# CENTRALIZED CONTROL SCHEME FOR ENERGY MANAGEMENT IN SMART MICROGRIDS

by

Wla Elshafye Malik Elamin

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## Approval Signatures

We, the undersigned, approve the Master's Thesis of Wla Elshafye Malik Elamin

Thesis Title: Centralized Control Scheme for Energy Management in Smart Microgrids.

**Signature** **Date of Signature**
(dd/mm/yyyy)

___________________________ _______________
Dr. Mostafa Shaaban
Assistant Professor, Department of Electrical Engineering
Thesis Advisor

___________________________ _______________
Dr. Ahmed Osman
Associate Professor, Department of Electrical Engineering
Thesis Committee Member

___________________________ _______________
Dr. Raafat Aburukba
Assistant Professor, Department of Computer Science and Engineering
Thesis Committee Member

___________________________ _______________
Dr. Nasser Qaddoumi
Head, Department of Electrical Engineering

___________________________ _______________
Dr. Mohamed El-Tarhuni
Associate Dean for Graduate Affairs and Research,
College of Engineering

___________________________ _______________
Dr. Richard Schoephoerster
Dean, College of Engineering

___________________________ _______________
Dr. Khaled Assaleh
Interim Vice Provost for Research and Graduate Studies

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*To my mother…*

**Abstract**

The development in smart grid technologies will authorize consumers to participate in the decision making of their electricity consumption. This participation in decision making is the called demand side management (DSM). DSM allows the customers to optimally manage their loads and hence reduce their energy bills and overall consumption. This work proposes a new real-time energy management system (EMS) for smart microgrids (MGs) including DSM with several distributed energy resources (DER) technologies, such as photovoltaic panels, dispatchable distributed generation (DG), capacitor banks, and battery energy storage systems (BESS). The developed EMS consists of three main units that are controlled by the centralized MG controller (MGC). The aim of the MGC is to optimally schedule the grid and customers' assets to benefit both the grid operators and the customers. The MGC utilizes the rolling horizon concept to manage real-time information and to provide the plug-and-play option for all controllable devices such as controllable loads and DER. The three units managed by the MGC are the data collection and storage unit, the forecasting unit and the optimization unit. The optimization unit receives the current and forecasted information from the other units; then, it develops the optimal scheduling decisions for all controllable devices with the target of reducing the overall operating costs while meeting the customers' requirements. The MG can either operate in grid-connected mode or in islanded mode of operation. In this work, both modes are considered. Simulation results on a typical MG system of the proposed approach are compared to the results of the traditional day-ahead approach. The proposed approach results show same savings as the day-ahead approach. However, unlike the day-ahead approach, the proposed approach is more robust to disturbances and fast changes of PV panels' output. Moreover, the proposed approach can accommodate changes in customers' preferences and new connected equipment in a timely manner.

**Keywords:** ***Demand side management; distributed energy resources; microgrid; smart grids; rolling horizon.***

**Table of Contents**

## List of Figures

**List of Tables**

## List of Abbreviations

| | |
|---|---|
| ADN | Active Distribution Networks |
| BESS | Battery Energy Storage System |
| CPP | Critical Peak Pricing |
| CREMS | Centralized Real-time Energy Management System |
| DER | Distributed Energy Resources |
| DG | Distributed Generation |
| DLC | Direct Load Control |
| DSM | Demand Side Management |
| EMS | Energy Management System |
| ILC | Indirect Load Control |
| MGs | Microgrids |
| MINLP | Mixed Integer Non-Linear Programming |
| MPC | Model Predictive Control |
| PCC | Point of Common Coupling |
| PV | Photo Voltaic |
| RTH | Rolling Time Horizon |
| RTP | Real Time Pricing |
| TOU | Time of Use |

# Chapter 1. Introduction

In this chapter, a short introduction to the energy management concepts is provided. Then, the problem investigated in this study as well as the thesis contribution are presented. Finally, the general organization of the thesis is presented.

## 1.1. Overview

Recent advances in smart grids encouraged electric system operators to involve more renewable resources in the generation and to introduce the demand side management concept to control these new resources and loads.

The idea of microgrid was first discussed in the technical literature in [1] and [2] as a solution for the amalgamation of Distributed Energy Resources (DERs), including energy storage units and controllable loads. The microgrid would be seen by the main grid as a single entity that makes use of the control signals and responds back to them. Yet, there is no one exact definition of microgrids as a technical term, a microgrid can be described by its characteristics as a group of loads, Distributed Generation (DG) units, and Battery Energy Storage Systems (BESSs) that work together to efficiently supply electricity. The adoption of microgrids as the model for the engagement of DER will permit the ability to work in a decentralized manner in solving different parts problems [3].

Demand Side Management (DSM) is the adjustment of consumer use of energy using different strategies. However, commonly demand side management strategies are adopted only during peak demands or in cases where the power system reliability is jeopardized. The day-ahead fails to address real-time measurements from the grid, resulting in nonapplicable strategies, whereas online measurements and calculations are more accurate. This is because the day-ahead based approaches are not tailored to deal with the intermittent nature of renewable energy resources [4], [5]. Hence, traditional offline operational planning studies do not guarantee the desired accuracy level of calculations and are currently being replaced with the online planning methods.

There are two different control schemes, the centralized control scheme where a central controller is responsible for all decision making and distributed control in which the decisions are taken via distributed local controllers. Despite the advantages of the distributed control schemes over the centralized control schemes, grid operators prefer centralized control systems. The centralized control systems proved their robustness for decades in managing power systems and they are characterized by decreased risk of technological malfunction. Thus, the presented work focuses on centralized control schemes.

### 1.2. Thesis Objectives

Motivated by the environmental compliance and the concerns of the increasing greenhouse gas emissions, we will deal with energy management system that makes use of environmentally friendly resources. Moreover, the recently introduced renewable energies are mainly represented in wind power and photovoltaic systems are characterized by high degree of uncertainty and variability in nature, and cannot be controlled in terms of their generation amount. These resources depend on the weather conditions and hence, their energy can only be used once it is produced or stored for later use.

Smart grids are the new systems who will replace the old existing electric grid. The smart grid has the properties of two-way communication and functionalities to adapt the high penetrations of renewable energy resources. The objective of this work is to introduce a new real-time and day-ahead energy management scheduling algorithm for distributed system assets and customers equipment. The algorithm takes into consideration the customer preferences and variability of the generation and the loading in the system plus the plug-and-play option.

### 1.3. Research Contribution

The contributions of this research work can be summarized as follows:

- Develop a centralized control scheme for optimal energy management in smart microgrids.
- Develop a new methodology for DSM that takes into consideration the interaction between the customers and their appliances.
- Test the results of applying the proposed energy management control scheme on a distribution system with different DER technologies in the grid connected mode of operation.
- Test the results of applying the proposed scheme on a distribution system in the islanded mode of operation.

## 1.4. Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 provides background about the concepts of smart grids, microgrids, demand side management and model predictive control. In addition, Chapter 2 provides a brief background to distributed energy resources, demand response programs and pricing techniques that will be used in the work. Moreover, a detailed literature review related to this research is discussed.

The employed methods and algorithms are discussed in Chapter 3 along with the implementation of the proposed architecture and the mathematical formulation of the problem. Chapter 4 presents the test systems. Chapter 5 summarizes the performance evaluation of results obtained from the testing systems. Finally, Chapter 6 concludes the thesis and outlines the future work.

# Chapter 2. Background and Literature Review

In this chapter, we discuss the fundamentals and definitions related to the DER, modernized electrical grid and the DSM. Then, we present the different techniques used in energy management systems. Finally, we discuss the related work in this field of research.

## 2.1. Background

### 2.1.1 Distributed energy resources.

According to IEEE, the DG is defined as, "The generation of electricity by facilities that are sufficiently smaller than central generating plants so as to allow interconnection at nearly any point in a power system" [6]. The definition of DERs is more general compared to DG. DER units can produce only or produce/absorb energy. DER units can be categorized to energy generation DER, energy storage DER or a combination of both, Table 2.1 shows some of the DER examples [7].

Table 2.1: DER categories

| Energy generation DER | Energy storage DER |
|---|---|
| • Diesel unit.<br>• Natural gas unit.<br>• Dual fuel unit.<br>• Microturbine.<br>• Combustion turbine.<br>• Fuel cell.<br>• PV<br>• Wind turbine. | • Uninterruptible power supply.<br>• Battery system.<br>• Flywheel.<br>• Superconducting magnetic energy storage.<br>• Hybrid systems. |

The DER ranges from small scale (residential size) to the large scale (utility scale). The distributed scheme of the DER has a huge benefit when dealing with only part of the grid is needed. Such a distributed scheme and resources provide islanded areas [8]. Installing DER units in distribution networks results in many technical and economic benefits, such as increasing the system reliability because they can be used to overcome supply and demand imbalances. Hence, it is much useful to use a more distributed generation in the network rather than centralized one. Furthermore, the overall power flows in the lines are reduced resulting in stress, losses and cost reductions [9]. Benefits of the DER are summarized in Table 2.2, the benefits include environmental advantages, improvements from an economic point of view, and technical benefits [10].

Table 2.2: DER benefits

| **Environmental benefits** | **Economic benefits** | **Technical benefits** |
|---|---|---|
| • Intensive use of friendly energy resources.<br>• Use of combined heat and power reduces thermal pollution of the environment.<br>• Reduction of greenhouse gas emissions. | • DGs can reduce or avoid the need for building new transmission and distribution lines.<br>• DGs can be assembled easily anywhere as modules; thus, they have much less construction time compared to central generation facilities.<br>• Combined heat and power DGs can use their waste heat for heating or for improving their efficiency by generating more power.<br>• DGs can reduce the wholesale power price by supplying power to the grid, which leads to a reduction in the effective demand. | • DGs have a positive impact on the distribution system voltage profile and power quality problems.<br>• DGs reduce the distribution network power losses<br>• DGs have the ability to respond to fast demand changes.<br>• DER can improve the reliability of the electric supply for customers.<br>• They provide transmission capacity release. |

**2.1.2. Smart grids.** There is no one global definition for the smart grid and a fair definition could be "A smart grid is a modern electric system. It uses communications, sensors, automation and computers to improve the flexibility, security, reliability, efficiency, and safety of the electricity system. It offers consumers increased choice by facilitating opportunities to control their electricity use and respond to electricity price changes by adjusting their consumption" [11]. Old traditional power systems have many different problems associated with it, whereas civilized communities need the power system to be more credible, scalable and controllable as well as being cost dynamic, safe and interoperable. Benefits of smart grids includes, the improved reliability; increased physical, operational, and cyber security and resilience against attack or natural disasters; ease of repair, particularly remote repair; increased information available to consumers regarding their energy use; increased energy efficiency along with the environmental benefits gained by such efficiency; the integration of a greater percentage of renewable energy sources, which can be inherently unpredictable in nature; the integration of plug-in electric vehicles; and, a reduction in peak demand [11].

Smart grid may include electricity networks equipped with the technologies required to facilitate the fluent interaction of all users connected to it [12]. Recent growth in communication and sensing technologies enabled the evolution of smart grid, this calls for the need of a communication network that is parallel to the present power grid which enables the flow and exchange of both communication and control.

Smart grid technologies enable bidirectional communication between different players, such as power supplier and different types of consumers. Such bidirectional communication may be used by consumers to optimize their energy consumption profiles to minimize their electricity bill.

With the advancements in smart metering and smart devices technologies and the increasing interest in smart grid infrastructure, it is possible to interact between generation and load for the benefit of delivering the energy optimally. This increased the need for new optimization approaches. In addition to the complexity of controlling the renewable energy sources added, which is offered by the smart grid system adding management, control and communication capabilities to the existing electrical infrastructure [13]. A comparison between both current traditional grid and the future smart grid is tabulated in Table 2.3. The traditional grid is electromechanically operated whereas the smart grid is modernized and operated using different technologies. Moreover, the smart grid has a two-way flow of both energy and information and it depends on sensors for its operation and decision making. The whole network of the smart grid can be monitored in screens and we don't have this privilege in the current grid. If any fault happened in the traditional grid it requires some personnel to go to the fault place, on the other hand in the smart grids thanks to SCADA systems we will have an alarm when such faults happen and its location and maybe the possible causes and solutions [14].

**2.1.3. Microgrids.** Traditional distribution systems are passive, i.e. characterized by unidirectional power flow. However, when DER units are installed, they become active distribution networks (ADN) with bi-directional power flow and communication. This results in some parts with a generation capacity that is part of the network and can provide all or part of the local load requirements. These are known as microgrids (MGs) [15].

The microgrid has been defined by the US department of energy as "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid (and can) connect and disconnect from the grid to enable it to operate in both grid-connected or islanded-mode" [14].

Microgrids can operate in two modes, parallel to the grid or grid connected and isolated from the grid, where its structure is made specifically to be able to adapt the islanded operation. In islanded mode of operation, the local load is completely supplied by the microgrid. In this mode, there are many technical issues that must be addressed; load matching, power quality, and reliability. In grid-connected mode, the microgrid is responsible for supplying all or part of the consumption. In cases of excess or shortage of the supply, the main grid can absorb or provide the difference through the point of connection with the grid, which is known as the point of common coupling (PCC) [16].

Table 2.3: Comparison between current and smart grids

| Grid / Property | Current grid | Smart grid |
|---|---|---|
| **Operation** | Electromechanical | Modernized |
| **Communication** | One-way | Two-way |
| **Generation** | Centralized generation | Decentralized generation |
| **Control structure** | Hierarchical | Lattice structure |
| **Sensors** | Limited | Throughout |
| **Monitoring** | Short sightedness | Monitoring capability |
| **Disconnections** | Brownouts and blackouts | Adaptive and islanding |
| **Faults** | In place check and test | Distant check and test |
| **Control** | Restricted | Spreading |
| DSM | Minimum customer involvement | Involves customer participation |

The control model of microgrids can be one of three types; centralized, distributed or hybrid. The centralized model control receives all data from the microgrid and makes decisions according to certain constraints. On the other hand, in distributed control scheme, measurements and communications are done through local controllers, which then communicate with each other. While this approach facilitates the integration of energy resources, it adds more complexity to the system. Lastly, there is the hybrid control example which combines both aforementioned models, the distributed energy resources are ordered in groups then a centralized control applied to them separately, where distributed control model governs the groups [11].

The droop control is an effective method to control the generation sources in the islanded microgrid to regulate the frequency and the output voltage. The droop control permits the generators to engage in the frequency and the voltage control. Thus, the droop control fulfills the islanded microgrid reliability condition and accomplishes operation management and resource optimization. Frequency is considered a global variable. Hence, the real power produced is divided between generators according to their active static droop gain. Moreover, the output voltage is count as a regional variable. Therefore, the reactive power distribution is influenced by the reactive static droop gain as well as the vicinity of the generator to the load [17].

Each unit uses the frequency to control the active power flow and on the other hand, the voltage output depends on the reactive power. This is summarized by the two equations given in (1) and (2).

$$f = f_0 - k_p \ (P - P_0) \tag{1}$$

$$V_1 = V_0 - k_v \ (Q - Q_0) \tag{2}$$

where $f_0$ and $V_0$ are the base frequency and voltage. $P_0$ and $Q_0$ are temporary set points of real and reactive powers of the unit. Example plots of droop control are shown in Figure 2.1 and Figure 2.2, the two figures explain the relation between the active power and frequency as well as, reactive power and voltage. The relationship between the quanteties is explained as constant slope shown in the figures.

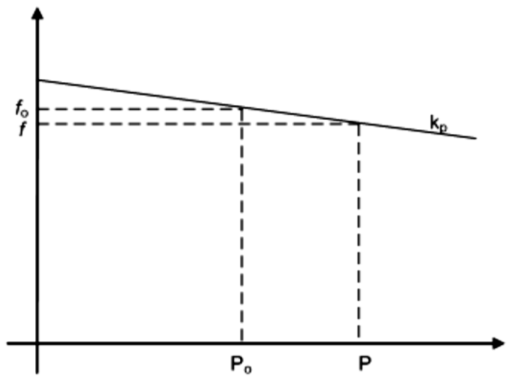


Figure 2.1: Droop control characteristics of real power [18]

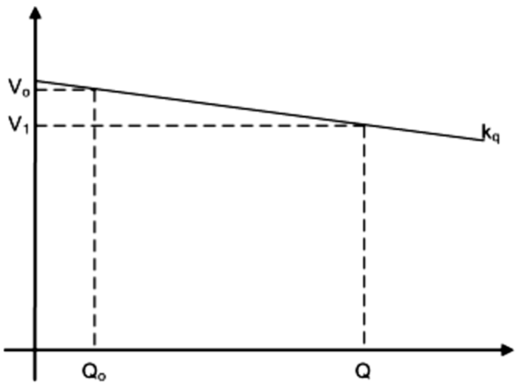


Figure 2.2: Droop control characteristics of reactive power [18]

**2.1.4. Demand side management.** DSM is defined as, the process that manages energy demand and supply with the goal of users gratification as well as price and power savings. The process follows a specific schedule that is updated continuously. DSM focuses on the consumer side or as named lately as prosumer. The prosumer is defined as, a prospective consumer who is involved in the design, manufacture, or development of a product. Prosumer is considered both producer and consumer of power. This process involves communication between both the consumers and operators [19].

DSM is the delineation, realization, and control by grid operators in the form of strategies. The aim is to impact the use of electricity and advance or reconstruct the load curve by flattening the demand curve or optimize it for a specific desired pattern. DSM helps maintain a balance between supply and load to achieve reliable operation of the power grid. This provides a mean for the end user and appliances to realize the high cost and peak demand times and then, take actions in responses to that. Different load shaping objectives include peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shape [8].

Benefits of the DSM can be counted for both users and operators and include; attaching discontinuous energy resources at distribution level, demand response, incentivizing the customers and hence reducing the peak time consumption, flexible power system as the consumers contributes by turning off devices at heavy load and savings in energy as consumers aware of their own consumption [20].

The main goal of the demand response programs is to encourage the participation of demand-side resources in the planning of the grid [21]. Two types of control on the load are available; direct load control (DLC) and indirect load control (ILC).

The DLC system is mainly designed to curtail or shed loads. For example, the thermostatically controlled loads such as air conditioners and water heaters can be controlled during high demand hours based on some previous agreements of specific temperature values. In the ILC process, the reliability is on variable prices, economic incentives, and/or penalties to encourage customers to schedule their loads. The goal is to improve efficiency, reduce peak demand and reduce electricity bills. ILC depends on customer’s cooperation. However, its implementation involves many complicated and sophisticated issues in educating the consumers and raise their awareness of such programs and equipping or providing the buildings with the suitable tools. Additionally, its pattern is hard to be predicted and redistributing the load is not an easy task and may introduce conflict to other parts of the grid [22],

**2.1.5. Electric utility rate structure.** There are different pricing techniques adopted by utilities such as time-of-use pricing (TOU), Critical-Peak Pricing (CPP) and Real-Time Pricing (RTP). In the first type, prices depend on the time of day and are set in advance. Secondly, in the CPP technique if the demand reaches its peak the price is raised. Lastly, in the RTP, the prices are changed continuously on an hourly basis. This is explained by the fact that as the demand increases the utility has to include additional generation units and hence, the cost increases [23]. In RTP the role of a retailer is to buy energy from the electricity markets and sell it back to the consumers at the lowest prices as possible. The availability of these types of information practically is the main bone of the demand response [24],

**2.1.6. Model predictive control.** Model Predictive Control (MPC) or the rolling time horizon (RTH), is a popular advanced control technique. The control decisions are taken over future trajectories in receding horizon. At each time horizon, the decision-making process is applied simultaneously. The process is repeated for the next and subsequent time horizons.

MPC is a good tool for the applications of energy and active load management in the systems with renewable energy sources. Also, MPC is suitable for the real-time applications that require predictions [25].

Figure 2.3 shows a simple concept of the MPC [26]. The present time is $t_K$ and the prediction is done for the next intervals ($t_{K+1}$, $t_{K+2}$, $t_{K+3}$..., $t_{K+H}$), where $H$ is the length of the prediction horizon or the window size, $N$ is the length of the control horizon, and $K$ is the sampling interval or step size.

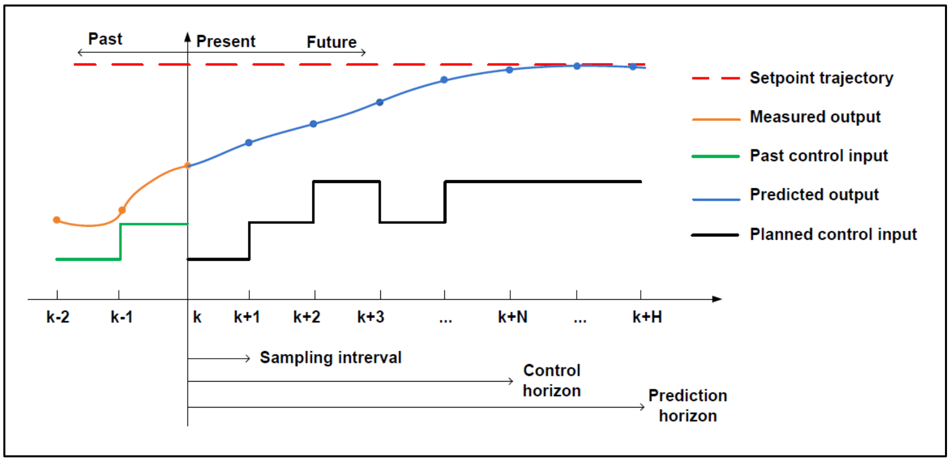


Figure 2.3: Model predictive control concept [29]

**2.1.7. Optimization techniques.** Optimization is defined as the procedure of obtaining the terms or solution that give the minimum or maximum value of a function. An optimization problem has three main components; objective function to be minimized or maximized, unknown variables that control the objective function value, and constraints that limits the values of the variables [27]. Optimization techniques can be classified according to the nature of the solution to exact methods and heuristic methods. The exact optimization methods guarantee finding an optimal solution and the heuristic optimization methods do not guarantee that an optimal solution is found [28]. Some of the exact and heuristic optimization methods are explained briefly as follows:

***2.1.7.1. Optimization methods for linear, continuous problems (linear programming).*** In linear programming (LP), the objective function and the constraints depend linearly on the decision variables. One of the known methods to solve LP problems is the simplex method. This method relies on the fact that the solution is on the border of the feasible region (convex set). Thus, the solution can be obtained by examining the vertices of the simplex and select the one that results in an optimal solution.

***2.1.7.2. Optimization methods for linear discrete problems.*** This includes but not limited to:

- Branch and bound method: this method recursively decomposes a problem into subproblems by fixing or introducing additional constraints. The subproblems are solved using linear programming methods. Bounding is done by removing any subproblem that resulted in a solution that violates some of the limits [28].

- Dynamic programming: this is an exhaustive search method that intelligently enumerates all solutions of a combinatorial optimization problem. The idea is to start with the last decision and to work backward to the earlier ones [28].

***2.1.7.3 Optimization methods for nonlinear discrete problems.*** These methods focus on nonlinear functions and include but not limited to:

- The substitution method: this method considered the simplest for solving nonlinear problems. Involves solving constraints equations in terms of other variables and later substitute these equations into the objective function [29].
- Mixed integer nonlinear programming: some of the decision variables in this method are restricted to integer variables. The first step is to solve the MIP problem as an ordinary LP problem neglecting the integer restrictions. The procedure ends if the values of the basic variables which are constrained to take only integer values happen to be integers in this optimal solution [27].

***2.1.7.4 Heuristic optimization methods.*** Heuristic optimization methods do not guarantee finding an optimal solution but are usually faster than the approaches that rely on numerical methods. Heuristic optimization methods do not aim at finding an optimal solution but at developing optimum solution procedure.

- Particle Swarm Optimization algorithm: this is a parallel evolutionary method inspired by the demeanor of bird flocking, it begins by having a population of nominee solutions and iteratively tries to improve these nominee solutions [30].
- Genetic algorithm: this is a search based algorithm that does not use calculus. The search starts around particular point and then proceed in one direction that is increasing or decreasing, the obtained decision solutions are obeying a specific fitness function. With each iteration, there is an improvement of the objective function, and the improvements are applied by reproduction, crossover, and mutation. This algorithm simulates the human gene operation [31].
- Simulated annealing algorithm: this method was established from ideas of statistical mechanics, stimulated by the physical annealing of a solid. The goal is to start from random state and bring the system to the minimum state.

## 2.2. Related Work

DSM via controlling customers' equipment is already implemented with many grid operators in North America, such as New York independent system operator (NYSO) [32] and Ontario independent electricity system operator (IESO) [33]. However, DSM strategies have been adopted only during peak demands or in cases where the power system reliability is jeopardized. Three strategies can be applied to realize the DSM programs [4]: 1) customers can interrupt their equipment consumption, 2) they can shift their consumption to off-peak periods, and 3) they can use distributed energy resources (DER) to manage their demand profiles. In this context, several approaches have been proposed in the literature. A centralized control system was implemented in [9] to increase the system security. The proposed scheme utilized a distributed control for DER units. Reshaping consumption could be made by ways of a difference in the price of electricity (Price-Based Programs) or reward and penalty bills [34] and [35]. However, this is a very hard task using the existing centralized dispatch methods [36], [37], [38] and [39].

According to the results obtained by [40], consumers are very susceptible to the power prices. Encouragement and mind of consumers to participate in the DR program can appear in different ways. For example, the authors in [41] used a factor that is equal to one when a rigorous cost reduction is needed, a little higher than one when average cost reduction is needed, and way higher than one when a cost reduction is not needed. However, this type of exemplification might be a simple way to efficiently reflect the link between the reduction in the electricity bill and the economic status of the customer. The authors in [42] Proposed a load management scheme that took into account the purchase of energy of the customers in a real-time pricing DR program, optimized the discussion and agreement between the consumer and retailer. The scheme requires prediction of renewable powers production, load, and electricity prices for the next day.

The work in [43] introduced a scheme for the control of energy streams on a single house and a large group of houses. The scheme presumed every house has microgenerator and controllers. In this scheme, global and local controllers were used in three stages. Firstly, a forecast is made for energy production and consumption for one day ahead. Then, the local controller defines the aggregated profile and sends it to the global controller. Secondly, the schedule for each house is done for the next day. Thirdly, the algorithm determines how the consumption is supplied. Two examples were tested, and the results proved that it is possible to schedule for a group of houses based on a one-day forecast. However, any forecasting error impacts and changes the outcomes of this approach.

Authors in [44] and [13] introduced approaches that manage loads according to their priority, where the customers specify their priorities for different loads according to their preferences. Another DSM method was proposed in [13], which relies on grouping the loads based on their characteristics. Some loads are considered to be thermostatically controlled and others are price dependent. However, there is no clear identification of the real-time management of information from and to the controller and it is not a preferable technique for the customers as they have no prior information about when their functions will be done, and they do not contribute on deciding a period at which they operate.

The DSM approach proposed in [45] didn’t include customers’ preferences. Also, the work proposed in [46] focused on managing the household owned energy storage systems (ESS). The proposed approach aimed at reducing the overall system capital and operating costs, the paper could not solve the optimization problem as a centralized problem due to the unavailability of complete information. Furthermore, it assumed that the demand of each user is known a day ahead which is not true for real cases. In addition, the approach proposed in [47] used 24 hours scheduling of the next day which is not accurate, although they implemented an operational planning model considering multiple demand response programs with the objective function of minimizing operation cost and emission. Using a window of 16 hours was implemented by [48] focusing on the residential buildings with three different price schemes. A simple day-night tariff, a day-ahead dynamic tariff, and a real-time dynamic tariff. However, such large time steps will not give a higher accuracy, and there is no clear mention of how often the system data updated; moreover, there is no consideration of schedules or customers preferences. Another strategy used by [49] concentrated on charging the energy storage system when the load curtailments are within the specified limits. The action may lead to a more unjustified delay of appliances operations if the system is charging. On the other hand, integration of the battery helps reap more benefit from demand response. It does not only reduce the peak load but further flattens the entire profile and reduce the demand variation.

Work represented in [23] and [24] used dynamic pricing strategy to shift the loads with fixed demand profile. Both papers did not include any real-time or online measurements. So, optimization could not be updated frequently to include the irregular pattern of plugging the appliances. Also, the procedure suffers from limiting the supply of user appliances to a certain maximum amount of power. The use of a weighted average price prediction filter to the actual hourly based price has the benefit of assisting the customers in tailoring their response efficiently and automatically [41].

Day-ahead based approaches are not tailored to deal with the intermittent nature of renewable energy resources; whereas online measurements and calculations are more accurate resulting in a nonapplicable strategy (short-sightedness) [4], [5]. In recent work, the day-ahead approaches are still proposed as in [50], [51], [52], [53], [54] and [55]**.** In addition, these approaches do not allow decision update; thus, any change in customers' behavior or any new appliance connected will not be accompanied by decision update. On the other hand, real-time approaches can offer more flexibility by updating their decisions every short period, which can be defined prior to deploying the EMS. In real-time operation, the consumers can change their preferences at any time and connect new equipment.

The work in [56] implemented a demand response algorithm to minimize the cost of energy usage taking into account the load divergence limits, hourly load, and price forecast uncertainty. This algorithm assumed that prices and decisions in the previous hour are already known ahead. In the current moment (hour t), the price and power demand are known. Prices in the next 24 hour are approximated using an autoregressive integrated moving average (ARIMA)-based model with a confidence interval. Using this data, the optimization model establishes a ground base for daily consumption and ramping down/up limits are solved. This procedure is repeated each hour on a scheduling horizon of one day. The work in [57] suggested a methodology for demand response that considered the customers' preferences for the operation of specific appliances during peak hours by means of the Analytic Hierarchy Process. This quantification of customer preferences is used to determine which appliances must be used during the peak hours. Solving the Knapsack Problem, wherein the numerical preference obtained by the Analytic Hierarchy Process for a specific appliance is considered as a measure of the benefit obtained by its use. The authors sealed that this method authorizes enhancement in both customers' bills and the total energy consumption on the electrical grid.

From the perspective of the controller design, all the work in the literature can be divided into two categories regarding the location of the controller(s): centralized controllers [58], [59], [60] and [61] and decentralized controllers [62], [63] and [64]. Despite the advantage of the distributed control schemes over the centralized control schemes, which have one point of failure, grid operators prefer centralized control systems, as they proved their robustness for decades in managing power systems and they are characterized by decreased risk of technological malfunction.

Based on the aforementioned discussion, this work introduces new centralized real-time energy management system (CREMS) for smart MGs. The aim of this work is to develop an MG centralized controller, which optimally schedules the system assets in real-time to benefit both the grid operators and the consumers. MGs can operate in two modes: grid-connected and isolated mode of operation. For the ease of practical implementation and real-time information management, a rolling time window (RTW) is utilized in this work to control the grid and customers' assets. The real-time optimal energy management problem is formulated as mixed-integer non-linear programming (MINLP).

# Chapter 3. Proposed Methodology

In this chapter, we describe and explain the methodology prevailed in this work. A new centralized control scheme including customer participation is proposed. This proposed scheme aims to increase security, reliability and consumers satisfaction. The next sections describe the proposed centralized control scheme, the problem description, and the problem formulation.

## 3.1. System Model

Figure 3.1 shows the proposed centralized real-time energy management system (CREMS). The system is composed of three units, controlled by the central MG controller (MGC). The real-time process can be explained in six sequential stages, which are highlighted in Figure 3.1 and discussed in the next subsections. To manage real-time data, RTH is utilized with the structure as shown in Figure 3.2. The Moving window parameters are the step size ($\Delta t$) and window width ($Tw$). The six stages of the MGC full cycle are to be executed within a time step $\Delta t$. To include information about future forecasted generation, demand, and energy prices, the MGC solves the energy management problem for the duration of the moving time window $Tw$ in the future. After completing a successful cycle of the MGC, the optimal decisions are sent to local controllers and information is sent to users, which are stored in their local database (DB). These decisions and information should be update in the next cycle after time $\Delta t$. However, due to delays in the MGC units or due to communication delays or failure, this update might be delayed. In this case, the local controllers should utilize the latest information in their local DB till the MGC update their status. The whole cycle, which includes the six stages, is repeated every time $\Delta t$. The rolling horizon parameters can be adjusted according to the grid operator preferences and subject to the changing frequency of the system. If the system changes more frequent then the step size might need to be decreased. Reducing the step size and increasing the time window duration increases the accuracy but also increases the computational time and processing requirements. Thus, it is a trade-off between accuracy and computational time.

As a secondary backup, the day-head scheduling problem for the next 24-h is solved and sent to the system in case of long duration or long delays, communication loss, or any element failure.

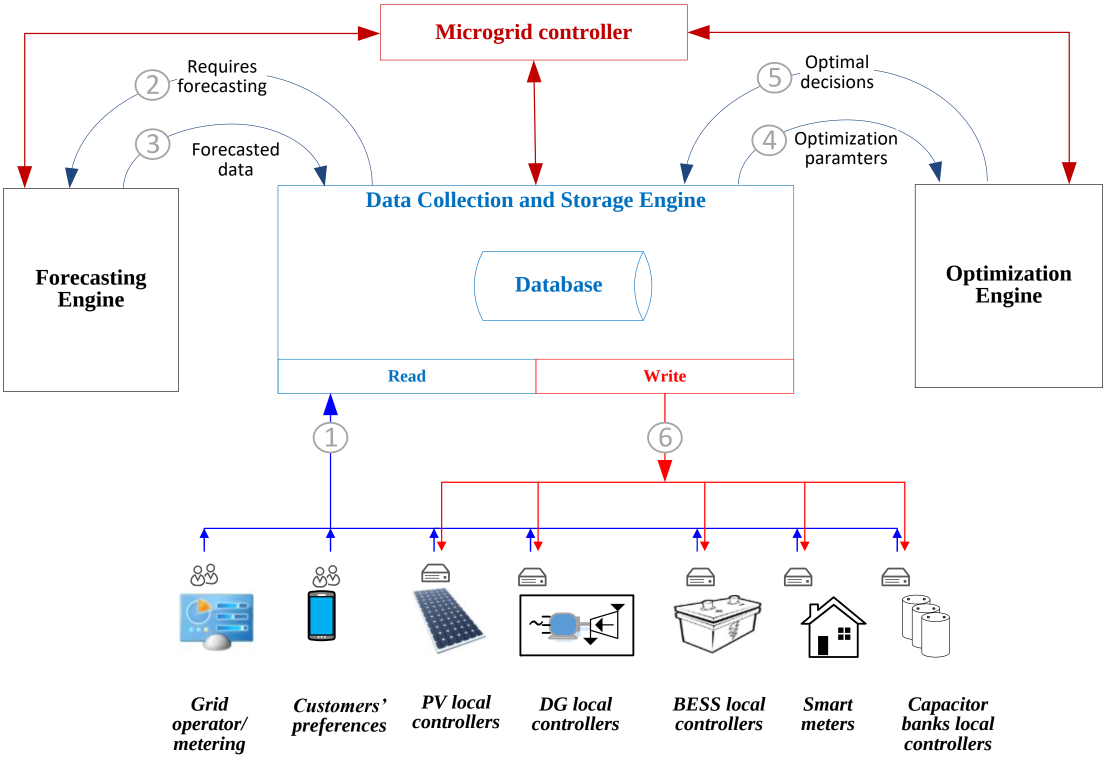


Figure 3.1: The centralized real-time energy management system structure

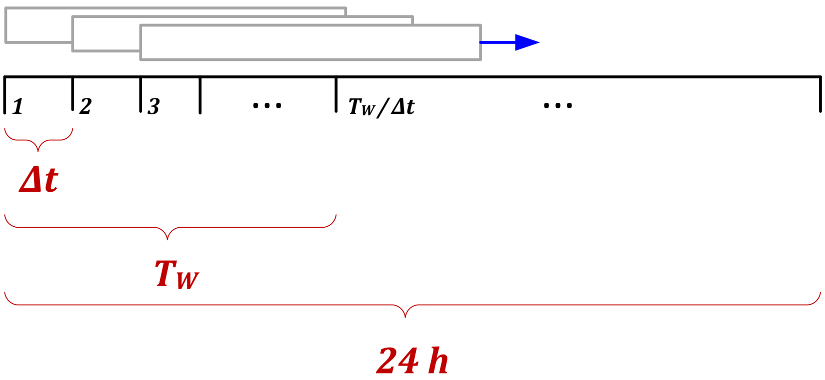


Figure 3.2: Rolling time horizon implementation

**3.1.1. Data collection and storage unit.** This unit is responsible for collecting data from system sensors or SCADA metering nodes (currents and voltages), local controllers of different equipment (generated/consumed power by DER, state-of-charge of BESS... etc.), grid operators (price), and consumers preferences for DSM. Collecting the required data is denoted as stage one, as illustrated in Figure 3.1. The collected data are stored in the database to be used by other units.

Moreover, this unit sends the output data to these pre-mentioned units. The outputs can be either for controlling equipment or for informing users. Sending the data back to the system is denoted as stage six, which is executed at the end of the whole process,

**3.1.2. Forecasting unit.** A moving window algorithm will be used to manage the real-time decision taking in the proposed EMS. The forecasting unit receives generation and demand data from the data collection and storage unit; this is denoted as stage two in Figure 3.1. Then, it forecasts the generation and demand based on the width of the RTH, which is sent by the MGC. Stage three involves sending back the forecasted information to the data collection and storage unit,

**3.1.3. Optimization unit.** The optimization unit receives the current and forecasted information from the data collection and storage unit as stage four. Then, it solves the optimization model for the next $T_W/\Delta t$ time steps with the target of reducing the overall operating costs while maximizing the customers' satisfaction. Finally, the optimization unit sends the optimal decisions back to the data collection and storage unit as stage five.  Optimization process includes Comparing the data within the time window and try to match the supply with the load subject to some constraints of the system and reducing or/and shifting some of the controllable loads if it is the best decision (and only if this is allowed by the customer preference). Optimization process is repeated each time step

## 3.2. Problem Description

The plug and play option that the algorithm provides suits the home appliances pattern. The home appliances depend on consumer's habits which are unpredictable. Each equipment has an ID operation that is assigned to it. This ID is linked to a matrix with its consumption profile. Preferred starting and ending times are set by the consumer and sent to the local controller to decide the possible schedules for each equipment. However, if the consumer didn't specify starting or ending time this makes the load as uncontrollable and should be supplied once it's initiated. The algorithm makes sure that once any equipment starts it will never be interrupted and will continue for its whole cycle. The CREMS receives the matrix with different equipment possible schedules. The optimization unit decides which schedule to be implemented as described in the problem formulation in the next section. Once this decision is made all other options should be cleared to zero to prevent any inconvenience or false operations.

Other optimal decisions are decided based on the updated data received. These decisions include the amount of reactive power taken from the capacitors, curtailment from the PV units, power from the diesel generator, and the battery charging or discharging actions. The flow chart of the complete process is explained by the flow chart in Figure 3.3 and the read cycle of the local controllers is shown in Figure 3.4.

The matrix of possible schedules is generated by the smart meters and sent to the optimization unit through the database unit to select the optimum schedule. An example of equipment with the time specifications is presented in Table 3.1. Schedules generated for this equipment are shown in Table 3.2. There are 10 different options based on 10 minutes step sent to the optimization unit and only one option will be chosen. If the decision variable corresponding to an option is one this means that this option is selected, and zero value for an option means the option is not selected. The schedule is fixed only if it will be executed in the current time step, and in this case, all the other schedules will be cleared. Otherwise, the equipment operation will be rescheduled in the next time window with as a maximum number of schedules as permitted by the user deadline.

Table 3.1: Time specification example

| | |
|---|---|
| **Duration** | 2 hours |
| **Earliest** | 7:00 pm |
| **Deadline** | 10:30 pm |

### 3.3. Grid Connected Mode Mathematical Problem Formulation

The proposed scheduling problem for the grid connected mode is formulated as an MINLP, which is solved by the optimization unit in Figure 3.1. The objective function and the constraints are presented in the next subsections.

**3.3.1. Objective function.** The objective function of the CREMS is to minimize the total sum of the costs shown in (3). The operating costs for this system are the costs of purchased energy from the grid and the dispatchable DGs operation as illustrated in (4). The cost of the DGs is specified by the amount of fuel consumed, which in turns depends on the real power produced

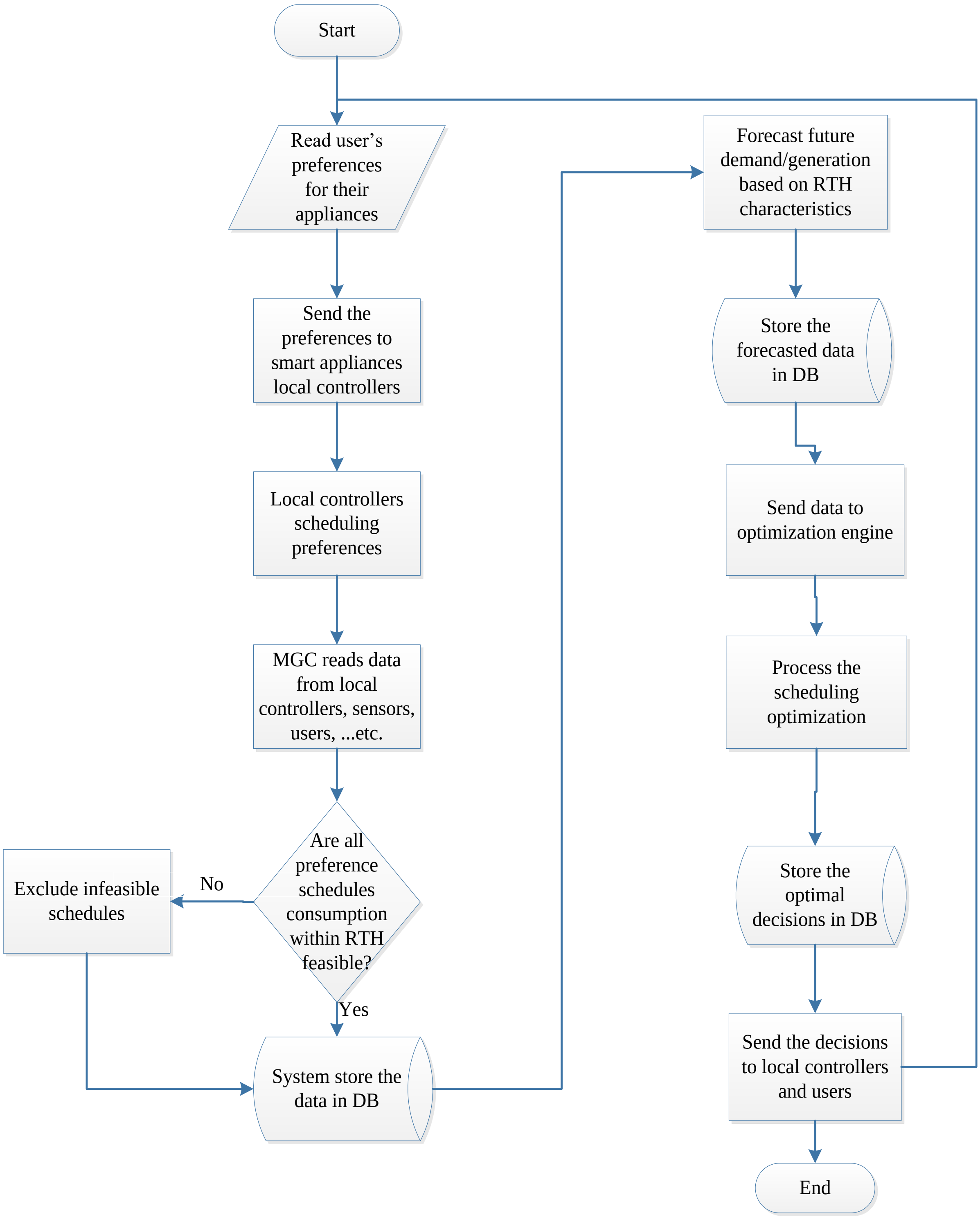


Figure 3.3: Proposed algorithm flow chart

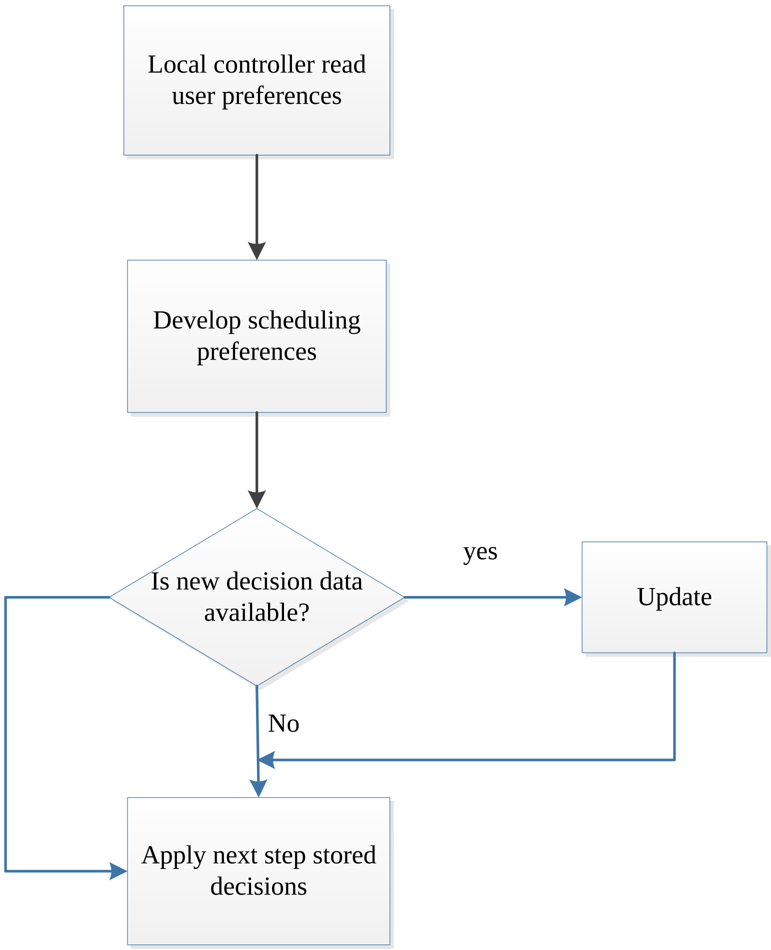


Figure 3.4: Read cycle of the local controllers

Table 3.2: Generated schedules

| Time | Schedule1 | Schedule2 | Schedule3 | Schedule4 | Schedule5 | Schedule6 | Schedule7 | Schedule8 | Schedule9 | Schedule10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **7:00 PM** | 0.181 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **7:10 PM** | 0.170 | 1.181 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **7:20 PM** | 0.159 | 1.170 | 0.181 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **7:30 PM** | 0.150 | 1.159 | 0.170 | 0.181 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **7:40 PM** | 0.142 | 1.150 | 0.159 | 0.170 | 0.181 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **7:50 PM** | 0.135 | 1.142 | 0.150 | 0.159 | 0.170 | 0.181 | 0.000 | 0.000 | 0.000 | 0.000 |
| **8:00 PM** | 0.129 | 1.135 | 0.142 | 0.150 | 0.159 | 0.170 | 0.181 | 0.000 | 0.000 | 0.000 |
| **8:10 PM** | 0.123 | 1.129 | 0.135 | 0.142 | 0.150 | 0.159 | 0.170 | 0.181 | 0.000 | 0.000 |
| **8:20 PM** | 0.118 | 1.123 | 0.129 | 0.135 | 0.142 | 0.150 | 0.159 | 0.170 | 0.181 | 0.000 |
| **8:30 PM** | 0.114 | 1.118 | 0.123 | 0.129 | 0.135 | 0.142 | 0.150 | 0.159 | 0.170 | 0.181 |
| **8:40 PM** | 0.110 | 1.114 | 0.118 | 0.123 | 0.129 | 0.135 | 0.142 | 0.150 | 0.159 | 0.170 |
| **8:50 PM** | 0.106 | 1.110 | 0.114 | 0.118 | 0.123 | 0.129 | 0.135 | 0.142 | 0.150 | 0.159 |
| **9:00 PM** | 0.102 | 1.106 | 0.110 | 0.114 | 0.118 | 0.123 | 0.129 | 0.135 | 0.142 | 0.150 |
| **9:10 PM** | 0.000 | 1.102 | 0.106 | 0.110 | 0.114 | 0.118 | 0.123 | 0.129 | 0.135 | 0.142 |
| **9:20 PM** | 0.000 | 0.000 | 0.102 | 0.106 | 0.110 | 0.114 | 0.118 | 0.123 | 0.129 | 0.135 |
| **9:30 PM** | 0.000 | 0.000 | 0.000 | 0.102 | 0.106 | 0.110 | 0.114 | 0.118 | 0.123 | 0.129 |
| **9:40 PM** | 0.000 | 0.000 | 0.000 | 0.000 | 0.102 | 0.106 | 0.110 | 0.114 | 0.118 | 0.123 |
| **9:50 PM** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.102 | 0.106 | 0.110 | 0.114 | 0.118 |
| **10:00 PM** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.102 | 0.106 | 0.110 | 0.114 |
| **10:10 PM** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.102 | 0.106 | 0.110 |
| **10:20 PM** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.102 | 0.106 |
| **10:30 PM** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.102 |

The array of the decision variables $Z$ in (5) includes decisions related to the capacitor banks switching, curtailment power from PV units, generated active and reactive powers from diesel generators, the binary decision to select optimum schedule and BESS charging/discharging actions.

$$\min_{Z} \sum_{t} C_t^{total} \tag{3}$$

$$C_t^{total} = (\Delta t/60) S_{base} \left( P_t^{grid}\, C_t^{grid} + \sum_{i} \left( P_{i,t}^{DG}\, C_{i,t}^{DG} \right) \right) \tag{4}$$

$$Z = [X_{i,t}^{BAT}, X_{i,t}^{CAP}, X_{i,t}^{PV}, X_{i,t}^{DG}, d_{i,e,ts}] \tag{5}$$

Table 3.3: Objective function notations

| Notation | Description |
|---|---|
| Z | Array of decision variables to be minimized |
| $t$ | Index of time slot |
| $S_{base}$ | Base power in kVA |
| $C_t^{total}$ | Total sum of the costs |
| $\Delta t$ | Time resolution in minutes |
| $P_t^{grid}$ | Real power supplied from the grid (p.u.) |
| $C_t^{grid}$ | Cost of power from the grid ($/kWh) |
| $P_{i,t}^{DG}$ | Total real power from dispatchable DGs at bus *i* (p.u.) |
| $C_{i,t}^{DG}$ | Cost of the dispatchable DG at bus *i* ($/kWh) |

**3.3.2. Constraints.** The objective function of the system is minimized subject to constraints, which compromise the model and are specified by the problem. There are two types of constraints; equality constraints and inequality constraints.

***3.3.2.1 Equality constraints.*** The near optimal developed decisions must satisfy the active and reactive power balance constraints in (6) and (7).

$$P_{i,t}^{G} + P_{i,t}^{PV} + P_{i,t}^{DG} + P_{i,t}^{BAT} - P_{i,t}^{Load} = \sum_{j} V_{i,t} V_{j,t} Y_{i,j} \cos(\theta_{i,j} + \delta_{j,t} - \delta_{i,t}) \tag{6}$$

$$Q_{i,t}^{G}+Q_{i,t}^{DG}+Q_{i,t}^{BAT}+Q_{i,t}^{CAP}-Q_{i,t}^{Load}=-\sum_{j}V_{i,t}V_{j,t}Y_{i,j}\sin(\theta_{i,j}+\delta_{j,t}-\delta_{i,t}) \tag{7}$$

Table 3.4: Power balance constraints notations

| Notation | Description |
|---|---|
| $P_{i,t}^{PV}$ | Injected real power from photovoltaic(p.u.) |
| $Q_{i,t}^{DG}$ | Dispatchable DGs reactive power (p.u.) |
| $Q_{i,t}^{BAT}$ | Reactive power transferred from the battery energy storage system (p.u.) |
| $P_{i,t}^{BAT}$ | Active power transferred from the battery energy storage system (p.u.) |
| $Q_{i,t}^{CAP}$ | Capacitor reactive power (p.u.) |
| $P_{i,t}^{Load}$ | Active power of normal load (p.u.) |
| $Q_{i,t}^{Load}$ | Reactive power of normal load (p.u.) |
| $P_{i,t}^{G}$ | Generated active power at bus *i* (p.u.) |
| $Q_{i,t}^{G}$ | Generated reactive power at bus *i* (p.u.) |
| $i$ , $j$ | Buses indices |
| $Y_{i,j}$ | Admittance matrix element (*i*,*j*) magnitude (p.u.) |
| $\theta_{i,j}$ | Admittance matrix element (*i*,*j*)angle (radiance) |
| $V_{i,t}$ | Voltage magnitude (p.u.) |
| $\delta_{i,t}$ | Voltage angle (radians) |

Moreover, the capacitor bank injected reactive power is proportional to the squared voltage magnitude as in (8), where the decision variable $X_{i,t}^{CAP} \in [0,1]$ controls the capacitor switching. The injected active power from the PV units can be curtailed according to (9), where $X_{i,t}^{PV} \in [0,1]$ represents the allowed fraction of the maximum generated active power to be injected to the grid. For the BESS, the decision variable for charging/discharging is $X_{i,t}^{BAT} \in [-1,1]$. The amount of active power injected by the different DGs is controlled by the decision variable $X_{i,t}^{DG} \in [0,1]$ as introduced in (10). The stored energy is updated as in (11), while the charging/discharging power is represented in terms of the kW capacity as in (12). The possible schedules of the controlled equipment are multiplied by a binary variable to select a single option. Hence, this binary variable should sum to one for each equipment at each bus as shown in (13) and (14).

$$Q_{i,t}^{CAP} = X_{i,t}^{CAP}\left(V_{i,t}\right)^2 Q_i^{CAP-0}/S_{base} \qquad \forall t, i \in \mathcal{I}_{CAP} \tag{8}$$

$$P_{i,t}^{PV} = X_{i,t}^{PV} P_{i,t}^{PV-MAX}/S_{base} \qquad \forall t, i \in \mathcal{I}_{PV} \tag{9}$$

$$P_{i,t}^{DG} = X_{i,t}^{DG} P_{i,t}^{DG-MAX}/S_{base} \qquad \forall t, i \in \mathcal{I}_{DG} \tag{10}$$

$$E_{i,t}^{BAT} = E_{i,t-1}^{BAT} + X_{i,t}^{BAT} P_{i,t}^{BAT-MAX} \quad \Delta t/60 \qquad \forall t, i \in \mathcal{I}_{BAT} \tag{11}$$

$$P_{i,t}^{BAT} = X_{i,t}^{BAT} P_{i,t}^{BAT-MAX}/S_{base} \qquad \forall t, i \in \mathcal{I}_{BAT} \tag{12}$$

$$P_{i,t}^{var\ Load} = \sum_{ts}\sum_{e} d_{\,i,e,ts}\ Var_{\,i,e,t,ts} \tag{13}$$

$$\sum_{ts} d_{\,i,e,ts} = 1 \tag{14}$$

Table 3.5: Equality constraints notation

| Notation | Description |
|---|---|
| $Q_i^{CAP-0}$ | Nominal reactive power injected from the capacitor bank (kVAR) |
| $\mathcal{I}_{CAP}$ | Sets of buses for the capacitor banks |
| $P_{i,t}^{PV-MAX}$ | Maximum possible generated power from PV unit (kW) |
| $P_{i,t}^{DG-MAX}$ | Maximum possible generated power from DG unit (kW) |
| $\mathcal{I}_{PV}$ | Sets of buses for the PV units |
| $\mathcal{I}_{DG}$ | Set of DGs buses |
| $E_{i,t}^{BAT}$ | Stored energy at time $t$ in the BESS (kWh) |
| $P_{i,t}^{BAT-MAX}$ | Capacity of the BESS in kW |
| $\mathcal{I}_{BAT}$ | Sets of buses for the BESS |
| $P_{i,t}^{var\ Load}$ | Controllable load consumption (p.u.) |
| $Var_{\,i,e,t,ts}$ | Matrix of the appliances consumption profile including all options |
| $d_{\,i,e,ts}$ | Binary decision variable to select one option |
| $ts$ | Number of possible schedules allowed |

***3.3.2.2 Inequality constraints.*** These constraints are used to limit the active, reactive, and apparent powers for the diesel generator and BESS as in (15) and (16). Moreover, the stored energy in the BESS is limited to the maximum allowable storage energy as in (17) and the amount of power transferred to or from the battery is limited by (18).

$$\left(S_i^{DG-MAX}/S_{base}\right)^2 \geq \left(P_{i,t}^{DG}\right)^2 + \left(Q_{i,t}^{DG}\right)^2 \qquad \forall t, i \in \mathcal{I}_{DG} \tag{15}$$

$$\left(S_i^{BAT-MAX}/S_{base}\right)^2 \geq \left(P_{i,t}^{BAT}\right)^2 + \left(Q_{i,t}^{BAT}\right)^2 \qquad \forall t, i \in \mathcal{I}_{BAT} \tag{16}$$

$$E_{i,t}^{BAT} \leq E_i^{BAT-MAX} \qquad \forall t, i \in \mathcal{I}_{BAT} \tag{17}$$

$$\left|P_{i,t}^{BAT}\right| \leq P_{i,t}^{BAT-MAX} \qquad \forall t, i \in \mathcal{I}_{BAT} \tag{18}$$

Different sets of inequality constraints are required to limit the voltage and thermal limit. (19) and (20) shows the allowed tolerance of the voltage and the current limit to maintain the thermal boundaries.

$$V_{min} \leq V_{i,t} \leq V_{max} \tag{19}$$

$$I_{i,j,t} \leq I_{i,j,t}^{MAX} \tag{20}$$

Table 3.6: Inequality constraints notations

| Notation | Description |
|---|---|
| $S_i^{DG-MAX}$ | Rated apparent power of the DGs (kVA) |
| $S_i^{BAT-MAX}$ | Rated apparent power of the battery (kVA) |
| $E_i^{BAT-MAX}$ | Allowable maximum stored energy in kWh for the BESS unit |
| $P_{i,t}^{BAT-MAX}$ | Allowable maximum power transfer for the BESS unit (p.u.) |
| $V_{min}$ and $V_{max}$ | Minimum and maximum voltage limits respectively. |
| $I_{i,j,t}$ | System current (Amp) |
| $I_{i,j,t}^{MAX}$ | Maximum system current (Amp) |

## 3.4 Islanded Mode Mathematical Problem Formulation

The proposed optimal scheduling problem for the islanded mode is formulated as an MINLP as well. The problem is solved by the same optimization unit in Figure 3.1. The objective function and the constraints are presented in the next subsections.

**3.4.1 Objective function.** The objective function of the CREMS is to minimize the total sum of the costs shown in (3). The operating costs for this system in the islanded mode of operation are the costs of energy from the dispatchable DGs operation as illustrated in (21). The array of the decision variables $Z$ in (22) includes decisions related to the capacitor banks switching, curtailment power from PV units, generated active and reactive powers from diesel generators, BESS charging/discharging actions, the binary decision to select optimum schedule and the no load characteristics that decide the amount of the active and reactive powers from the generation units in the droop control.

$$C_t^{total} = (\Delta t/60) S_{base} \left( \sum_i \left( P_{i,t}^{DG} C_{i,t}^{DG} \right) \right) \tag{21}$$

$$Z = [X_{i,t}^{BAT}, X_{i,t}^{CAP}, X_{i,t}^{PV}, X_{i,t}^{DG}, d_{i,e,ts}, fo_{i,t}, Vo_{i,t}] \tag{22}$$

**3.4.2 Constraints.**

***3.4.2.1 Equality constraints.*** The scheduling problem must satisfy the power mismatch constraints in (23) and (25), which are the same as (6) and (7) with the two terms related to the grid energy eliminated. In addition, the scheduling problem is subject to all the constraints in (8-14).

$$P_{i,t}^{PV} + P_{i,t}^{DG} + P_{i,t}^{BAT} - P_{i,t}^{Load} = \sum_j V_{i,t} V_{j,t} Y_{i,j} \cos(\theta_{i,j} + \delta_{j,t} - \delta_{i,t}) \tag{23}$$

$$Q_{i,t}^{DG} + Q_{i,t}^{BAT} + Q_{i,t}^{CAP} - Q_{i,t}^{Load} = -\sum_j V_{i,t} V_{j,t} Y_{i,j} \sin(\theta_{i,j} + \delta_{j,t} - \delta_{i,t}) \tag{24}$$

Two equality constraints of droop controlled characteristics are added in the islanded mode and shown in (25) and (26). The two equations control the admissible frequency and voltage ranges. Values of the droop gains and frequency are selected according to the desired power sharing among different units.

$$P_{i,t}^{DG} = mp_{i,t}\left(fo_{i,t} - f_t\right) \qquad \forall t, i \in \mathcal{I}_{DG} \tag{25}$$

$$Q_{i,t}^{DG} = nq_{i,t}\left(Vo_{i,t} - V_{i,t}\right) \qquad \forall t, i \in \mathcal{I}_{DG} \tag{26}$$

Table 3.7: Droop control notations

| Notation | Description |
|---|---|
| $mp_{i,t}$ | Active static droop gain (kW/Hz) |
| $nq_{i,t}$ | Reactive static droop gain (kVAR/Hz) |
| $fo_{i,t}$ | DG unit output frequency at no load (Hz) |
| $f_t$ | System frequency (Hz) |
| $Vo_{i,t}$ | DG unit output voltage at no load (p.u.) |

***3.4.2.2 Inequality constraints.*** In addition to the constraints presented in the grid connected mode, i.e. (15-20), limits on the no-load characteristics are added in (27-29), those values are decided from experience to be able to output the maximum generation from the units.

$$Vo_{min} \leq Vo_{i,t} \leq Vo_{max} \tag{27}$$

$$fo_{min} \leq fo_{i,t} \leq fo_{max} \tag{28}$$

$$f_{min} \leq f_t \leq f_{max} \tag{29}$$

Table 3.8: Islanded mode inequality constraints notations

| Notation | Description |
|---|---|
| $mp_{min}$ and $mp_{max}$ | Minimum and maximum active static droop gain limits respectively (kW/Hz) |
| $np_{min}$ and $np_{max}$ | Minimum and maximum reactive static droop gain limits respectively (kVAR/Hz) |
| $Vo_{min}$ and $Vo_{max}$ | Minimum and maximum DG unit output voltage at no load respectively (p.u.) |
| $fo_{min}$ and $fo_{max}$ | Minimum and maximum DG unit output frequency at no load respectively (Hz) |
| $f_{min}$ and $f_{max}$ | Minimum and maximum frequency limits respectively (Hz). |

# Chapter 4. Case Studies

In this chapter, the case studies are presented and discussed. Two case studies are presented: grid connected case and islanded case. In each case, three scenarios are presented. The first scenario represents the base case with no control. The second scenario is the day-ahead scheduling problem adopted in literature, where the forecasted generation/demand is assumed to be known day-ahead. In addition, the energy prices are assumed to be known day-ahead, which is a reasonable assumption from the energy market perspective. The third scenario represents the proposed CREMS. The proposed CREMS is tested on a 38-bus system with components on the next subsections and data in [59]. Planning the location of DER is a complicated process that requires detailed technical and economic models, which is out of the scope of the presented work. Thus, the DER units are located arbitrarily in the system.

## 4.1. System Structure

**4.1.1 Grid connected mode.** Figure 4.1 shows the 38-bus system under test. This microgrid system is connected to the main grid (grid connected mode) to compensate for system balance and ensure continuity of the operation. One BESS units of 1 MW and 3 MWh ratings is located on bus 25, as shown in Figure 4.1. One diesel DG is located on bus 34 with 1 MVA rating and 0.5 MW PV unit is located on bus 10. The diesel DG operating cost is assumed to be 0.03 $/kWh. Finally, 1 MVAR nominal rated capacitor bank is located on bus 18, details of connected components are listed in Table 4.1.

Table 4.1: System components for grid connected mode

| **Bus number** | **Device** | **Specifications** |
|---|---|---|
| 25 | Battery | 3 MWh capacity, 1 MW power rating |
| 18 | Capacitor | 1 MVAR capacity |
| 34 | DG | 1 MW, 0.03$/kWh |
| 10 | PV | Depending on weather (Figure 4.2) |

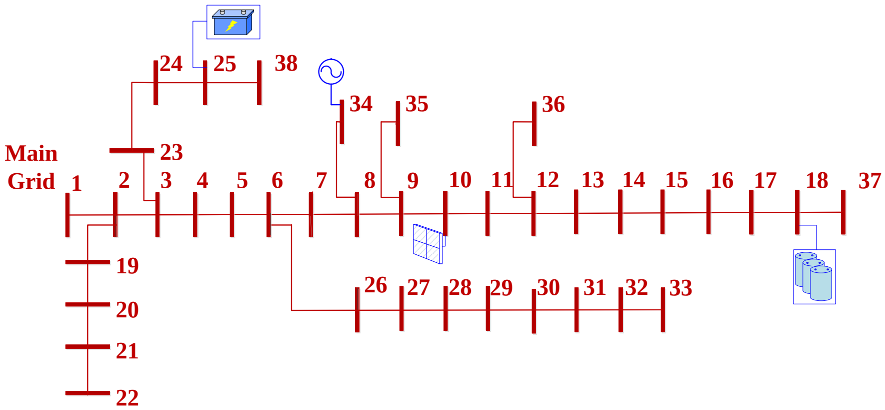


Figure 4.1: Modified 38-bus IEEE system connected to the grid

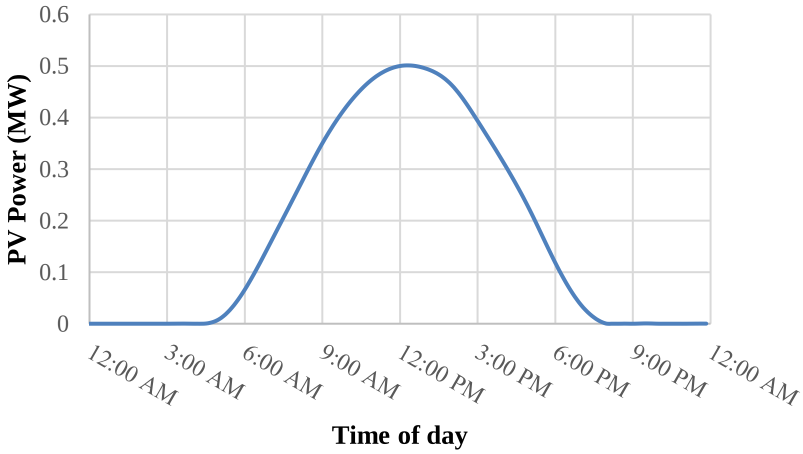


Figure 4.2: PV profile

The pricing scheme adopted for the energy prices from the grid is shown in Figure 4.3. The energy price is known day-ahead. A typical profile for the load curve that has been used is the case study is shown in Figure 4.4. Price and load curves have the same manner, two maxima's accruing at 1:00 am and 8:00 am. The load is light and the price is low at the first hours in the morning till around 9:00 am and also at 3:00 pm. The PV power output starts at the morning around 5:00 am with very low energy. Then, the output power starts to increase during the day and reaches the maximum at noon and after that starts to decrease again, as shown in  Figure 4.2.

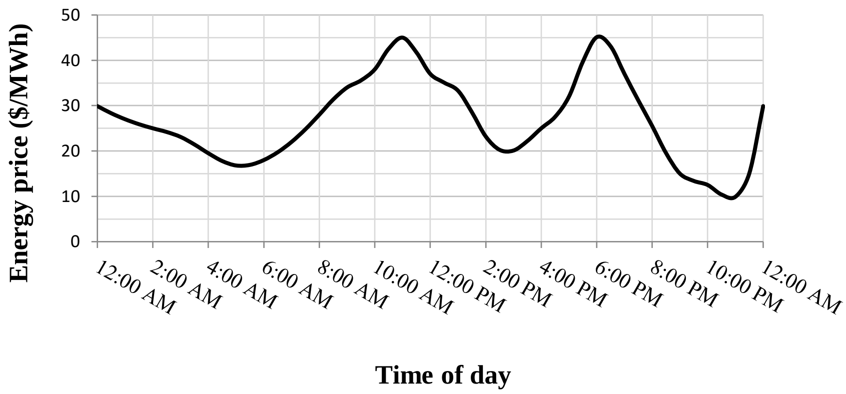


Figure 4.3: pricing scheme adopted

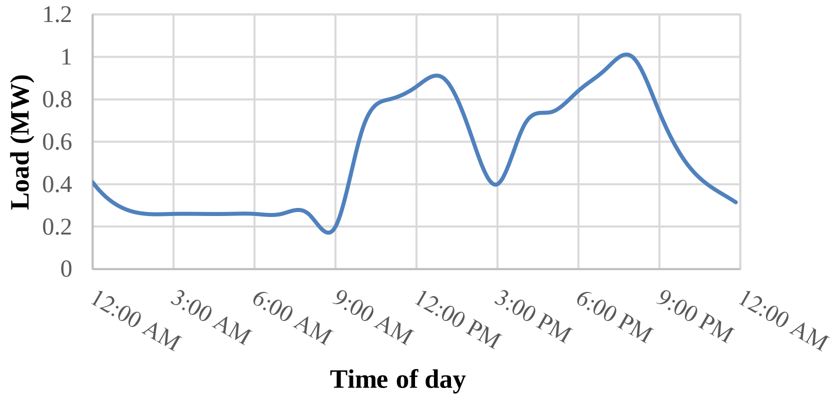


Figure 4.4: load profile

**4.1.2 Islanded mode.** Figure 4.5 shows the system while it is disconnected from the grid (islanded mode). List of devices attached to this system is shown in Table 4.2. Two BESS units of 1 MW and 3 MWh ratings is located on buses 25 and 33. Five diesel DGs are located on buses 8, 12, 22, 25, and 29 with ratings and operating costs details in Table 4.2. Two 1 MW PV units are located on buses 10 and 37. Finally, 1 MVAR nominal rated capacitor bank is located on bus 18. The islanded mode is the main feature of the microgrid, which enables it to operate in remote areas or areas with an unstable grid. Droop control technique is used to control the DGs output power (droop-controlled units), in order to have stable frequency and voltage. The frequency allowed to have only 1% tolerance of the nominal frequency. The voltage has limits of 0.9 to 1.1 p.u. range. The battery energy storage system is a critical part of such a system. Batteries help preserve the power balance in the system with the renewable resources. It can absorb the excess power in the system and also recompense the generation shortage. Settings of the droop gain values used in this work are shown in Table 4.3.

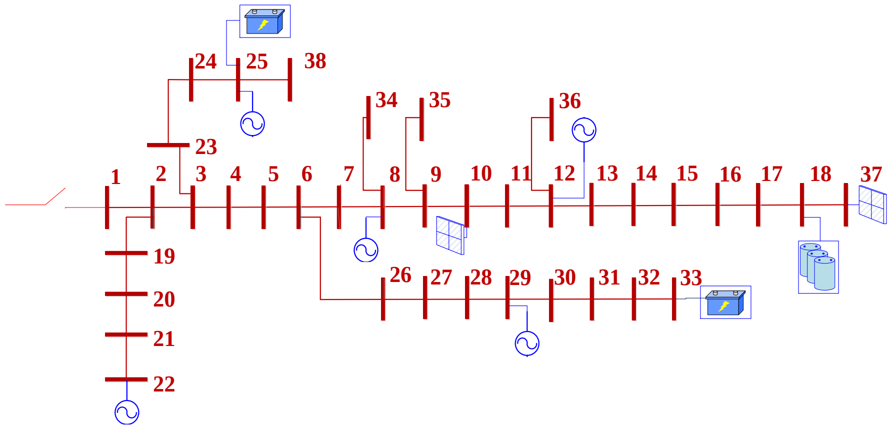


Figure 4.5: Modified 38-bus IEEE system islanded from grid

Table 4.2: System components for islanded mode

| **Bus number** | **Device** | **Specifications** |
|---|---|---|
| 25, 33 | 2 Batteries | 3 MWh each capacity |
| 18 | Capacitor | 1 MVAR maximum output |
| 8 | DG#1 | 0.5 MW, (0.024) $/kWh |
| 12 | DG#2 | 2.5 MW, (0.058) $/kWh |
| 22 | DG#3 | 2 MW, (0.054) $/kWh |
| 25 | DG#4 | 2 MW, (0.051) $/kWh |
| 29 | DG#5 | 0.5 MW, (0.022) $/kWh |
| 10, 37 | PV | 1 MW capacity each (Figure 4.2) |

Table 4.3: Active and reactive droop gain settings

| **DG number** | **Active droop gain ($mp_{i,t}$) (kW/Hz)** | **Reactive droop gain ($nq_{i,t}$) (kVAR/Hz)** |
|---|---|---|
| DG#1 | 10 | 0.2 |
| DG#2 | 2 | 0.04 |
| DG#3 | 2.5 | 0.05 |
| DG#4 | 2.5 | 0.05 |
| DG#5 | 10 | 0.2 |

## 4.2 Optimization Solvers

**4.2.1 Exact solution solver.** The solver used in this optimization problem to find the exact solution was KNITRO. KNITRO is characterized by finding local solutions to both continuous smooth optimization problems, with or without constraints, and discrete optimization problems with integer or binary variables. KNITRO performs both state-of-the-art interior-point and active-set methods in solving nonlinear optimization problems.

The interior method or the barrier method replaces the nonlinear programming problem by a series of barrier sub-problems determined by a barrier parameter. The approach employs trust regions and a merit function to enhance the convergence. The algorithm carries out one or more minimization steps on each barrier problem, then reduce the barrier parameter, and iterates the operation until the original problem has been solved to the desired accuracy.

In the active-set sequential linear-quadratic programming (SLQP), the algorithm uses linear programming subproblems to estimate the active-set at each iteration. This active-set code may be preferable when a good initial point can be provided, for example, when solving a sequence of related problems [65] and [66].

**4.2.2 Heuristic solution solver.** A heuristic solution for the islanded mode was obtained in this work using the genetic algorithm. The genetic algorithm starts by generating random starting solution. Then, it makes a series of new solutions. At each stage, the genetic makes use of the existing generation to develop a new solution.

The production of new solutions is done by different steps. The fitness values of each existing population are calculated and those values are then transformed to more applicable values. After that, some members are chosen as parents based on their fitness values, other individuals with the lowest fitness are taken to the next population and those are called elite individuals. Children are generated by ways of mutation or crossover and the new children replace the existing population. The process is repeated till the stop criterion is met [67].

# Chapter 5. Results and Analysis

This chapter presents and discusses the simulation results achieved by the implementation of the proposed control scheme on the case studies described in Chapter 4. We also evaluate the performance of the three scenarios on the two modes of operation.

The proposed control scheme is implemented using GAMS and MATLAB environments. In this work, GAMS was used as the optimization unit. MINOS solver has been used to solve the MINLP problem introduced in Chapter 3. The MINLP variables are given initial values and bounding conditions to speed the optimization. MATLAB is used to host database unit and the forecasting unit. MATLAB also hosts the MGC that controls the optimization unit and then send the desired data to GAMS.

## 5.1. Grid Connected Mode

Three scenarios are presented in this case study as described in Chapter 4.

**5.1.1. Base case without control.** For this case, the total load of fixed and variable equipment is supplied once it is initiated, regardless of the system loading condition. The only sources of energy are the grid and the PV unit. The total cost of consumption per day is $1,523. Hence, no coordination with the batteries is introduced and all the loads are considered fixed, i.e. no options available.

**5.1.2. Day ahead control.** In this case, the injected active powers from dispatchable DG, PV units, and from the grid is shown in Figure 5.1. As shown in the figure, the dispatchable DG operation is controlled through the MGC to reduce the overall operating costs; thus, the dispatchable DG is operated during high energy prices around 11:00 am and 7:00 pm to reduce the purchased energy from the grid. Figure 5.2 shows two charging/discharging cycles for the BESS operation. As shown in Figure 5.2, the BESS is charged during low energy prices around 6:00 am and 4:00 pm; then, it is discharged during high energy prices around 11:00 am and 7:00 pm. Moreover, it can be seen in Figure 5.2 that the battery actions of charging or discharging also coincide with the load consumption.

In the day-ahead case, the controller is aware of the whole day data and develops perfect matching result for it; however, this is not the practical case. The total cost of consumption from the grid and the dispatchable DG is $1,297.

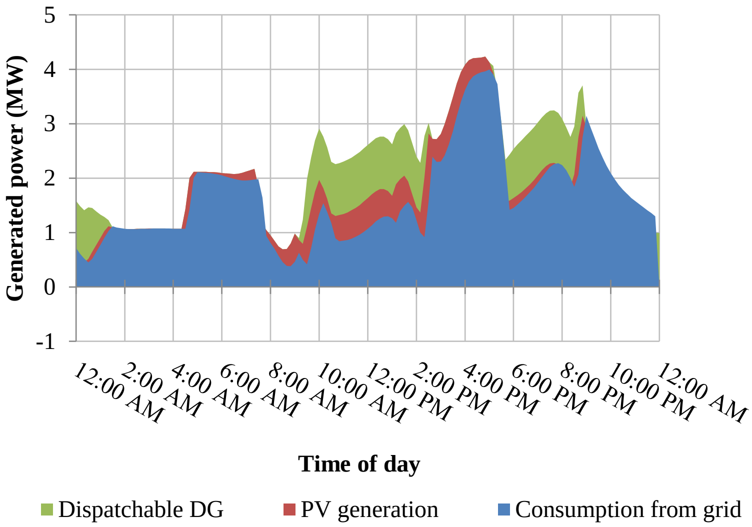


Figure 5.1: Generation from different sources for the grid connected day-ahead case

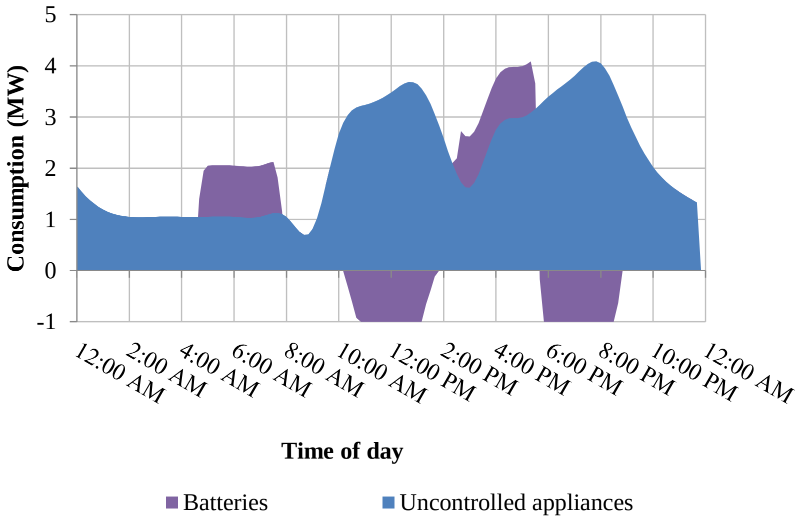


Figure 5.2: BESS and load profiles for the grid connected day-ahead case

**5.1.3. Real time control.** The rolling time horizon parameters settings is 10 mints for $\Delta t$ and three hours for the window width. The weather condition changes every moment, and the load increases or decreases randomly. This needs fast and accurate actions to be sent to local controllers. The RTW actions are sent and implemented immediately. Then, every period $\Delta t$, they are updated continuously to tune the decision with the latest available forecast.

As shown in Figure 5.3, by utilizing the RTW, the dispatchable DG operation duration is longer compared to the day-ahead case to serve the battery requirements. The battery charging/discharging actions are more sensitive to the prices variations. This is reflected in Figure 5.4 by three charging/discharging cycles. This is due to the short-sightedness of the controller, i.e. the length of the time window, which is a trade-off between accuracy and computational time, as mentioned earlier. In this figure, the system had a third charging cycle without a final discharge, this is due to the nature of the folding time window. The total cost of consumption is $1,299.

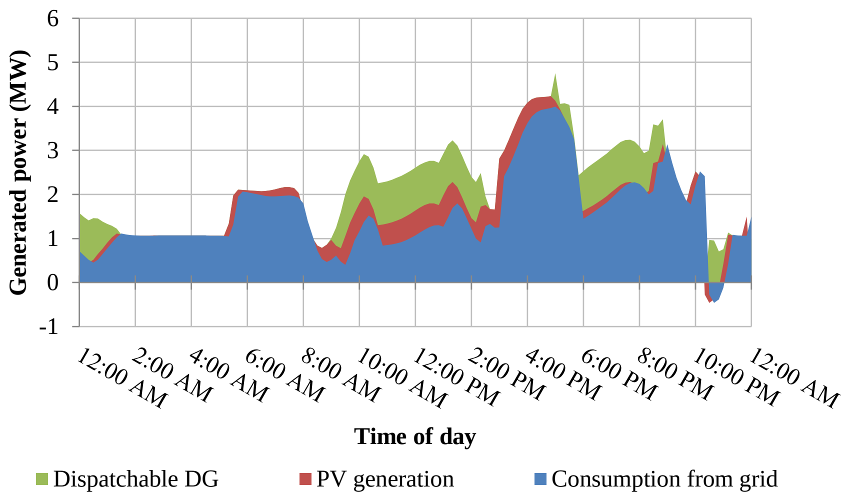


Figure 5.3: Generation from different sources for the grid connected real-time control

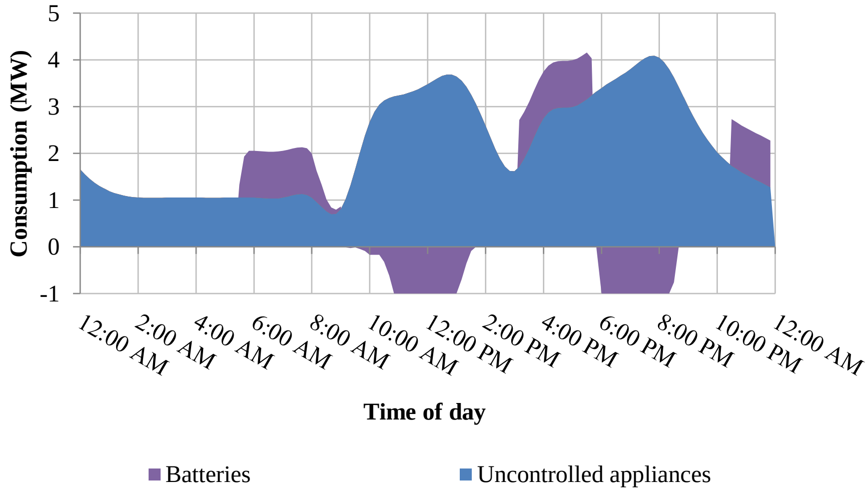


Figure 5.4: BESS and load profiles for the grid connected real-time control

## 5.2. Islanded Mode

**5.2.1. Base case without control.** The sources of energy are the DGs and the PV only. Also, no coordination with the batteries is involved and all the appliances require an immediate operation, i.e. options provided by the local controller are not available. The DGs are working according to the droop control parameters setting to reduce the cost and keep the voltage and frequency levels. The total cost of the energy consumption in this situation per day is $2,178.

**5.2.2. Day ahead control.** In this case, the injected active powers from dispatchable DG and PV units are shown in Figure 5.5. The dispatchable DGs operation controlled by the MGC with the specified droop control characteristics, the insertion is done by the cheapest DG. As the load increase, more DGs are inserted according to their ratings. In this mode, we don’t have the price of grid energy as a controlling element for the DGs insertion and battery decisions. However, the system should satisfy the load at all times. Figure 5.6 shows also two charging/discharging cycles with slow charging at the beginning between 12:00 am and 10:00 am when the load is light. Most of the power discharged during the time of high demand between 6:00 pm and 10:00 pm. The total energy cost represented by the generators cost is $2127.152.

Results of the frequency and voltage limits for the day ahead scenario obtained by the droop settings are shown in Figure 5.7 and Figure 5.8. Although these values are not constant, they successfully stayed within their specified limits.

**5.2.3 Real time control.** The cheapest DG serves as a base for the generation with its full power output rating as shown in Figure 5.9. The output generation follows the load cycle as well. In Figure 5.10 charging and discharging process is being nearly random. Many small charging and discharging cycles are shown, because of the lack of the generation and load information of the times beyond the moving window width. Also, the charging/discharging pattern is affected by the slight variations of consumption. However, the charging decisions are still performed during the light load and discharges during peak load. The total daily cost for the consumption is $2090.92.

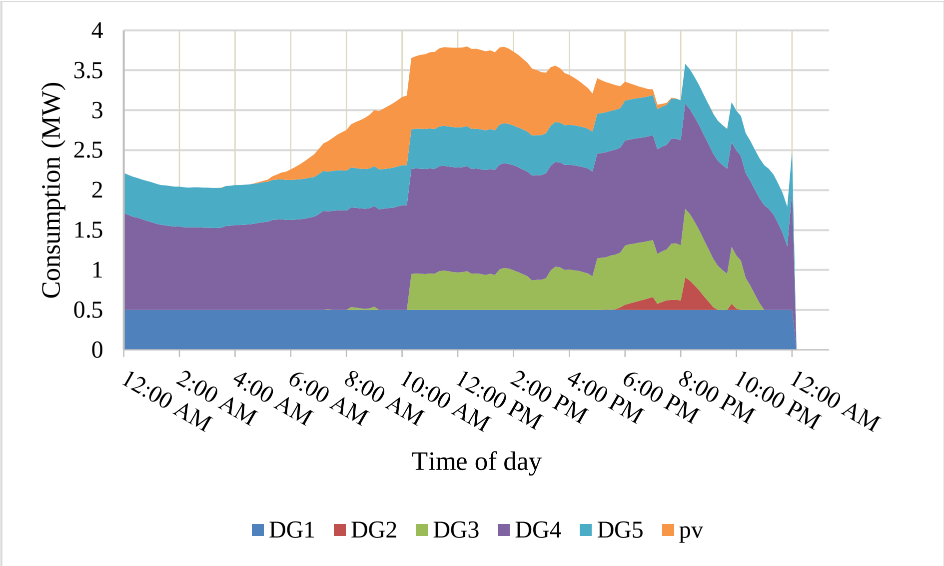


Figure 5.5: Generation from different sources for the islanded day-ahead case

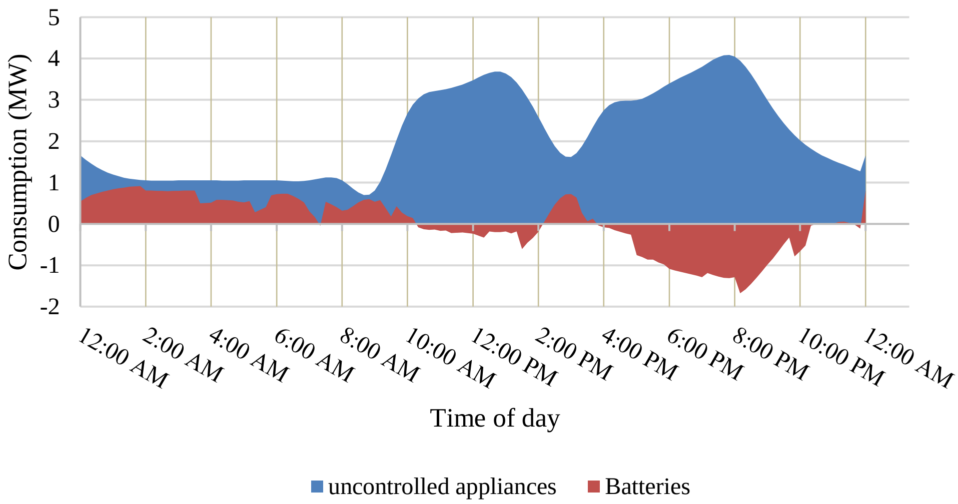


Figure 5.6: BESS and load profiles for the islanded day-ahead case

Figure 5.11 and Figure 5.12 show the system frequency and the voltage values respectively. Many frequent changes in the frequency appear in Figure 5.11which are due to the moving window nature. All the values maintained within the specified boundary values.

Two types of solution for the islanded mode were obtained; MINLP exact solution and genetic algorithm heuristic solution. The exact solution obtained gives the minimum cost of consumption but at the expense of long computational time. On the other hand, the heuristic solution obtained does not guarantee minimum cost. However, the reduction in the computational time is extremely enormous. The summary of computational time and cost for the two types of solution are listed in Table 5.1.

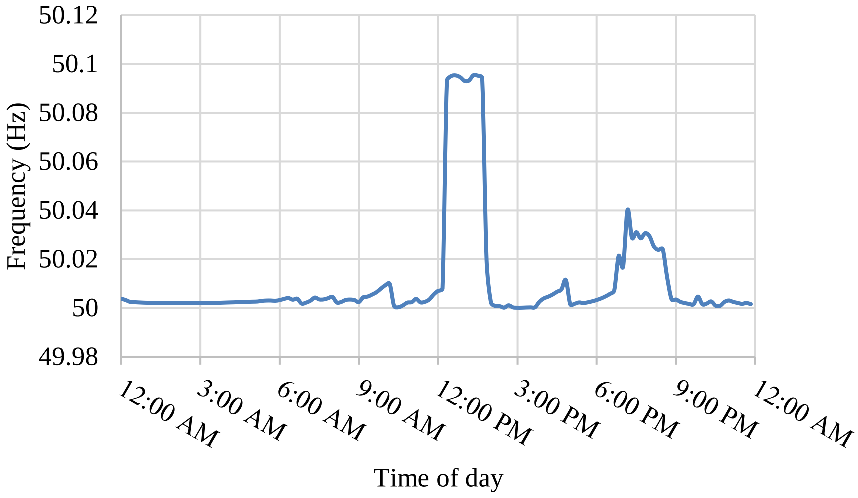


Figure 5.7: Day ahead frequency

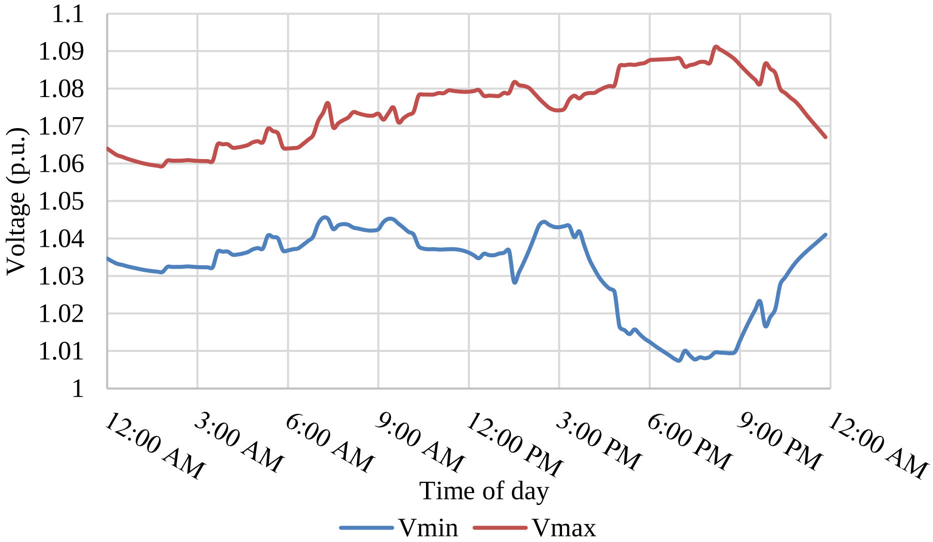


Figure 5.8: Day ahead maximum and minimum voltage

Evidently, from our experiments and previous results, we can notice that the base case scenario has the highest cost. Then, both the day-ahead and real-time cases have near costs, a summary of the costs for both cases are given in Figure 5.13 and Figure 5.14. Table 5.2 also shows a detailed comparison between the different cases and the reduction in the daily cost compared to the base case without control.

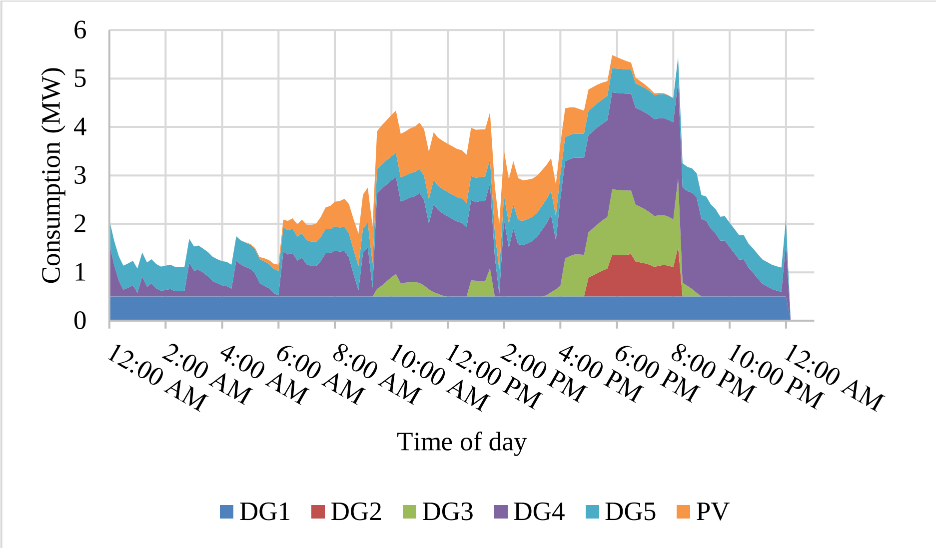


Figure 5.9: Generation from different sources for the islanded real-time control

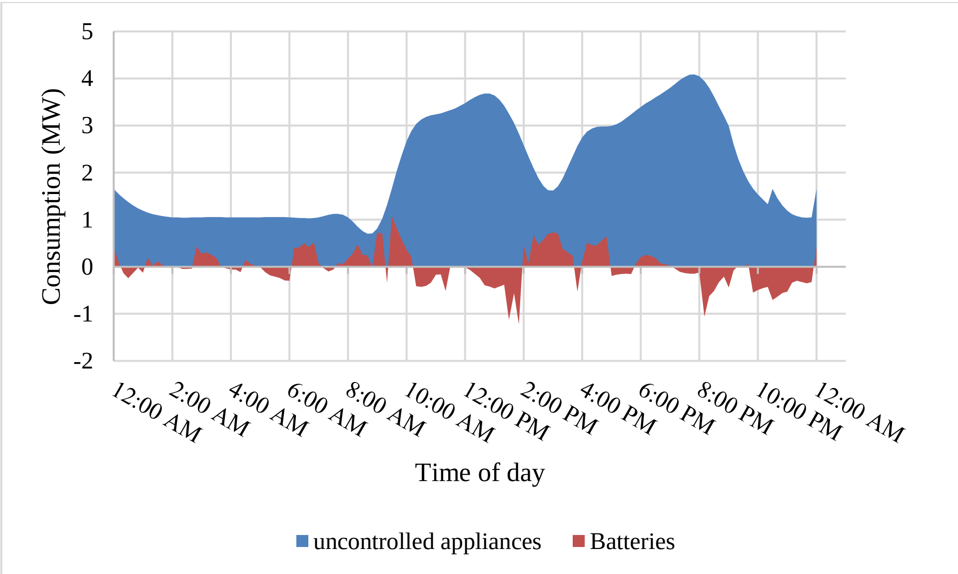


Figure 5.10: BESS and load profiles for the islanded real-time control

Table 5.1: Islanded mode exact and heuristic solutions

| **Solution** | **Exact solution** | | **Heuristic solution** | |
|---|---|---|---|---|
| | Day ahead | Real-time | Day ahead | Real-time |
| Cost ($) | 2127.15 | 2090.92 | 2197.573 | 2175.757 |
| Computational time (sec) | 467.349991 | 7466.886368 | 41.67 | 600 |

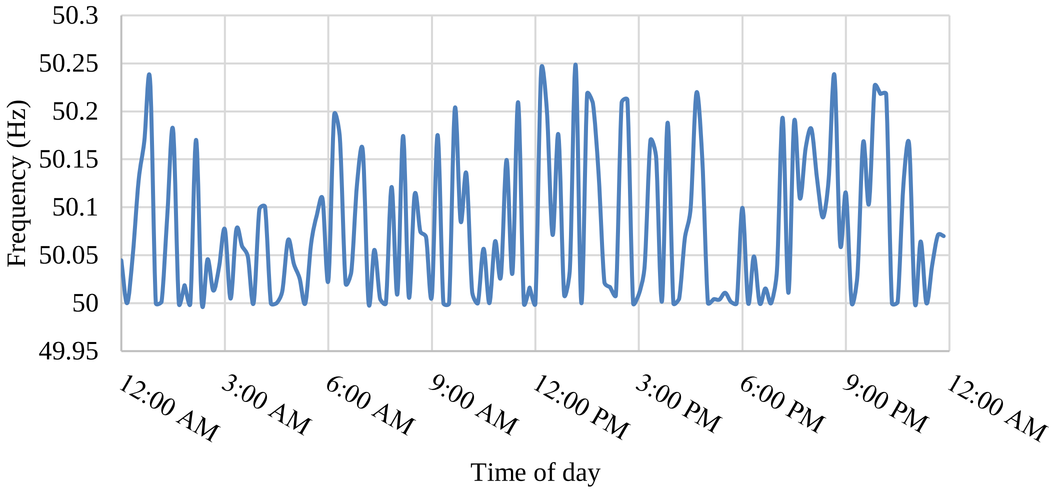


Figure 5.11: Real-time frequency values

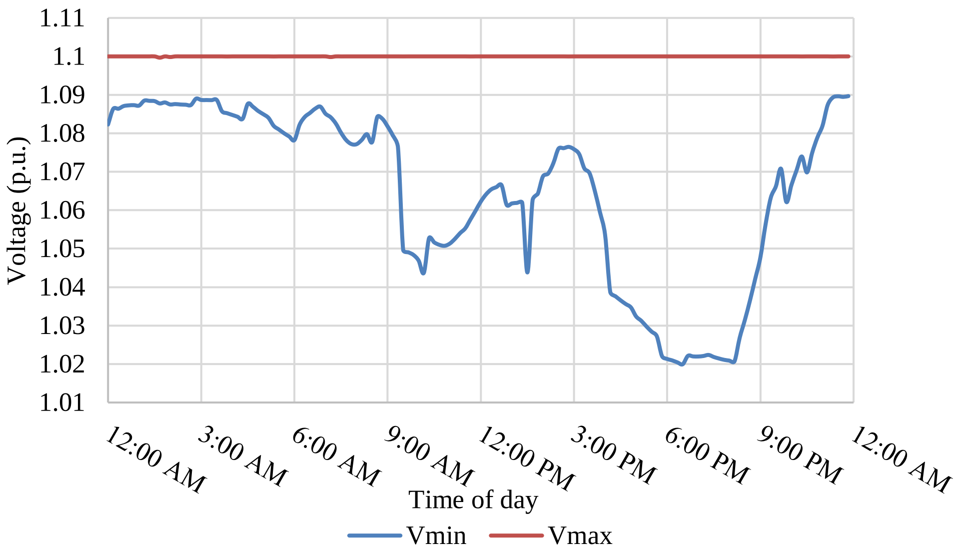


Figure 5.12: Real-time maximum and minimum voltages

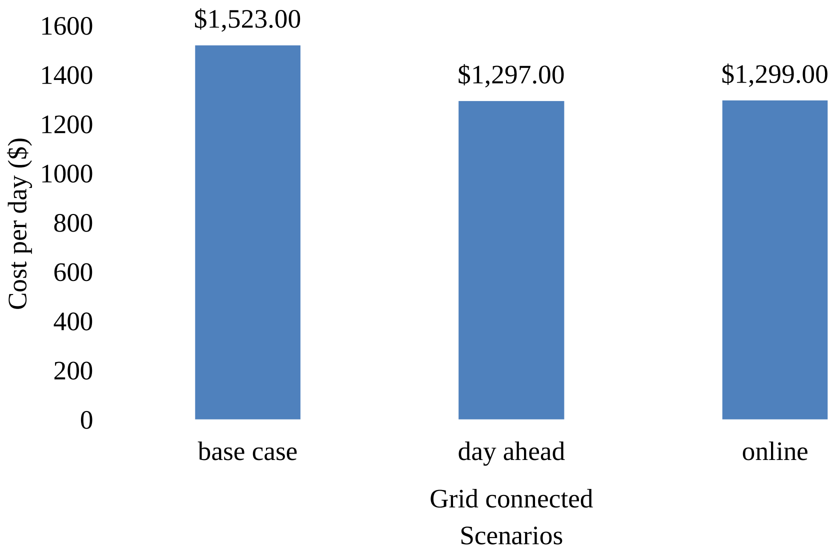


Figure 5.13: Comparison of three cases cost for grid connected mode

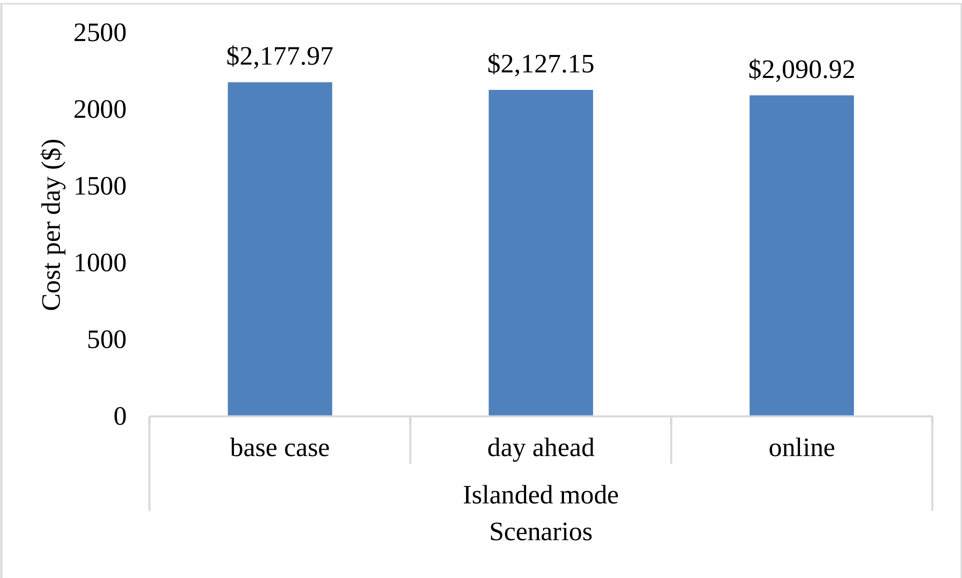


Figure 5.14: Comparison of three cases cost for islanded mode

Table 5.2: comparison of the daily costs with base case

| **Case** | **Grid connected mode** | | | **Islanded mode** | | |
|---|---|---|---|---|---|---|
| | Base case | Day ahead | Real-time | Base case | Day ahead | Real-time |
| **Cost ($)** | 1523 | 1297 | 1299 | 2177.97 | 2127.15 | 2090.92 |
| **Reduction compared to base** | - | 14.8% | 14.7% | - | 2.33% | 4% |

# Chapter 6. Conclusion and Future Work

This thesis proposes a centralized energy management scheme for microgrids that efficiently coordinates the grid and customers’ assets to reduce the operating cost. The proposed approach relies on rolling time horizon to manage real-time data exchange and to update the control decisions based on the real-time and the forecasted information.

Although day-ahead based approaches are more commonly used in literature, they fail to address the customers’ preferences changes, new connected appliance, and intermittent nature of renewable resources. On the other hand, the proposed real-time approach offers more flexibility by updating the control decisions every short period according to the most recent information; thus, allowing the plug-and-play option.

The problem was modeled as mixed-integer non-linear programming and is not convex in nature, as a result, the proposed solution does not guarantee finding the global optimal solution at all times. The solution could be trapped with a local optimal solution only. To develop the real-time optimal decisions, the proposed approach utilizes three units: data storage unit, forecasting unit, and optimization unit.

Simulation results on a typical smart microgrid prove the effectiveness and robustness of the proposed approach, which results in almost the same saving as the ideal day-ahead approach. Although, the proposed approach utilizes the system assets more than the day-ahead approach; the real-time approach presents a more practical case. The variable parameters of the time step and moving horizon are decided depending on how often the loads are plugged. Either it needs a fast adoption or not, and the controller must compromise between having high accuracy and computational time. In addition, choosing the time window and step durations have a significant impact on the results. A longer duration of the time window and a shorter duration of the time step would provide more accurate results, but on the expenses of a longer computational time. Thus, it is a trade-off between accuracy and computational time. On the other hand, the heuristic solution obtained using the genetic algorithm saves more computational time and the obtained results are close to the exact solution and hence, could be implemented for real time measurements.

As a future work, the proposed control scheme could be implemented as a hardware unit. We need a communication media between the control unit and all the components that we need to read/write from or to. The forecasting unit that was not designed in this work will need to be implemented to have the future data.

The work presented here is centralized control where all the decisions are decided through the microgrid controller. However, the problem could be implemented in a different way with the local controllers at the consumer side contribute in the control process. This is realized by a decentralized control scheme that manages different objectives of the consumer.

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# Vita

Wla Elamin was born in 1991, in Portsudan, Sudan. She received her primary and secondary education in Portsudan, Sudan. She received her B.Sc. degree in Electrical and Electronic Engineering from the University of Khartoum in 2013. From 2013 to 2014, She worked as an Operation and Maintenance Engineer in Sea Ports Corporation.

In September 2015, she joined the Electrical Engineering master's program at the American University of Sharjah as a graduate teaching assistant. During her master's study, she co-authored one paper which will be presented in the IEEE general meeting 2017. Her research interests are in reliability of the power systems, energy management systems and load scheduling, microgrids, smart grids, planning and operation of renewable resources and storage systems.