa} \times P(t) \tag{3.15}$$

where $P(t)$ is the nominal power consumed by AC unit, η is the efficiency of the system, $\kappa \neq 0$ is the thermal conductivity. Note, $\eta/k > 0$ means AC units work in heating mode, and $\eta/k < 0$ means AC unit work in cooling mode.

$$|P_h(t)| \leq P_{max} \qquad \forall t : t \in \mathscr{T} \tag{3.16}$$

where $P_{max} > 0$ is the maximum amount of heat that can be removed or added to the room.

$$T_{min} \leq T_{in}(t) \leq T_{max} \qquad \forall t : t \in \mathscr{T} \tag{3.17}$$

where T_{min} and T_{max} are the minimum and maximum room temperature, respectively. Note that in case of cooling R_{eq} must be negative value.

The total amount of energy consumed by AC unit over specific time can be calculated using the following equation

$$P_i = \int P(t)dt. \tag{3.18}$$

3.4.2.2 Plug-in Hybrid Electric Vehicle (PHEV)

PHEV is fast becoming an essential instrument in smart grids because it is energy efficient, convenient, environmentally friendly, and low running cost. PHEV is also known as a plug-in hybrid vehicle (PHV). This kind of automobiles have rechargeable batteries that powers electric motor and an internal combustion engine. Regarding the modeling of PHEV, it is considered as an electronic storage system or batteries.

Frameworks [131–133] provides models for PHEV.

$$\overline{\Theta} = \int (C(t) - P_{loss})\, dt \qquad \text{Charging phase,} \tag{3.19}$$

$$\underline{\Theta} = \int (D(t) + P_{loss})\, dt \qquad \text{Discharging phase,} \tag{3.20}$$

where $C(t)$ is charging rate, and $D(t)$ is discharging rate, $\overline{\Theta}$ is the final state of charge of PHEV's battery after charging, $\underline{\Theta}$ is the final state of charge of PHEV's battery after discharging phase.

The state of charge of PHEV's battery at any time, $\vartheta(t)$, can be estimated by the following equation:

$$\vartheta(t) = \vartheta(t-1) + \frac{1}{4} \times \mu \times P(t) \qquad \text{Charging mode,} \tag{3.21}$$

$$\vartheta(t) = \vartheta(t-1) - \frac{1}{4} \times \rho \times P(t) \qquad \text{Discharging mode,} \tag{3.22}$$

where μ is battery charging efficiency, ρ is the battery discharging efficiency. Note that P_{loss} has been disregarded for simplicity. For technical issue the state of charge of the battery must not be less than $\underline{\Theta}$, and the battery has maximum capacity of $\overline{\Theta}$

$$\underline{\Theta} \leq \vartheta(t) \leq \overline{\Theta} \tag{3.23}$$

The desired charging level, Θ, can be achieved by using following constraint,

$$\vartheta(t_{end}) = \Theta, \tag{3.24}$$

where t_{end} is the deadline for charging the battery.

The total amount of energy consumed by PHEV unit can be calculated using the following equation,

$$P_i = \int P(t) dt. \tag{3.25}$$

The most general way to model the appliance power consumption (in each phase, if necessary) is with the power obeying some kind of probabilistic law. In our thesis, it is assumed that the law is degenerated, and the power is fixed, but the most general setting in the problem defined in Section 4.3 will be described.

3.5 Power Profile Approximation and Sampling.

The power profile of household appliance is incredibly complex to model as it is not constant over time. Further, the manufacturers of electric household appliances usually give an estimated consumed energy (NOT the power) of the appliance[2] in kWh. For example, let us consider uni-phase appliance (e.g. electric heater); if the nominal energy of electric heater is $\alpha = 1.2$ kWh, then the actual consumed power at any time t, when the appliance is ON, is around 1.2 kW (e.g it could be 1.15, 1.23, etc.). So, the real consumed power of any uni-phase appliance is fluctuating around value of α. The value of this fluctuation depends on many factors such as the nominal power itself (α), the quality of the appliance (power-efficiency), the stability of electricity, the voltage (120 or 220 Volt), and electricity frequency (50 Hz or 60 Hz). To model the power profile of household appliance, $P(t)$ needs to be simplified in order to reduce the complexity of the problem. To cope with the fluctuation in power profile, there are many ways to approximate the power profile; the first way is by running the appliance many times and then take the average of the consumed power, the second way is by using the maximum consumed power, or the minimum consumed power. In this thesis, the average consumed power was used. Figure 3.9 and 3.10 show how the power profiles of two household appliances have been approximated. Also, it demonstrates how the power profile of the appliance is sampled.

Regarding multiphase appliances, it is is more difficult to model them as the nominal power is not constant over time. These kind of appliances work in different modes so that it needs different amount of power. For example, dishwasher work in at least 4 phases which are adding water to the tanker, heating the water, shooting the water, and drain the dirty water. Figure 3.10 shows real data (red in color) of power profile of a washing machine, whereas the black line shows the approximated power profile. The approximation of power profile can be modeled by using the maximum value of the actual power of each phase or by using the average value of each phase or the minimum value of each phase. In this thesis, the average value will be used.

To make our modeling more precise, the power profile of appliance i is sampled with rate τ (time unit) in order to generate a factor of α_j, $j = 1, \ldots, \Delta$ that represent accurately the power profile of the appliance. The value of τ should be chosen carefully because it effects the model considerably. In addition, the smaller τ, the less error in modeling. However, the resolution of sampling increases the size of the optimization problem significantly. Therefore, a trade-off between the sampling resolution and problem size is needed, see Figure 3.10. For the purpose of this study, it is assumed that each appliance i operates in $\Delta_i > 0$ (nominal) phases and for each appliance, it is possible to define a power profile vector $(\alpha_1^i, \ldots, \alpha_{\Delta_i}^i)$ describing its energy needs,

[2] The average consumed power over period of time (usually one hour, in kWh)

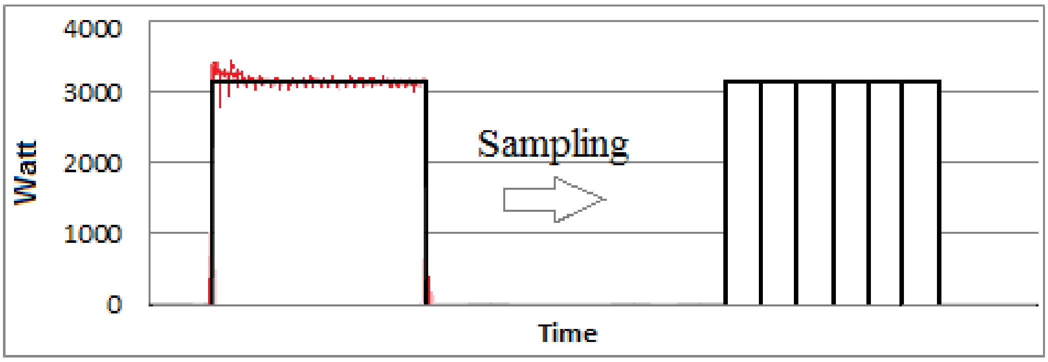


Figure 3.9: Uni-phase profile formalization and sampling

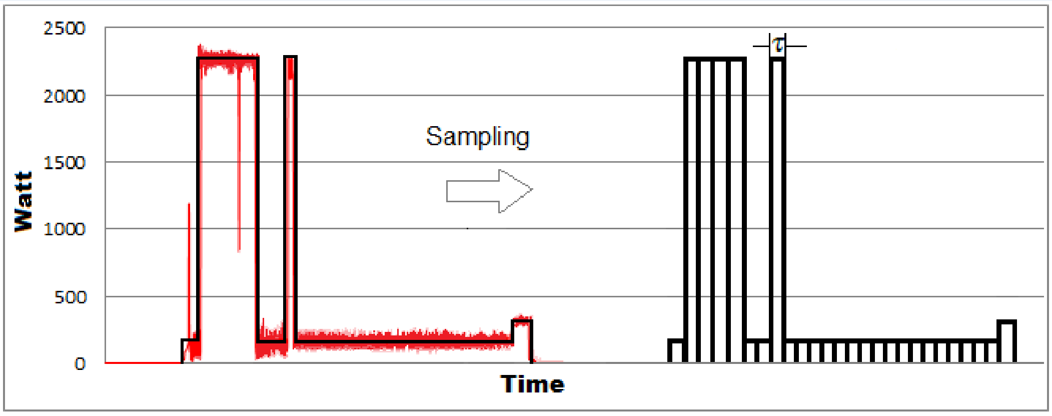


Figure 3.10: Multiphase profile formalization and sampling

where $\alpha_j^i \geq 0$, and $0 < j \leq \Delta_i$. It is also assumed that $\Delta_{\min} > 0$ is length of the shortest phase, see Figure 3.11. Each α_j^i is a non-negative real number, corresponding to the average amount of power used by the appliance during its jth phase. When switched on, appliance i progresses through each of its phases, starting from phase 1 up until phase Δ_i at which point the appliance is switched OFF. It is also assumed in this thesis that for each appliance i, it is known whether the appliance is interruptible or not, and the number of times it must be used, n_i. Note that such model fits the different types of appliances described before.

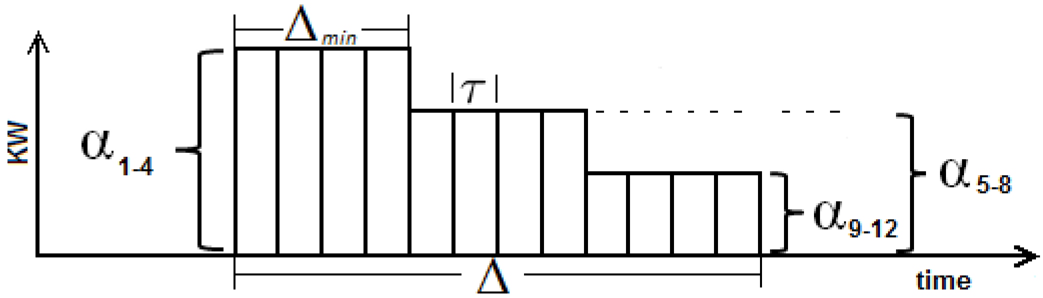


Figure 3.11: The power profile of multiphase appliance

Figure 3.12 shows power profile of uni-phase appliances after approximation.

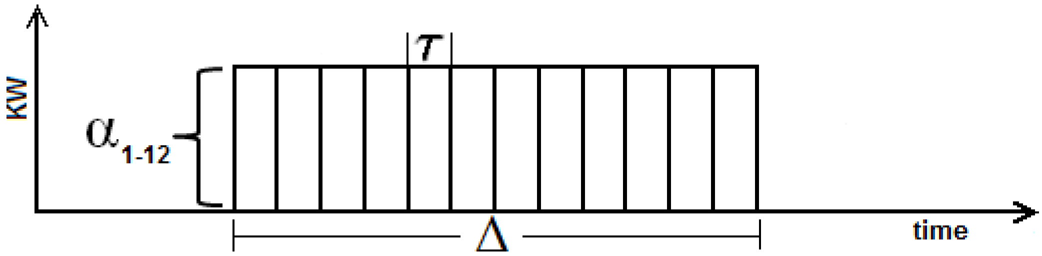


Figure 3.12: The power profile of uni-phase appliance

Arrays can be used to represent the power profile of any household appliances. Consider the following example, assume that it is needed to represent a uni-phase appliance (Figure 3.12) and a multiphase appliance (Figure 3.11). Further, the approximated nominal power of uni-phase appliance $\alpha_{1-12} = 1.1$ kW and Δ=12. On the other hand, multiphase appliance has three phases ($\alpha_{1-4} = 3.2$, $\alpha_{5-8} = 2.1$, α_{9-12}=1.4), and Δ=12. Figure 3.13 demonstrates how the approximated power profiles (in Figure 3.11 and 3.12) have been represented in two single dimensional arrays.

Multi-phase

3.2	3.2	3.2	3.2	2.1	2.1	2.1	2.1	1.4	1.4	1.4	1.4

Uni-phase

1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1

Figure 3.13: Array representation of power profile

3.6 Summary

This chapter has presented a unique, comprehensive mathematical model for micro-grids working in smart grids setting. The chapter has defined the potential power exchange between agents in the micro-grid. It has also provided models for a set of renewable micro-plants (PV array and Wind turbine) and household electrical appliances. Finally, the approximation and sampling process of the power profile of electrical appliances has been described in detail in this chapter.

Chapter 4

Computational Problems

> "Two signs of an educated person are acceptance of other people's criticism, and being knowledgeable about the angles and dimensions of rhetoric and debate"
>
> *Al-Hussein Ibn Ali*

This chapter defines the computational problems that have been tackled in this thesis. To illustrate the power and generality of the proposed framework, it is shown that how it is suitable to define various power allocation problems in micro-girds. Three different energy allocation problems working in a smart grid environment have been tackled in this thesis, some of these problems use predictive control system, and one of them is a reactive control system. The first problem (shown in Section 4.1) is maximizing the profit of each agent (house or micro-plant) in a micro-grid, a predictive control system has been used to solve this problem. Furthermore, two special cases of our general model of the micro-grid have been examined. In the first particular case, the thesis has considered a micro-grid which consists of a single large building (with a wide range of AC units), and a single micro-plant. A predictive control system has been used to tackle this problem, and the primary objective is to minimize the electricity cost and the discomfort level in the building, see Section 4.2. In the second special case, a micro-grid consisting of a single house is reviewed. The house has a set of appliances and an only micro-plant. This uses a reactive control system; the primary objective is to maximize the utilization of renewable power in single house based on user preferences, see Section 4.3. Section 4.4 provides a summary of the chapter. In the forthcoming sections, each of these problems will be defined.

4.1 Power Allocation Problem in a Micro-grid

The definition of micro-grid and power exchange in micro-grid was given in 3.1. The thesis will focus on agent interactions as our main contribution, in this problem, lies in this modeling part. The main work was published in papers [130, 134].

4.1.1 Problem Definition

Consider a micro-grid (as shown in Figure 4.1) which consists of a set of houses $\mathscr{H}$ (each house $h \in \mathscr{H}$ has a set of rooms $\mathscr{M}_h$), and a set of micro-generation plants (or generators) $\mathscr{R}$ (some of these micro-plants may belong to house h, $\mathscr{R}_h \subset \mathscr{R}$). Each house $h \in \mathscr{H}$ has a set of electric household appliances, $\mathscr{A}_h$. Each house and micro-plant are considered as independent agent (e.g. a house is independent from its top-roof micro generator and other micro-plants in the micro-grid). The power exchange between these agents is explained in Section 3.2.

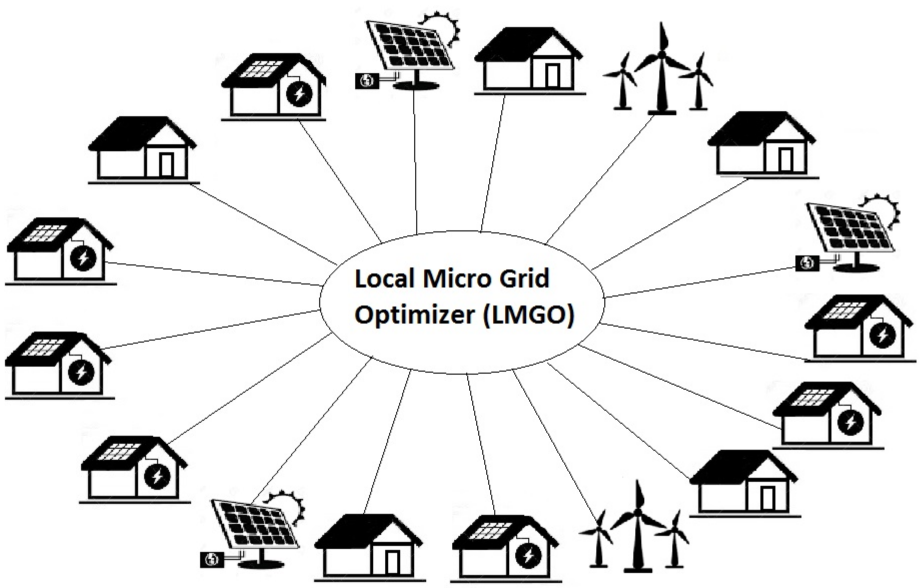


Figure 4.1: Micro-grid

It is, also, assumed in this thesis that the given house, $h \in \mathscr{H}$, is equipped with control system that can be used to control a set of electric household appliances in the house h, $\mathscr{A}_h$, the number of these appliances is $N^h \geq 0$. The residents of the house can specify, via user interface, a list of tasks or jobs (washing, heating, etc.) to be carried out next time window. They can, also, put a set of preferences (e.g. time, temperature, etc.). Moreover, user can put b_i^h time windows (time preferences) $(I_1^{h,i}, \ldots, I_{b_i^h}^{h,i})$ to each task or appliance, i, (start time $t_{start}^{h,i}$ and end time $t_{end}^{h,i}$). For example, $I_1^{h,i} = \{t_{start}^{h,i}, \ldots, t_{end}^{h,i}\}$, and $I_{b_i^h}^{h,i} = \{t_{start}^{h,i}, \ldots, t_{end}^{h,i}\}$) (e.g. user would like to switch on washing machine between 23:00 and 06:00). If the job of the appliance depends on other preferences (the job of air conditioner depends on temperature), users can determine their comfortable temperature as well. In such cases, each room m is fitted with a set of AC units (identified by some label m) , $\mathscr{A}_{AC}^{h,m} \subset \mathscr{A}_h$, which are capable of cooling down or heating up the environment. In addition, room m has $n_m^h \geq 0$ AC unit(s), whereas the total number of AC units in the building h is $N_{AC}^h = \sum_{m \in \mathscr{M}} n_m^h \geq 0$. It is assumed in this thesis that each room m, in house h is equipped with a single thermostat that is used to define its internal temperature $T_{in}^{h,m}(t)$ at any given time t. Moreover, the dwelling's owner may want to be able to specify constrains on the environment's temperature at different times of the day (e.g. "user would like room temperature to be around $T_{opt}^{h,m,1} = 20.0°\text{C}$ with minimum room temperature, $T_{min}^{h,m,1} = 18.0°\text{C}$ and maximum room temprature $T_{max}^{h,m,1} = 22.0°\text{C}$ between $t_{start}^{h,m,1}$= 06:00 am and $t_{end}^{h,m,1}$ = 09:00 am and around $T_{opt}^{h,m,2} = 22.0°\text{C}$ with $T_{min}^{h,m,2} = 20.0°\text{C}$ and $T_{max}^{h,m,2} = 24.0°\text{C}$ between $t_{start}^{h,m,2}$ =11:00 and $t_{end}^{h,m,2}$ =15:00"). Additionally, it is assumed that a house, h, may have set of PHEV, $\mathscr{A}_{PHEV}^h \subset \mathscr{A}_h$. The electricity demand of PHEV depends on the state of charge of its battery. Therefore, usually the charging task specified by $\theta_i^h(t_{end}^{h,i}) = \Theta_i^h$. Figure 3.2 describes the possible energy exchanges between a house, a generator, and the NEG. Houses (and their appliances) can only use electricity. The electricity comes in the house either from a generator (internal to the house or external from local generators) or the NEG.

The primary objective of this problem is to maximize the profit of each agent in the micro-grid (minimize the electricity cost for each house, and maximize the profit for each micro-plant) over a specific time by using load shifting, and allowing renewable energy sharing among agents in the micro-grid. This system is a predictive which means that it uses predicted data to maximize the profit of each agent.

4.1.2 Optimization Problem

It is evident that a micro-grid consists of various agents each with their own goals and priorities. Houses, as agents, need the energy to run their set of appliances according to pre-defined plans, whereas generators, as agents, produce energy that can be sold to the houses in the micro-grid or the NEG; houses want to purchase cheap energy (minimizing their electricity bills), whereas generators want to make profit (maximizing their profit). In this setting, a cost function Ψ_h is associated with each house $h \in \mathscr{H}$ and for generality, the time limit of the integration will not be specified here (users may assume that the time interval limit is from t_1 to t_2):

$$\Psi_h = \int \lambda_h(t) L_g^h(t) dt + \sum_{r \in \mathscr{R}} \int \gamma_h^r(t) G_h^r(t) dt, \tag{4.1}$$

where $L_g^h(t)$ describes the amount of energy from the NEG used by house h at time t, and $G_h^r(t)$ the amount of energy generated from plant r and used by house h at time t.

Similarly, a profit function Ξ_r is associated with each $r \in \mathscr{R}$:

$$\Xi_r = \int \zeta_r(t) E_g^r(t) dt + \sum_{h \in \mathscr{H}} \int \gamma_h^r(t) G_h^r(t) dt, \tag{4.2}$$

in such formula, $E_g^r(t)$ describes the amount of energy produced by r at time t that is sold to the NEG.

It is also assumed that each room m in house h has a discomfort factor or function, Υ_m^h, defined as follows:

$$\Upsilon_m^h = \int |T_{in}^{h,m}(t) - T_{opt}^{h,m}| dt, \tag{4.3}$$

the discomfort factor for whole residential building is Ω_h, $\Omega_h = \sum_{m \in \mathscr{M}} \Upsilon_m^h$. Note, the time limit of integration has not been specified here for generality, and it will be specified later where required.

The problem of allocating energy to houses in a micro-grid (Π) in a way that is cost effective for the houses and profitable for the grid's power plants can then be cast as a multi-objective optimization problem [135].

$$\min(\Psi_h - \sum_{r \in \mathscr{R}_h} \Xi_r : h \in \mathscr{H}; -\Xi_r : r \in \mathscr{R} \setminus \mathscr{R}_h; \Omega_h : h \in \mathscr{H}), \tag{4.4}$$

where $\mathscr{R}_h$ is a set of micro-plants that belongs to house h.

Chapter 5 will present MILP formulation of the problem, the proposed heuristic algorithm, the findings, and the discussion of the results.

4.2 Cost-Effective Management of a Temperature Controlled Environment

The first special case of our general model of the micro-grid is explained in this section. The main problem here is to allocate domestic renewable power and grid power into a set of of AC units in single large building. The main work was published in papers [136, 137].

4.2.1 Problem Definition

Let us consider a special case of smart grid (single building and single micro-plant). Our model is well-suited for large buildings (residential building, hospital, company,or commercial, etc.) or a set of houses or flats that have the same owner (as shown in

Figure 4.2) . In this thesis, it is assumed that the given building consists of a set of rooms, $\mathscr{M}$. The total number of rooms in the building is $M > 0$, each room (identified by some label m) is fitted with a set of AC units, $\mathscr{A}_m$, perhaps spread around different rooms, which are capable of cooling down or heating up the environment. In addition, room m has n_m appliances, whereas the total number of AC units in the building is $N = \sum_{m \in \mathscr{M}} n_m$. Each AC unit is designed to be switched ON/OFF at any time without affecting its efficiency and without any technical issues. In general, each AC unit has three working modes: it can be "Off mode", "Cooling mode" or "Heating mode". If the appliance is "Off", it may be assumed that the appliance uses no power. However, if it is "On", it may be in "Cooling mode" or "Heating mode". Furthermore, if it is in "Cooling mode", without loss of generality, it is assumed that AC unit has k_c different ways to cool the place, whereas if it is in heating mode, it has k_h different ways to produce heat. Let $\alpha_1, \ldots, \alpha_{k_c}$ and $\beta_1, \ldots, \beta_{k_h}$ be the amount of power required by each of the cooling, and heating ways, respectively. In other words, it is assumed (in this thesis) that AC unit has k nominal power. In reality, there is no such AC unit. However, this system can be constructed by using k AC units to cool/heat one room. Additionally, using k AC units, each of which has α nominal power, is more effective than using one large AC unit with nominal power $k \cdot \alpha$. Also, it smooths out the change in room temperature and electricity demand. By contrast, it increases the complexity of the system (increase the complexity of optimization problem). For more detail about AC modeling, see Section 3.4.2.1.

Each room is equipped with a single thermostat that is used to define its internal temperature $T_{in}^m(t)$ at any given time t. It is assumed (in this thesis) that the dwelling's owner may want to be able to specify constrains on the environment's temperature at different times of the day (e.g. "user would like the room temperature to be at 20°C (optimal temperature, T_{opt}^m) with tolerant comfortable range between 18.0°C and 22.0°C between 06:00 and 09:00 and at 21.0°C with tolerant comfortable range between 19.0°C and 23.0°C between 14:00 and 22:00"). The building is also equipped with a micro-generation plant. The electricity from such plant can either be used immediately at the property (at a unit cost of $\xi(t)$), or exported to the NEG and the building is awarded a monetary premium of $\zeta(t)$ pounds (or dollars) per kWh. All AC units in the building are controlled by an *energy manager*, whose primary task is to minimize the cost of the electricity used by the AC units and the discomfort factor which is sum of temperature deviation from the optimal one, $\sum |T_{in}^m(t) - T_{opt}^m|$, in the room within pre-specified limits. Such goal is achieved by using the thermostats, weather information (providing readings for the external temperature $T_{out}(t)$) as well as instantaneous information on the electricity unit cost from the NEG, $\lambda(t)$, and the eventual export benefit for the locally produced renewable power. See Figure 4.2.

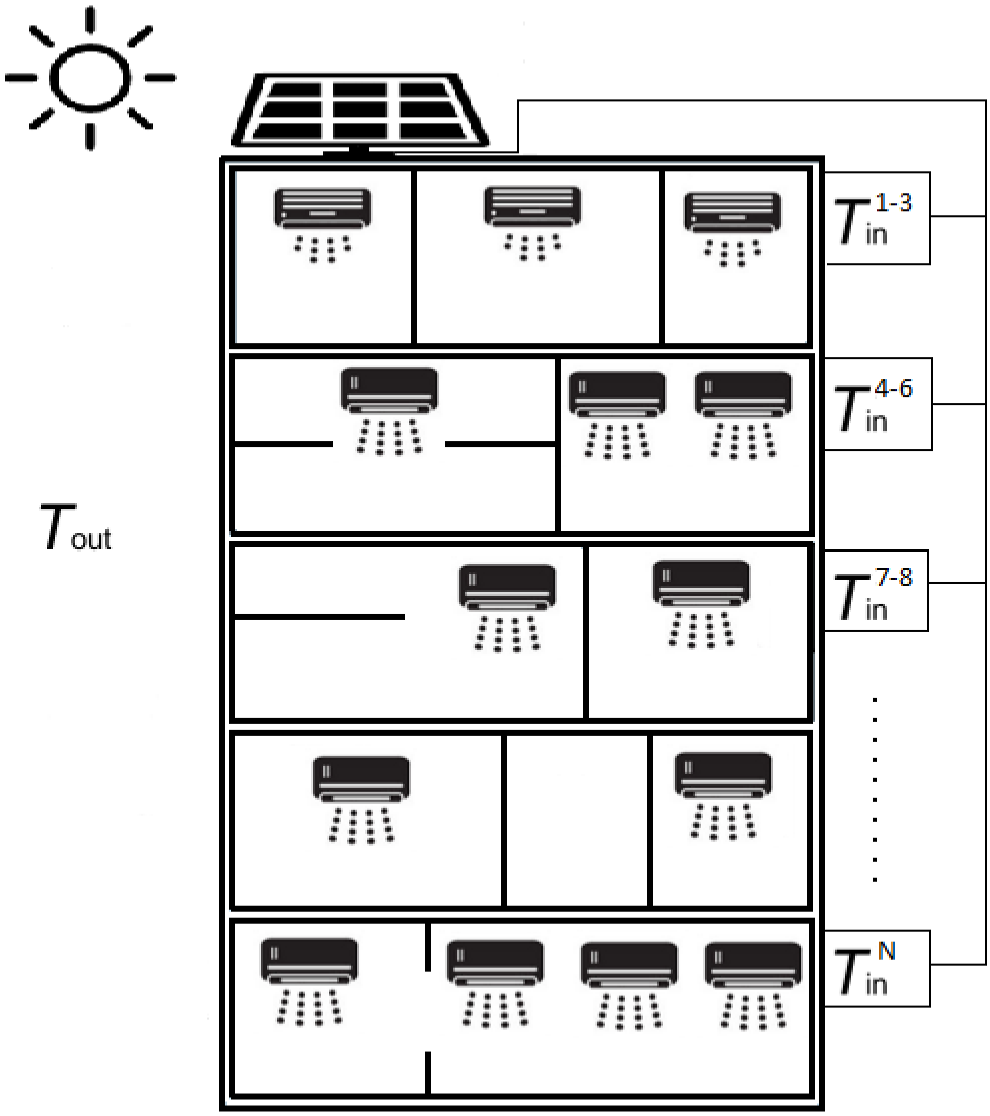


Figure 4.2: Our model: a building split up in rooms with independent appliances and thermostats

4.2.2 Optimization Problem

A cost function Ψ is associated with the whole building, defined as follows:

$$\Psi = \int \lambda(t)L_g(t)dt + \int \xi(t)L_r(t)dt - \int \zeta(t)E(t)dt, \tag{4.5}$$

where $L_g(t)$ describes in whole building, $\lambda(t)$ is the NEG electricity price, $L_r(t)$ is the amount of renewable power used in the whole building, $\xi(t)$ is the cost of local renewable power, $E(t)$ the amount of surplus renewable power exported to NEG, and $\zeta(t)$ is the export rate in Feed-in tariff scheme. In addition to this equation, another equation presents the discomfort level. Assume that each room, m, has a discomfort factor or function, Υ_m, defined as follows:

$$\Upsilon_m = \int |T_{in}^m(t) - T_{opt}^m| dt, \tag{4.6}$$

Discomfort factor for whole building is Ω, where $\Omega = \sum_{\forall m} \Upsilon_m$. The problem of allocating electrical energy to a set of AC units in a way that satisfies a set of given temperature constraints and is cost-effective for the users, Π, is equivalent to minimizing both functions, Ψ and Ω.

$$\min(w_1 \cdot \Psi, w_2 \cdot \Omega), \tag{4.7}$$

where w_1 and w_2 are weights.

Chapter 6 will present MILP formulation of the problem, the proposed heuristic algorithms, the findings, and the discussion of the results.

4.3 Smart Domestic Renewable Energy Management

This section defines the second special case problem of the general model of the micro-grid (maximizing the utilization of domestic resources). The first special case problem of our general model of the micro-grid is explained in this section. The main problem here is how to allocate the available local renewable power to a set of AC units in single large building. The main objective here is to maximize the utilization of domestic renewable power. The main contribution of this work was published in paper [138].

4.3.1 Problem Definition

In some residential buildings (could be stand-alone house) that are equipped with domestic renewable power micro-plant, the surplus of renewable energy is not utilized for many reasons (e.g. there is no storage system in the building to accommodate the surplus of renewable power, or there is no feed-in tariff, etc.). Therefore, in such cases, the best that can be done is to maximize the utilization of the local renewable power based on user preferences without considering the cost of NEG electricity. Assume that a micro-grid consists of a single residential building and a single micro-plant. The given residential building (as shown in Figure 4.3) is equipped with renewable micro-plant (PV array) that generate $P_s(t)$ at time t, the building does not have storage system to accommodate the surplus renewable energy, also it can not export the surplus renewable power to NEG. The building have set of smart appliances (electric heaters, water heaters, etc.), $\mathscr{A}$, the number of these appliances is N, each of these appliances have value, v (user preference), and weight w (nominal power, $w = \alpha$). Each appliance, $i \in \mathscr{A}$, is designed to be switched ON/OFF at any time without effecting its efficiency and without any technical issues. In general, each appliance has two working modes: it can be "Off" or "On". If the appliance is "Off", it may be assumed that it uses no power, whereas when it is "On", it consumes w watt.

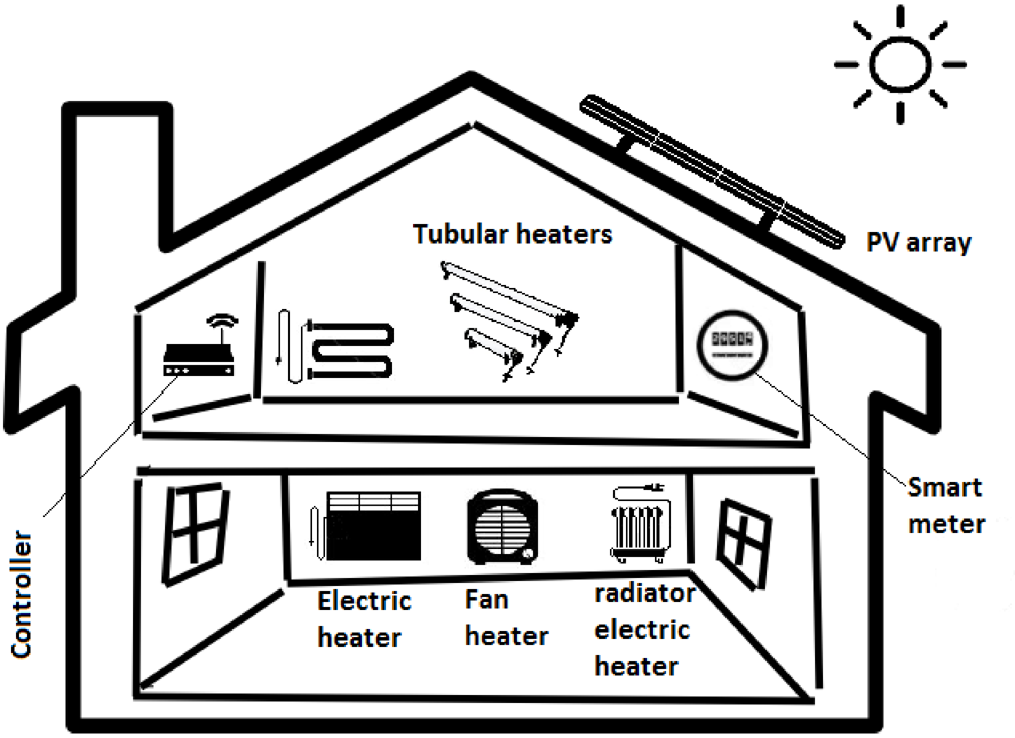


Figure 4.3: Smart house

4.3.2 Optimization Problem

In this setting, a profit function Φ is associated with the whole building, this function is defined as follows:

$$\Phi = \int \sum_{i \in \mathscr{A}} v_i \cdot \delta_i(t) dt \tag{4.8}$$

s.t.

$$\sum \alpha_i \cdot \delta_i(t) \leq P_s(t), \forall t \tag{4.9}$$

where $\alpha_i > 0$ is the power needed by appliance $i = 1, \ldots N$, $v_i > 0$ is the value of the appliance (user preference), $\delta_i(t) \in \{0, 1\}$ is delta function to represent if the appliance i is on or off, $P(t)$ is the available renewable power at time t.

The problem of allocating local renewable energy to set of household appliance in a way that satisfies a set of given constraints and is cost-effective for the users (Max-Utilization), is equivalent to maximizing the function Φ. Chapter 7 will present problem formulation, the proposed algorithm, the findings, and the discussion of the results.

4.4 Summary

This chapter has defined a set of electricity power allocation problems in smart grids. Further, it has identified and mathematically modeled these computational problems by associating a cost and profit function.

Part III

Results and Discussions

Chapter 5

Heuristic Algorithm for Coordinating Smart Houses in a Micro-grid

"If people realize the value of science and knowledge, they will sacrifice themselves for earning it."

Ali ibn Al-Hussein (Zain al abidin)

Micro-grid is relatively new research topic. This chapter illustrates the proposed MILP formulation of the micro-grid problem presented in Section 4.1.2. The chapter starts with MILP formulation of household appliances in Section 5.1. Then, Section 5.2 proposes a heuristic algorithm that has been used to tackle the hardness of the optimization problem. Section 5.3 provides an empirical evaluation of the proposed model and algorithm. Section 5.4 discusses the results in detail. Finally, Section 5.5 summarizes this chapter.

5.1 MILP Formulation

This section presents the proposed MILP-based formulation of the multi-objective optimization problem of micro-grid (described in Section 4.1.2).

5.1.1 Appliances Modeling and Linear Constraints

This subsection will provide MILP formulation of household appliances (Multiphase and uni-phase).

Portion of this chapter was published in: Heuristics algorithm for coordinating smart houses in micro-grid. In *IEEE SmartGridComm*, pages 49–54, Nov 2015. And another part will be published in: Minimizing the electricity cost of coordinating houses on micro-grids. In *IEEE/PES ISGT EUROPE*, pages 1–6, Oct. 2016.

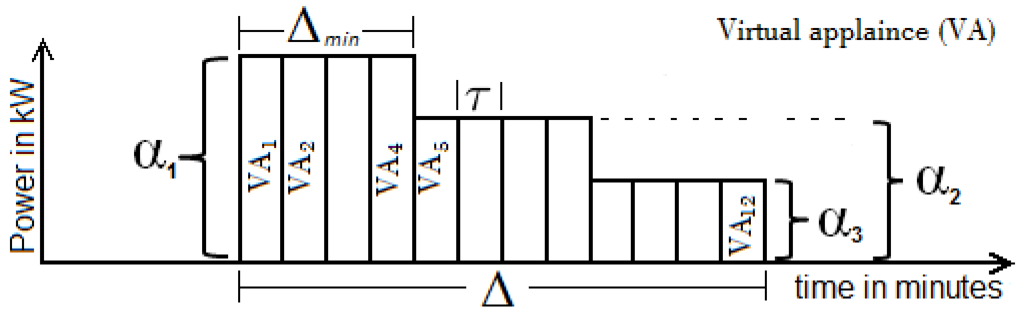


Figure 5.1: The power profile of multiphase appliance is split into a set of virtual appliances (VA)

5.1.1.1 Multiphase Appliances

In this thesis, it is assumed that each instance of the problem is solved over a fixed time horizon (say 24 hours) and that time within such time horizon is divided into a finite set of time slots, $\mathscr{T} = \{t_1, t_2, \dots, t_T\}$, all of the length τ with $0 < \tau < \Delta_{min}$. Suppose that τ divides the length of each phase within the system. We identify the m_h multiphase appliances and n_h uni-phase appliances in house h with the numbers $1, 2, \dots, m_h$, and $1, 2, \dots, n_h$, respectively. Without loss of generality, it is assumed that each appliance i runs through Δ_i^h (real) phases, of length τ, and divided to set of phases or virtual appliances ($\mathscr{J}_i^h$). Further, virtual appliances was introduced to improve the accuracy of the power allocation process especially with multiphase appliances where the consumed power is not constant, see Figure 5.1. It is also assumed that real phases are grouped into clutches of length Δ_{min} corresponding to the nominal phases and the appliances are uninterruptible within each clutch (Figure 5.1 shows appliance with three clutches). A dedicated binary decision variable $x_{i,j}^h(t)$ is used for each virtual appliance $j \in \mathscr{J}_i^h$. The variable holds the appliance ON/OFF state at time slot t. The power profile of the appliances can be formulated by the following equation:

$$P_{i,j}^h(t) = \alpha_{i,j}^h \cdot x_{i,j}^h(t) \in \left\{0, \dots, \alpha_{\Delta_i^h}^h\right\}, i \in \{1, \dots, m_h\}, \, j \in \mathscr{J}_i^h, h \in \mathscr{H}. \tag{5.1}$$

For example, consider a single house in a micro-grid; this house has just one electric appliance. Figure 3.13 illustrates the array representation of two type of appliances, the multiphase appliance has different values of α(s) ($\alpha_{1,1}^1 = 3.2$, $\alpha_{1,5}^1 = 2.1$, and $\alpha_{1,12}^1 = 1.4$ kW).

It is assumed in this thesis that appliance i in house h can only be run between time slot $t_{start}^{h,i}$ and $t_{end}^{h,i}$ (with $t_{start}^{h,i} \le t_{end}^{h,i}$), in a so-called comfort interval specified by the user, if needed. This time interval is modeled by using the following constraints:

$$\sum_{t=0}^{t_{start}^{h,i}-1} x_j^{h,i}(t) + \sum_{t=t_{end}^{h,i}+1}^{t_T} x_j^{h,i}(t) = 0, \quad \forall h : h \in \mathscr{H}, \forall i : i \in \{1,\ldots,m_h\}, \forall j : j \in \mathscr{J}_i^h, \tag{5.2}$$

where previous constraint may vanish, if $t_{start}^{h,i} = 1$ or $t_{end}^{h,i} = t_T$. If both equalities hold (say if the user does not specify a comfort interval) the constraints vanish as well.

To enforce that appliance i in house h runs n_i^h times in $\{t_{start}^{h,i}, \ldots, t_{end}^{h,i}\}$, the following constraints are needed:

$$\sum_{t \in \{t_{start}^{h,i},\ldots,t_{end}^{h,i}\}} x_j^{h,i}(t) = n_i^h, \quad \forall h : h \in \mathscr{H}, \forall i : i \in \{1,\ldots,m_h\}, \forall j : j \in \mathscr{J}_i^h. \tag{5.3}$$

As known, washing machine performs a sequence of cycles, and each cycle consumes a particular amount of energy (e.g. wash cycle, rinse cycle, and spin cycle). Furthermore, by splitting the power profile into a set of virtual appliances, the controller considers each virtual appliance as an independent appliance, which means it may schedule spin cycle phase before wash cycle, etc. Therefore, the order of power phases of washing machine needs to be kept in the right order. Therefore, phases or virtual appliances can be kept in right order for multiphase appliances by imposing the following constraints:

$$\sum_{t \in \mathscr{T}} \left[t \cdot x_{j+1}^{h,i}(t) - t \cdot x_j^{h,i}(t) \right] \geq 1. \quad \forall h : h \in \mathscr{H}, \forall i : i \in \{1,\ldots,m_h\} \forall j : j \in \mathscr{J}_i^h. \tag{5.4}$$

The following constraint is used to prevent interruption between any two consecutive phases or virtual appliances, say VA_1 and VA_2 in Figure 5.1. For example, the controller must allocate two adjacent time slots for switching on virtual appliances VA_1 and VA_2:

$$\sum_{t \in \mathscr{T}} \left[t \cdot x_{j+1}^{h,i}(t) - t \cdot x_j^{h,i}(t) \right] = 1. \forall h : h \in \mathscr{H}, \forall i : i \in \{1,\ldots,m_h\}, \forall j : j \in \mathscr{J}_i^h. \tag{5.5}$$

5.1.1.2 Uni-phase Appliances

These kind of appliances can be considered as a special case of multiphase appliances. In order to reduce the complexity of the problem (by reducing the number of binary decision variables), special MILP formulation will be used for uni-phase appliances. It is assumed in this thesis that each house, h, has a set of uni-phase appliances, n_h. The power profile of uni-phase appliances, shown in Figure 5.2, is split into set of identical phases, called virtual appliance $\mathscr{J}_i^h$. Then, the algorithm or the controller can pick one phase and run it Δ_i^h times.

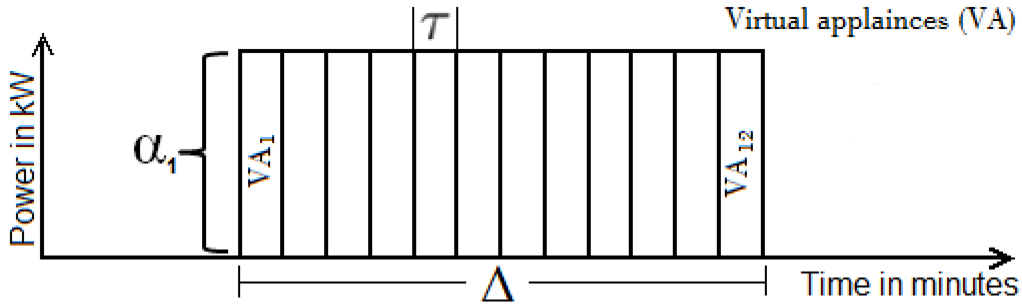


Figure 5.2: The power profile of uni-phase appliances

Equation (5.6) demonstrates mathematical model of the power profile of uni-phase appliance:

$$P_i^h(t) = \alpha_i^h \cdot x_i^h(t) \in \left\{0,\, \alpha_i^h\right\}. \quad \forall i : i \in \{1,\ldots,n_h\}, \forall h : h \in \mathscr{H}, \forall t : t \in \mathscr{T}. \tag{5.6}$$

The following constrain is used to specify the potential operating time of uni-phase appliance. In other words, users can specify the comfortable time for running their appliances.

$$\sum_{t=0}^{t_{start}^{h,i}-1} x_i^h(t) + \sum_{t=t_{end}^{h,i}+1}^{t_T} x_i^h(t) = 0 \quad \forall i : i \in \{1,\ldots,n_h\}, \forall h : h \in \mathscr{H}. \tag{5.7}$$

The sequences or the order of virtual appliances (phases) is not necessary for uni-phase appliances because it does not make any affect the functionality of the appliance, the task, or the electricity cost. Therefore, to reduce the number of decision variables in the problem (lessen the complexity of the optimization problem), just one virtual appliance can be used. For example, if the power profile is split into 12 virtual appliances (see Figure 5.2), the controller can use only one virtual appliance (say VA_1) and switched it on 12 times to model the power profile of the uni-phase appliance shown in the figure. Virtual appliances (VA_1 to VA_{12}) can be allocated to a set of adjacent time slots with the aid of the auxiliary binary variable $\delta_i^h(t) \in \{0,\, 1\}$ and the following set of constraints:

$$x_i^h(t) + \delta_i^h(t) \leqslant 1 \quad \forall t : t \in \mathscr{T}, \forall h : h \in \mathscr{H}, \forall i : i \in \{1,\ldots,n_h\}, \tag{5.8}$$

$$\delta_i^h(t-1) - \delta_i^h(t) \leqslant 0 \quad \forall t : t \in \mathscr{T}, \forall h : h \in \mathscr{H}, \forall i : i \in \{1,\ldots,n_h\}, \tag{5.9}$$

$$x_i^h(t-1) - x_i^h(t) - \delta_i^h(t) \leqslant 0 \quad \forall t : t \in \mathscr{T}, \forall h : h \in \mathscr{H}, \forall i : i \in \{1,\ldots,n_h\}. \tag{5.10}$$

As mentioned before in Chapter 3, the operation of some appliances depends on external conditions rather than initial user demands. For instance, charging a battery depends on: i) battery's state of charge ($\vartheta_i^h(t)$), ii) charging rate of the battery (α_i^h), iii) the initial state of charge of the battery ($\underline{\Theta_i^h}$), and iv) the desired state of charge by user ($\overline{\Theta_i^h}$), whereas the task of an Air Conditioning (AC) unit depends on: i) the room temperature ($T_{in}^{h,m}(t)$), ii) the outside temperature ($T_{out}(t)$), and iii) the appliance heating or cooling power (β_i^h or α_i^h respectively). In the case of batteries, Equations (5.11) and (5.12) are needed to model the battery:

$$\vartheta_i^h(t) = \vartheta_i^h(t-1) + \frac{1}{4} \cdot \pi_{h,i} \cdot P_i^h(t) \quad \forall t : t \in \left\{t_{start}^{h,i}, \dots, t_{end}^{h,i}\right\}, \tag{5.11}$$

$$\vartheta_i^h(t_{start}^{h,i}) = \underline{\Theta_i^h}, \text{ and } \quad \vartheta_i^h(t_{end}^{h,i}) = \overline{\Theta_i^h}, \tag{5.12}$$

where $\underline{\Theta_i^h}$ is the initial state of charge of the battery, $\overline{\Theta_i^h}$ is the desired final state of charge of the battery (usually full), and $\pi_{h,i}$ is the battery charging efficiency.

In the case of heating/cooling units, the main task of the given unit is to keep the room temperature within the comfort level $[T_{min}^{h,m}, T_{max}^{h,m}]$ during b_i^h specified time intervals $I_1^h, \dots, I_{b_i}^h$. The relationship between room temperature and the power allocated to the appliance is shown in Equations (5.13) and (5.14):

$$T_{in}^{h,m}(t) = \varepsilon_{h,i} \cdot T_{in}^{h,m}(t-1) + \left(1 - \varepsilon_{h,i}\right) \left[T_{out}(t) - \frac{\eta_h}{\kappa_h} P_m^h(t)\right] \forall t, \forall i, \forall h, \tag{5.13}$$

$$T_{min}^{h,m} \leq T_{in}^{h,m}(t) \leq T_{max}^{h,m} \quad \forall t : t \in I_1^h \cup \dots I_{b_m}^h, \forall h : h \in \mathscr{H}, \tag{5.14}$$

where $P_m^h(t)$ is the allocated power to room m in house h, $\varepsilon_{h,i}$ is the appliance inertia, η_h is efficiency of the system (with $\eta_h > 0$ for a heating appliance and $\eta_h < 0$ in the case of cooling), κ_h is the thermal conductivity, and $T_{out}(t)$ is outside temperature at time t.

5.1.2 Objective Function and Additional Constraints

For the purpose of experiments, the general model presented in Section 4.1.2 is simplified. The cost function in Equation (4.1) is replaced by the following piecewise linear function,

$$\Psi_h = \sum_{t \in \mathscr{T}} \left\{ \lambda(t) L_g^h(t) + \sum_{r \in \mathscr{R}} [\gamma_h^r(t) G_h^r(t)] \right\} \forall h : h \in \mathscr{H}, \tag{5.15}$$

and similarly, the profit function in Equation (4.2) is replaced by,

$$\Xi_r = \sum_{t \in \mathscr{T}} \left\{ \zeta(t) E_g^r(t) + \sum_{h \in \mathscr{H}} [\gamma_h^r(t) G_h^r(t)] \right\} \forall r : r \in \mathscr{R}. \tag{5.16}$$

It is assumed that the cost of the energy from the NEG, $\lambda(t)$, and the profit obtained selling energy to the grid, $\zeta(t)$, may vary over time but are otherwise identical for all houses and generators in the system. Also if r belongs to h then $\gamma_h^r(t)$= 0 $\forall t$, and Ψ_h is the right-hand side of Equation (5.15) minus Ξ_r.

Few constraints related to renewable power need to be added to the system. These constraints are modeled as follow:

$$E_g^r(t) + \sum_{h \in \mathscr{H}} G_h^r(t) = P_{ren}(t) \;\; \forall t : t \in \mathscr{T}, \forall r : r \in \mathscr{R}. \tag{5.17}$$

The allocated power to all houses in the micro-grid from micro-plant r and the allocated power to the NEG from micro-plant r at any time t must equal to the generated power $P_{ren}(t)$.

$$L_g^h(t) + \sum_{r \in \mathscr{R}} G_h^r(t) = \sum_{i \in \mathscr{A}_h} \sum_{j=0}^{\Delta_i^h} P_j^{h,i}(t), \;\; \forall t : t \in \mathscr{T}, \forall h : h \in \mathscr{H}. \tag{5.18}$$

The key idea is to reduce the multi-objective optimization problem to a single objective optimization problem using **modified version** of ε-constraint method (Hybrid ε-constraint method and scalarizing method) [139], see the objective function in Equation (5.19). Then using an MILP solver to find a feasible allocation. In $\varepsilon-$constraint method, the solver will focus on one objective function (single house or single micro-plants) and consider the rest objective functions as constraints which will cause fairness problem. To this purpose, it is considered that the MILP model obtained by using the constraints listed in the previous sections along with the following objective function,

$$\text{Min} \left\{ \sum_{h=1}^{|\mathscr{H}|} w_h \cdot \Psi_h - \sum_{r=1}^{|\mathscr{R}|} w_r \cdot \Xi_r \right\}, \tag{5.19}$$

and the following extra constraints:

$$\Psi_h \leq \widetilde{\Psi}_h \qquad \forall h : h \in \mathscr{H}, \tag{5.20}$$

$$\Xi_r \geq \widetilde{\Xi}_r \qquad \forall r : r \in \mathscr{R} \setminus \bigcup_h \mathscr{R}_h, \tag{5.21}$$

where $\widetilde{\Psi}_h$, and $\widetilde{\Xi}_r$ are the optimal costs of the energy allocation problem for house h and renewable plant r, considered as isolated units connected solely to the NEG

(Independent houses and renewable micro-plants), and w_h and w_r the weights. These extra constraints are used to guarantee that nobody will lose and to improve the fairness in the micro-grid. However, the profit of houses and micro-plants remain an open issue as the current version of the model does not guarantee fair distribution of the profit.

5.2 MILP-based Heuristic

Let MINCOST denotes the version of optimization problem (defined in Section 4.1) restricted to a single house, with m uni-phase household appliances, to be allocated in one of two possible time slots. Also, it is assumed that the available renewable power is always $\frac{1}{2}\sum_{i=1}^{m}\alpha_i$, and the NEG electricity price is $\lambda(t) > 0$. Furthermore, a straightforward reduction from the PARTITION problem [140] shows that MINCOST is NP-hard optimization problem. Therefore, there is a little hope that the MILP-based mathematical model defined in the previous section might be solved quickly if the number of appliances is large. In fact, the optimization algorithm may not be able to find a feasible solution and run-time could go to infinity. In experiments, the author resorts to an MILP-based heuristic algorithm to get a feasible solution in acceptable time. The basic idea is to use an off-the-shelf LP-solver to generate a feasible solution but without running the optimization process to completion. The LP-solver uses dual relaxation to find a lower bound on the optimum and stops as soon as the difference between the cost of the best feasible solution so far and the lower bound on the optimum becomes smaller than a predefined threshold. Also, time limit or deadline can be put to stop the heuristic optimization algorithm.

5.3 Empirical Results

All the experiments in this thesis have been done on a PC with an Intel(R) Core(TM) i7-2600 CPU @ 3.4 GHz, RAM is 16 GB, 64-bit Operating System (Windows 7). Also, Gurobi has been used to solve LP and MILP problems, whereas Java is used to model the optimization problem (the software development platform is Netbeans IDE 7.0.1).

5.3.1 Common Input Settings

three case studies have been carried out in this study to examine the performance of the proposed model. In all these case studies, the same time slot resolution, $\tau = 5$ minutes has been used. Figure 5.4 demonstrates the electricity prices ($\lambda_h(t)$), that are used in experiments. The electricity price is assumed to be the same for every house h. In this case study, it is assumed that $\zeta_r(t) = 0.045$ £/kWh, $\gamma_r^h(t) = 0.085$ £/kWh for

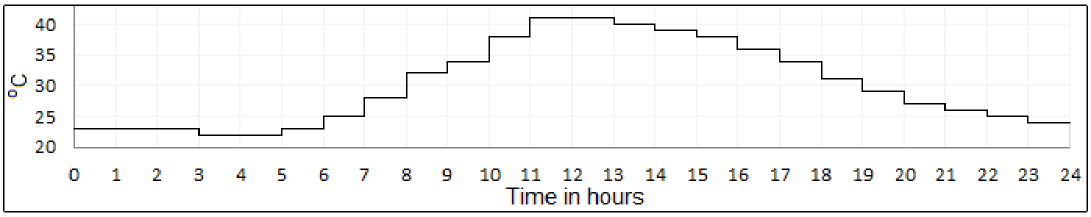


Figure 5.3: Predicted outside temperature

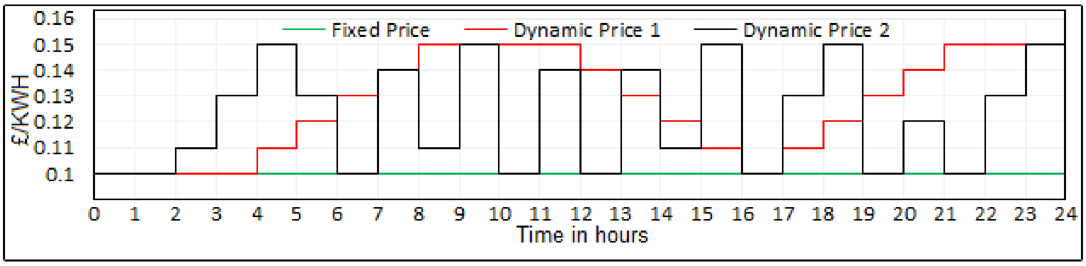


Figure 5.4: Electricity price for all houses, fixed pricing and two dynamic pricing strategies

all r, h and t. Also, $\pi = 0.8$, $\rho = 0.96$, $\eta = 30$ kWm, $\kappa = 0.98$, $T_{min} = 18.0$°C, and $T_{max} = 22.0$°C, w_h=1 $\forall h : h \in \mathscr{H}$, w_r=1 $\forall r : r \in \mathscr{R}$. In addition, Figure 5.3 illustrates the predicted outside temperature for all houses.

Figures 3.4 and 3.6 depict solar and wind power (generated in Liverpool, UK (53 24'N 2 59'W)) using 2 kWh wind turbine and 3.5 kWh PV array. These data will be approximated and scaled up/down to model different sets of PV arrays and wind turbines.

5.3.2 First Case Study

The main objective of this case study is to illustrate the effect of renewable power demand on saving or profit that is made by houses and micro-plants in the micro-grid.

5.3.2.1 Input Setting

Consider micro-grid with 23 agents. Further, the micro-grid consists of 20 houses with different renewable power generation capacities in the micro-grid, as shown in Table 5.1, and three independent renewable plants: i) PV array with maximum generation capacity of 5 kWh, ii) wind turbine with maximum generation capacity of 1 kWh, and iii) wind turbine with maximum generation capacity of 10 kWh). The micro-grid with

Table 5.1: The generation capacity of house's PV array

House No.	5, 10, 15	1, 6, 11, 16, 19	2, 7, 12, 17, 20	3, 8, 13, 18	4, 9, 14
Capacity (kW)	0.0	1.0	1.5	2.0	2.5

Table 5.2: Multiphase uninterruptible appliances

Laundry Dryer	α in kW	3.2	0.28	0.0	3.2	0.28
	Δ_{min} in minutes	15	10	5	20	10
Dishwasher	α in kW	0.2	2.7	0.2	2.7	0.2
	Δ_{min} in minutes	5	15	15	20	5
Washing machine	α in kW	2.2	0.28	2.2	0.28	-
	Δ_{min} in minutes	10	20	10	20	-

these agents (houses and micro-plants) will be examined to investigate the performance of the proposed MILP-based heuristic algorithm.
Dynamic pricing 1 (as depicted in Figure 5.4) will be used in this case study. Three scenarios will be carried out to examine the proposed model of micro-grid and the MILP-based heuristic algorithm, these scenarios are : i) Low-demand scenario, ii) Medium-demand scenario, iii) and High-demand scenario in this case study to examine the effect of electricity demand on saving. Furthermore, in the High-demand scenario, each house uses 8 appliances (20x8 appliances in the micro-grid). In Medium-demand scenario, 98 appliances are used in the micro-grid. In Low-demand scenario, 80 appliances are used in the micro-grid. Appendix B gives further detail about houses and appliances in these scenarios.

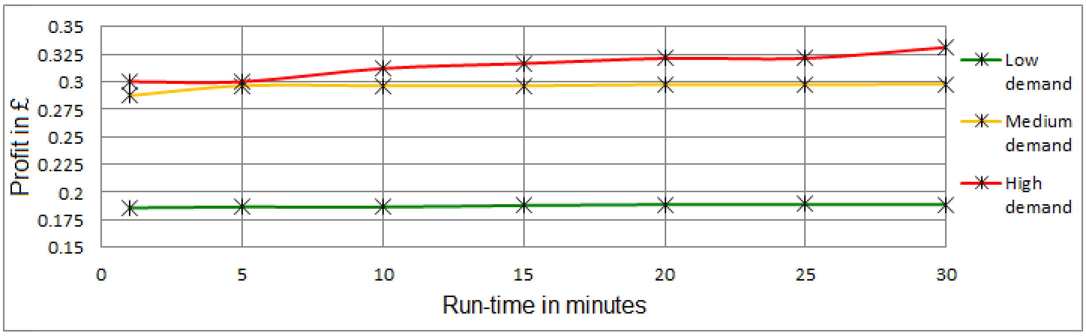
The power profiles of uninterruptible appliances are shown in Table 5.2, whereas the power profile of interruptible appliances are given in Table 5.3.

Table 5.3: Interruptible appliances

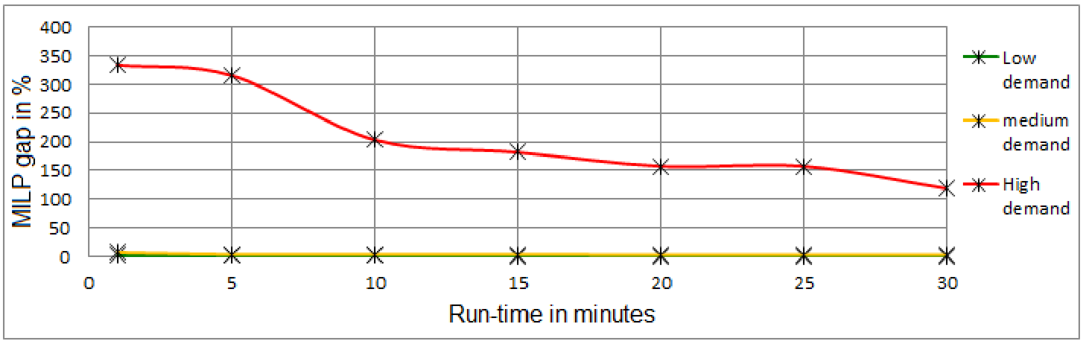
Interruptible appliance	α kW/t	Depends on
Water heater	3.1	-
Electric towel radiator	1.5	-
Electric cooker	2.5	-
Plug-in Hybrid Electric Vehicle	0.35	$\Theta(t_{start})$= 2.0, $\Theta(t_{end})$=16.0
Air conditioner	2.3	T_{min}=18°C, T_{max}=22°C

5.3.2.2 Findings

Figure 5.5a has displayed the average profit of houses and renewable micro-plants (micro-grid agents) in different three scenarios, which are Low-demand, Medium-demand, and High-demand scenarios working in a micro-grid setting. The houses and micro-plants in High-demand scenario, in general, have made more profit because the relationship between saving and renewable power consumption is positive (more renewable power consumption will give users more saving), whereas the micro-grid agents, in Medium-demand scenario, have made the second best profit for the same



(a) The average profit that has been made by a set of houses working in micro-grid in three different scenarios



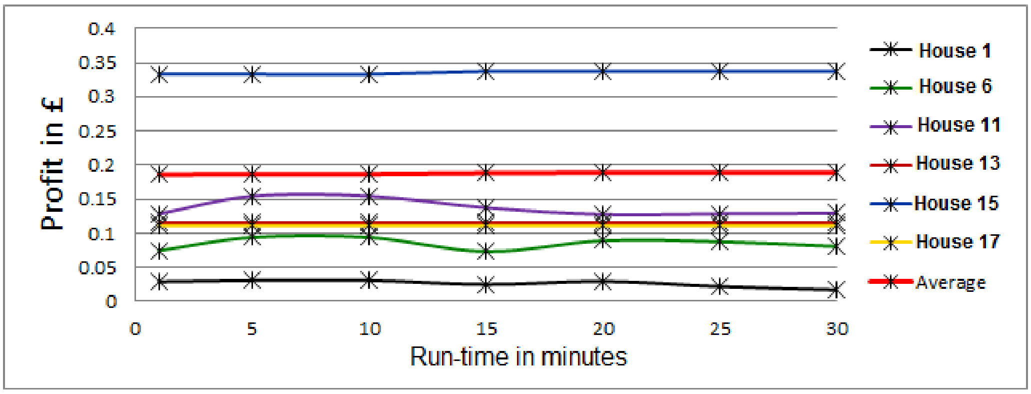
(b) The relative MILP Gap of MILP-based heuristic algorithm in three different scenarios

Figure 5.5: The results of Low-demand, Medium-demand, and High-demand scenarios in micro-grid.

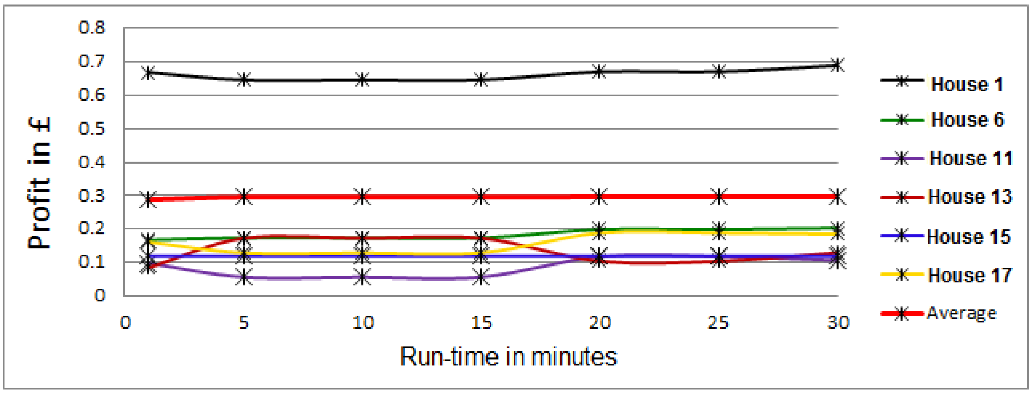
reason. Finally, the agents in Low-demand scenario have made the less profit than the previous scenarios.

In contrast, Figure 5.5b has illustrated the relative MILP Gap (duality gap %) of the three different scenarios (Low-demand, Medium-demand, and High-demand). The figure has also depicted that MILP Gap of High-demand scenario remains above 100% after 30 minutes of calculation time which means the solution could be far away from optimality; it could be so close to optimality, though. Besides, MILP Gap in the Low-demand and Medium-demand scenarios illustrates that the solution found is very close to the optimal solution because MILP Gap has reached 1% within a couple of minutes of calculation time. To sum up, MILP gap depends on the number of decision variables (binary variables) in the model which is specified by the total number of appliances in the micro-grid and time resolution.

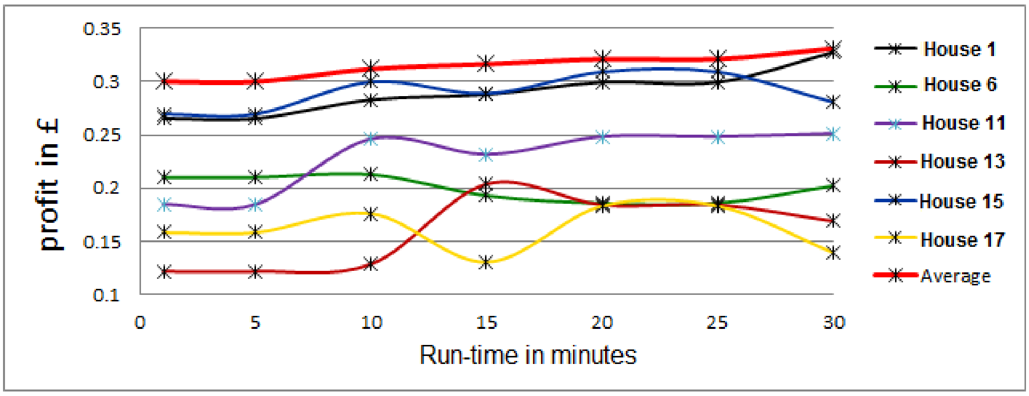
Figure 5.6 demonstrates profit stability in Low-demand scenario (Figure 5.6a), Medium-demand scenario (Figure 5.6b), and High-demand scenario (Figure 5.6c). Note that just 6 houses have been picked and displayed because it would not be clear if the figure shows the curves of 20 houses. Generally, the relationship between run-time of the algorithm and the average profit of all entities is positive which means that the more time users give to algorithm, the best overall solution algorithm can achieve, but it does not always hold for each agent in the micro-grid. For instance, House No.17, in Figure 5.6c, have made more profit after 1, 5, and 10 minutes of calculation time than after 15 minutes of computation time but in general the average profit increases with time until it reaches optimality as shown in Figure 5.5a.



(a) The proift made by a set of houses working in micro-grid in Low-demand scenario.



(b) The profit made by a set of houses working in micro-grid in Medium-demand scenario.



(c) The profit made by a set of houses working in micro-grid in High-demand scenario.

Figure 5.6: Results of Low-demand, Medium-demand, and High-demand scenarios.

Figure 5.7 shows the profit that has been made by each agent in the micro-grid in three different scenarios (Low-demand, Medium-demand, and High-demand). Furthermore, the first five houses in the Medium-demand scenario have made more profit than the first five houses in the High-demand scenario. This contradicts with the results in Figure 5.5a because the first five houses in the Medium-demand scenario have a number of household appliances between 7 and 8 (see Figure B.3 in Appendix B). In addition, the MILP gap of the Medium-demand scenario, Figure 5.5b, shows that the solution is so close to optimality. By contrast, it is still far to the optimal solution in the High-demand scenario. This explains why the first five houses in the Medium-demand scenario have made more saving than their counterparts in the High-demand scenario. Also, a couple of houses have made more profit in the Low-demand scenarios than in others that are because these houses in the Low-demand scenario have eight appliances. see Figure B.2 in Appendix B.

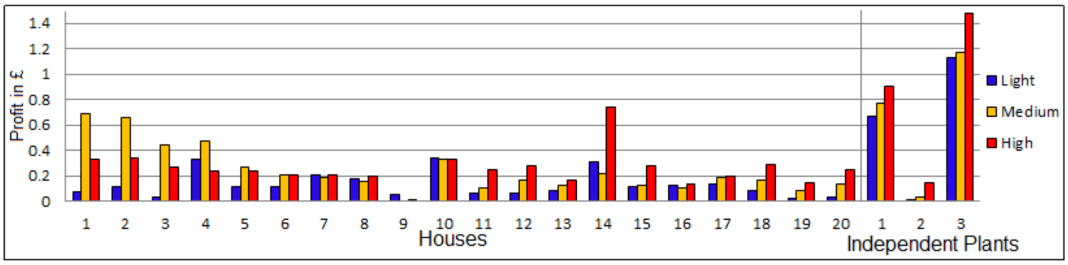


Figure 5.7: The profit made by each agent in micro-grid in three different scenarios

Figure 5.7 supports author's claim that nobody will lose in micro-grid environment. Also, the figure illustrates that just one house (House number 9) in Medium-demand scenario has made almost nothing (£0.01), whereas the rest of houses made considerable profit in the micro-grid setting compared with stand-alone setting. However, the same house may make more profit in another day. Unfortunately, the research can not tell how much each house will make for sure. This issue might be addressed in future work.

5.3.3 Second Case Study

The primary purpose of this empirical experiment is to examine the performance of the proposed micro-grid model and MILP-based heuristic algorithm (MILP-H) concerning the saving in three different pricing strategies, presented in Figure 5.4.

5.3.3.1 Input Setting

This case study will use almost the same input data that have been used in the third scenario (High-demand) in the first case study (Section 5.3.2.1), but the experiments

The definition of Stand-alone house is a house that is not connected to the national electricity grid. However, in this setting, stand-alone house means the house that does not work in micro-grid or independent house that does not share its renewable power with neighbors.

will be carried out with three different pricing strategies (two different dynamic pricing and one fixed pricing strategy).

5.3.3.2 Findings

Figure 5.8 shows the percentage of the profit made by each agent in the micro-grid with various three pricing strategies (Dynamic price 1, Dynamic price 2, and Fixed price). MILP gap of 25% has been used to stop searching for a better solution. The findings illustrate that micro-grid agents can make more profit in dynamic pricing strategy than in fixed pricing strategy. The main reason for using two pricing strategy is to emphasize that any dynamic pricing strategy is better than the fixed pricing one.

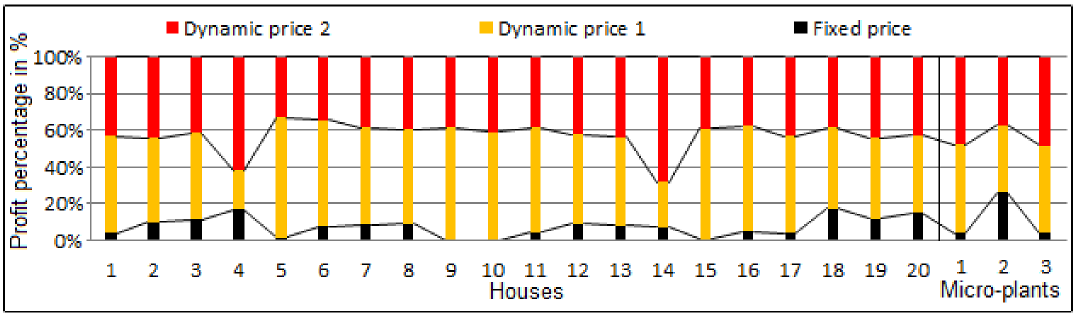


Figure 5.8: The percentage of the profit that have been made by each agent in the micro-grid using three pricing schemes.

5.3.4 Third Case Study

The main goal of this case study is to examine the effect of number of houses in micro-grid on the performance of the proposed model and the heuristic algorithm. Further, two scenarios will be demonstrated here.

5.3.4.1 Input Setting

In the first scenario, up to 30 identical houses (have the same power demand and generation capacity) will be used, each house has eight household appliances, the detail of the nominal power for all appliances and their comfortable time periods are the same as in the first case study. Each house equipped with PV array with a maximum generation capacity of 2.5 kWh. There is no independent micro-plant in this scenario.

In the second scenario, up to 30 house and three independent micro-plants (in the micro-grid) will be examined. Almost the same input data are used in this scenario as in the third scenario (High-demand scenario in the first case study). The only difference here is that the number of houses is varied from 1 to 30 to examine the performance of the proposed mathematical model of micro-grid and the proposed heuristic algorithm.

5.3.4.2 Findings

Figure 5.9 has illustrated that the average profit increases with fluctuation up to a point (house no.9) then it decreases with fluctuation. The main reason behind this is that the calculation time is fixed to 5 minutes (deadline =300 sec), whereas the number of houses is increasing for each experiment (it increases the complexity of the optimization problem, As shown in Figure 5.10). Moreover, a micro-grid with two houses (in general) will reach optimality or near-optimality faster than a micro-grid with 5, 10, or 30 houses. Plus, the figure has illustrated that the relationship between MILP Gap and the number of houses in the micro-grid is overall positive with some fluctuation. This fluctuation is normal behavior in MILP problems. Additionally, the relationship between MILP Gap and profit is negative. This explains why the curve of profit starts decreasing when MILP Gap curve starts increasing. To sum up, the number of agents in the micro-grid plays key role in the proposed model and heuristic algorithm.

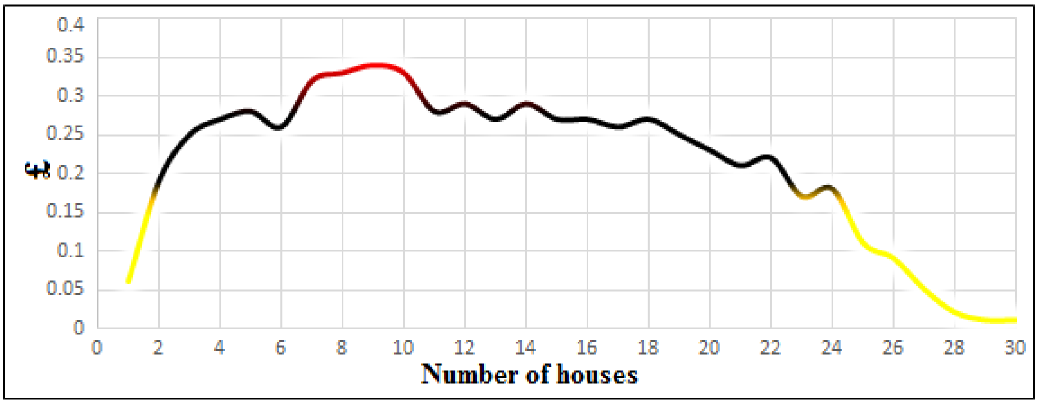


Figure 5.9: The average profit of houses in the first scenario in the third case study

Moreover, Figure 5.11 has demonstrated the average profit of houses in the micro-grid in the second scenario, whereas Figure 5.12 has illustrated the MILP gap in % of the optimization problem of allocating power to a set of houses in the micro-grid.

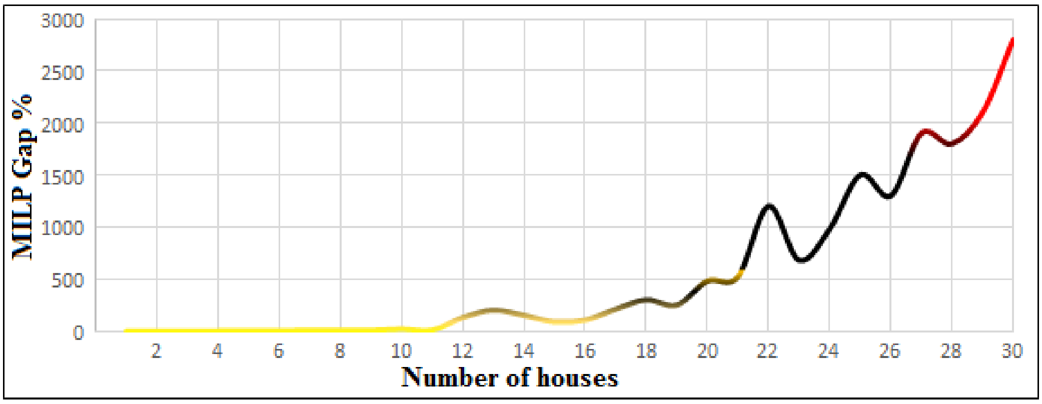


Figure 5.10: MILP gap of houses in the first scenario in the third case study

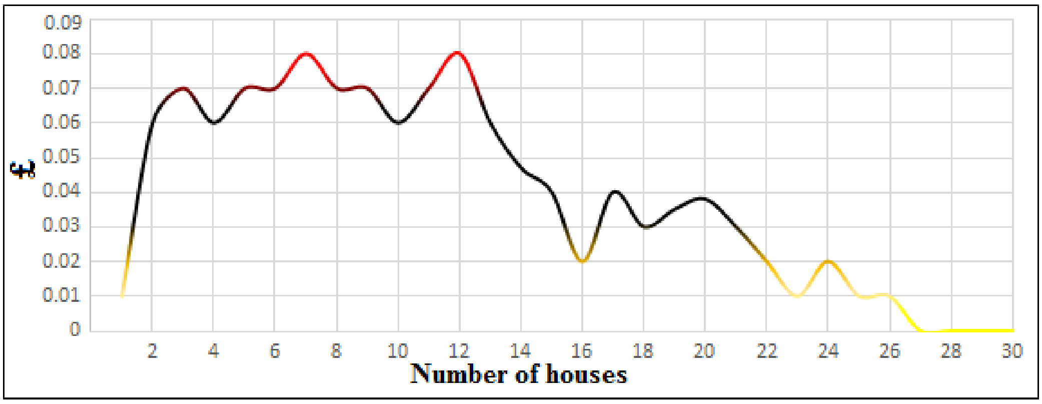


Figure 5.11: The average profit of the second scenario in the third case study

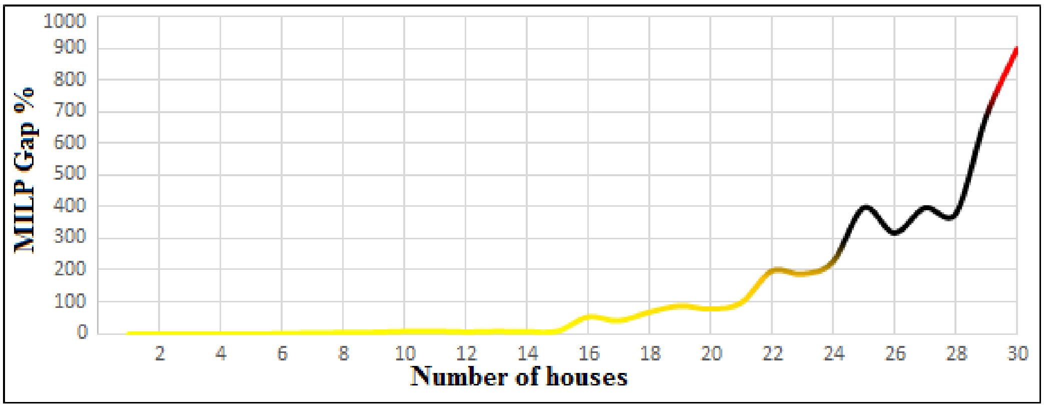


Figure 5.12: MILP gap of the second scenario in the third case study

Generally, the figure depicts the same behavior of the first scenario. To sum up, the results have revealed that having more agents in the micro-grid does not mean the agents would make more profit.

5.4 Discussion

5.4.1 Fairness Issues

By converting the problem from multi-objectives to single objective one and using the ε-constraint method, fairness issue could raise (some agents may make more profit than others even with the same number of appliances and the same generation capacity). Therefore, the objective function of ε-constraint method has been modified, Equation (5.19), to tackle this fairness problem. The total cost of all agents is minimized (not just one of them as in ε-constraint method), and a set of constraints has been added so that nobody will lose in micro-grid setting. Figure 5.7 shows the individual profit of each agent. Further, house no. 5, 10, and 15, which are the houses that do not have PV array, have made a profit higher than house no. 9 (equipped with PV array). The main reason for this fairness issue is that the input setting is different in each scenario. Also, because the total cost of all houses has been minimized, not just the cost of one house. More investigations are needed to cope with this issue, probably prioritizing the agent can solve this problem.

5.4.2 Profit Stability

The stability of the profit of each agent depends on the size of the problem (the number of integer decision variables) and MILP Gap. If the problem is small, the algorithm will reach optimality/near-optimality relatively fast and the profit will be almost stable for the micro-grid and for each agent, and vice versa. See Figure 5.5 and Figure 5.6. Figure 5.5b shows, after 30 minutes of run-time, the MILP gap is still around 100%, which means that the solution may be still far away from optimality; it could be very close, however. Because the MILP gap gives users an indication about the sub-optimal solution but it does not tell exactly how far the sub-optimal solution is from the optimality.

5.4.3 Scalability

Although there is a positive relationship between the number of agents in a micro-grid and the saving, this statement does not always hold with the proposed heuristic algorithm. Figure 5.9 and Figure 5.11 have revealed that the relationship between the number of houses and the payoff is not always positive using the proposed heuristic algorithm. as has been pointed out in both scenarios, the correlation between the number of homes and the average profit is positive up to a point, then it becomes negative, that is because increasing the number of houses will add more complexity to the optimization problem. Consequently, the algorithm will take longer to come up with a decent sub-optimal solution. By contrast, adding more micro generator to the micro-grid will not increase the complexity of the problem as these agents will not add any binary variables to the system.

5.5 Summary

This chapter has introduced MILP formulation of a set of agents working collaboratively in a micro-grid. The chapter has also proposed a way to convert multi-objective optimization problem to a single objective optimization problem. Furthermore, it has proposed an MILP-based heuristic algorithm. Finally, it has provided the finding along with discussions about the issues related to the outcomes.

Chapter 6

Heuristic Algorithms for the Cost-Effective Management of a Temperature Controlled Environment

> "Whoever acts without knowledge, what he corrupts is greater than what he fixes."
>
> *Umar Ibn Abdul Aziz*

This chapter illustrates the MILP formulation of the power allocation problem (presented in Section 4.2) in Section 6.1. Section 6.2 discusses the hardness of the problem. Section 6.3 describes how LP relaxation and rounding strategy have been used. It also gives empirical evaluation for our single objective optimization problem using LP relaxation and Cumulative Round Linear Programming (CRLP) strategy. Section 6.4 illustrate Multi-objective optimization model using LP relaxation and Minimum Deviation Rounding (MDR) strategy. it also provide results and discussions. Finally, Section 6.5 summarize the chapter. in this chapter.

6.1 MILP Formulation

The computational problem defined in Section 4.2 lends itself naturally to a simple linear programming formulation. From now on, it is assumed (in this thesis) that each instance of the given problem is solved over a finite time window and that the time horizon is subdivided into a finite number of time slots or a set of time slots, $\mathscr{T} = \{t_1, t_2, \ldots, t_T\}$, each time slot has length of τ.

Portion of this chapter was published in the following papers: Heuristics for the cost-effective management of a temperature controlled environment. In *IEEE ISGT ASIA*, pages 1–6, Nov 2015. Heuristic Algorithm for Minimizing the Electricity Cost of Air Conditioners on a Smart Grid. In *IEEE EnergyCon*, pages 1–6, April 2016.

6.1.1 Air Conditioning Unit

AC units usually have four working modes: Off, Fan, cooling, and heating mode. However, for generality in this thesis, It is assumed that each AC unit has $k_c^i > 1$ cooling mode and k_h^i heating mode. Without loss of generality, this can be achieved by using $n_m > 1$ AC unit to cool down or heat up the environment in room m. In other words, it is assumed that any percentage of power can be allocated to AC unit in case of cooling and heating (e.g., it is not ON or OFF).

$$P_i(t) = \sum_{j=1}^{k_c^i} \alpha_j^i x_j^i(t) + \sum_{j=1}^{k_h^i} \beta_j^i y_j^i(t) \qquad \forall i : i \in \mathscr{A}, \forall t : t \in \mathscr{T} \tag{6.1}$$

where, the allocated power to AC unit is $P_i(t)$ kW/unit time, α_j^i is the nominal power of AC unit when it works in cooling mode, β_j^i is the nominal power of AC unit when it works in heating mode, and $x_j^i(t)$ and $y_j^i(t)$ are binary variables, called a binary decision variables in optimization problems.

$$x_j^i(t), y_j^i(t) \in \{0,1\} \quad \forall i : i \in \mathscr{A}, \forall j : j \in \{1,\dots,k_c^i\} \cup \{1,\dots,k_h^i\}, \forall t : t \in \mathscr{T} \tag{6.2}$$

AC unit works in a single mode, constraint (6.3) will be used to make sure that AC unit works in a single mode

$$\sum_{j=1}^{k_c^i} x_j^i(t) + \sum_{j=1}^{k_h^i} y_j^i(t) \leq 1 \qquad \forall i : i \in \mathscr{A}, \forall t : t \in \mathscr{T} \tag{6.3}$$

In case, there is more than one AC unit heating up or cooling down the same room, the total allocated power to these appliances in room m at time t is presented in the following constraint

$$P_m(t) = \sum_{i=1}^{n_m} P_i(t) \qquad \forall t : t \in \mathscr{T}. \tag{6.4}$$

The possible allocated power to a set of identical AC units cool down/heat up room m, could be $\Gamma = \{0, \alpha, 2\alpha, \dots, n_m k_c^i \alpha\} \cup \{\beta, 2\beta, \dots, n_m k_h^i \beta\}$, the number of working mode is $n_m \times (k_c^r + k_h^i) + 1$, whereas if the AC units are not identical, it is $2^{n_m \times (k_c^i + k_h^i)}$. Additionally, the permissible allocated power to the AC unit could be one of any combination of the nominal power of AC units.

The primary task of the AC units in each room is to keep the interior temperature within the comfort level specified in b_r time intervals $I_1^m, \dots, I_{b_m}$ by a lower bound $T_{min}^{m,j}$ and an upper bound $T_{max}^{m,j}$, where $j = 1, \dots, b_m$.

Section 3.4.2.1 presents our model for AC units. The relationship between a room temperature, an external temperature and the allocated power to a set of AC units in room m as follows:

$$T_{in}^{m}(t) = \varepsilon \cdot T_{in}^{m}(t-1) + (1-\varepsilon)\left[T_{out}(t) - \frac{\eta}{\kappa}P_m(t)\right], \tag{6.5}$$

where $P_m(t)$ is the allocated power to a set of AC units in room m, and the comfortable room temperature constraint as follows:

$$T_{min}^{m,j} \leq T_{in}^{m}(t) \leq T_{max}^{m,j} \qquad \forall t : t \in I_j^m. \tag{6.6}$$

6.1.2 Objective Function and Additional Constraints

For the purpose of our experiments, the general model presented in Section (4.2) is simplified. The cost function Ψ in Equation (4.1) is replaced by the piecewise linear function

$$\Psi = \sum_{t \in \mathscr{T}} \{\lambda(t) \cdot L_g(t) + \xi(t) \cdot L_r(t) - \zeta(t) \cdot E(t)\}, \tag{6.7}$$

and the discomfort function in (4.6) is replaced by the following piecewise linear function

$$\Omega = \sum_{m \in \mathscr{M}} \sum_{t \in I_j^m} |T_{in}^{m}(t) - T_{opt}^{m}(t)|, \quad j = 1, \ldots, b_m \tag{6.8}$$

The objective function is presented in the following equation:

$$\mathrm{Min}\,(\Psi, \Omega) \tag{6.9}$$

subject to all the constraints defined in this section as well as few more involving functions $L_g(t)$, $L_r(t)$ and $E(t)$. Thus, the exported renewable power to NEG and the consumed renewable power at any time must be equal to the predicted renewable power,

$$E(t) + L_r(t) = P_{rew}(t) \;\; \forall t : t \in \mathscr{T}, \tag{6.10}$$

where $P_{rew}(t)$ is the renewable power available at time t. The power allocated to the building at any time slot, t, must be equal to building demand,

$$L_g(t) + L_r(t) = \sum_{m \in \mathscr{M}} P_m(t), \;\; \forall t : t \in \mathscr{T}. \tag{6.11}$$

Also, users can put a limit to the amount of grid power that could be used,

$$L_g(t) < \bar{L_g}(t), \quad \forall t : t \in \mathscr{T}, \tag{6.12}$$

where $\bar{L_g}(t)$ is the maximum amount of power that can be consumed by a set of AC units from electricity grid (NEG) at time t.

6.2 Complexity Considerations

The framework presented so far leads to a straightforward implementation of an MILP-based algorithm for problem Π which is defined in Section 4.2. Nevertheless, there is strong evidence suggesting that the allocation problem may be rather difficult computationally even with one building with large number of AC units. The experiments in this chapter support our claim (see results in Table 6.7); many experiments have been carried out. The results clearly suggest that the underlying LP solver speed is heavily affected by the number of time slots and the number of appliances (the number of binary variables in the problem) in the building. Furthermore, the optimization problem is, in fact, NP-hard [141] even if the building has a single room and a single AC unit (with many power levels and high time resolution). The outcomes of such analysis led us to the study of efficient heuristics that can be used to obtain good quality feasible solutions relatively quickly. Therefore, LP relaxation and two unique rounding techniques have been used to achieve this goal.

This chapter will present the results of two the different models, the first model is a single objective model using CRLP rounding strategy and the second one is multi-objective model using MDR rounding strategy.

6.3 Single Objective Model with CRLP

In this model, the temperature comfort level in Equation (6.8) is ignored so that the objective function in Equation (6.9) is replaced by Equation (6.13):

$$\text{Minimize } \Psi \tag{6.13}$$

So, the main object here is to minimize the electricity cost.

6.3.1 LP Relaxation and Rounding

LP relaxation and rounding is a well-known approach to cope with the computational intractability of an MILP formulation. LP relaxation is achieved by removing all constraints restricting the values of some variables to be integer numbers; in this optimization problem, all the integer variables are binary variables [142]. In the specific of Π this can be done by replacing all constraints described in Equation (6.2) by the following constraint:

$$0 \leqslant x_j^i(t) \leqslant 1, \text{ and } 0 \leqslant y_j^i(t) \leqslant 1. \tag{6.14}$$

Solving the resulting problem can be done effectively and will lead to a solution that will have cost no larger than that of an optimal solution for the original problem. However, there is no guarantee that all decision variables forced to take binary values in the initial formulations will do so in the relaxed version. Note that, for Π, this also implies that constraints (6.3) and (6.2) may not be satisfied. Thus, the resulting solution does not immediately translate into a schedule for the building's appliances. For example, if $x^i_j(5) = 0.42596$, do the controller turn the appliance i "On" at level j or not?. this chapter presents a *rounding* strategy that can be used to get feasible solutions for Π.

Algorithm CRLP (pseudo-code below) works on the solution produced by the LP relaxation and generates (in polynomial time) a sub-optimal feasible solution for the initial MILP optimization problem. Then, different rooms are treated independently. Let us assume that Γ_m is the set of all permissible nominal power values for set of appliances working in room m. The rationale behind CRLP algorithm is to loop through all time slots t and check whether $P_m(t)$ is permissible value in room m or not. If that is the case, CRLP set $\widetilde{P_m}(t) = P_m(t)$ and the room controlling variables $x^i_j(t)$ and $y^i_j(t)$ are set accordingly to 0 or 1. In the opposite case ($P_m(t)$ is not permissible in room m) CRLP round $P_m(t)$ to the closest value in Γ_m, and the controlling variables are set to 0 or 1 as required.

Algorithm 1 Cumulative Rounding based on Linear Programming (CRLP)

1: **procedure** CRLP
2:     **for** $m \in \mathscr{M}$ **do**
3:         **for** $t \in \mathscr{T}$ **do**
4:             **if** $P_m(t) \in \Gamma_{N_m}$ **then**
5:                 $\widetilde{P_m}(t) \leftarrow P_m(t)$
6:             **else**
7:                 $Sum \leftarrow Carry + P_m(t)$
8:                 Round Sum to closest working level in Γ_{N_m}
9:                 $\widetilde{P_m}(t) \leftarrow$ Rounded Sum
10:                 $Carry \leftarrow Sum - \widetilde{P_m}(t)$
11:             **end if**
12:             CHECK FEASIBILITY of solution
13:         **end for**
14:     **end for**
15: **end procedure**

The rounding process described so far does not guarantee that the rounded solution satisfies the temperature constraints in Equation (5.13). Step 12 in CRLP (described by the additional pseudo-code below) explains how this issue has been fixed.

Example 6.3.1.

To explain the mechanism of converting continuous/ real values to integers by using our CRLP rounding strategy, let us consider the following numerical example.

Algorithm 2 Checking Feasibility(CF) of CRLP's solution

procedure CHECK FEASIBILITY
  for each time slot, $t \in I_1^m \cup, \ldots, I_{b_i^m}^m$ **do**
    Calculate $\widetilde{T_{in}^m}(t)$ using $\widetilde{P_m}(t)$.
    if $\widetilde{T_{in}^m}(t) > T_{max}$ **then**
      Adjust $\widetilde{P_m}(t)$, $\widetilde{P_m}(t) \leftarrow \widetilde{P_m}(t) + \alpha$, in case of cooling mode, or
        $\widetilde{P_m}(t) \leftarrow \widetilde{P_m}(t) - \beta$, in case of heating mode.
    end if
    if $\widetilde{T_{in}^m}(t) < T_{min}$ **then**
      Adjust $\widetilde{P_m}(t)$, $\widetilde{P_m}(t) \leftarrow \widetilde{P_m}(t) - \alpha$, in case of cooling mode, or
        $\widetilde{P_m}(t) \leftarrow \widetilde{P_m}(t) + \beta$, in case of heating mode.
    end if
  end for
  Update All dependent variables.
end procedure

Table 6.1: Numerical example explains the mechanism of CRLP.

t	1	2	3	4	5	6	7	8	9	10
$P_m(t)$	0.3	0.0	1.8	1.0	2.5	0.2	0.5	1.1	0.0	1.6
sum	0.3	-	2.1	-	2.6	-0.2	0.3	1.4	-	2.0
$carry$	0.3	-	0.1	-	-0.4	-0.2	0.3	0.4	-	0.0
$\widetilde{P_m}(t)$	0.0	0.0	2.0	1.0	3.0	0.0	0.0	1.0	0.0	2.0

Consider studio flat with one AC unit, and time horizon is split into 10 time slots. The optimal allocated power to AC unit is $P_m(t)$. In addition, assume that residents need to keep room temperature within comfort level between 18°C, and 22°C. Also, assume that the permissible allocated power to AC unit is $\Gamma = \{0.0, 1.0, 2.0, 3.0\}$. First of all, CRLP algorithm will check if the allocated power to AC unit at $t = 1$, $P_m(1) \in \Gamma$ or not. If $P_m(1) \in \Gamma$ then CRLP do not need to round the allocated power and CRLP goes to the next time slot. Otherwise, CRLP will round it to closest permissible power in $\mathit{\Gamma}$ and add the carry to the next allocated power to AC $P_m(t)$, and so on and so forth. See Table 6.1

6.3.2 Empirical Results

All the experiments in this thesis have been done on a PC with an Intel(R) Core(TM) i7-2600 CPU @ 3.4 GHz, RAM is 16 GB, 64-bit Operating System (Windows 7). Also, Gurobi 6.2.1 has been used to solve LP and MILP optimization problems, whereas Java is used to model our problems (the software development platform is Netbeans IDE 7.0.1).

This section presents our empirical results related to the optimization problem defined in Equation (4.7). Two case studies are demonstrated, both of these studies based

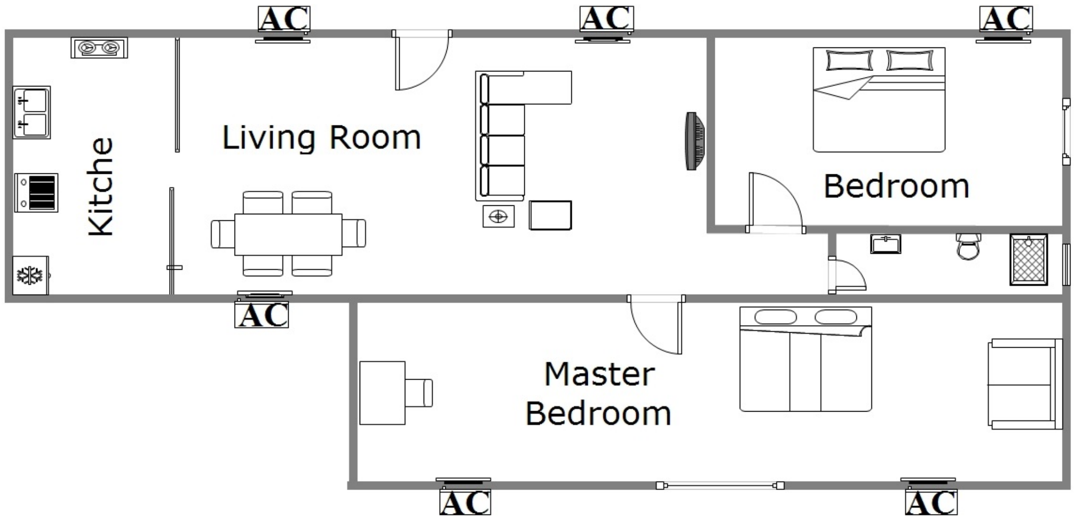


Figure 6.1: Two bedrooms flat with 6 small AC units

Table 6.2: Two comfortable periods in the flat where inside temperature should be in comfortable range

	First period		**Second period**	
Room number	*Start time*	*Finish time*	*Start time*	*Finish time*
$m = 1$	05:00:00	10:00:00	17:00:00	18:00:00
$m = 2$	05:00:00	13:00:00	14:00:00	23:00:00
$m = 3$	09:00:00	11:00:00	16:00:00	20:00:00

on the following scenarios. Firstly, consider a small residential building including three rooms, $m = 3$, see Figure 6.1, and that the resident needs to keep the inside temperature within the comfort level in each of these rooms. The system includes $N = 6$ identical AC units: $n_1 = 3$, $n_2 = 2$ and $n_3 = 1$ each of which has one working level. Thus, the possible allocated power sets to the living room is $\Gamma_1 = \{0, 2.3, 4.6, 6.9\}$, whereas the possible allocated power to the master bedroom is $\Gamma_2 = \{0, 2.3, 4.6\}$, and the possible allocated power to the second bedroom is $\Gamma_3 = \{0, 2.3\}$. In other words, three AC units working in living room works as single AC unit with three cooling modes, each mode consumes different amount of energy. Each room has a thermostat, measuring the inside temperature, and the thermal parameters have the following values: $\varepsilon_1 = \varepsilon_2 = \varepsilon_3 = 0.96$, $\eta_1 = 10$, $\eta_2 = 20$,$\eta_3 = 30$, and $\kappa_1 = \kappa_2 = \kappa_3 = 0.98$ kW/ °C, respectively. Comfort intervals for the three rooms in the building are described in Table 6.2. Also, T^m_{min}= 18.0 and T^m_{max}= 22.0°C are the same for all rooms.

Assume that the residential building is equipped with a domestic micro-generation plant, say a PV array. These PV arrays generate a maximum amount of 4.1 kWh of solar power, three shapes of renewable power are used, zero (cloudy day), bell shape (sunny day), and intermittent form (partly cloudy day), see the second chart in Figure 6.2.

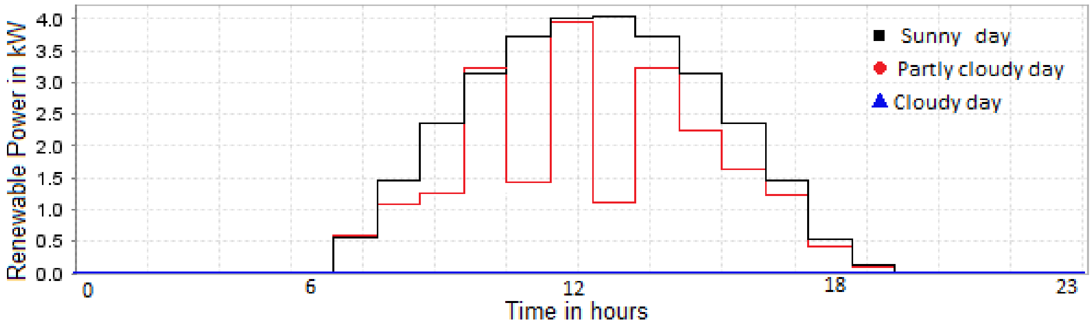


Figure 6.2: Hourly forecasting of renewable power for three different days, sunny day, partly cloudy day, and completely cloudy day

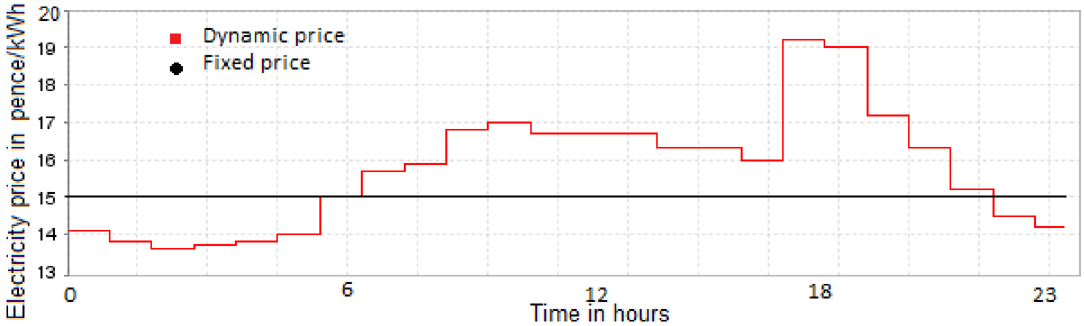


Figure 6.3: Two electricity pricing strategies, dynamic and fixed

Locally generated renewable energy costs nothing ($\xi = 0.0$ £/kWh), and the residential building benefits of an export tariff $\zeta = 0.05$ £/kWh. Furthermore, two pricing strategies will be used in our empirical study for the NEG electricity: a "Fixed pricing strategy" and a "Dynamic pricing strategy", as described in Figure 6.3.

Figure 6.4 shows the outside temperature, $T_{out}(t)$, for three different days that is used in these experiments.

6.3.2.1 First Case Study

The main purpose of this study is to investigate the performance of the four processes concerning cost and the effect of input data on cost. Input data is as given above.

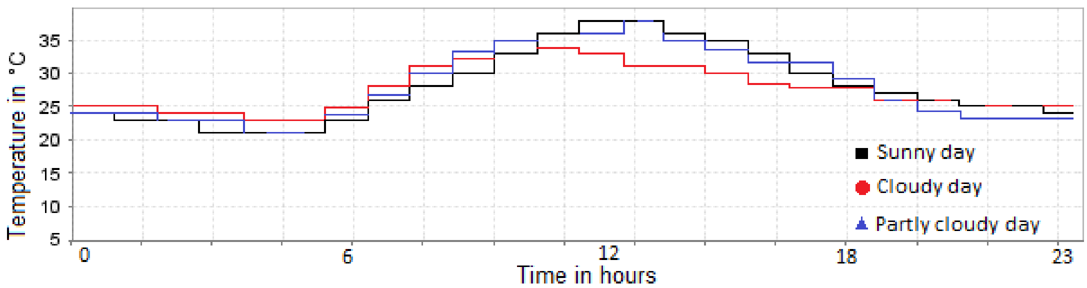


Figure 6.4: The hourly predicted outside temperature for three different days, sunny day, cloudy day and partly cloudy day

Table 6.3: The optimal solution, the maximum cost (worst-case cost), run-time, and the maximum saving of the power allocation problem using exact algorithm

	Electricity price	Maximum cost (£)	Minimum cost (£)	Run-time	Maximum saving (%)
Day 1	*Fixed*	*3.88*	*3.88*	76 Sec.	00.0
	Dynamic	5.24	4.23	147 Sec.	*19.1*
Day 2	*Fixed*	3.16	1.50	4 h, 34 m	52.5
	Dynamic	3.66	1.69	19 h, 47 m	*53.8*
Day 3	*Fixed*	3.16	1.10	13 h, 22 m	65.2
	Dynamic	3.73	1.19	17 h, 02 m	*68.1*

The time horizon is split into $T = 288$ time slots, $\tau = 5$ minutes. Six scenarios will be illustrated to investigate the effect of input data on maximum saving, defined in Equation (6.15). Input data for three different days will be used, in each day, two different pricing strategies will be used which generate a total of six different scenarios.

Table 6.3 shows the maximum saving, calculated using Equation (6.15), using MILP-based exact algorithm. To get an idea of the quality of our algorithmic solutions, in our experiments, we have compared the cost values of the various heuristics (column Min cost) with a quantity we call (Max cost). This is defined as the cost obtained by solving the maximization version of Π with the extra constraint that the total amount of energy used by the solution must match the one corresponding to the optimal solution of Π. The right-most column in the table is computed as follows:

$$\text{Maximum Saving} = \frac{|\text{Worst cost} - \text{Optimal cost}\,|}{|\text{Worst cost}|} \times 100\%, \tag{6.15}$$

Table 6.3, also, highlights the run-time of our MILP-based exact algorithm. Furthermore, the run-time depends on the electricity price and predicted renewable power. The first row in the table shows that the run time is a couple of minutes when electricity price is fixed and there is no renewable power, whereas in the last four rows, the run-time is between 4 to 17 hours which is completely unpractical.

On the other side, Table 6.4 illustrates the performance of CRLP-V algorithm concerning the cost of electricity and the computation time of our optimization algorithm. Moreover, the results, in the table, back our claim that by using LP relaxation, NP-hard problems can be solved in polynomial time. Surprisingly, the sub-optimal cost of some experiments looks cheaper than the optimal cost, that is because, CRLP-V algorithm violates temperature constraints (the inside/room temperature can go outside the specific range, if cheaper solution can be found). As a result, the AC units consume less electricity.

Table 6.5 shows the performance of our heuristic algorithms CRLP regarding the cost and run-time. The algorithm can find solution in polynomial time. Nevertheless,

Table 6.4: The suboptimal solution, the maximum cost (worst-case cost), run-time, and the maximum saving of the power allocation problem using CRLP-V algorithm

	Electricity price	Maximum cost (£)	Minimum cost (£)	Run-time (seconds)	Maximum saving (%)
Day 1	*Fixed*	3.88	3.59	0.038	07.40
	Dynamic	5.24	3.96	0.050	24.42
Day 2	*Fixed*	3.16	1.44	0.047	54.43
	Dynamic	3.66	1.48	0.045	59.56
Day 3	*Fixed*	3.16	1.07	0.059	66.13
	Dynamic	3.73	1.24	0.049	66.75

Table 6.5: The suboptimal solution, the maximum cost (worst-case cost), run-time, and the maximum saving of the power allocation problem using CRLP algorithm

	Electricity price	Maximum cost (£)	Minimum cost (£)	Run-time (seconds)	Maximum saving (%)
Day 1	*Fixed*	3.88	3.88	0.044	00.00
	Dynamic	5.24	4.27	0.051	18.51
Day 2	*Fixed*	3.16	1.80	0.048	43.10
	Dynamic	3.66	2.02	0.064	44.80
Day 3	*Fixed*	3.16	1.50	0.076	52.53
	Dynamic	3.73	1.69	0.079	54.96

it is a bit slower than CRLP-V that is because it needs more time to do feasibility check (the time needed for Algorithm (2) to guarantee feasibility).

Table 6.6 explains the results of MILP-Heuristic algorithm (provided by MILP solver). Additionally, all the results of the experiments are obtained after allowing 10 minutes of calculation time.

Figure 6.5 depicts a comparison between our heuristic algorithms concerning running cost. Note that in fixed pricing strategy in Day 1 MILP-H and CRLP does not make any saving because when there is no renewable power and price is fixed the cost

Table 6.6: The suboptimal solution, the maximum cost (worst-case cost), run-time, and the maximum saving of the power allocation problem using MILP H algorithm

	Electricity price	Maximum cost (£)	Minimum cost (£)	Run-time (seconds)	Maximum saving (%)
Day 1	*Fixed*	3.88	3.88	600.0	00.00
	Dynamic	5.24	4.25	600.0	18.89
Day 2	*Fixed*	3.16	1.51	600.0	52.22
	Dynamic	3.66	1.70	600.0	53.60
Day 3	*Fixed*	3.16	1.12	600.0	64.87
	Dynamic	3.73	1.32	600.0	67.56

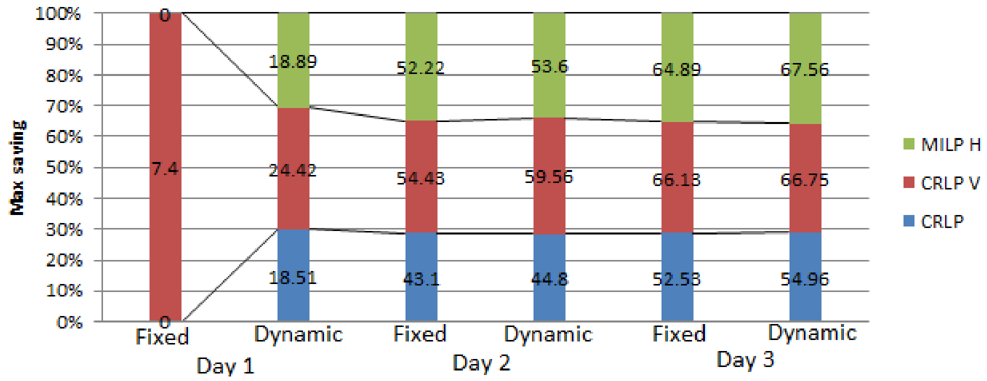


Figure 6.5: Comparison between our heuristic algorithm regarding maximum saving

Table 6.7: The average computation time, in seconds, of exact algorithm

	Time slots, τ, in minutes					
Number of AC units N	30	20	15	10	5	1
1	0.698	0.705	0.735	0.945	2375.87	∞
5	5.905	31.677	3451.01	∞	∞	∞
10	2151.74	4586.41	∞	∞	∞	∞
50	∞	∞	∞	∞	∞	∞

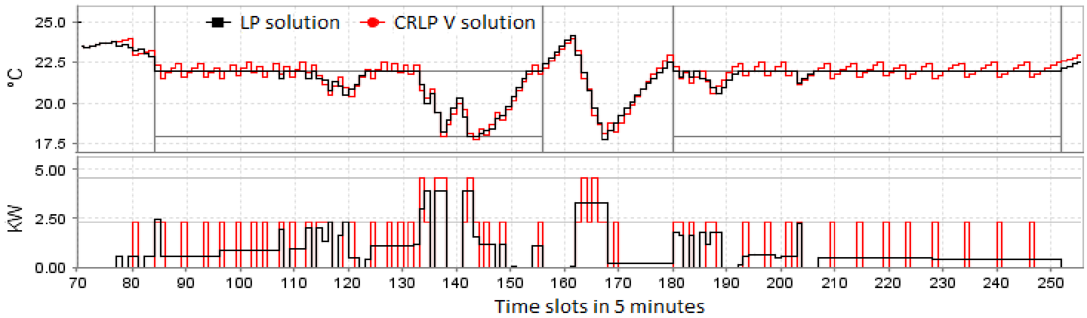
will be the same, but CRLP-V has made 7.4% profit, that is because the allocated energy to the building in CRLP-V is less than the allocated energy to the building in exact MILP algorithm.

Figure 6.6 gives an even more detailed picture. It shows the allocated power and inside temperature in the master bedroom using CRLP (Figure 6.6a) and CRLP-V (Figure 6.6b), respectively. Based on this picture, we may argue that although CRLP-V does not guarantee feasibility in practice the algorithm never goes astray, and in fact returns reasonably cheap solutions.

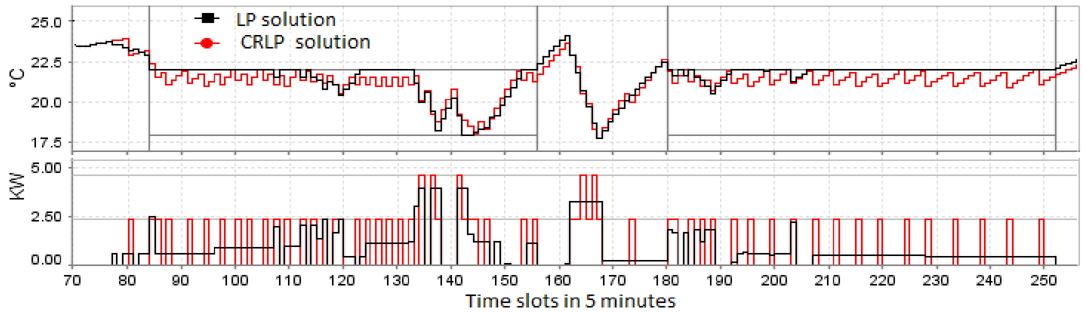
6.3.2.2 Second Case Study

The main purpose of this case study is to perform scalability test. In other words, the primary goal is to investigate the performance of the various heuristics in terms of computation time when there is a large number of AC units and high time resolution (a large number of binary decision variable). Almost the same input data that have been used in the first case study will be used in this case study, just time resolution and the number of AC units in the building will be varied.

Table 6.7 illustrates the average run-time of our MILP-based exact algorithm. As expected, the results show that the exact algorithm can not obtain an optimal feasible solution for large problems where the number of appliances or time resolution is significant due to the hardness of the optimization problem. Furthermore, the table shows that the exact algorithm (MILP) is capable of solving small problems and some of



(a) The red line presents solution of CRLP and black line presents LP solution before rounding.



(b) The red line presents solution of CRLP-V and black curve presents LP solution before rounding.

Figure 6.6: The allocated power and room temperature of the master bedroom ($n = 2$ AC units)

Table 6.8: The average computation time, in seconds, of CRLP-V.

	Time slots, τ, in minutes					
Number of AC units N	30	20	15	10	5	1
1	0.002	0.003	0.004	0.005	0.007	0.061
5	0.007	0.011	0.013	0.021	0.033	0.548
100	0.027	0.049	0.074	0.157	0.461	3.111
300	0.113	0.237	0.298	0.549	0.992	9.044

the medium size problems only, whereas it could not handle any of large optimization problem. Note, there is no safe generalization about MILP problems apart from your mileage (run-time) will vary.

By contrast, the proposed heuristic optimization algorithms can find feasible solution relatively quickly, especially CRLP-V and CRLP. The time provided in Table 6.8 is achieved by CRLP-V only. In addition, MILP-H can not beat CRLP-V or CRLP in term of calculation time. Also, CRLP is a bit slower than CRLP-V by just a few milliseconds, as it uses these milliseconds to check and guarantee that no other constraints are violated by the process of rounding the allocated power. Therefore, there is no need to present it here.

Table 6.9 shows a comparison between MILP-H (deadline is 10 minutes), and CRLP-V algorithms in terms of predicted cost. The results illustrate that when the

Table 6.9: MILP-Heuristic vs CRLP-V

	Time slots, τ, in minutes				
Number of ACs	30	20	10	5	1
N=1	**MILP-H**	**MILP-H**	**MILP-H**	**MILP-H**	CRLP-V
N=10	**MILP-H**	**MILP-H**	CRLP-V	**MILP-H**	CRLP-V
N=50	**MILP-H**	**MILP-H**	**MILP-H**	CRLP-V.	CRLP-V.
N=100	**MILP-H**	CRLP-V.	**MILP-H**	CRLP-V.	CRLP-V.
N=200	**MILP-H**	**MILP-H**	CRLP-V.	CRLP-V.	CRLP-V.
N=300	CRLP-V.	CRLP-V.	CRLP-V.	CRLP-V.	CRLP-V.

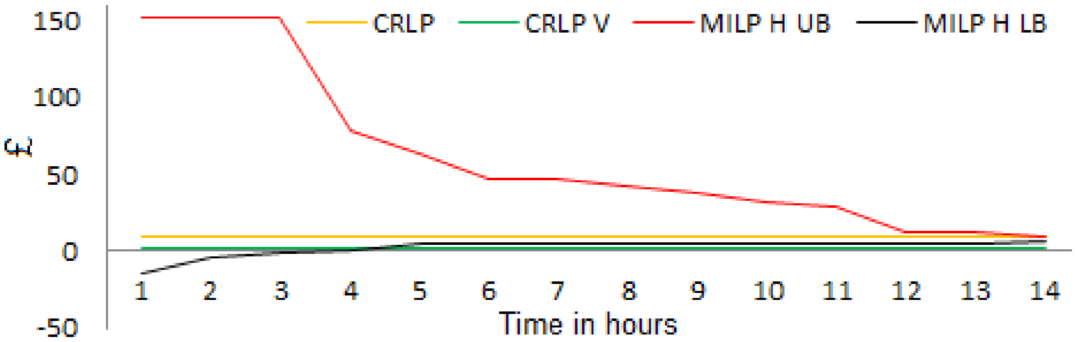


Figure 6.7: The cost of electricity in the building using MILP-H, CRLP, and CRLP-V algorithms for 200 AC units, when $\tau = 1$ minutes. MILP-H UB present the best known solution, whereas MILP-H LB is the best known bound.

problem is large CRLP-V gives a better solution in terms of cost and run-time and vice versa. The results may change slightly if the input data is changed, but, in general, this is the general pattern of their results.

Figure 6.7 compares between CRLP, CRLP-V and MILP-H heuristic algorithms for a building that has large number of AC units (200 AC units) and high time resolution ($\tau = 1$ minute). The results illustrate that when MILP-H can find a solution that is better than CRLP and CRLP-V. According to our finding, MILP-H can not beat CRLP and CRLP-V in a large problem in reasonable time.

6.3.3 Discussions

Regarding first case study, the findings, in Table 6.3, illustrate that the exact MILP-based algorithm can only be used for small problems (buildings with a handful of AC units and low time resolution ($\tau > 10$ minutes)) because this is an NP-hard problem and the computation time could go to infinity if the size of the problem is increased by increasing the number of appliances, the time horizon, or time resolution. The run-time varied considerably (from 76 seconds to 27 hours) for the same problem just by changing the electricity price and predicted renewable power; This is a common behavior in MILP problems as the computation time vary a lot by changing the value of variables.

Tables 6.4, 6.5, and 6.6 demonstrate that the maximum saving provided by any of the three heuristics is close to the optimal solution shown in Table 6.3. These algorithms can be used in large and medium problems (of course, it is possible to combine various heuristics, even run all of them and pick the best solution. Additionally, CRLP-V algorithm can find a cheaper solution than the optimal solution of MILP that is because CRLP-V violate temperature constraint in Equation (5.13) which mean that it could allocate less power to the building than the exact MILP-based algorithm. Of course, the efficient use of our system hinges on reliable weather forecasts, and the accuracy of this data depends on the country or the area where this model will be used. For instance, the weather in Mediterranean and Middle Eastern countries is more stable than in North Europe, especially in the summer. The error in weather forecasting and the uncertainty of electricity pricing are outside of the scope of this framework, and more investigations are needed to tackle this issue.

6.4 Multi-Objective Model with MDR

This section presents MILP formalization of the computational problem discussed in Section 4.2. Although the similar problem has been dealt with in the previous section (Single Objective Optimization Problem (SOOP)), this problem is a Multi-Objective Optimization Problem (MOOP). It considers the discomfort factor inside the residential building.

6.4.1 MILP Formulation Issues

There are two issues with the objective function in Equation (6.9). The first one is that, to the best of our knowledge, there is no LP solver can tackle MILP-based multi-objective optimization problem (MOOP). Therefore, MOOP needs to be converted into Single Objective Optimization Problem (SOOP). The second issue is that the absolute variable cannot be used directly in linear programming. Therefore, Equation (6.8) needs to be represented to eliminate absolute sign. Any absolute value function can be represented by introducing an auxiliary variable (e.g. Min $|f(x)|$, can be represented as Min Z subject to $f(x) \leq Z$ and $-f(x) \leq Z$) [142]. So, to reformulate absolute value, $| T^m_{in}(t) - T^m_{opt} |$, another auxiliary binary variable $\delta(t) \in \{0, 1\}$ is needed and three more constraints, illustrated in Equations (6.16), (6.17), and (6.18).

$$-T^m_{in}(t) + T^m_{opt} \leq \delta(t) \qquad \forall t : t \in \mathscr{T}, \forall m : m \in \mathscr{M} \tag{6.16}$$

$$T^m_{in}(t) - T^m_{opt} \leq \delta(t) \qquad \forall t : t \in \mathscr{T}, \forall m : m \in \mathscr{M} \tag{6.17}$$

$$\Phi = \sum_{m \in \mathscr{M}} \sum_{t \in I_j^m} \delta_m(t) \tag{6.18}$$

Having coped with the absolute sign issue, another problem needs to be dealt with which is the converting MOOP into SOOP. Linear scalarization technique [143] will be used to convert MOOP into SOOP, the objective function in Equation (4.7) will be replaced by the following function (6.19),

$$\mathrm{Min}(w_1 \Psi + w_2 \Phi), \tag{6.19}$$

where $w_1 > 0$ and $w_2 > 0$ are weights to bias the optimization toward either cost or comfort.

6.4.2 LP Relaxation and Rounding

LP relaxation can be done in problem Π by replacing all integer constraints described in Equation (6.2) by the following constraints

$$0 \leqslant x_j^i(t) \leqslant 1, \text{ and } 0 \leqslant y_j^i(t) \leqslant 1. \tag{6.20}$$

Solving the resulting problem can be achieved efficiently and will lead to a solution that will have cost no larger than that of an optimal solution for the original problem. Nevertheless, there is no guarantee that the allocated power to any AC unit, in case of cooling, α, will be equal to any of $\alpha_1, \ldots, \alpha_{k_c^i}$. Thus the resulting solution does not immediately translate into a schedule for the building's appliances. Note that $0.4785 \times \alpha_j$ cannot be allocated to AC unit, doing so could damage the AC unit or make it operate in an inefficient way. A rounding strategy that can be used to get practical solutions for Π is presented. Minimum Deviation Rounding (MDR) works on the solution produced by the LP relaxation and generates (in polynomial time) a feasible solution for the initial MILP problem. Let us assume that $\Gamma_r = \{\alpha_1, \beta_1, \ldots, \alpha_{k_{c,i}^r}, \beta_{k_h^i}\}$ is a set of all permissible power values for room m. The rationale behind algorithm MDR is to round the allocated power to the first permissible power value, say $\widetilde{P_m}(t) = \alpha_1$, and calculate the deviation between $T_{in}^m(t)$ and $\widetilde{T_{in}^m}(t)$, where $\widetilde{T_{in}^m}(t)$ is the room temperature in case α_1 is allocated to the AC unit. Then, do the same with the rest. After that, the best permissible power value that gives the smallest temperature deviation is picked and approved as a solution as long as it does not violate other constraints. Equation (6.21), Equation (6.22), and Equation (6.23) show how does MDR work in case of cooling. Note, in case of heating swap α with β.

$$\Delta_k = \mid \widetilde{T_{in}^{m,k}}(t) - T_{in}^m(t) \mid \; \forall m, \forall t, \; k = 0, 1, \ldots, K \tag{6.21}$$

$$\widetilde{P_m}(t) = \alpha_s, \; (\beta_s \,\text{in case of heating}) \tag{6.22}$$

$$\Delta_s \leq \Delta_j, \; s \neq j, \; j \,\text{and}\; s = 0, 1 \ldots, K, \tag{6.23}$$

where $\widetilde{T_{in}^{m,k}}(t)$ is the temperature of m^{th} room when $\widetilde{P_m}(t) = \alpha_k$ (or β_k in case of heating).

To understand how does our rounding strategy work, pseudo code of MDR is introduced in Algorithm 3 and 4.

Algorithm 3 Minimum Deviation Rounding (MDR)

procedure MDR
    for each room $m \in \mathscr{M}$ **do**
        for each time slot $t \in \mathscr{T}$ **do**
            for each α and $\beta \in \Gamma_m$ **do**
                Calculate $T_{in}^{m,k}(t)$, and $\Delta(k)$ using Equation(6.21).
            end for
            Find Minimum Deviation, Δ_s using Equation(6.23) & (6.23).
            Check Feasibility of solution using Algorithm 4
        end for
    end for
end procedure

Algorithm 4 Checking Feasibility of MDR's Solution

procedure CHECK FEASIBILITY
    for each time slot, $t \in I_1^m \cup, \ldots, I_{b_i^m}^m$ **do**
        Calculate $\widetilde{T_{in}^m}(t)$ using $\widetilde{P_m}(t) \leftarrow \alpha_s$ or β_s.
        if $\widetilde{T_{in}^m}(t) > T_{max}$ **then**
            Adjust $\widetilde{P_m}(t)$, $\widetilde{P_m}(t) \leftarrow \alpha_{s+1}$ or β_{s-1}.
        end if
        if $\widetilde{T_{in}^m}(t) < T_{min}$ **then**
            Adjust $\widetilde{P_m}(t)$, $\widetilde{P_m}(t) \leftarrow \alpha_{s-1}$ or β_{s+1}.
        end if
    end for
    Check that MDR does not violate (5.13)
    Update All dependent variables.
end procedure

6.4.3 Empirical Results

All the experiments in this thesis have been done on a PC with an Intel(R) Core(TM) i7-2600 CPU @ 3.4 GHz; RAM is 16 GB, 64-bit Operating System (Windows 7).

Also, Gurobi has been used to solve LP and MILP problems, whereas Java is used to model our problems (the software development platform is Netbeans IDE 7.0.1).

This section compares two different heuristic ways of finding feasible solutions for our optimization problem (Π) defined in Section 4.2, using a truncated version of the MILP (MILP-H), using MDR algorithm, or a slightly faster version of the same process, named MDR-V, which omits the process of checking the feasibility of the solution in procedure MDR. Three case studies will be demonstrated in this section in order to compare between these heuristic algorithms.

6.4.3.1 Communal Input Setting

All case studies will use the same input data presented in this section. All AC units have the same inertia, $\forall i$, $\varepsilon_i = 0.96$, and $\forall r$, κ_r= 0.98 kW/°C. Also, all scenarios will use T^m_{min}= 18.0, T^m_{max}= 22.0 and T^m_{opt}= 20.0 °C. Locally generated renewable energy costs nothing ($\xi = 0.0$ £/kWh), and the building benefits of an export the surplus renewable power via FIT, $\zeta = 0.05$ £/kWh. Note that the same input data as in our previous Section 6.3.2 is used here, so that the results can be compared. Additionally, $w_1 = w_2 = 1$ are used in our multi-objective optimization problem. Figure 6.3 shows two pricing strategies that will be used for all cases, a "Fixed" and "Dynamic" pricing. Additionally, Figure 6.2 illustrates the predicted renewable power in three different days, completely cloudy day (0.0 kW), partly cloudy, and sunny day (blue sky). Finally, Figure 6.4 demonstrates the outside temperature on three different days.

6.4.3.2 First Case Study

The primary purpose of this case study is to compare the enhanced rounding technique, MDR, with the previous rounding technique, CRLP, presented in Section 6. Therefore, this case study uses the same input data used in the last section so that a comparison can be done between them. Consider a small residential building consists of 3 studio flats or rooms and that users need to cool these flats/rooms and keep the temperature in comfort level in each of them. The system includes $N = 6$ identical AC units: $n_1 = 3$, $n_2 = 2$ and $n_3 = 1$. Thus the possible allocated power sets are $\Gamma_1 = \{0, 2.3, 4.6, 6.9\}$, $\Gamma_2 = \{0, 2.3, 4.6\}$, and $\Gamma_3 = \{0, 2.3\}$, respectively. Each flat has a thermostat, measuring the inside temperature, and the thermal parameters have the following values: $\eta_1 = 10$, $\eta_2 = 20$, and $\eta_3 = 30$, respectively. Comfort intervals are shown in Table 6.2. It is assumed that the building is equipped with a domestic micro-generation plant, say a PV array. These PV arrays generate a maximum amount of 4.1 kWh of solar power. Figure 6.2 shows the predicted renewable power in three different days.

Table 6.10 illustrates comparison between MDR and CRLP strategies. The results show that when there is no renewable power and electricity price is fixed, both

Table 6.10: Comparison between CRLP and MDR in terms of cost, IMP stand for improvement in saving using MDR.

	Fixed price			Dynamic price		
	Day 1	Day 2	Day 3	Day 1	Day 2	Day 3
Maximum cost (£)	3.88	3.16	3.16	5.24	3.66	3.73
CRLP (£)	3.88	1.80	1.50	4.27	2.02	1.79
MDR (£)	3.88	1.76	1.43	4.26	1.93	1.63
Maximum Saving (MS) %	0.00	44.3	54.8	18.6	47.3	56.3
Improvement in MS %	0.00	2.22	4.66	0.23	3.07	8.93

techniques have achieved the same results. By contrast, MDR saves more money in dynamic pricing. MS shows the maximum saving that has been made by MDR.

The result, in general, shows an improvement in the saving. However, the saving is zero when there is no renewable power and the electricity price is fixed. Unfortunately, the author cannot tell the percentage of the improvement because it depends on so many variables such as the number of AC units, the generated renewable power, electricity pricing, outside temperature, and user preferences.

6.4.3.3 Second Case Study

The main purpose of this empirical experiment is to compare between three heuristic algorithms which are MDR, MDR-V, MILP-H concerning the cost and Average Discomfort Factor (ADF=$\frac{\Omega}{T}$). Firstly, these heuristic algorithms with MOOP will be examined. Then, the same experiment for SOOP will be carried out here and same input data will be used as in first case study. Moreover, discomfort factor has a negative relationship with the amount of consumed power by AC unit(s). However, consuming more energy does not mean that it is more expensive. For instance, consuming 2.0 kWh, in dynamic price environment in off peak hours, could be cheaper than consuming 1.0 kWh on peak hours.

Table 6.11 shows a comparison between three heuristic algorithms, MDR-V, MDR, and MILP-H concerning the cost and ADF. These algorithms are used to solve Single Objective Optimization Problem (SOOP).

The table depicts that MDR-V is the best algorithm in terms of cost. By contrast, it is the worst heuristic algorithm regarding the ADF that is because it violates temperature constraint in order to a get cheaper solution. As a result, users must compromise comfort (ADF goes high). MILP-H comes second in terms of electricity cost, whereas MDR comes last in terms of cost and ADF.

Table 6.12 illustrates the result of Multi Objective Optimization Problem (MOOP).

Maximum Saving (MS)= $(\text{Max} - \text{Min})/\text{Min} \times 100$

Table 6.11: Comparison between MDR-V, MDR, and MILP-H, for solving SOOP.

		MDR-V		**MDR**		**MILP-H**	
	Price	*Cost (£)*	*ADF*	*Cost (£)*	*ADF*	*Cost (£)*	*ADF*
First day	*Fixed*	3.59	3.13	3.88	1.85	3.88	1.81
	Dynamic	3.96	2.11	4.26	1.67	4.25	1.75
Second day	*Fixed*	1.44	2.12	1.76	1.74	1.51	1.74
	Dynamic	1.68	2.07	1.93	1.65	1.70	1.69
Third day	*Fixed*	1.19	2.05	1.43	1.84	1.12	1.69
	Dynamic	1.34	2.03	1.53	1.56	1.32	1.64

Table 6.12: Comparison between MDR-V, MDR, and MILP-H, for solving MOOP. Note, MILP-H is stopped after 600 sec.

		MDR-V		**MDR**		**MILP-H**	
	Price	*Cost (£)*	*ADF*	*Cost (£)*	*ADF*	*Cost (£)*	*ADF*
First day	*Fixed*	3.96	0.51	3.96	0.51	3.96	1.12
	Dynamic	4.26	0.47	4.26	0.47	4.37	0.97
Second day	*Fixed*	1.59	0.35	1.59	0.35	1.62	1.03
	Dynamic	1.76	0.28	1.76	0.28	1.78	0.89
Third day	*Fixed*	1.19	0.33	1.19	0.33	1.23	0.37
	Dynamic	1.44	0.24	1.46	0.24	1.37	0.54

It gives a comparison between three heuristic algorithms, MDR-V, MDR, and MILP-H concerning the cost and ADF. The results have shown that MDR and MDR-V give the best ADF. Note that ADF of MDR-V is the same as ADF of MDR because MOOP will force the temperature curve to be around T_{opt} and when the allocated power to AC unit rounded it never goes above T_{max} or under T_{min} (It does not violate temperature constraints).

6.4.3.4 Third Case Study

The main goal of this case study is to do scalability test or to examine the performance of our heuristic algorithms (MDR, MDR-V and MILP-H) in terms of computation time and the cost of proposed schedule (solution). Almost the same input data as in the first case study will be used here. Nevertheless, just τ and N will be varied.

In our previous case study 6.3.2.2, the results have showed that solving large problem with the exact algorithm is not applicable, and the results support our claim by empirical experiments in the second case study. Therefore, there is no need to repeat the same experiments in this section. Table 6.13 demonstrates the run-time of our heuristic algorithm (MDR) for solving MOOP using CRLP, whereas Table 6.14 depicts the run-time for our enhanced rounding strategy (MDR).

Table 6.15 shows a comparison between the built-in heuristic algorithm (MILP-H)

Table 6.13: The average computation time, in seconds, of CRLP heuristic algorithm

	Time slots, τ, in minutes					
Number of AC units N	20	15	10	5	3	1
1	0.004	0.005	0.006	0.005	0.009	0.066
10	0.008	0.012	0.015	0.026	0.037	0.554
100	0.031	0.052	0.088	0.079	0.475	3.111
300	0.122	0.240	0.908	0.301	0.998	9.142

Table 6.14: The average computation time, in seconds, of MDR.

	Time slots, τ, in minutes					
Number of AC units N	20	15	10	5	3	1
1	0.002	0.002	0.004	0.005	0.021	0.061
10	0.009	0.010	0.016	0.026	0.136	0.989
100	0.031	0.053	0.088	0.179	0.644	3.501
300	0.23	0.714	0.908	1.095	2.237	9.471

and our heuristic algorithm (uses rounding). The finding indicates that MILP-H can not beat MDR in large problems when the number of AC units is large or time resolution is high (a large number of binary decision variables). By contrast, MILP-H is the best choice for a small room and houses with just a couple of AC units.

Figure 6.8 highlights the difference between two techniques in terms of computation time. The results show that MDR is a bit slower than CRLP because it does more checks before rounding. However, this difference is acceptable, and this delay is the price to pay for better performance.

6.4.3.5 Discussions

The main propose of the first case study is to show the difference between our new rounding strategy, MDR, compared with our previous strategy CRLP. Table 6.10 shows that using MDR can save up to around 8% of our profit in this settings. However, in some settings it gave 0% improvement. This depends on the number of appliances,

Table 6.15: Comparison between MILP-H vs MDR in terms of cost.

	Time slots, τ, in minutes					
Number of ACs	20	15	10	5	3	1
N=1	**MILP-H**	**MILP-H**	**MILP-H**	**MILP-H**	**MILP-H**	MDR
N=10	**MILP-H**	**MILP-H**	MDR	**MILP-H**	MDR	MDR
N=50	**MILP-H**	**MILP-H**	**MILP-H**	MDR	MDR	MDR
N=100	**MILP-H**	**MILP-H**	**MILP-H**	MDR	MDR	MDR
N=200	**MILP-H**	**MILP-H**	MDR	MDR	MDR	MDR
N=300	**MILP-H**	MDR	MDR	MDR	MDR	MDR

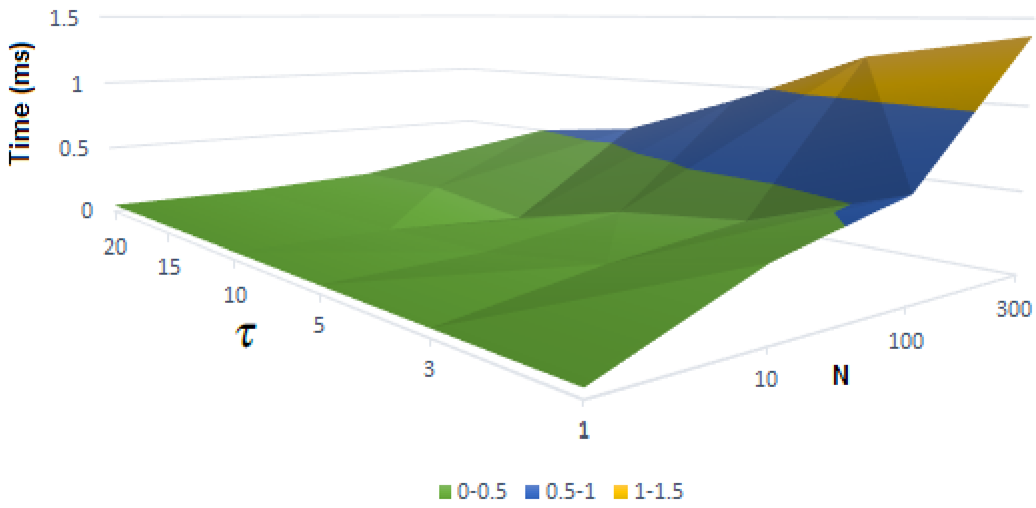


Figure 6.8: Increment in run-time using MDR for MOOP compared with CRLP for MOOP

electricity price and the amount of renewable power. Therefore, it was difficult to tell exactly how much profit will make using MDR algorithm compared with the previous rounding strategy CRLP presented in the previous chapter.

In addition, the finding shows that MDR-V, with SOOP, performs better than its counterpart with MOOP in terms of cost. However, the Average of Discomfort Factor (ADF) in MOOP is better than its counterpart in SOOP. Surprisingly, MDR in MOOP is better that MDR in SOOP (in terms of cost and comfort) and that is because adding discomfort factor forces the temperature to be a bit far from T^m_{min} and T^m_{max}. Therefore, fewer changes are made on the allocated power to AC units in the rounding process. By contrast, MILP-H gives a cheaper solution in SOOP but again the discomfort factor is higher in MOOP. So, it is a matter of trade-off between the cost and comfort and it is ultimately up to the end users which option they prefer.

Table 6.15 depicts that MILP-H gives the best solution when the size of the problem is small or medium, whereas MDR gives the best solution when the size of the problem is large. However, When $N = 10$ and $\tau = 10$, MDR was better than MILP H. This behavior is common in MILP. The only safe generalization with MILP is that the calculation time will vary.

6.5 Summary

This chapter has presented two case studies (optimization problems). These problems are special cases of our general model of the problem of power allocation in micro-grids. The chapter has illustrated MILP formulation of the problem presented in Section 4.2. It has also suggested two LP-based heuristic algorithms. Finally, the chapter has presented the results of these case studies along with a comprehensive discussion of the issue related to these finding.

Chapter 7

Smart Domestic Renewable Energy Management Using Knapsack

"What regresses, never progresses"

Umar Ibn Al-Khattab

We start the empirical analysis of the problems described in Section 4.3 by looking at the Max-Utilization problem. In the forthcoming sections, a reactive formulation of this problem is studied, in which time is discrete and (re-)optimization is performed at every time step. The proposed probabilistic model works only with interruptible appliances. This chapter looks at the problem of maximizing the amount that is immediately used at the site before any excess is dumped to the NEG. Combinatorial optimization techniques may help the decision making in this setting, by dynamically modulating the household energy needs in response to changes in the amount of generated power. Section 7.1 presents ILP formulation of the problem. Empirical Evaluation is given in Section 7.2. The results are discussed in Section 7.3. Finally, Section 7.4 summarize the chapter.

7.1 Integer Linear Programming (ILP) Formulation of the Problem

A reactive control system could convert a large proportion of the generation surplus into thermal energy which could be used to regulate the building temperature. Moreover, the mathematical formulation of the core allocation method provides guarantees on the quality of its results. This chapter describes experiments involving a PV array

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system, but the method can be used to manage any type of domestic renewable energy plant. A variety of appliances can be actively controlled. The Knapsack formulation can be used to obtain allocations optimizing different criteria, such as the amount of allocated power, the number of appliances switched on, or giving special priority to a selected set of appliances (e.g. situated in specific parts of the house).

In combinatorial optimization, Knapsack problem is choosing a subset of items from a set of n possible items in order to maximize the profit of these elements without exceeding the capacity of the Knapsack, see Figure 7.1a. The 0-1 Knapsack problem is a special case of Knapsack problem where fractions of the articles are not allowed. 0-1 Knapsack admits an ILP formulation:

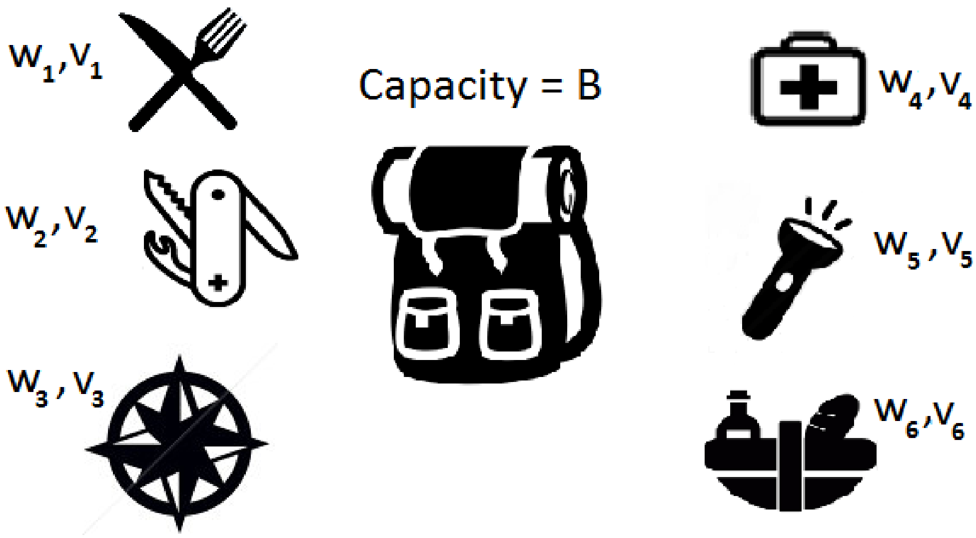
$$\text{maximize} \sum_{j=1}^{n} v_j \cdot x_j \tag{7.1}$$

$$\text{subject to} \sum_{j=1}^{n} w_j \cdot x_j \leq B \tag{7.2}$$

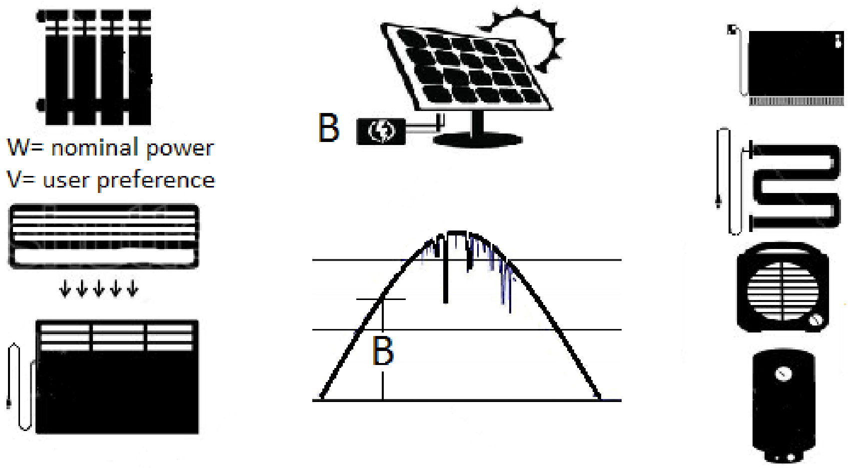
$$x_j \in \{0, 1\}, \text{ and } j = 1, \ldots, n \tag{7.3}$$

where v_j is the value of item j, and w_j is the weight, x_j is binary decision variable. Figure 7.1b shows a straightforward model of the Max-Utilization power allocation problem as Knapsack problem, where the available renewable power is modeled as the Knapsack capacity, the user preferences is modeled as the value of the item, and the allocated power is modeled as weight of the item.

However, a number of issues have to be addressed. An electric appliance will typically use a variable amount of power, only coarsely bound by the nominal power mentioned in the manufacturer's information sheet. A natural way to deal with this is to assume that the appliance loads are not fixed numbers but, rather, random quantities. Knapsack is an NP-hard problem [144]. Exact algorithms for such problems are typically quite slow. Sometimes approximation heuristics offer advantages, but the available performance guarantees are too weak in the case at hand. This chapter shows how a particular Knapsack variant can be used to solve the dynamic energy allocation problem at hand. The effectiveness of the proposal hinges on the fact that the relevant instances do not involve large numbers (typical domestic micro-generation plants are capable of producing no more than a few kilowatts of power per hour) and their combinatorial size is quite restricted too. Thus, the instances can then be solved by standard dynamic programming. In particular, the look-up tables employed by such method are small and do not have to be recomputed from scratch in successive iterations of the allocation process, provided that the set of controlled appliances is not modified. Note that uninterruptible multiphase appliances cannot be used in this setting because



(a) Knapsack optimization problem



(b) Renewable power allocation to a set of interruptible household appliances

Figure 7.1: Knapsack problem

it is an online allocation algorithm which means that the appliances may be switched On/Off as required. So, appliances that can be used are interruptible uni-phase (e.g. water heaters, AC units, heaters, storage systems, etc.).

The most relevant to the scope of this study is the so-called chance constrained Knapsack (CHKNAPSACK). Where the item sizes (the nominal power) w_j are independent random variables with known distribution and, for each j, the profit $p_j = r_j.w_j$, for some fixed number $r_j \geq 0$. The aim is to find a set of items $\mathscr{S} \subset \mathscr{A}$ that maximizes the sum of the expected profits $\sum_{j \in S} r_j.E(w_j)$ subject to the probabilistic constraint

$$\Pr\left[\sum_{j \in S} w_j > B\right] \leq p, \tag{7.4}$$

where $p \in (0, 1/2]$ is the infeasibility probability, i.e. the chance that the chosen solution will be infeasible. In general, CHKNAPSACK(P) cannot be solved very efficiently. An alternative way will be presented to relate CHKNAPSACK(P) to KNAPSACK.

Let c be a positive real number. For any given instance Π of CHKNAPSACK(P), define its associated instance $\Pi'(c)$ of (KNAPSACK), on the same number of items, and using the same capacity B. For each j, the weight (profit) of item j in $\Pi'(c)$ is $\mu_j + c \cdot \sigma_j$ (respectively $r_j.\mu_j$). Here μ_j and σ_j are, respectively, the mean and standard deviation of w_j. Solutions for both problems are sets of items satisfying some feasibility conditions. For any set of items $\mathscr{S}$, $\sigma(S) = \sum_{j \in S} \sigma_j$. The following result expresses an important property of the above reduction. The theorem is stated for the case of normal weights.

Theorem 7.1.1. *Let Π be an instance of* KNAPSACK*(P). If the items of Π have normal distribution then every feasible solution of the associated instance Π' where* $\Pi'(\sqrt{2log(1/p)})$ *is also a feasible solution of Π.*

Proof. Let S be a feasible solution to $\Pi'(c)$ where $c = \sqrt{2 \cdot log(1/p)}$. The random variable $W = \sum_{j \in S} w_j$ has normal distribution with parameters $\mu = \sum_{j \in S} \mu_j$ and $\sigma = \sum_{j \in S} \sigma_j$. Hence $\Pr[W > \mu + c \cdot \sigma] \leq exp(-c^2/2)$. Also, $\Pr[W > B] \leq \Pr[W > \mu + c \cdot \sigma]$ by monotonicity, as $\mu + c \cdot \sigma \leq B$ for any feasible solution S of Π'. The result follows from the given definition of c. Feasible solutions of KNAPSACK(P) can thus be found by solving instances of the classical Knapsack problem. □

Feasible solutions of CHKNAPSACK(P) can thus be found by solving instances of the classical Knapsack problem. The rest of the chapter provides empirical support to the claim that these solutions are in fact good.

7.2 Empirical Evaluation

A prototype Energy Manager (EM) including the implementation of both the standard dynamic programming and the most elementary exhaustive search method for solution of KNAPSACK was implemented as part of this project. The former was used to get feasible solutions of CHKNAPSACK(P) via reduction described above. Exhaustive search was used to solve CHKNAPSACK(P) exactly.

7.2.1 The Prototype

Figure 7.2 depicts the architecture of the EM system that have been used in this project. It consists of a computer running the main reactive control application, connected to a generation and a usage monitor. The software controls some sockets (household appliances) via radio signals. Furthermore, the household appliances are attached to the house electricity circuit through such sockets. Depending on the amount of generated power, the reactive control system varies the household power load by deciding which sockets should be turned on or off. The system, also, allows the end-users to specify a list of controlled appliances and, for each appliance, (the average and standard deviation of) its power usage, and its allocation priority. Additionally, the end-users can set the rate at which the system will recompute the allocation. In practice, such quantity is constrained by the speed of a single run of the particular allocation algorithm and the rate at which new data become available. For the case study described in this section, such algorithms typically complete a run in few milliseconds and new generation data arrives every 10 seconds. The allocation process consists of a loop that repeatedly executes the following operations:

* Read the current amount of generated power $P_s(t)$ and house load $L_r(t)$;
* Compute the amount of available power B as $P_s(t) - (L_r(t) + u(t))$, where $u(t) = \sum_{j \in S} \mu_j$, is the average of the amount of power allocated at the previous allocation step;
* Calculate new allocation using the appropriate Knapsack solver and capacity equals to B;
* Turn appliances On/Off as required.

The architecture described in Figure 7.2 was deployed in the summer of 2012 at a household in the North-West of the UK (Liverpool, Coordinates: 53°24´N 2°59´W), fitted with an array of PV arrays (total nominal power 3.95 kWh), feeding power to an inverter connected to a generation meter and the grid.

7.2.2 Experiments

A prototype EM including the implementation of both the standard dynamic programming and the most elementary exhaustive search method for the solution of KNAPSACK was implemented as part of this project. The former was used to get feasible solutions of CHKNAPSACK(p) via the reduction described above. An exhaustive search was used to solve CHKNAPSACK(p) exactly, for benchmark purposes.

The system has been in use for two years, and daily data has been collected during this time. The variability of the energy source and the electrical quantities involved makes it tough to come up with statistically meaningful results. However, the selection of experiments presented suggests that the proposed reduction of a deterministic problem is efficient, flexible, and compares well with more sophisticated optimal strategies. In all experiments, c = 1.35373... (corresponding to an unfeasibility probability

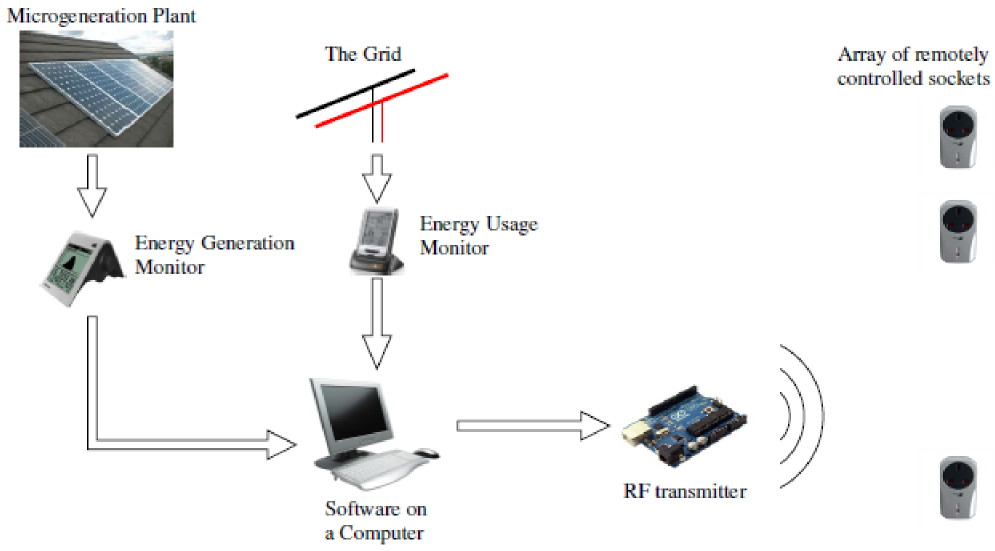


Figure 7.2: The energy manager architecture

of 40%) yet the resulting allocations are quite large, and they only rarely use more energy than is available. The payoff of each experiment is computed as the cumulative difference between the generated and the used power, restricted to those intervals of time where the former is no smaller than the latter. More precisely, if the experiment runs from time t_1 to t_2, let $P_s(t)$ denotes the quantity of generated power and $L_r(t)$ the household power load at time t. Let P_{s_T} denote the total amount of generated power, between t_1 and t_2.

$$P_{s_T} = \int_{t_1}^{t_2} P_s(t)dt. \tag{7.5}$$

The payoff of the given experiment is

$$1 - \frac{1}{P_{s_T}} \int_{\mathcal{T}} (P_s(t) - L_r(t))\, dt \tag{7.6}$$

where $\mathcal{T}$ is the set of those $t \in [t_1, t_2]$ for which $P_s(t) - L_r(t) \geq 0$. For the purpose of the experiments the integrals were approximated using standard numerical methods.

Real-life Setting:

Figure 7.3 displays a snapshot of the generation and usage curve (power measured in watts) during approximately an hour work of the allocation process. The picture shows how the process adapts to an evolving generation pattern. As the amount of generated energy (dark line) grows the system allocates the best possible load subject to the given priorities. The light gray line shows the resulting energy usage. The broad peak in such plot between 10:36 AM and 10:37 AM is due to a kettle being

Table 7.1: Appliances used in the experiments

Appliance number (j)	**Appliance Type**	μ_j	σ_j	**nominal power** (P_j)
1	Water Tank Heater	1768	82	1771
2	Oil Heater	569	16	601
3	Fan Heater	957	56	955
4	Halogen Heater	297	9	31
5	Halogen Heater	283	10	31
6	Tubular Heater	178	9	176
7	Tubular Heater	187	41	201
8	Tubular Heater	78	6	8
9	Tubular Heater	77	22	8

switched on. The graph shows a certain latency in the allocation process (light gray line shifted to the right of the dark gray one). Decreasing the value of the allocation rate reduces such effect. The top of Figure 7.3 shows the generation/usage graph obtained by running the EM between approximately 7 AM and 8 PM on a sunny day in late March 2013. The experiment resulted in 20 kWh being generated. The allocation payoff was approximately 88.5%. The drops in the allocation values are due to either thermostated appliances switching themselves off or the recovery process which takes place when the system's prediction for the amount of available power is inaccurate. These and other implementation issues are discussed at the end of this chapter. The experiment supports the idea that the proposed approach is worthwhile: almost 90% of the renewable power available at the particular household on the day of the experiment was immediately converted into thermal energy which was used to heat up the water tank and the household. The rest of this section describes experiments performed using artificial appliances.

Simulated Setting

The simulated setting of the experiments are explained in this section. The prototype is designed so that generation and usage data are regularly dumped to a text file. The data collected over time allows performing realistic experiments in artificial/simulation settings. The parameters of this simulated environment can be controlled and thus different allocation strategies or different settings of the EM can be compared. Figure 7.4a demonstrates the result of simulating the EM on the same generation data that is used in the Figure 7.4b. Table 7.2 summarizes the results of the experiments in the simulated setting. All experiments were run on the same generation and usage data used in the Figure 7.4a. Each number in the table is an average over 100 repetitions of the same experiment. The two parts of the table display average payoffs and percentage of allocated appliances for different values of the infeasibility probability and different allocation algorithms. As expected, higher values of p allow more slackness, and

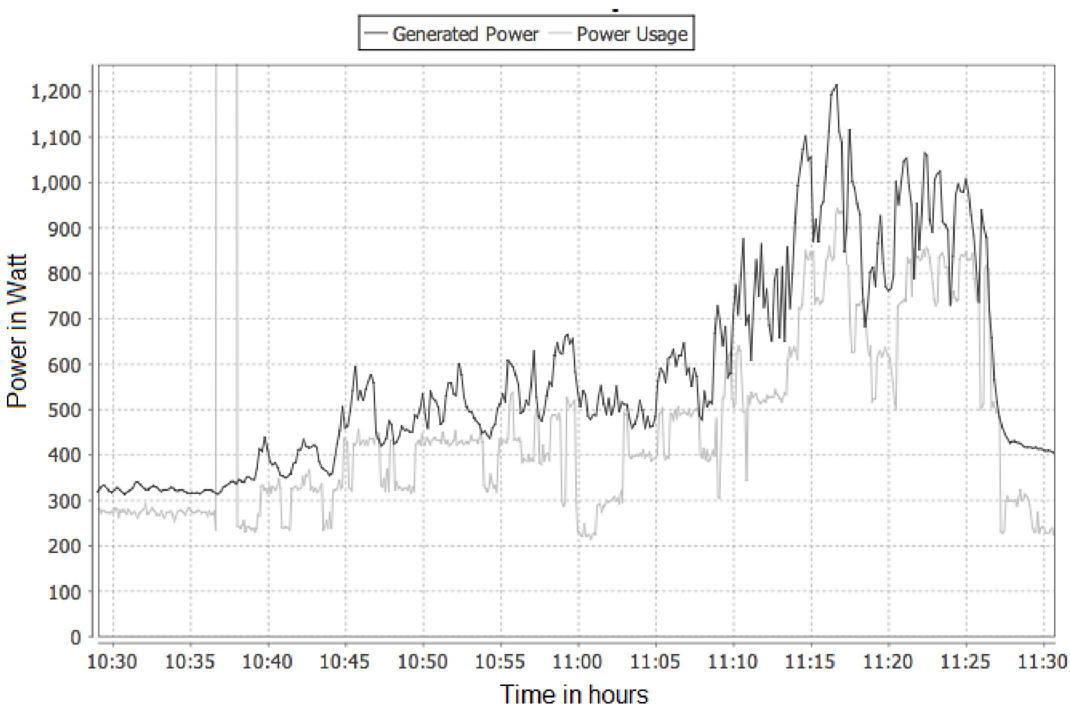


Figure 7.3: A snapshot of the allocation process.

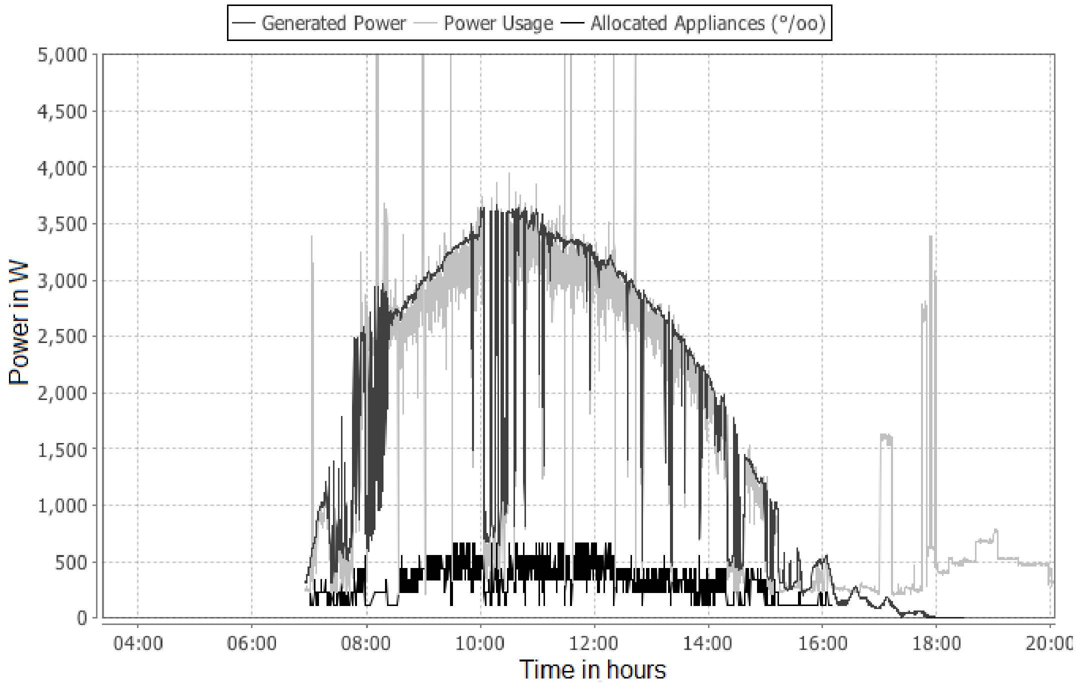
Table 7.2: Results of the simulations

p	**Algorithm**	**Priorities as in Table 7.1**		**All priorities set to one**	
		Payoff %	*Allocation %*	*Payoff %*	*Allocation %*
10%	*Dynamic*	87.10	24.91	73.88	48.79
	Exhaustive	89.21	26.48	77.29	52.42
40%	*Dynamic*	91.03	26.49	77.52	52.84
	Exhaustive	94.85	29.16	85.46	57.98

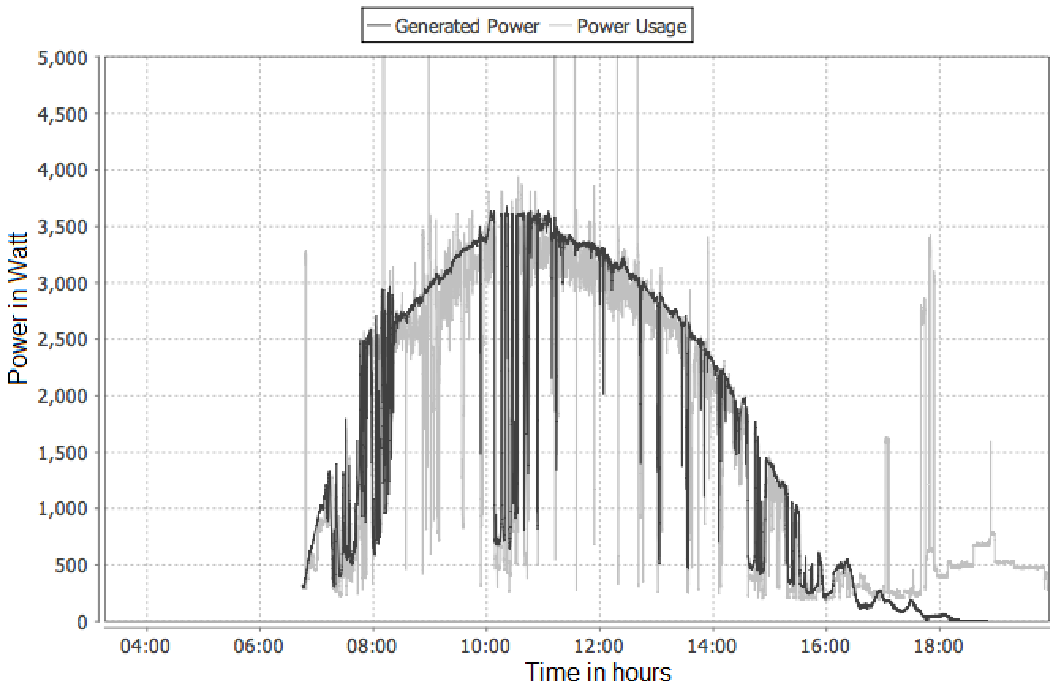
the resulting allocations have a higher power consumption. The table also provides evidence of the effectiveness of the proposed approach: solving CHKNAPSACK by reducing it to the deterministic Knapsack leads to a minor reduction in the payoff but removes the need to use the exact complicated algorithm for CHKNAPSACK. Finally, the figures in the rightmost column illustrate the flexibility of the Knapsack based optimization approach. They correspond to the case when all priorities are set to one. In such setting, the allocation process maximizes the number of appliances used, rather than the total allocated load. Similarly, priorities can be set to favor certain appliances and inhibit some others.

7.3 Discussion

This result shows how an appropriate Knapsack formulation can be used to solve an important dynamic energy allocation problem in a straightforward and flexible way. A number of issues aside from the obvious usability ones have to be considered before the system is deployed for general use.



(a) The EM in simulated mode using the same generation data in Figure 7.4b. The thick black plot at the bottom of the graph is the per mille of allocated appliances.



(b) The real-life allocation process on a sunny spring day

Figure 7.4: Simulated results

7.3.1 Power Variability

If the appliance loads had been fixed quantities, the energy management problem would have been reduced to an instance of the classical KNAPSACK. In the proposed reactive control system (EM), the information always flows in one direction, from the controller software to the controlled sockets and there is no feedback from the sockets. As electricity fluctuates, the appliance loads are not fixed quantities. A crucial side effect of this is that the EM cannot calculate precisely the background power consumption. At any moment in time, the difference between the house load and the total load of the allocated appliances can only be estimated using, for instance, the appliances average values μ_j. Many appliances are allocated, or when there is a sudden drop in the household power consumption, such estimate may become negative. In this case, the EM cannot run the regular allocation process, and therefore it enters a recovery phase. During this period, the set of allocated appliances is updated by removing from it one appliance at a time. This will eventually take the system back to a normal state, possibly with no allocated appliance, and from then on the regular allocation process can be resumed.

7.3.2 Appliances Issues

Three issues are related to the choice of which appliances to control. First of all, the EM works by repeatedly switching appliances on and off. It is, therefore, evident that in its current version it is best suited for a small number of interruptible resistive appliances (heaters, fans, coolers, or electric cookers) with no internal power controls. In fact, as explained below, the system also copes with thermostated appliances, but the processing in such case departs from the pure Knapsack based optimization strategy. On the other hand, there is probably a relatively little point in using the Manager to control a collection of lamps or other light fittings. The management of more intelligent uninterruptible appliances such as washing machines, fridge, cookers or ovens, will require further investigation.

7.3.3 Feedback Information

The limitation of the current system is that no information is fed back from the appliances to the reactive control system. The proposed reactive control system cannot be certain about the nature of the drop or, alternatively, a drop due to a thermostated appliance switching itself off could be compensated (and those go un-noticed) by an increase in the energy consumption due to other reasons. This becomes relevant with appliances including a local decision mechanism (e.g. thermostats) or in coping with faults. If the fact that an allocated appliance did not switch on is not reported back to the Manager, the sudden drop in the household power usage cannot be adequately addressed.

7.3.4 System Usability

Finally, thorough consideration is to be given to users' needs, not only concerning usability of the interface, which at the moment is simple and very technical but especially regarding performance tailoring. User modeling and adaptation of the level of optimization to a learned model of the individual household behavior is envisaged as the long-term natural evolution of this case study.

7.4 Summary

This chapter has presented an exclusive case study (optimization problem) of power allocation problem in micro-grids. The proposed model has used a reactive control system to optimize the renewable power usage based on user preferences. The chapter has also provided a simulated and real-life finding along with discussion related to the issue associated with the proposed model.

Chapter 8

Conclusions and Future Research

> "Two signs of educated person are acceptance of other people's criticism, and being knowledgeable about the angles and dimensions of rhetoric and debate"
>
> *Al-Hussein Ibn Ali*

This concluding chapter illustrates a comprehensive summary of the work described in this thesis, along with the main findings and contributions. Furthermore, this chapter provides some suggestions and advice for future research.

8.1 Conclusions

The thesis has tackled a critical electricity demand problem in residential buildings in micro-grids working in smart grid settings. The fundamental intentions of this framework were to reduce electricity bills in residential buildings, increase the utilization of renewable power, and lessen the demand for peak hours without affecting the comfortable level of the residents. Finding an optimal solution to such problem is not easy because these kind of optimization problems are NP-hard. Therefore, the main challenge was to find a powerful optimization algorithm that can tackle such problems. Having done a lot of literature review (at the beginning and during this research), heuristic algorithms have been chosen as an optimization tools as there is a little hope to make any significant contribution by using exact optimization algorithms.

The main contributions of this research lie in two parts (modeling and heuristic optimization algorithms). During our research, a various number of optimization problems have been tackled. Also, different models of micro-grids have been used in this thesis, and two control systems (reactive and predictive) have been proposed for residential buildings.

The thesis has presented a comprehensive mathematical model for a micro-grid working in the smart grids environment. Besides, the thesis has proposed a mathematical model for each entity in the micro-grid. The thesis has proposed a hybrid method to convert the multi-objective optimization problem to a single optimization problem to guarantee some fairness of sharing renewable power in the micro-grid. Also, the research suggested renewable power exchange rate among agents in a micro-grid. Additionally, the research has suggested an MILP-based heuristic optimization algorithm. In general, the results presented in Chapter 5 have revealed that the proposed heuristic algorithms and the predictive control system can manage power allocation problems in micro-grids with less than twelve houses, and time resolution is around 5 minutes. The proposed algorithm can manage power allocation problem in micro-grid with more houses if time resolution is lower than 5 minutes. In the proposed model, the number of power plants would not affect the complexity of the problem. The proposed algorithm can manage power allocation problem of a micro-grid with even a 1000s plants if the number of houses is less than twelve that is because power plants do not need decision variables (Binary variables are responsible for making the problem hard to solve).

The thesis has also tackled a particular case of power allocation problem in a micro-grid. It has addressed power allocation problem in a micro-grid with just one large building with a broad range of AC units. The main contribution in this special case lies in modeling and heuristic algorithms. The thesis has proposed a predictive control system in this case. Regarding the modeling, two comprehensive mathematical models of air conditioning system have been introduced. The models assume that AC unit can work in $k > 2$ levels. One of these models considers minimizing the discomfort function as well as minimizing electricity cost (Multi-objective model), whereas the other is a single objective model, it just minimizes the cost of electricity. Regarding the heuristic algorithm, the thesis has proposed a set of heuristic algorithms to tackle this problem, each of which has advantages and disadvantages. The results revealed that the heuristic algorithm can solve the huge optimization problem in polynomial time.

Another special case of our general model of the power allocation problem of micro-grid has been addressed; a reactive control system and optimization algorithm have been introduced for optimizing the utilization of renewable resources in a stand-alone house. The study has presented simulation and real-time evaluation results. In general, the results are promising (around 90 % of the domestic renewable power is allocated to household appliances).

8.2 Open Issues and Future Research

Due to the broad range of power allocation problems, the thesis has dealt with, there are many open questions in the current version of the framework, and many potential future directions can be considered for future works. These directions are listed below:

* **Energy Efficiency:** the proposed model for sharing domestic renewable power in a micro-grid presented in chapter 3 does not consider energy loss in the power lines. Therefore, this issue can be tackled in future work. Our first thought it is that the loss of renewable energy in power lines can be minimized by giving priority to sell/buy domestic renewable power to/from close houses rather than far houses. This idea and others can be investigated in future frameworks.

* **Fairness of Power Allocation:** All houses in the micro-grid, including those that do not participate in generating renewable power, currently have the same priority. For example, let us assume that there is a high demand for local renewable energy at the particular time, 3.5 kWh say. Also, let us suppose that the available renewable power is 2.5 kWh. In this case, the predictive control system or the LMGO cannot provide everybody with cheap local renewable power. However, it allocates the 2.5kWh to the houses in the micro-grid without any preferences and it has to allocate the rest of the demand from the NEG. The issue here is that some houses that do not participate in electricity generation (houses with no renewable plants) could get cheap renewable power whereas other houses with some renewable power generation capacity have to buy electricity from NEG for a higher rate. Our suggestion is that houses that equipped with renewable plants should be given priority to buy surplus power just to encourage everybody to install renewable plant and participate in renewable power in the micro-grid. Therefore, prioritizing the houses in micro-grid based on their generation capacity could be considered in further researches.

* **Scalability Issues:** The finding has revealed that the proposed MILP-based heuristic algorithm cannot minimize the cost of electricity in large micro-grids (micro-grid with more than ten houses and with high time resolution). Therefore, future frameworks may investigate using another suitable heuristic algorithm that can solve large power allocation problem in micro-grids. From our point of view, using LP relaxation and rounding would not be an easy job, but it is not impossible.

* **Technical Issues:** The proposed heuristic optimization algorithm does not consider the effect of switching air conditioning unit On and Off very frequently which may affect the efficiency of the system. Therefore, if future researchers can investigate the effect of turning the appliance On/Off on the internal tem-

perature, that would improve the performance of our current system. Our first thought about this issue is that minimizing the number of switching On/Off.

* **Model Assumptions:** For simplicity, in our current model of air conditioning system, the number of people occupying the building has not been considered as they affect the temperature inside the building. Also, it was assumed, for the same reason, that all doors and windows are closed. Therefore, finding a model that can consider the status of doors and windows (Opened/Closed) would be a real achievement.
* **Appliance Limitation:** Our online algorithm presented in Chapter 7 is designed for interruptible appliances only (Electrical heaters). Therefore, future researchers could investigate using uninterruptible appliances such as washing machine, dishwasher, etc.
* **LP Relaxation:** In chapter 6, LP relaxation has been used with two rounding techniques to reduce the complexity of the problem. Future work could work in this area, but the author thinks there is small room for any contribution there. So, research should work hard to find a research gap in this area.

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Appendix A

The real power profile of household appliances

This Appendix presents real power profile of a set of household appliances. Figure (A.1) shows the power profile of a dishwasher. Note that a dishwasher could have many power profiles depends on the setting, or washing program.

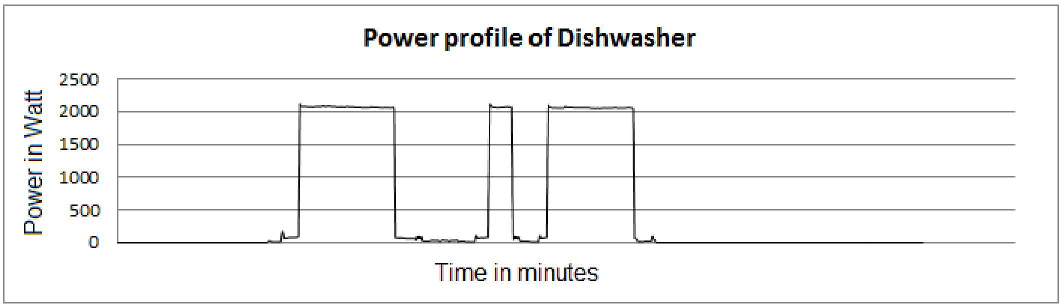

Figure A.1: The real power profile of Dishwasher appliances [5]

The power profile of washing machine is illustrated in Figure (A.2). Note that the power profile can be different from one setting to another.

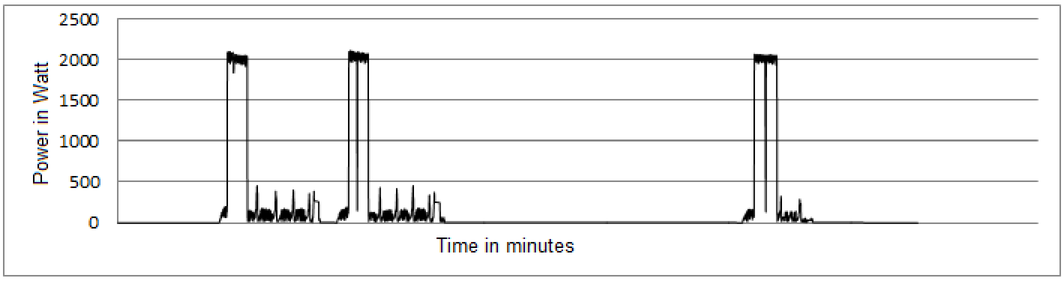

Figure A.2: The real power profile of Washing Machine appliance [5]

Figure (A.3) demonstrates the power profile of electric cooker. Additionally, this power profile could be changed from electric cooker to another. Also, it could be different for the same cooker if we changed the cooking settings.

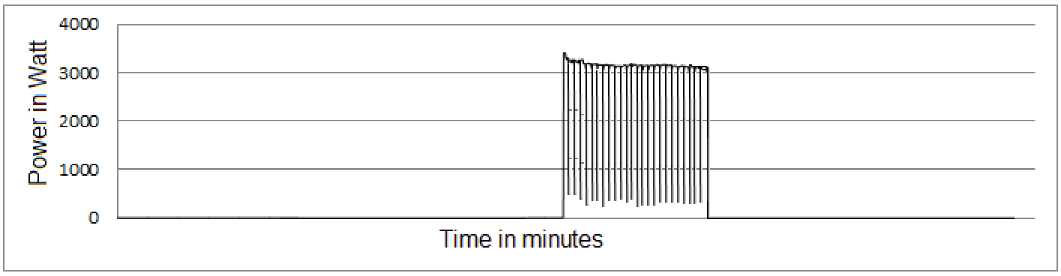

Figure A.3: The real power profile of Electric Cooker appliance [5]

Figure (A.4) demonstrates the power profile of laundry dryer. Additionally, this power profile could be changed from laundry dryer to another. Also, it could be different for the same dryer if we changed the drying settings.

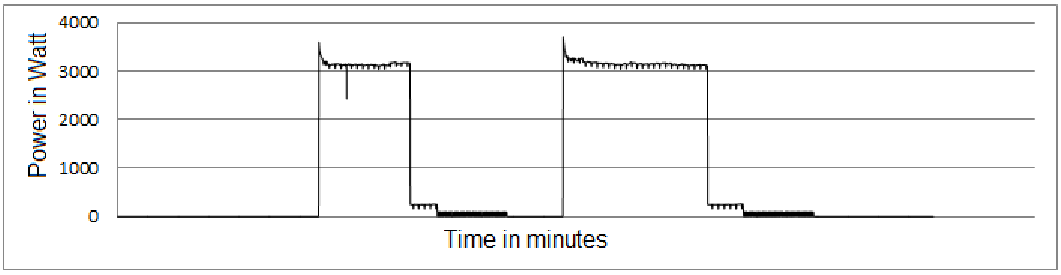

Figure A.4: The real power profile of Laundry Dryer appliance [5]

Figure (A.5) demonstrates the power profile of electric water heater. Additionally, this power profile could be changed from water heater to another. Also, it could be different for the same water heater if it is not programmed to work in specific time (depends on water temperature).

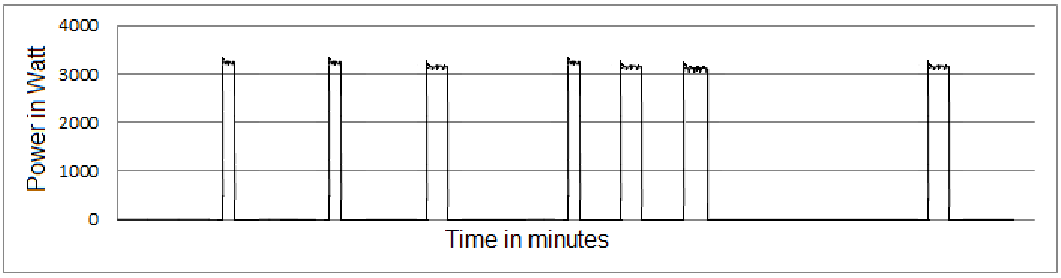

Figure A.5: The real power profile of Water Heater [5]

The power profile of PHEV is illustrated in Figure (A.6). The length of charging time depends on battery state of charge. Therefore, it is different from day to another.

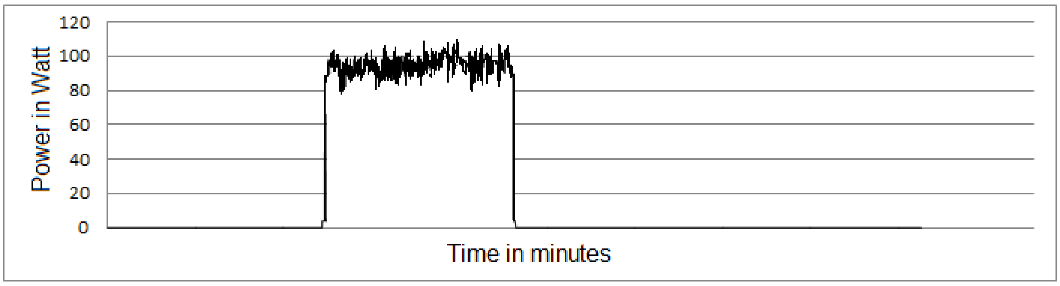

Figure A.6: The real power profile of PHEV [5]

Appendix B

Input setting for case study

This appendix presents input information for the experiments in Chapter 5.

Table B.1: Comfortable time for house appliances

House	Washing machine	Laundry dryer	Dishwasher	Water heater	Electric Radiator	Electric cooker	PHEV	AC, first period	AC, second period
1	10:00-13:00	13:00-17:00	19:00-23:00	00:00-05:00	08:00-13:00	17:00-19:00	16:00-23:00	13:00-15:00	17:00-19:00
2	9:00-12:00	12:00-16:00	00:00-06:00	00:00-06:00	00:00-07:00	14:00-17:00	00:00-06:00	13:00-19:00	13:00-19:00
3	11:00-14:00	14:00-18:00	00:00-07:00	10:00-17:00	00:00-05:00	17:00-19:00	00:00-08:00	13:00-19:00	13:00-19:00
4	12:00-15:00	15:00-19:00	15:00-23:00	13:00-17:00	09:00-17:00	17:00-19:00	00:00-09:00	12:00-17:00	12:00-17:00
5	8:00-11:00	11:00-15:00	14:00-19:00	02:00-07:00	10:00-13:00	16:00-18:00	00:00-05:00	12:00-17:00	12:00-17:00
6	9:00-12:00	12:00-16:00	19:00-23:00	10:00-16:00	17:00-2300	16:00-20:00	13:00-17:00	12:00-17:00	12:00-17:00
7	10:00-13:00	13:00-17:00	00:00-06:00	08:00-17:00	11:00-16:00	18:00-20:00	09:00-20:00	10:00-12:00	16:00-18:00
8	8:00-11:00	11:00-15:00	10:00-15:00	16:00-20:00	09:00-12:00	19:00-22:00	11:00-19:00	10:00-12:00	16:00-18:00
9	10:00-13:00	13:0017:00	08:00-16:00	08:00-20:00	00:00-23:00	16:00-22:00	17:00-23:00	12:00-17:00	12:00-17:00
10	10:00-13:00	13:00-17:00	19:00-23:00	00:00-05:00	08:00-13:00	17:00-19:00	16:00-23:00	13:00-15:00	17:00-19:00
11	9:00-12:00	12:00-16:00	00:00-06:00	00:00-06:00	00:00-07:00	14:00-17:00	00:00-06:00	13:00-19:00	13:00-19:00
12	11:00-14:00	14:00-18:00	00:00-07:00	10:00-17:00	00:00-05:00	17:00-19:00	00:00-08:00	13:00-19:00	13:00-19:00
13	12:00-15:00	15:00-19:00	15:00-23:00	13:00-17:00	09:00-17:00	17:00-19:00	00:00-09:00	12:00-17:00	12:00-17:00
14	8:00-11:00	11:00-15:00	10:00-15:00	16:00-20:00	09:00-12:00	19:00-22:00	11:00-19:00	10:00-12:00	16:00-18:00
15	9:00-12:00	12:00-16:00	00:00-06:00	00:00-06:00	00:00-07:00	14:00-17:00	00:00-06:00	13:00-19:00	13:00-19:00
16	8:00-11:00	11:00-15:00	14:00-19:00	02:00-07:00	10:00-13:00	16:00-18:00	00:00-05:00	12:00-17:00	12:00-17:00
17	8:00-11:00	11:00-15:00	10:00-15:00	16:00-20:00	09:00-12:00	19:00-22:00	11:00-19:00	10:00-12:00	16:00-18:00
18	9:00-12:00	12:00-16:00	00:00-06:00	00:00-06:00	00:00-07:00	14:00-17:00	00:00-06:00	13:00-19:00	13:00-19:00
19	8:00-11:00	11:00-15:00	10:00-15:00	16:00-20:00	09:00-12:00	19:00-22:00	11:00-19:00	10:00-12:00	16:00-18:00
20	8:00-11:00	11:00-15:00	10:00-15:00	16:00-20:00	09:00-12:00	19:00-22:00	11:00-19:00	10:00-12:00	16:00-18:00

Table B.2: The household appliances in each house in Low-demand scenario in micro-grid

House	Washing machine	Laundry dryer	Dishwasher	Water heater	Electric Radiator	Electric cooker	PHEV	Air conditioner
1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2	Yes	No	Yes	No	No	No	No	No
3	Yes	No	No	No	Yes	No	Yes	No
4	No	Yes	No	Yes	No	Yes	Yes	No
5	Yes	Yes	No	No	Yes	Yes	Yes	No
6	Yes	No	Yes	Yes	Yes	Yes	Yes	No
7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
11	No	No	No	No	No	Yes	No	No
12	No	No	Yes	No	No	No	No	No
13	Yes	No	No	Yes	No	No	No	Yes
14	No	Yes	No	Yes	Yes	No	No	No
15	Yes	Yes	No	Yes	Yes	No	No	No
16	Yes	No	No	No	No	Yes	No	Yes
17	No	No	No	Yes	Yes	No	No	Yes
18	Yes	No	Yes	No	No	Yes	No	No
19	No	No	No	No	No	No	No	No
20	No	No	No	No	No	No	No	No

Table B.3: The household appliances in each house in Medium-demand scenario in micro-grid

House	Washing machine	Laundry dryer	Dishwasher	Water heater	Electric Radiator	Electric cooker	PHEV	Air conditioner
1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
11	No	No	No	No	No	Yes	No	No
12	No	No	Yes	Yes	No	No	No	No
13	Yes	No	No	Yes	No	No	No	Yes
14	Yes	No	No	No	No	Yes	No	Yes
15	Yes	Yes	No	Yes	Yes	No	No	No
16	Yes	No	No	No	No	Yes	No	Yes
17	No	No	No	Yes	Yes	No	No	Yes
18	Yes	No	Yes	No	No	Yes	No	No
19	No	No	No	No	No	No	No	No
20	No	No	No	No	No	No	No	No