Model-based Development and Design of Microgrid Power Systems

Modellbasierte Entwicklung und Auslegung von Microgrid Energieversorgungssystemen

Dissertation

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Saarbrücken, September 2018 Mohammed Hijjo

Abstract

The motivation of this contribution is the study of the Microgrid (MG) power systems, specifically Solar-Battery-Diesel systems, which are used to support unreliable grids and provide a continuous electricity supply to the areas which have limited or even no access to the grid. The main research focus in the scientific community lies on the development of general energy management strategies (EMSs) for optimal power routing on the one hand, and providing an optimized layout-design of the MGs on the other hand. However, none of these two issues can be adequately handled in isolation from one another because they have a direct impact on each other. This work aims at tackling *Model-Based Development and Design of Microgrid Power Systems* by addressing the challenges of the EMSs and the layout-design based on the system model and operational requirements. For this purpose, several EMSs for scheduling generation side in the MG are developed in accordance with the operational constraints. Besides, a forecast-driven power planning approach is developed for MGs that incorporate smart shiftable loads. Furthermore, this work proposes an integrated layout-design method for optimizing the size of the microgrid considering the applied EMS. Finally, to highlight the usefulness of the developed EMSs and design approach, different examples inspired from a real case-study are presented.

Diese Arbeit befasst sich mit dem Thema Microgrid (MG)-Energieversorgungssysteme, hauptsächlich Solar-Batterie-Diesel-Systeme, die vor allem zur Unterstützung der unzuverlässige Netze eingesetzt werden oder als eine zuverlässige Stromversorgung für Gebiete, die nur begrenzten oder sogar keinen Zugang zu elektrischem Strom haben. Der aktuelle Forschungsschwerpunkt in der Wissenschaft liegt einerseits in der Entwicklung allgemeiner Energiemanagementstrategien (EMS) für eine optimale Energieführung und andererseits in einem optimierten Design der MGs. Keines dieser beiden Probleme kann jedoch isoliert betrachtet werden, da sie sich direkt aufeinander auswirken. Diese Arbeit zielt darauf ab, die *Modellbasierte Entwicklung und Auslegung von Microgrid-Energieversorgungssystemen* anzugehen, indem die Herausforderungen der EMS und des Layout-Designs basierend auf dem Systemmodell und den betrieblichen Anforderungen adressiert werden. Zu diesem Zweck werden mehrere EMS zur Planung der Erzeugungsseite in dem MG in Übereinstimmung mit den Betriebsbeschränkungen entwickelt. Außerdem wird für die Microgrids, die intelligent verschiebbare Lasten enthalten, eine prognosebasierte Betriebsstrategie entwickelt. Diese Arbeit schlägt auch eine integrierte Layout-Design-Methode vor, um die Auslegung des Microgrids unter Berücksichtigung des angewandten EMS zu optimieren. Um die Wirksamkeit der entwickelten EMS und des Entwurfsansatzes hervorzuheben, werden schließlich verschiedene Beispiele vorgestellt, die von einer realen Fallstudie inspiriert sind.

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1 Introduction

1.1 Problem Definition

The continuous depletion of fossil fuels and the increasing awareness toward harmful emissions lead to a reconsideration of energy politics and consumers behavior, particularly with regard to the sustainable usage of electricity. Today, a lot of projects and investments are dedicated for electrification challenges, especially for developing efficient and affordable solutions for a successful energy transition on the one hand, and enabling socio-economic development in terms of energy policies on the other hand. In the developing countries, the governments and the electric utilities are still paying too much consideration to power outage problems, especially to the long-lasting blackouts that occur due to insufficient local resources or power supplies. Generally, stockholders arrange local backup systems to cover at least their basic needs of energy during the outages. Such systems commonly include on-site diesel generators which are expensive and environmentally hazardous. A small residential building for instance can consume up to 10 K liters of diesel per year just to cover a daily power outage of ten hours. Besides, these generators release approximately 2.6 Kg of carbon dioxide into the atmosphere per liter of diesel fuel [FvL2018].

Recently, as demand for clean and affordable energy increases, hybrid energy systems – instead of diesel alone– entered into force. In Germany for instance, the German Federal Government has recognized the importance of utilizing clean energy sources and therefore has set down an annual target of 2.5 GW new installations of PVs to support the "***Energiewende***" (energy transition) [EEG2017]. On the other side, in the less-developed countries, the value of utilizing renewable energy sources (RES) has been significantly realized. According to the National Energy Efficiency Action Plan (NEEAP) for Palestine, the Palestinian Energy Authority (PEA) has set down a group of indicative targets to sustainably develop the Palestinian economy while mitigating greenhouse emission and reducing considerably the dependence on imported energy. The plan has also initiated different measures for renewable energy utilization in all energy consuming sectors for that purpose [NEEAP], [NjM2016].

Although it is recommended to deploy RES to lessen the dependency on the conventional sources and help in reducing gas emissions, there is still a need for developing and realizing efficient energy management solutions (EMSs) in order to optimally achieve the system requirements, especially maximizing the net benefit from RES while minimizing the lost energy and the operational costs of the whole system. Consequently, affordable cost of energy can be attained using efficient EMSs because the effective price of the system will be reduced accordingly. With the progressive drop in prices of RESs and batteries, and as a preliminary step towards energy transition, societies in the near future are expected to draw power from these new elements such as PVs and batteries in addition to the existing legacy infrastructure, e.g., grid and diesel.

This will introduce a complex energy management scenario, which motivates the need to explore innovative strategies that can optimally dispatch and distribute energy from these elements based on their availability and associated costs. To this end, different supply and demand side management strategies should be explored. On the supply side, diesel generators –the commonly used backup power supplies– may be partially assisted or totally replaced with renewables, e.g. PV Solar Generation, and energy storage, e.g. battery. On the demand side, a further step can be made to achieve this goal, namely: load control. This will increase the degree of flexibility and give a chance to influence the consumption behavior through shedding some unnecessary loads or/and shifting their time of operation to another acceptable time span, where the energy price is much lower. Once explored, this will allow a seamless shift of a part of the consumption from the high energy price regimes (or outages) to other regimes. However, realistic scenarios and operation conditions must be used to investigate the feasibility and effectiveness of the proposed solutions.

1.2 Motivation and Goals

It is observed that significant and substantial developments are currently made on the existing power systems as a natural reaction to the revolution in ***Renewable Energy***. In spite of all encouraging advantages of RES, there are still some important barriers that need to be overcome for a seamless integration into the current power systems. Yet, innovative and holistic approaches are still needed to make maximum use of them in the most optimum way. To this end, the concept of ***Microgrids*** has emerged with the beginning of the 21st century to handle these issues. As an emerging conception of the future power systems, *microgrids* can overcome the expected barriers of the associated challenges of ***Energy Transition***. *Microgrids* are miniature models of power systems incorporating different controllable power sources and loads [Lr2002], [DoE2011]. Meanwhile, they are forming a key milestone in the future paradigm of the power systems.

The main motive for this contribution is, therefore, the study of the Microgrids. The majority of the preceding research works conducted in this context fall under two categories:

1. The problem of Layout-Design (components' sizing) of the Microgrids.
2. Development of Energy Management Systems for special purposes.

However, none of these two issues can be adequately handled in isolation from one another because each of these issues has a direct impact on the other.

To the knowledge of the author, there is a lack of comprehensive studies that addressed the aforementioned issues in a well-structured way starting from the elementary requirements of the handled systems and passing through the applied energy management system and ending with the optimized operation of the whole system in order to make the best possible use of the installed RES.

For this purpose, this work aims at tackling **Model-Based Development and Design of Microgrid Power Systems** by addressing the challenges of the Layout-Design and Energy Management System based on the system model and operational requirements.

In addition to the above-mentioned objective, this study seeks to conceptualize a general perception of the main components of the Microgrids' and develop an adequate but simple and straightforward EMS that can be efficiently used and applied to achieve the maximum degree of sustainable and reliability.

Unlike other case-oriented works, this work aspires to give a general understanding of the most important challenges related with the **Microgrid Operation** by elaborating realistic case studies with the corresponding operation scenarios and thus, a part of this contribution is dedicated not only to handle such emerging power problems correspond to modern societies, but also to some of the most demanding electrification problems in the developing countries. In spite of that, an intensive explanation of a relevant case study, e.g. Gaza-city, is introduced in **Chapter 2** where such emerging problems are worth to be explored.

1.3 The Scope of the Work

This work is mainly concerned with the system level modeling which is very important for efficient and adequate development of EMSs. Thus, the scope of this work does not pay consideration for the voltage stability, power quality, or even the transient response in a very short time span. In contrast, it tackles the uppermost control level, which has the longest discrete time steps, e.g. ranging from intra-hours to intra-days. For this reason, the modeling method used here does not care about very detailed modeling that will ultimately lead to huge computation time, complex scheduling, and of course inapplicable operating scenarios. Consequently, the concept of model-based development used here deals with the generic models of the system's components which can be mathematically formulated to abstractly describe the dynamic behavior of an individual component of the microgrid.

Furthermore, and not only for comparison purposes, a part of this work tracks a former and well-known EMS as a preliminary management method, e.g., rule-based method, which has been given several names in the literature. The author has recognized enhancement potential and therefore, this method will be addressed firstly, as in **Chapter 3**, in order to highlight some weaknesses that can be treated to increase the efficiency of the system.

As introduced in the section of problem definition, this work tackles not only the problem of assets management, e.g. supply side, but also the demand side. This will be addressed in the course of **Chapter 4**, where a set of controllable loads are going to be used to allow for more flexibility of the system. In another meaning, the pattern of this work starts with modeling each element of the system and moves to discuss the energy management from the supply side and afterwards tackles the problem of scheduling the controllable loads in the demand side. Yet, this will form the first part of the study.

The second part will take care about the design of a microgrid considering the involved energy management criteria, where the general framework will be discussed firstly in **Chapter 5** presenting the impact of the applied EMS on the resulting values of the components. In the course of this work, it is expected to use an optimization technique that can accelerate the searching process. For that reason, the Genetic Algorithm (GA), as a stochastic optimization technique, is adopted to track the solution in the shortest possible time.

1.4 Thesis Organization

There are six main chapters forming this thesis starting from the state of the art of microgrids and moving towards the full development to fulfill the objectives of this work. Microgrids are the core of the thesis and so **Chapter 2** starts with the basics of MGs. Therefore, MGs are described in general, followed by the major topologies. Further, this chapter describes the major MGs' structures are going to be used in this work referring to the most common operational constraints or/and hypothesis. Besides, an intensive description of the case study and the corresponding operation conditions is introduced in this Chapter too.

The development of the EMS is going to be addressed in details in **Chapter 3**. This chapter starts with reviewing the classical rule-based EMS in order to highlight the enhancement potential and the need to optimize the operation of the MG under consideration. It moves afterwards to describe the framework of the improved version of this method. Subsequently, a forecast-driven solution of the EMS is presented in this Chapter. The later approach is mathematically formulated using the classical dynamic programming (DP) technique. Nevertheless, this approach is developed after that to be solved in s shorter time by applying a stochastic optimization technique, e.g. GA. Lastly, the faster approach is used to facilitate an uncertainty-tolerance EMS using the concept of Model-Predictive Control.

Another opportunity of managing the controllable assets is demonstrated in **Chapter 4**. This chapter tackles the problem of load scheduling in a smart building as an important function of the tertiary level in controlling future microgrids. To this end, this chapter offers a proactive scheduling plan for a set of some smart loads which announce their desired operation pattern or the associated consumption profiles in advance.

The 'best case' scenario solution is presented firstly considering a perfect prediction of these loads as well as the power generation profiles. Afterwards, it overcome the problem of uncertainty by adapting the fast responsive assets, e.g. generation side, accordingly.

Chapter 5 presents the developed design framework. It aims at selecting the most appropriate components of the MG correspond to the some performance factors, e.g. the self-consumption and utilization level. The kindness of this method is that the applied EMS is integrated when optimizing the capacity or the size of each component.

Chapter 6 concludes the dissertation by summarizing the main research challenges and highlighting the main achieved results. It illuminates also the potential work that can be conducted in the future.

A graphical description of the thesis organization starting from the second chapter is shown in Figure 1.1

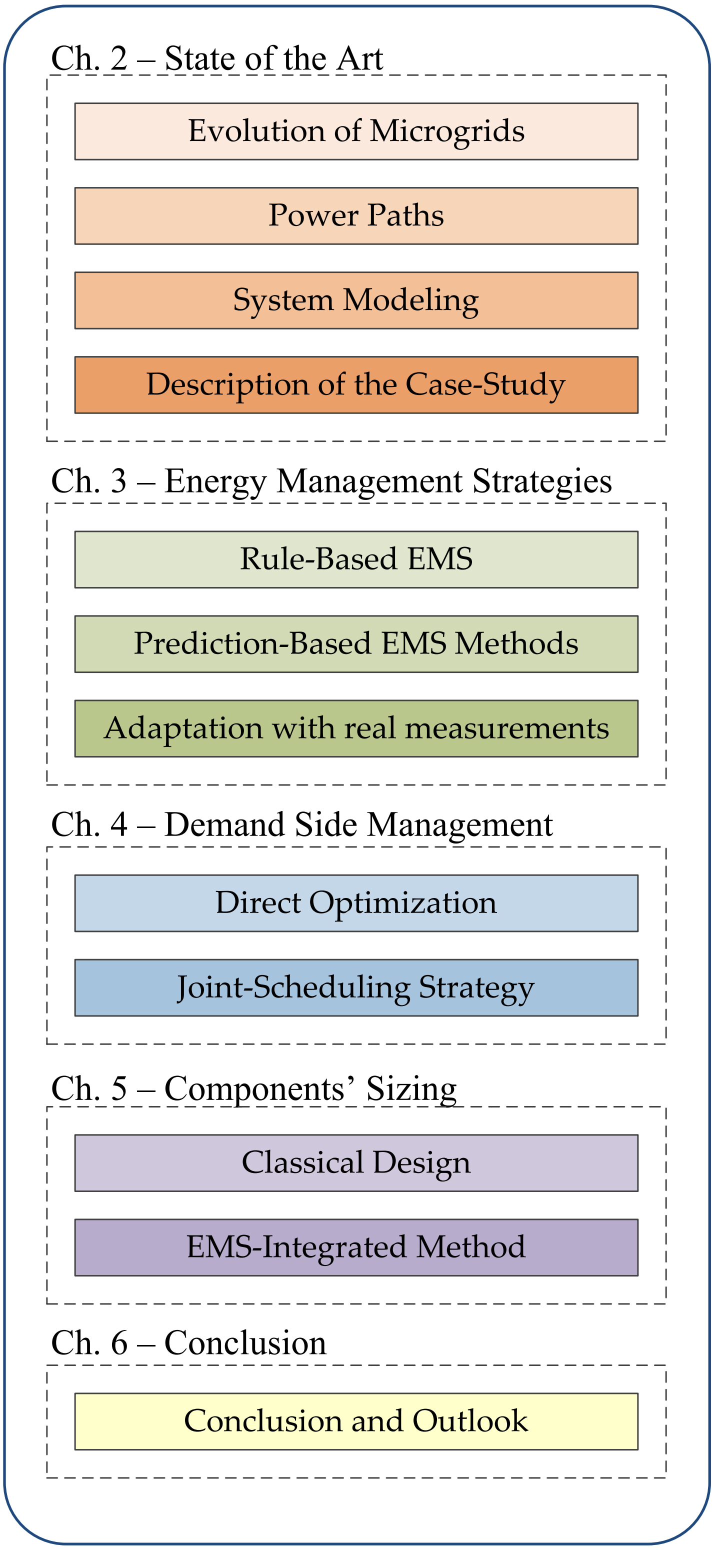


Figure 1.1: Thesis organization diagram.

2 State of the Art

*The increasing need of energy and the rising cost of the conventional generation along with the climate changes are the major drivers of the transition process of energy systems. These challenges necessitate continuous development of the electrical sector. Microgrid concept emerged to cope with the requirements of the new paradigm of energy systems. "**A microgrid is 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 microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode**"[DoE2011]. In this chapter, a brief background about Microgrid systems is introduced followed by the mathematical modeling of the most common operational hypothesis that are going to be applied in this thesis. Finally, a detailed description of the concerned case study is presented.*

2.1 Evolution of Microgrids

Given the fact that most of the existing electrical grids were built in the past decade and are mostly powered by fossil fuel, the next generation of power system are expected to depend merely or at least partially on regenerative resources other than the depleting fossil fuel. Essentially, the legacy power systems are thermal in nature and can mostly convert one-third of fuel energy into electricity. Moreover, nearly 8% of the generated electricity is lost along the transmission system, while 20% of their generation capacity exists to meet peak demand only (i.e., it is in use only 5% of the time). In addition to that, due to the hierarchical topology of its assets, the existing electricity grid suffers from the cascade failure effect [Farh2010].

On the other side, the broad vision of the future grid, known as the "smart grid" is expected to address and tackle the major shortcomings of the existing grid. Figure 2.1 depicts the salient features of the smart grid in comparison with the existing grid.

Existing Grid	Intelligent Grid
Electromechanical	Digital
One-Way Communication	Two-Way Communication
Centralized Generation	Distributed Generation
Hierarchical	Network
Few Sensors	Sensors Throughout
Blind	Self-Monitoring
Manual Restoration	Self-Healing
Failures and Blackouts	Adaptive and Islanding
Manual Check/Test	Remote Check/Test
Limited Control	Pervasive Control
Few Customer Choices	Many Customer Choices

Figure 2.1: The smart grid compared with the existing grid [Farh2010].

In light of this, the governments and stakeholders have been starting with the deployment and installation of on-site generation as an alternative solution to lessen the burden on the main grid and to overcome the problem of energy loss in transmission system. Such an auxiliary system is basically formed by a group of small generation units referred to as distributed energy resources (DER) [VirT2007]. Obviously, DER systems are expected to have a higher degree of flexibility than the conventional energy systems where they comprise hybrid generation components that cannot fail together. Such systems typically use RES such as solar and wind power in addition to the storage system.

"*The significant potential of smaller DER to meet customers' and utilities' needs can be best captured by organizing these resources into Microgrids*" [CERTS2003]

A Microgrid system is commonly used as a secondary or a provisional power supply integrating different micro power resources and storage unit [Farh2010]. Therefore, it should have also the ability of interaction with the main distribution grid to supply the load in case of grid outages according to a designated power management criteria.

2.2 Power paths

Unlike the traditional paradigm of the electricity grids, microgrids are small-scale grids that can operate cooperatively with the main (macro)grid as in the grid-connected mode or function autonomously as in the islanded or isolated mode. Figure 2.2 gives an overview of the possible energy conversion paths among a microgrid system incorporating PV field, Battery, Generator, and a unidirectional grid, i.e. cannot accommodate the surplus PV production.

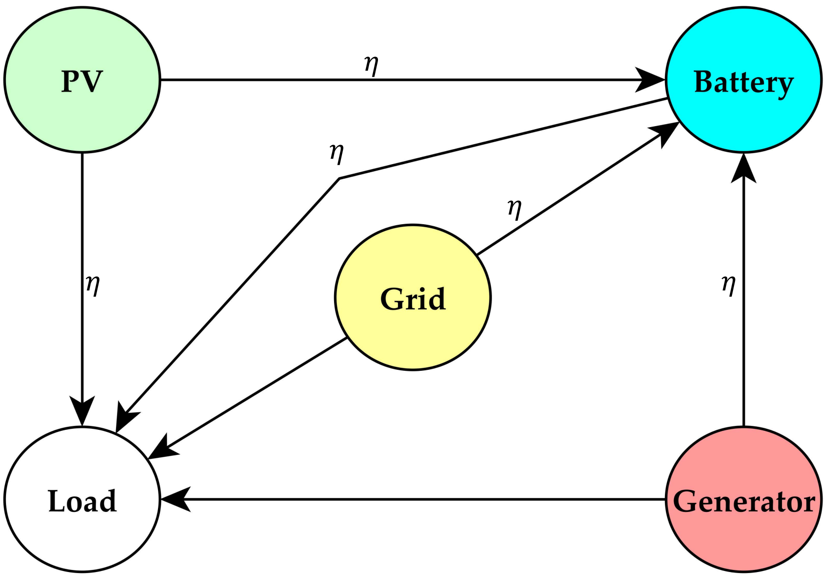


Figure 2.2: Possible energy conversion paths in Microgrid.

2.3 System Modeling

The considered microgrid system here is composed of a PV-array, a battery storage, and a diesel generator set (GenSET), all together representing the proposed backup supply for the essential loads, which all are connected to main grid through the point of common coupling (PCC) as depicted in Figure 2.3

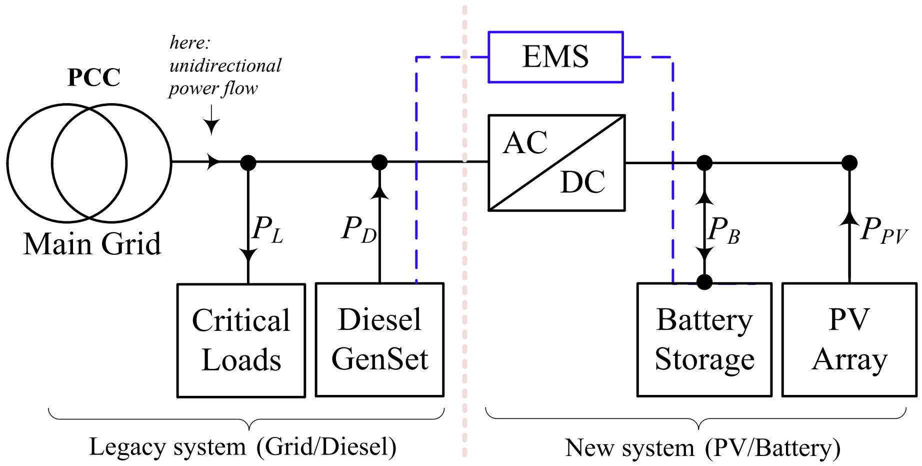


Figure 2.3: General model of a PV-Battery-Diesel Microgrid system

Following is an abstract model of each system's component and/or its main operational constraints:

2.3.1 *Load Demand*

The load demand or profile represents the instantaneous power consumption of the load and can be modeled by discrete values $P_L(\tau)$ over a fixed time horizon (e.g., a day), where $\tau \in [t_0, t_0 + T]$. Obviously, the most important part of proposing an efficient management strategy later on is to identify the consumption patterns and maintain power supply even in blackouts, rather than to save energy. To this end, a method is required to mockup a load profile for a relatively long period from available basic data. For the purpose of testing control strategies, the load forecasting model should avoid complicated configuration processes [PeBo2011]. Essentially, such a method is advantageous when a comprehensive monitoring action is not possible either. Considering a load profile $P_L(\tau)$ is available over a specific period which represents the basic data window. The consumption pattern could be constant or assumed to have some slight changes over the original one (e.g., over the specified period), in which the load of the next window can be described as a term of the main window but including a scaling factor and time delay, then the load profile for the next day can be mathematically formulated as in Equ. (2.1):

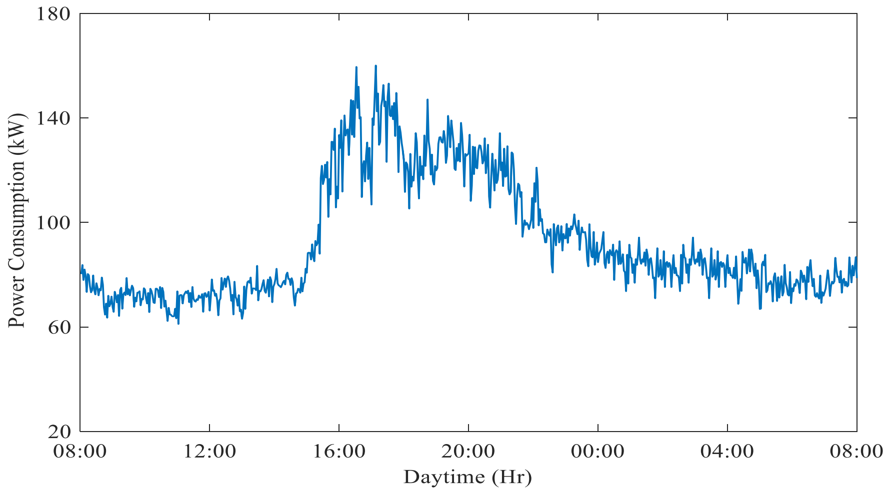
$$P'_L(\tau) = \alpha^i P_L(\tau + \beta^i) \tag{2.1}$$

Where:

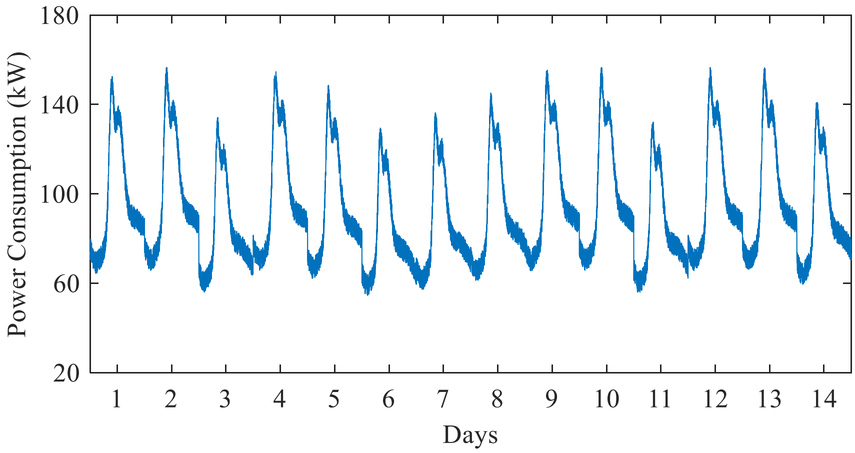
α^i is the weighting factor indicating the uncertainties of the power demand of the next window (day) referred to the basic data window, i.e. if its value is equal to 1.15 this means that the whole load profile of the day I is 1.15 times the basic load profile.

B^i is the shifting factor representing the global shift over the next day referred to the basic day.

These two factors are generated using uniformly distributed random variables within a proper range of uncertainty. Figure 2.4 presents a sample load profile with the corresponding generated profile over 14 days for the purpose of simulation in later chapters.



(a)



(b)

Figure 2.4: Sample load profile: (a) Basic load profile (b) Generated load profile over two weeks

2.3.2 *Main Grid*

The main grid can have two states: ON (available) and OFF (unavailable) and can supply the load adequately whenever it is in ON state. However, a frequent power outage can occur because of insufficient energy resources or/and restriction on the logistics, which requires another standby supply. Such a timely grid behavior is depicted in Figure 2.5. These outages can be scheduled in advance or take place unexpectedly due to unpredictable faults. At the PCC with the main grid, only a unidirectional power flow from the main grid to the microgrid can be occurred (cf. Figure 2.2). That is, the residual PV power will not be fed to the main grid. Consequently, power quality compliancy with the main grid is no issue in this context.

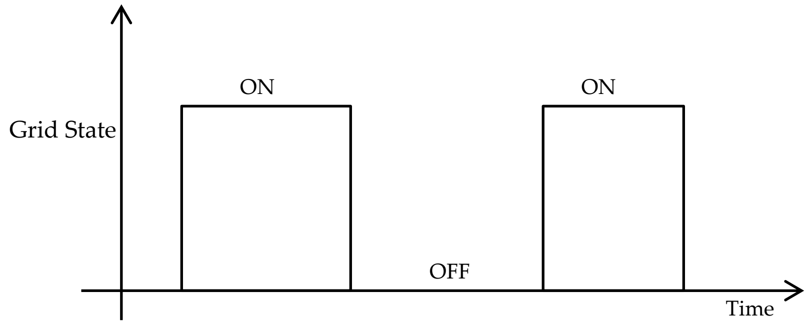


Figure 2.5: Binary grid states (ON and OFF)

One scenario is that the grid outages can be scheduled in advance according to the energy deficit and the public are informed about the time zones in which the outage will take place. In other circumstances, outages may occur unexpectedly without prior notice, due to uneven measures or unpredictable faults. In such cases, the outages may obey a uniform probability distribution $T_n \in \{T_1, T_2, T_3, \ldots, T_N\}$. Therefore, the probability of occurrence of each duration in T_n equals ($1/N$).

Without loss of generality, other synthetic distributions can be used to model outages of a certain utility according to the given records and measures. The grid is classic and supports only one-way flow of electricity, means that it cannot handle the surplus RES. In case of isolated MG, the grid will simply be considered OFF all the time.

2.3.3 *PV array*

The output power of the photovoltaic array (P_{PV}) is the total sum of the generated power of each panel at standard test conditions (STC) considering the actual irradiance in the field and ambient temperature as well. The applied model adopts equation (2.2) as follows:

$$P_{PV} = N_{PV} P_{STC} \frac{G_s}{G_{STC}} [1 + \vartheta(T_s - T_{STC})] \tag{2.2}$$

where P_{PV}, N_{PV}, P_{STC}, G_s, G_{STC}, ϑ, T_s, and T_{STC} are the output power from a the PV array at the maximum power point (MPP), the total number of PV-modules that composed the solar plant, the rated PV power at the MPP and STC, the irradiance level at the operating point and at the STC, the power temperature coefficient at MPP, the panel temperature, and the temperature at the STC, respectively.

The measure conditions at the STC are: G_{STC} = 1000 W/m², T_{STC} = 25°C, and relative atmospheric optical quality is AM1.5. Note that the output from the *PV array* are connected directly to a dc-dc power converter which has inside a maximum power point tracking unit (MPPT) to maximize power extraction under the different operational conditions.

The panel temperature T_s is of course related to the ambient temperature T_{amb} and the nominal operating cell temperature NOCT. It can be derived using equation (2.3) as follows:

$$T_s = T_{amb} + \frac{G_s}{800} \times (NOCT - 20) \tag{2.3}$$

Further details regarding the applied model can be found in [DjBw2013].

2.3.4 *Battery Bank*

The battery bank, is the most essential part of most microgrids. It is, therefore, necessary to have a well-sized battery bank in order to ensure that the power supplied by RESs during high generation periods will be available when the load requires it [MaY2014]. The strategy of managing batteries can significantly impact the performance of the overall system. The following condition is imposed to limit the power in/out flows of the battery:

$$|P_B| \leq P_B^{max} \tag{2.4}$$

where P_B is the power thrown from or injected into the battery. It is positive at discharging and negative at charging. It should not exceed a predefined limit in, P_B^{max} all modes of operation in order to slow down the degradation process [Jen2008]. Besides, another variable that should be kept within a certain range is the state of charge (*SoC*). It can be expressed as:

$$SoC(\tau) = \frac{E_{Bat}(\tau)}{C_{Bat}} \tag{2.5}$$

$$SoC_{min} \leq SOC \leq SoC_{max} \tag{2.6}$$

where E_{Bat}, C_{Bat}, SoC_{min} and SoC_{max} are the actual energy stored in the battery at time τ, the total energy capacity of the battery, and the minimum and maximum allowed state of charge of lead-acid batteries, respectively.

The SoC value at time $(\tau + \Delta)$ is determined by the SoC value at time τ and the battery power during the time period. It can be expressed by the following equations:

$$E_{Bat}(\tau + \Delta) = E_{Bat}(\tau) - P_{Bat}(\tau) \times \Delta \tag{2.7}$$

$$SoC(\tau + \Delta) = SoC(\tau) - \frac{P_{Bat}(\tau)}{C_{Bat}} \times \Delta \tag{2.8}$$

The charging efficiency and discharging efficiency are both assumed to be $\eta_b = 95$ %. [PwrSnc].

Another important factor is the cumulative damage of the battery (C_D), which can be estimated by calculating the total cycles pass through the battery.

In particular, the number of cycles to failure (C_{FL}) which defines the total lifetime of the battery is the core factor to estimate C_D. It depends mainly on how many cycles are passed through the battery and how deep these cycles are, namely, the depth of discharge (DoD).

Basically, if a single cycle consumes (1/ C_{FL}) of the whole life, then C_D will become equal to unity after C_{FL} similar cycles and the battery will need to be replaced [VreP2011]. For example, if the battery bank goes annually through K cycles, then the cumulative annual damage is equal to:

$$\mathrm{C}_D = K(1/C_{FL}) \tag{2.9}$$

This factor is also essential from an economical point of view to know the number of storage unit replacement over the project period. Figure 2.6 shows the cycling behavior of a commercial battery used for solar application under ideal operating conditions.

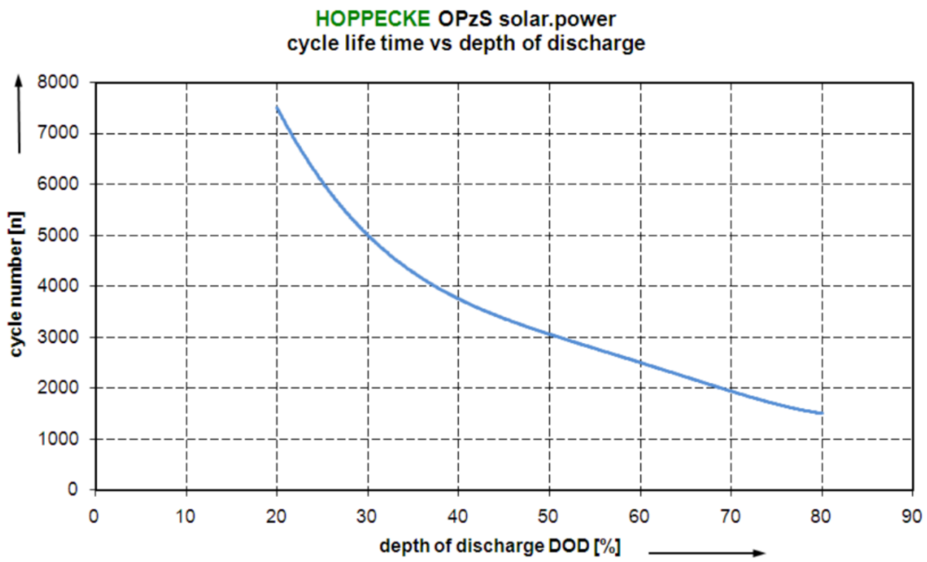


Figure 2.6: Cycle lifetime of a commercial OPzS battery as a function of DoC (at 20 ºC)

2.3.5 *Diesel Generator*

The diesel generator is the elementary component of the legacy system and acts as a backup power supply in case of power outage or a complete disconnection from the utility grid. On the other hand, it will assist the rest of microgrid's components in case of insufficient power production or weak charge in the storage system. The point of interest here is the driver or the power provider which is the fuel. The relation between power production and fuel consumption can be described using the fuel consumption chart of the diesel Generator [MoP2014].

Mathematically, it can be modeled as a linear or quadratic function in accordance with the given fuel consumption chart by the manufacturers [Dss2018]. The total fuel cost results from the integration of the fuel consumption over the time. Equation (2.10), (2.11) and (2.12) represent the generation limits, the total fuel consumption (F_c) in Liters and the fuel cost.

$$P_{Gen}^{min} \leq P_{Gen} \leq P_{Gen}^{max} \tag{2.10}$$

$$F_c(P) = \sum (aP^2 + bP + c) \times \Delta \tag{2.11}$$

$$Fuel\ Cost = D_c F_c(P) \tag{2.12}$$

Observably, the power generation efficiency of the diesel generator is affected by its loading factor (i.e., generated power w.r.t nominal capacity).

Figure 2.7 shows the chart of energy efficiency in (kWh/L) of a typical diesel generator of 250 kW as a function of its loading factor. It can be noted that when the DG operates near 20% of its rated power, the efficient generated energy is about 2.3 kWh per one liter of fuel. Theoretically, according to the given model, the maximum reachable fuel efficiency is about 3.4 kWh/L and corresponds to about 80% of its rated power. Obviously, this results in a great fuel saving; thus a good efficiency may be obtained if the DG operates close to a higher load factors. This result is largely consistent with the conclusion of [Asha1999] saying that DGs have typically a maximum fuel efficiency of about 0.33 L/kWh when run above 80% of its rated power.

Observable, the diesel price per energy unit is getting cheaper at higher generation levels as the generation efficiency is increasing. However, it is recommended to leave a safety margin before the highest possible generation limit P_{Gen}^{max} as a compromise of lifetime and instantaneous efficiency from one side and in order not to put too much stress on the generator in case of extensive operation time, here it's chosen at 85% loading factor and denoted by P_{Gen}^{best}.

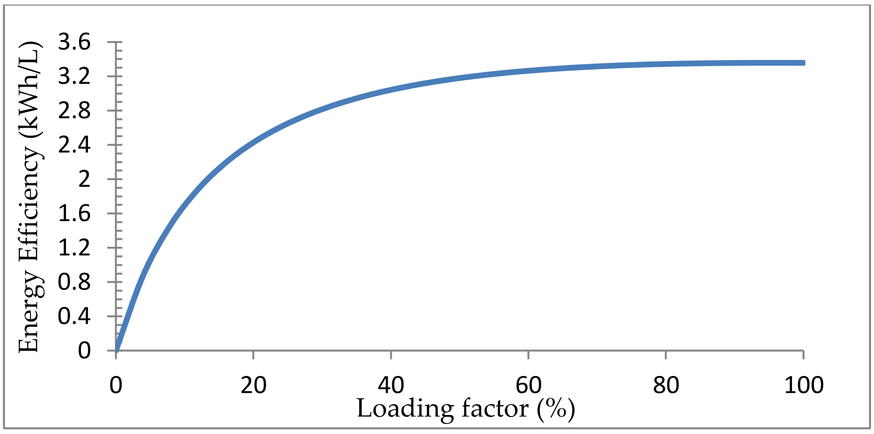


Figure 2.7: Diesel generator efficiency characteristics

2.3.6 Power Inverter:

A bi-directional power inverter is assumed to perform the needed power conversion between AC and DC buses. The following equation describes an abstract model of the used inverter:

$$P_{out} = \eta_c P_{in} \tag{2.12}$$

where η_c is the efficiency of the power conversion.

Other approaches, such as in [RifB2011], provided a more detailed model formulating the efficiency of the power inverter as a function of the input normalized power, where losses are assumed to be a quadratic function. Figure 2.8 shows the efficiency curve measured and modeled from identification. The average error is 0.17%.

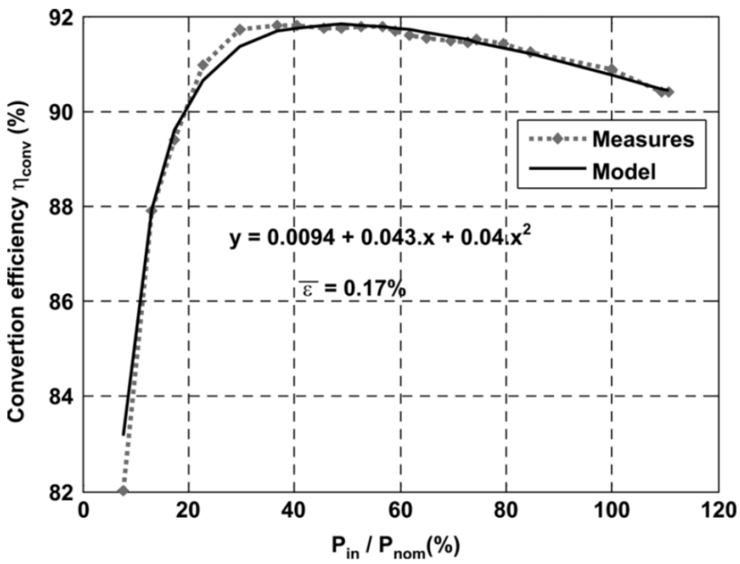


Figure 2.8: Measures and identified converter efficiency curves [RifB2011].

2.4 Description of the Case Study

As introduced in the first chapter, this work is not oriented for a specific case only but can be transformed to other environments according to the given requirements. Nevertheless, it is not that simple to give a clear perception of the subject without elaborating by a real example. For this reason, the presented case here will serve this purpose by incorporating the aforementioned components in a one complete microgrid system and the discussion later on will be on how to manage the operation of these components optimally without violating the predefined operation constraints.

The considered case has been discussed in [MuKg2011], where a hybrid wind-diesel power supply was proposed to cover a load profile of a hospital building in a more sustainable way. The region is suffering from an energy crisis which adversely affects the power supply of the hospital. A brief overview of the energy sector in that region will be presented firstly, followed by a detailed description of the case under consideration and finally the current applied energy management scheme of the existing backup power system there is going to be presented.

2.4.1 *Energy Sector in Gaza-Strip*

Gaza-Strip is located in the South-West of Palestine. Its total area is estimated at 360 km^2. Gaza city is the major province in Gaza-Strip. It has one of the highest population densities and overall growth rates in the world with its small total area of 45 square kilometers [CiAwb]. According to the United Nation Office for the Coordination of Humanitarian Affairs (OCHA) [OCHA2017]. Gaza-strip is supplied by electricity mainly through three parties, namely: Gaza Power Plant (GPP), Egyptian lines (EL), and Israeli Electricity Company (IEC). A detailed illustration of the power supply showing the distribution of the these lines and the power demand and deficit is shown in Figure 2.9, according to the situation in August 2014.

As depicted, Gaza-strip is suffering from an insufficient and irregular power supply. According to the latest information by the Gaza Electricity Distribution Company (GEDCO), the official body in charge of electricity supply in the Gaza Strip, power supply and deficit in Gaza-Strip can be summarized by the diagram in Figure 2.10.

The impact of power outage in Gaza-Strip makes it difficult for GEDCO to schedule the supply and distribute it in a proper way. Therefore, the authority in corporation with GEDCO use to schedule or recirculate the supply between the different zones according to the availability of power feeding lines. Depending on the status of GPP, the daily average time of power-outage in all zones in Gaza-Strip may exceed twenty hours; including hospitals and clinics. Further information about the energy sector in Gaza-Strip and the origin of the problem up to August 2014 is covered in [WeS2009].

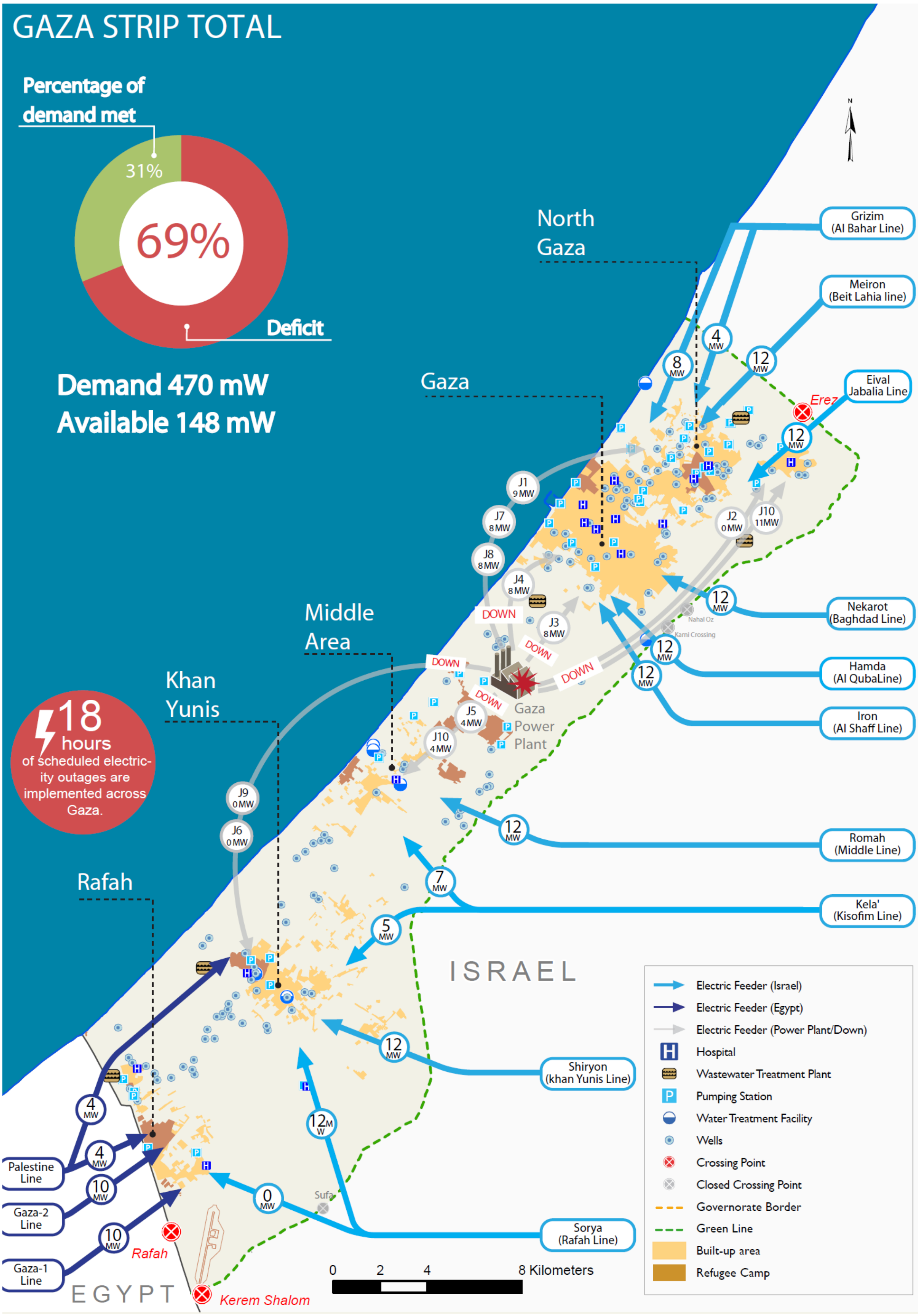
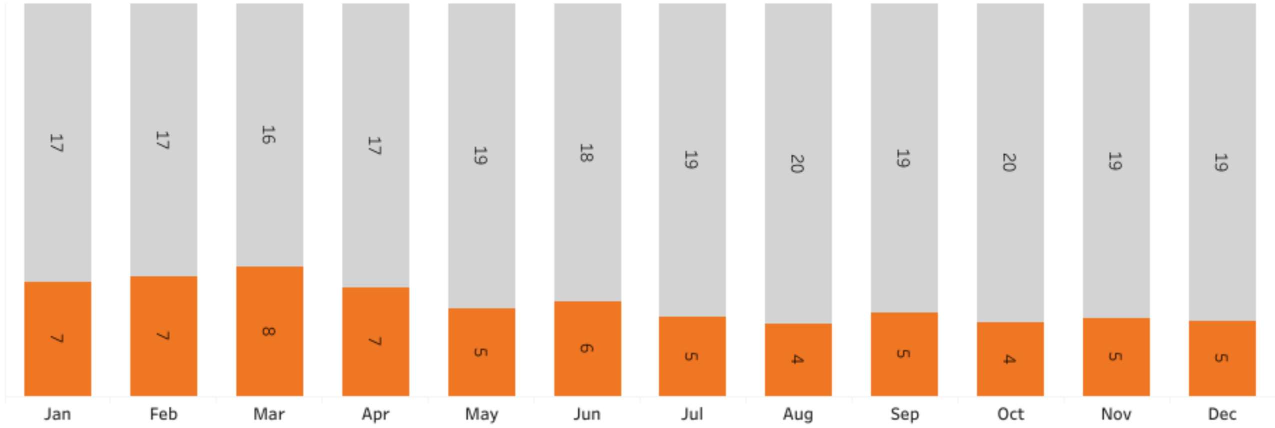
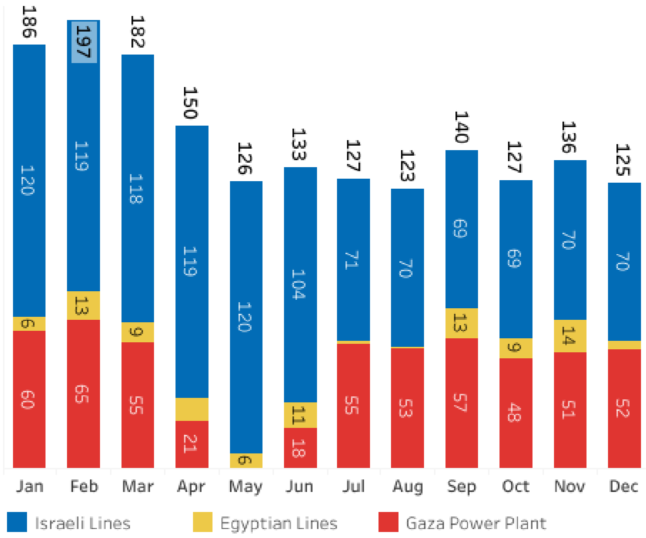


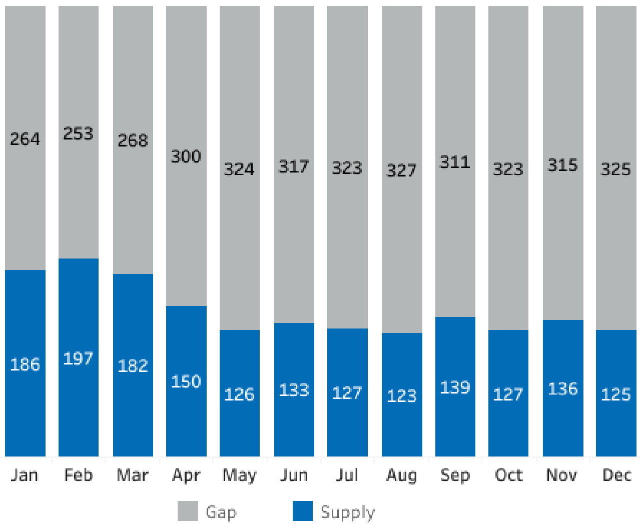
Figure 2.9: Gaza-strip map with electricity supply in details [OCHA]



(a)



(b)



(c)

Figure 2.10: Gaza-strip electricity supply, [OCHA]
(a) Availability of electricity per month (average hours per day),
(b) Electricity supply per month (average megawatts), (c) Supply vs. demand (average megawatts)

2.4.2 *Al-Shifa' Hospital in Gaza-city*

Al-Shifa' Hospital is the largest healthcare complex in Gaza-Strip. It has more than 600 beds and serves more than 40 % of the population of Gaza-Strip [MuKg2011]. It consists of more than 20 buildings and provides diagnostic, surgical care, emergency medical care, intensive care, hospitality and labs. In addition to that it provides also general services such as laundry, food preparation with delivery and personal cafeteria.

The hospital complex is supplied by medium voltage level (22 kV) from GEDCo through two different feeding lines which are located in the northern and southern side of the hospital. Each feeding line supplies two parallel MV-LV (22 kV/400 V – 0.85 MVA) three phase transformers equipped into the two sub-stations as depicted in Figure 2.11

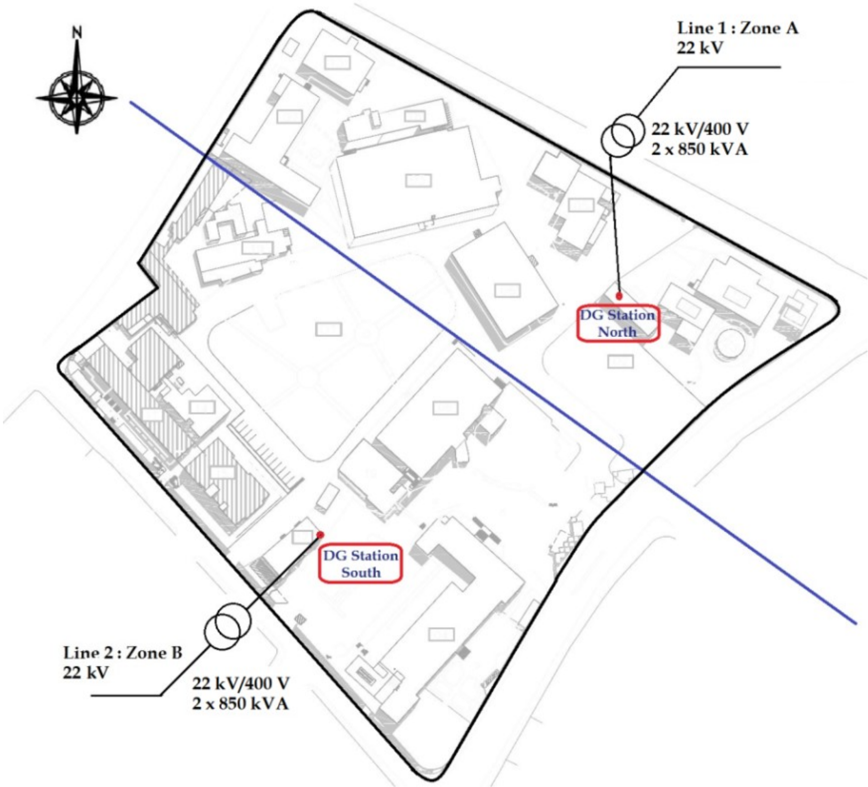


Figure 2.11: Al-Shifa' Hospital's power supplies [SkMoH]

Every sub-station is responsible of a group of buildings representing half of the hospital's total electric demand. Additionally, each sub-station is equipped with a group of different capacities' diesel generators (Standby Station N/S) that serve as an emergency power supply system to cover the essential loads when the grid is unavailable.

Indeed, no other options are available to increase the capacity of any of the feeding lines in order to meet all hospital's demand every time sufficiently; where the grid cannot maintain an acceptable voltage level at such high peak demand; otherwise, a huge modification need to be done on the grid which means great investment cost and longtime of operations with scarce income to both authority and distribution company.

The inevitable consequence of frequent and prolonged power outage, the administration of the hospital with the consultant of engineering office stores diesel in special tanks inside the hospital complex to operate the backup diesel generators when the grid is unavailable. These tanks are prepared to store enough fuel to operate generators for one week of regular power cut-off 12 hours/day in order to operate the essential loads normally. The authority in

Gaza-Strip gives the first priority to hospitals and healthcare facilities to supply them by enough fuel to face the daily exacerbated challenge, but in the time of conflicts it becomes impossible for authority to buy fuel directly.

Therefore, civil society organizations used to help as much as they can. 10 years ago, the total rated power of each backup generator set at the two sub-stations was not more than 650 kVA, but the electricity crisis started sharply after 2006, when the local power plant was partially destroyed [WiAlshifa]. Accordingly, the general administration of engineering and maintenance there started to increase the capacity of generators to cover the increasing load and to be on the safe side from the frequent power failure. In addition, during a prolonged power outage, some normally non-essential services become essential, such as laundry, catering or steam supply; these facilities cannot be stopped more than 16 hours in a daily routine. Further clarification about how the engineering team there tries to beat the absence of grid electricity every day is presented in the following subsection.

2.4.3 Existing Energy Management Experience

While load shedding of the hospitals in Gaza becomes a daily routine, all electric loads in the hospital complex are subdivided into three categories according to the level of importance as follows:

1. Essential loads (***EL***): These loads are essential to the life safety, critical patient care, and the effective operation of the healthcare facility, and these loads are supplied by the complete backup generators when the utility turns off to maintain the continuity of the basic services in the hospital and keep the patient comfort at an acceptable degree.
2. Very Important loads (***VIL***): This group of loads has a more sensitivity degree than the previous group and cannot wait for longer time till the supply is back. The included loads are automatically supplied by alternate power sources to supply any of them at any interruption even if short period; usually those types of loads are equipped with uninterruptable power supply (UPS) which can maintain good supply during a certain period of time (maximum 10 minutes).
3. Non-essential loads (***NEL***): They express the remaining loads after subtracting EL from all loads. They are not deemed essential to life safety, or the necessary operation for the healthcare facility, such as offices' air conditioning, incinerator, general lighting, general lab equipment, service elevators, and patient care areas which are not required to be backed up with an alternate source of power. However, they must run sometimes in a weekly manner to keep the patient care at a good situation.

In light of this information, the power system availability in Gaza's hospitals can be divided into three levels according to the available:

- The green level: when grid is available and the backup diesel generators are ready to operate without considerable concern about diesel transportation and logistics.
- The yellow level: when the grid is unavailable but the backup diesel generators can supply the essential load without fuel-logistic problems.
- The red level: when the grid is unavailable and there is a scarcity in fuel supply due to blocking in boarders or ports as occurred in conflicts.

The critical equipment such as in laboratories or clinics that are serious for a power outage even of a short period of time (10 minutes maximum) are supplied by special (UPS) systems. A set of UPS's are distributed on some critical buildings such as: Dialysis, Neonatal Care, Intensive Care Units, operatory rooms and some special diagnostic rooms.

The existing load management program in Al-Shifa' hospital can be described as the flowchart in Figure 2.12, where the first priority to supply all loads in hospital is given for the grid, then if there is no "emergency" and the grid is unavailable; the essential loads are supplied in the daytime by a larger generator set (GenSet 1) while they are supplied by smaller generator set (GenSet 2) in the nighttime [SkMoH].

The presented flowchart represents the developed scheme by the site engineering team of how they are managing the available power sources to supply different groups of loads in the hospital during the daytime considering the availability of the grid or the status of fuel supply. The term "***emergency***" is defined to deem an expected scarcity in fuel supply during blockades or conflicts. This means that the backup generators are available but the fuel supply is not; that is why they used to operate the least group of essential loads. Therefore, the ***VIL group*** should be maintained all the time.

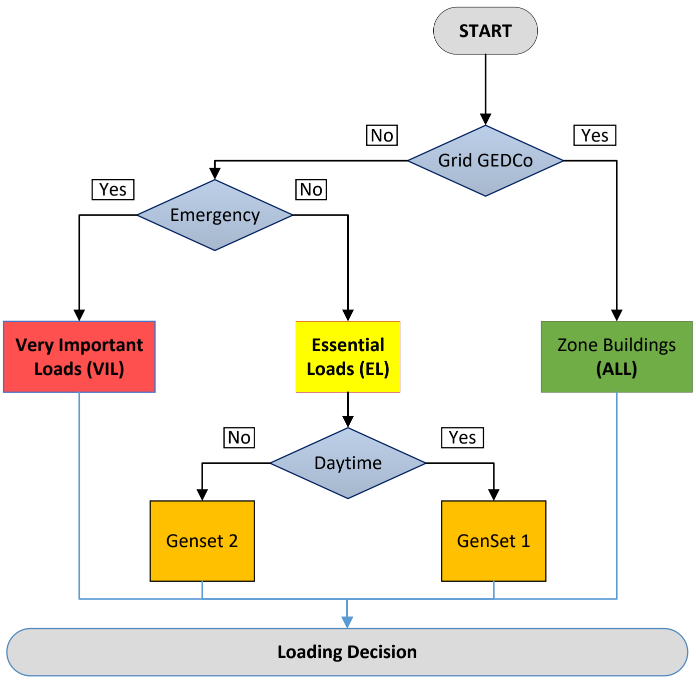


Figure 2.12: Loading decision at different circumstances.

This is done according to the experience of the operation engineers to save fuel and increase the life time of the two generator sets; where they prefer to maintain the loading factor to a certain generator round 85% and not less than 60 % of its rated capacity. In addition, it is well known that the majority of loads will be online at the daytime, which means that greater capacity is needed.

This is done according to the recommendation of several diesel generators' manufacturers, that the power generation limits of diesel generators correspond to the efficient fuel consumption [Asha1999].

Unfortunately, the existing infrastructure does not support an efficient energy management program as no monitoring-recording system has been installed yet; neither for the total consumption of the buildings inside hospital nor for a certain group of critical facilities.

Moreover, it lacks break-down details of electrical energy consumption for different loads. The availability of such a monitoring system can provide detailed load shapes of all different facilities, which are of great interest for the following reasons:

- Evaluating the consumption percentage of each load category according to the corresponding criticality rank.
- Auditing the total numbers of power failure or blackouts within a certain period of time, (yearly/monthly/weekly or even daily based).
- Following up the responding of backup system to the frequent power failures.
- Forecasting the load of different categories according to their historical behavior.
- Facilitating the prediction of the possible impact of the applied energy management strategies.

3 Energy Management Strategies

Energy Management Strategies (EMSs) for Microgrids *provide the key to ensure not only a cost-effective but also an adaptable operation to the actual measurements. This chapter highlights the major EMSs applied in this regard. It explores two approaches for power routing in microgrids incorporating solar generation as an example of RES, battery energy storage system (BESS), and a diesel generator, in addition to a unidirectional grid in case of grid-connected system. The first approach is conventionally known as a rule-based EMS, and the second one is a prediction-based which also known as an optimization-based EMS. Furthermore, this chapter presents also a hybrid method for the purpose of adaptation with the new measurements, which make use of both previous approaches to tackle the prediction uncertainty efficiently. Finally, a brief demonstration of an advanced EMS is presented, which is more resilient to the forecasting error and has the ability to realize the new configuration in a shorter time.*

3.1 Introduction

The continuous depletion of the fossil fuel and the global concerns about emission control along with the needs for affordable power supply, all together bring out the hybrid microgrids as promising alternative of the existing conventional power generation [Lr2002]. Such hybrid systems integrate a cluster of micro-sources, storage systems and loads, which can operate as a single entity [MicaG2015]. However, to supply the load demand efficiently in the most clean and economical way, the different incorporated energy resources must be managed in an optimal manner [Lr2002].

Optimal EMS of a microgrid appears as a challenging problem because of the associated challenges with the prediction. Namely, the fluctuating nature of the renewable energy resources (RES) and the unpredictable part of the load demand. Therefore, a certain degree of prediction is obviously needed to facilitate an optimal power coordination. In spite of that, finding the optimal solution for this problem is actually challenging and is still an active field of research because of the involved difficulties in solving such an optimization problem. The major challenge is that, the associated continuous and discrete variables are to be fixed. Fundamentally, defining the optimal switching time of each individual energy source to supply the load and finding the associated power transactions among them. Furthermore, a proper solution to this problem should also take care of maximizing the net utilization of the installed RES and meanwhile minimizing the operational costs of other conventional generation sources.

In the light of all these challenges, one can realize that a perfect EMS of a microgrid, such as the considered one in this thesis, should first and foremost coordinate the generated power of the conventional generation, the charging and discharging power of BESS, and the generated power RES, in order to match the load demand according to certain optimization criteria.

3.1.1 *Related works*

The literature is rich with the applied approaches for the purpose of power coordination in microgrids. Because of its simplicity, the so-called rule-based EMS is mostly applied. However, it cannot afford different objectives simultaneously. It is only oriented to cover the requested load based on some logical assumptions made to compare and decide on the least instantaneous price of available power from each generation element in the microgrid.

On the other hand, optimization-based approaches are mostly applied when a highly accurate feeding of prediction is available of both generation and load [ref]. In this sense, the most common technique used to solve this optimization problem is the linear programming (LP) [HpWB2009]. However, it can only handle linearly formulated systems, which is not always applied to such systems incorporate diesel generators of a quadratic function or contain other elements with nonlinear functions. Other approaches used mixed-integer LP (MILP) [PaGl2001], which are efficient to tackle the incorporated binary variables. Yet, the main limitations towards applying such a general method to solve this problem is the need for deploying the General Algebraic Modeling System (GAMS), or/and CPLEX which are commercial solvers mostly used for such problems [ZaES2012]. Obviously, these methods need further assistance to be able to reconfigure the microgrid and adapt the solution continuously according to actual measurement [RiBP2011].

For this reason, a simple but effective method should be developed in order to tackle the different operational constraints of the system and achieve the optimization requirements more efficiently.

Modern control approaches such as Rolling or Receding Horizon (RH) make use of optimization-based techniques and allow to tackle multiple objectives simultaneously [OlMe2014], [BjTS2010]. These approaches are essentially identical to Model Predictive Control (MPC) control where a rolling window is used for an optimization routine at each iteration of the controller. The optimization portion can be formulated as a Mixed Integer Linear Program (MILP) [HtLJ2011] or take on a nonlinear form [MfKh2007]. A comparison of a similar heuristic algorithm and an MPC based EMS has been performed in [PaRG2014], where the authors compare the total costs of an experimental microgrid in Athens, Greece. These approaches can efficiently deal with economics, battery aging, controllable loads, and many other important objectives concurrently. The reader is referred to [RaMS2013] for a review of energy management techniques for microgrids.

In this chapter, these two approaches are going to be presented and discussed for active power coordination for cost-efficient operation of a microgrid system consisting of PV, BESS, diesel generator in addition to a unidirectional and frequently interrupting grid that cannot buy or accept the surplus RES generation.

3.2 Rule-Based EMS

Rule-Based EMS is the simplest way to coordinate the power in microgrid. It represents in fact a natural evolution of the binary decision process, where one has to choose between two alternatives in order to take the present advantage of one of them, for instance might be because of its affordable price or cleanness and eco-friendliness or even some other case-specific conditions.

Suppose that a critical load is only supplied by a single power source, which can be called the ***Main***. As this is the only available power source, the cost of energy will be obviously dominated by the power price of the ***Main.*** Besides, the natural response in case of ***Main***'s failure is to find another source to supply that load, which can be called ***Auxiliary.*** For instance, if the price ***Auxiliary*** is lower than ***Main***, then it will be of course more preferred to supply the load. *However, the tradeoff does not only exist between the price of both sources, but also between the availability of each of them.* Thus, an according to the rule of alternative cost, the cost of NOT using the ***Auxiliary*** means the absence of the needed energy source. Likewise, if we have multiple ***Auxiliaries*** with different availabilities and running costs, then we have to rethink about some judging criteria, which can be specified by a group of logical rules to assign the coming power requests in accordance with these predefined preferences.

Simply, this approach is developed by assigning a priority to each power source according to specific criterions. Usually, these criterions are purely economic but they might also consider the fuel availability, or environmental issues. Fundamentally, the approach should assign the power source that can supply the load sufficiently to take the responsibility over other sources to supply the load at the moment. The remaining operational constraints, such as generation limits of the generator or the grid capacity or the battery charge, must be of course kept unviolated.

Principally, such a method dispatches energy based on the current measurements of the available power and the state of charge of the battery and does not pay so much attention to what will happen to the system afterwards. For instance, this method has been adopted in [ZbcW2013] to coordinate the power in an off-grid system supplying a seawater desalination project in the Dongfushan Island in China. It has been also explored in [RifB2009] to manage a grid-connected system composed of PV generators, batteries storage, loads demand and a bi-directional distribution grid.

Concerning the microgrid considered in this thesis, the developed Rule-Based EMS consists of two concurrent checks, namely:

(1) the GRID-availability.
(2) the State-of-Charge check.

In all operation modes, the first priority is given to the *PV* supply and the rest of power sources come to cover the deficit. The comprehensive explanation of these two checks and their resulting decisions are given below:

1- Firstly, the utility grid is considered the ***Main*** here because of its availability and the associated power price is commonly lower than the price of using other generators. Thus, it is given the first priority after the solar generation to supply the load in case of insufficient PV generation. However, as mentioned earlier, it cannot accommodate the surplus by means of buying or feed-in tariff as other developed grid infrastructures. Nevertheless, the grid in this operation mode is supposed to charge the battery up to a certain limit SoC_{max} as long as its capacity allows.

2- Concurrently, the battery *SoC* is going to be checked whether it can supply the deficit or not. In case of grid failure or power outage and insufficient *PV* too, the battery is expected to have enough charge to supply the deficit. Subsequently, if the battery *SoC* is lower than a predefined threshold, i.e. SoC_{min}, the request can then be directed to the diesel generator as a last resort to cover the deficit.

Apparently, the ***Auxiliary*** elements are : (1) the utility grid, (2) the BESS, (3) the diesel generator. And the priority is assigned to them respectively. However, once the BESS is depleted to its lowest threshold, it cannot be discharged again without being recharged from another power source. Hence, it acts occasionally as a load during the recharging process. Therefore, in order to keep the battery *SoC*, it is allowed to charge the battery from the diesel generator once requested to supply the deficit demand. Thus, the loading factor of the diesel generator can be further increased and its associated fuel consumption efficiency will be increased accordingly, *cf. Ch. 2, diesel generator model.*

Overall, the control strategy gives the priority of power supply to RES even if it is modest comparable with diesel GenSet. Basically, the diesel GenSet operates in case of grid outage and low *SoC* of the battery to supply the load demand and charge batteries (with excess power) up to a certain point SoC_{max} according to the constraint in Equ. (2.6).

Note that two maximum threshold are chosen to stop the charging process: SoC_{stp1} is chosen to stop the charging process from RES and SoC_{stp2} is chosen to stop the charging process either from grid or from the diesel GenSet while it is running. Here, SoC_{stp2} is chosen lower than SoC_{stp1} to maximize the usage of RES rather than depend too much on the grid or the diesel GenSet.

In addition, the control strategy aims to operate the diesel GenSet in its most efficient range by keeping the loading factor as high as possible instead of fluctuation according to load, where the excess power is used to charge the battery as long as it does not violate the charging constraints or the maximum permissible loading factor of the GenSet.

In order to avoid too fast (dis)charging of the batteries, another constraint is imposed to keep the BESS healthy and prolong its lifetime, as in Equ. (2.4). Besides, high frequent changes in the state of the diesel GenSet is prevented by allowing the generator to charge the battery once operated up to the aforementioned threshold SoC_{stp2}. The design parameters such as battery (dis)charging limit P_B^{max} and capacity of diesel GenSet P_D^{max} should be carefully chosen according to the system behavior and characteristics. This issue is going to be addressed in Chapter 5, Layout-Design.

A pseudocode of the developed rule-based EMS is presented in Figure 3.1

Declare state variables: P_L^i, P_{PV}^i, P_B^i, SoC^i, G^i, P_G^i, P_D^i, F_D^i

Declare GenSet coefficients: a, b, c

Declare parameters of operational constraints: SoC_{stp1}, SoC_{stp2}, SoC_{min}, P_B^{max}, P_D^{max}

Declare time-slot, Gen. Flag, and efficiency: ΔT, η, DG_F

Net deficit $P_{Def}^i := P_L^i - \eta \times P_{PV}^i$

IF $\left(P_{Def}^i \leq P_L^i\right)$ *% surplus PV generation*

    $P_D^i := 0$

    $P_B^i := -min\left\{\left|P_{Def}^i\right|, P_B^{max}, \left(SoC_{stp1} - SoC^i\right)\right\}$

    $P_G^i := 0$

ELSE

    IF$\left(G^i == 1\right)$ *% Grid is ON*

        $P_D^i := 0$

        $P_B^i := -min\left\{P_B^{max}, \left(SoC_{stp2} - SoC^i\right)\right\}$

        $P_G^i := P_{Def}^i - \left(\frac{P_B^i}{\eta}\right)$

    ELSE *% Grid is OFF*

        $P_G^i := 0$

        IF $\left(\left(SoC^i > \left(SoC_{min} + P_{Def}^i\right)\right) \text{ AND } \left(DG_F == 0\right)\right)$

            $P_B^i := \frac{P_{Def}^i}{\eta}$ *% BESS supplies the deficit load*

            $P_D^i := 0$

        ELSE

            $P_B^i := -min\left\{\left(\eta \times \left(P_D^{max} - P_{Def}^i\right)\right), P_B^{max}, \left(SoC_{stp2} - SoC^i\right)\right\}$

            $P_D^i := P_{Def}^i - \left(\frac{P_B^i}{\eta}\right)$ *% Diesel supplies the deficit load and charge BESS*

            $DG_F := 1$

            IF $\left(SoC^i \geq SoC_{stp2}\right)$

                $DG_F := 0$ *% Diesel is shut-down*

            END IF

        END IF

    END IF

END IF

$\mathrm{SoC}^{i+1} := \mathrm{SoC}^i - \left(\frac{\mathrm{P}_\mathrm{B}^i}{\Delta\mathrm{T}}\right)$ *% SoC update*

$F_D^i := \left(a{P_D^i}^2 + bP_D^i + c\right) \times \left(\frac{1}{\Delta\mathrm{T}}\right)$ *% Incremental fuel consumption*

Figure 3.1: A pseudocode of the developed rule-based EMS

3.3 Prediction-Based EMS

Unlike the former rule-based method, modern EMSs apply optimization techniques to discover the operation schedule of the microgrid's components while keeping several predefined objectives together. However, the performance of such advanced solutions depends strongly on the accuracy of the prediction. The goal is to determine how to route the power from the different energy sources to supply the load in an efficient manner. In this contribution, a holistic EMS is developed integrating three main stages:

1- Receiving the generation and load forecast based on up-to-date historical data.
2- Initiate the optimal scheduling strategy based on the fed inputs over a certain time horizon, which is the matter of this section, *prediction-based EMS*.
3- Apply the resulted scheduling strategy to the microgrid and adapt it with the real measurements, which will be discussed in the coming section of this chapter.

An overview of the developed EMS for the purpose of the addressed microgrid system is presented in Figure 3.2

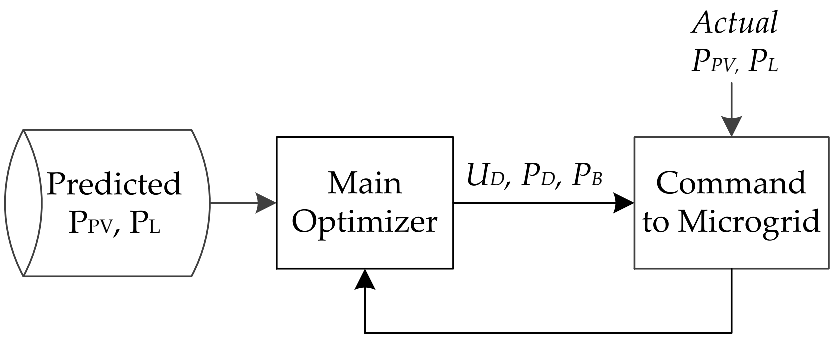


Figure 3.2: Proposed EMS overview.

In the first stage, the next day weather data and load profile are generated using a forecasting technique, based on the latest up-to-date historical data, which are going to be fed later on into the main optimizer. In this context, reliable forecasting techniques have been developed recently that can provide a highly accurate prediction [MeKs2008]. The second stage is dedicated to find out the optimal operation of the microgrid, in which, the switching time of the diesel GenSET, U_D, with its output power, P_D, and the charging/discharging power of the battery, P_B, that will result in optimum operation will be determined. In this stage, the schedule will be determined according to the fed data from the previous stage. Besides, demand response actions can be taken to further improve the system economics or/and stabilize its operation in case of any inevitable fault in the power resources. However, at present, this section focuses essentially on finding the optimal scheduling using the main optimizer in the second stage.

3.3.1 *Optimization Framework*

The addressed problem can be mathematically formulated as a multi-attribute optimization problem that seeks to provide a minimum operating costs (OC) and maximum utilization factor (UF) of a microgrid system, as well as guarantee that the operational constraints of the battery, i.e., Equ. (2.4) to (2.8), and of the diesel generator, Equ. (2.10), are not violated. Naturally, the power balance between generation and consumption must be achieved as in equation (3.1).

$$P_{PV} + \hat{U}_D \hat{P}_D + \hat{P}_B + P_L + P_{Loss} = 0 \tag{3.1}$$

Where P_D is the generated power by diesel generator, P_L is the instantaneous load demand, and P_{LOSS} is the total lost power, which are lost either in power conversion processes or not utilized because of load satisfaction and battery charge saturation. U_D denotes the status of the diesel generator. The hat refers to the controllable variables, for example the power that can be drawn from the diesel generator $\widehat{P}_D$ is controllable, however the solar generation P_{PV} is not directly controlled.

The value of OC is resulted mainly from the fuel consumption of the diesel GenSET and the purchased energy from the grid in case of a grid-connected system. Further hidden costs can be considered such as the aging of the battery and the total switching times of the diesel GenSET which will complicate the problem. For this reason, the operational limits of the battery and the generator are carefully chosen in accordance with the recommendation of the manufacturers in order to prolong their lifespan as much as possible, e.g. Equ. (2.4), (2.8) and (2.10).

By these definitions, the objective function can be then formulated as in equation (3.2) as follows:

$$J = \sum_{\tau=1}^{T} \Big(w_1 \big((U_D(\tau)) \times F_C(P_D(\tau)) \big) + w_2 \big(U_{PV}(\kappa_\tau) \big) \Big) \tag{3.2}$$

The value of U_{PV} is directly proportional with P_{LOSS}, and represents the net unutilized RES energy. It can be evaluated after applying the designated management strategy. Assuming that a nonempty set $K \neq \emptyset$ of finite integer elements $T \in \emptyset$ representing the total possible operation strategies, where $K = \{\kappa_1, \kappa_2, \kappa_3, \ldots, \kappa_T\}$, and each individual operation strategy will obviously produce a different value of U_{PV}, where:

$$U_{PV}(\kappa_\tau)\,, \quad 1 \leq \tau \leq T$$

- F_C is the fuel cost of the diesel generator corresponding to its generated power P_D
- U_D is a binary value represents the state of operation of the diesel generator at time τ
- $w_1$works as a weighting factor, whereas $w_2$works as a scaling and conversion factor that converts the unutilized RES energy into a cost, e.g. ($).

Both factors are selected upon the design preferences and can be adapted according the different operation scenarios to penalize the unutilized RES power and the usage of the diesel generator.

Obviously, the value of the objective function, (Equ. 3.2) is controlled mainly by the output power from the diesel GenSET, which is depending on the availability of the RES and battery charge, that will delay the request time of the diesel GenSET.

Therefore, the problem involves finding the operation strategy κ_τ which can bring the system to the optimal operation according to the aforementioned definitions. An operation strategy κ_τ can be defined via three main control variables, which are: $\hat{P}_D$

1- The diesel GenSET status of operation $\widehat{U}_D$
2- The diesel GenSET output power trajectory $\hat{P}_D$ corresponds to the periods of ON status.
3- Charging and discharging power trajectory $\hat{P}_B$

The developed offline optimization solution for this problem will be addressed in the following subsection.

3.3.2 *Offline Optimization*

The optimal schedule of the microgrid supply system will be explored in this work by applying the dynamic programming (DP) to minimize the overall cost over the whole prediction horizon (see Equ. 3.2). The idea of DP is to solve the multistage decision problem by dividing it into sub-problems or several steps in order to examine all possible solutions at each step and then combine these solutions in a way which leads to the best solution for the given problem. It looks for the global optimal path rather than picking locally optimal choices at each step which may result in a bad global solution. The advantage of the DP is that it can handle constraints from all the natures (linear or not, differential or not, convex or concave, etc.) and in meanwhile it does not need a specific mathematical solver to be implemented [RiBP2011]. Obviously, in our case, the state of the system at each time-slot depends on the previous state and the control variables, which can be replaced here, in the context of DP, by the transitions.

In the discrete-time format, the system model can be expressed as:

$$x(\tau + 1) = f\big(x(\tau), u(\tau)\big) \tag{3.3}$$

$x(\tau)$ is the state vector of the system, and basically it includes the value of SoC which controls the request of the diesel GenSET, and other variables which represent the rest system dynamics such as: P_{PV}, P_L.

$u(\tau)$ is the control vector and should contain the abovementioned variables that are all together controlling the selected operation strategy κ_τ. Both variables are defined explicitly as follows:

$$x(\tau) = [SoC \quad P_{PV} \quad P_L] \tag{3.4}$$

$$u(\tau) = [\hat{U}_D \quad \hat{P}_D \quad \hat{P}_B] \tag{3.5}$$

Conventionally, rule-based EMSs are applied to manage microgrid systems –as explained in the previous section–, where the diesel generator is requested to supply the load when the value of SoC goes beyond a certain limit SoC_{min} and turned off when there is sufficient RES supply or the value of SoC goes over a higher threshold SoC_{max}, the proposed method here is supposed to lead the system to the optimal trajectory by the assistance of prediction. These former strategies are priority-based and do not benefit from the prediction. Therefore, these so-called RB-based solutions, as developed also in [Hi++2016] and [RifB2009], may lead to a higher cost in the future.

In contrast, the developed approach here using DP is a prediction-based and can explore the optimal solution based on the fed forecast or planned load, so it can pick the optimal strategy κ_τ which will result in minimum objective value. Similarly, DP-based approaches have been used in the literature for the same purpose considering different objectives [RiBP2011], [BaLu2012] and [SobWu2012]. The main key for their implementation is to quantize the value of the BESS storage and consider the possible SoC states' transitions as the determinant of the solution. However, the main limitation of these methods is the high memory needs when the prediction horizon is long and discretized with a small time step [RiBP2011].

To overcome this issue, the former DP approach is enhanced here by using the status of the diesel GenSET $\hat{U}_D$ as the main coordinator to find the optimal strategy instead of using the value of SoC. By this relaxation, the operation time of the diesel GenSET will be determined firstly and then, the associated charging/discharging power trajectory of the battery can be found based on the power balance constraint, (Equ. 3.1). This approach is clearly presented by the graphical illustration of Figure 3.3.

To elaborate on the mechanism of the proposed approach, it is divided into two main stages, the first stage is to choose one of the candidate strategy κ_τ that will be fed later on, in the second stage, in order to explore its associated SoC trajectory. A candidate strategy κ_τ is a binary-elements set representing the sequence of operation of the diesel GenSET, (as in the upper part of the figure). It has the same length of the prediction horizon, (e.g, $T = 24$ time-slots).

Considering T is the total time-slots of the prediction horizon and there is two possible states of the diesel generator which define the charging status of the battery, the resulting search space is obviously 2^T.

Compared with the previously applied method in [RiBP2011], where the DP is used to select between N different levels of SoC at every time slot, the resulting number of iterations would be N^T. Therefore, the decomposition of the DP is proposed here as it enables the exploration of a wide range of strategies in a much shorter time.

In our case, less than 10^{24} iterations were examined until they converged to a solution, compared with 10^{24} if the *SoC* is quantized into ten levels. Notably, examining all strategies will result in increasing burden of computational complexity. Therefore, the infeasible solutions are firstly excluded, for instance, by eliminating the solutions which involve a prolonged discharging time of the battery because this will ultimately lead to an excessive discharging and of course passing the lower threshold SoC_{min}.

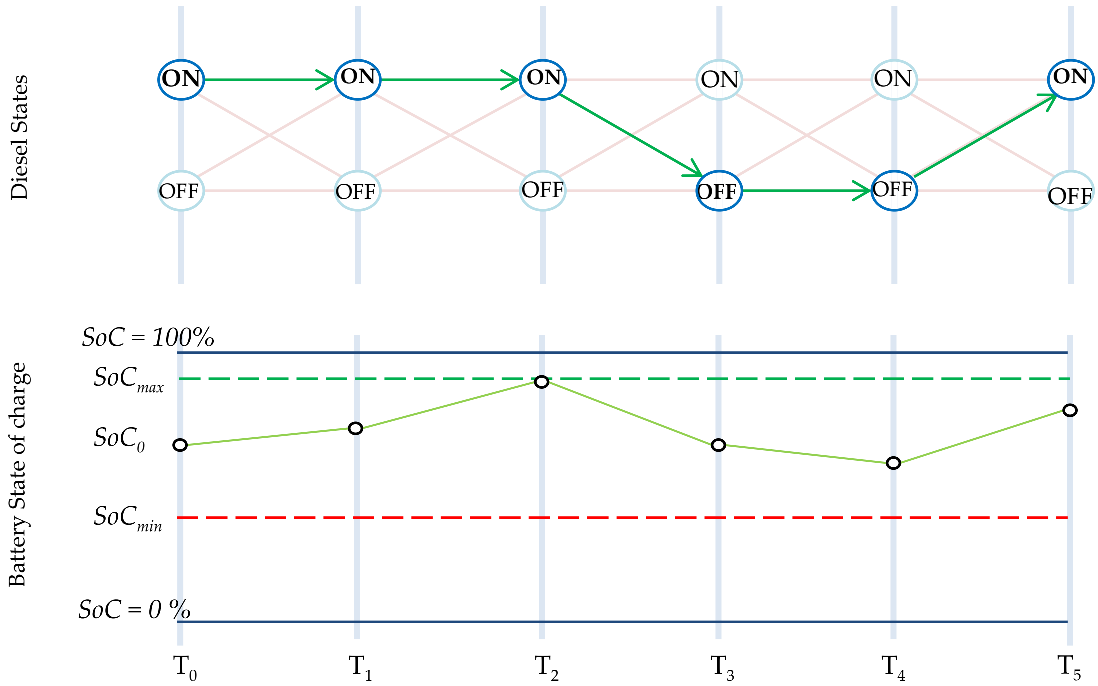


Figure 3.3: Relaxed DP searched-based EMS

3.3.3 *Adaptation with the real measurements*

Obviously, the resulting operation strategy from the previous stage, i.e. *offline optimization*, is highly dependent on the fed forecast. On the other side, the microgrid is operated with significant power fluctuating of the solar generation and the load profile as well. Thus, some reconfigurability is apparently needed to tackle the real measurements which are, of course, deviated somehow from the expected forecast, and this can be handled in the current stage.

In this stage, the scheduling operator κ_τ has the option to choose between the economic operation mode which considers a perfect prediction, and stable operation which can provide the sufficient supply to the actual net demand. Stable operation mode implies that, the derived strategy can be varied in accordance with the actual measurements of the generated *PV* power and load demand.

The selected strategy from the previous offline solution can be directly executed without adaptation either in case of economical operation mode, where the operator has to keep the derived schedule without changes, or whenever the prediction is totally perfect. However, these two conditions are rarely achieved. For this reason, we propose an autonomous adaptive operation strategy relying on the derived strategy in order to handle the expected deficit caused by lack of PV generation or/and increased demand. A pseudocode of this stage is illustrated in Figure 3.4

Declare state variables: P_L^i, P_{PV}^i, SoC^i

Declare system parameters: SoC_{min}, SoC_{max}, P_D^{min}, η, ΔT

Read a schedule $k_\tau = [U_D \quad P_D \quad P_B]$

Net deficit $P_{Def}^i := P_L^i - (\eta P_{PV}^i) - (U_D \times P_D) - dis(P_B)$

Loop

  Update P_{Def}^i

  IF $\left(\left(SoC^i - \frac{P_{Def}^i}{\eta}\right) \geq SoC_{min}\right)$

    P_D keeps *NO Change*

    BESS supplies

    $P_B = \frac{P_{Def}^i}{\eta}$

  ELSE

    $P_D = max\left(P_D^{min}, P_{Def}^i\right)$

    $P_B = \eta \times \left(P_D - P_{Def}^i\right)$

  END IF

  Update SoC := $SoC^{i+1} := SoC^i - \left(\frac{P_B^i}{\Delta T}\right)$

END Loop

Figure 3.4: A pseudocode of the adaptation stage, 3rd Block of EMS.

Firstly, the system parameters are identified in order not to violate the operation constrains and to keep the generator operated at a reasonable loading factor. The deterministic operation strategy is gathered from the previous stage of EMS and then the current measurements are fed. Consequently, a supplementary decision is taken to supply the deficit load either from BESS or diesel generator. The key determinant here is the reserve *SoC* and the deficit value. Obviously, the battery is preferred to cover the deficit if it has enough charge in order to operate the generator for short time.

However, if the diesel generator is the remaining choice because of insufficient SoC, it should not be operated at a lower loading factor than P_D^{min}.

3.4 Stochastic Optimization EMS

The optimization algorithm employs a Genetic Algorithm (GA), which is one of the metaheuristic stochastic optimization techniques that can provide a solution to an optimization problem with less computational effort than iterative ones [HiFr2018a]. Examining all strategies will result in increasing burden of computational complexity. The search space of the problem is obviously very large. Considering two possible status of the diesel generator at each time slot, the number of resulting iterations would reach (2^N) of iterations, each requiring k time-units to consider constraints, Equ. (2.4) to (2.8), (2.10), and evaluate Equ. (3.1), and (3.2). If all possible combinations will be checked; the resulting time-units will be ($T \times 2^{\mathrm{N}}$) and it is, of course, exponentially increased w.r.t chosen time horizon. Therefore, the GA is chosen as it enables the exploration of a wide range of allotted elements in a much shorter time. In our case, less than 60 generations were examined until they converged to the final solution (here: just a few seconds of computation time instead of minutes using the deterministic approach).

To improve the time performance of the algorithm, the infeasible solutions are firstly excluded by eliminating the solutions which include a prolonged discharging time of the battery because this will ultimately lead to an excessive discharging of the BESS and of course passing the lower threshold $\mathrm{SoC_{min}}$. The maximum durable discharging time, in hours, is calculated to exclude any operation strategy that will eventually lead to a wider discharging period. It is assumed that the battery bank is fully charged up the nominal capacity, e.g. E_B^{max}(kWh), and the load is the average net deficit that should be met either by the battery or the generator. This is presented by the equation 3.6

$$M = \left\lfloor \frac{E_B^{max}}{avg\left(P_{Def}\right)} \right\rfloor \tag{3.6}$$

Where M is the maximum nonstop discharging time, E_B^{max} is the nominal capacity of the battery bank in (kWh), and $avg\left(P_{Def}\right)$ is the average net deficit, in (kW).

The default settings of MATLAB-based GAs are applied to conduct the simulation. A population of chromosomes is randomly initialized (i.e., 200) in accordance to the possible number of solutions. The algorithm is supposed to be terminated when the stipulated number of generations (i.e., 500) is reached or when the magnitude in the change in fitness value does not vary more than a tolerance limit (i.e., 10^{-10}) for several subsequent generations (i.e., 50). A pseudo-code of the developed GA framework is depicted in Figure 3.5. Each selected candidate κ_τ will be examined at each generation to find out the best fitness function (Equ. 3.2).

01:	INPUTS: Set of all candidates K	
02:	Calculate M	*% maximum nonstop discharging time*
03:	Define $R = K - M$	*% Set of appropriate candidates*
04:	Select a random subset of operation strategies from R	
05:	Select the best strategy among this generation by applying Equ. 3.2 (Fitness Function)	
06:	Crossover and Mutation: Survival is for the fittest.	
07:	Terminate and Output: After exceeding the predefined time budget or achieving no improvements over the last best value for several generations.	

Figure 3.5: A pseudocode of the stochastic EMS framework.

3.5 Advanced Rolling Horizon EMS

In terms of adaptability with the new conditions and measurements of the system, the online solution is expected to be more fault-tolerant and have the ability to achieve better results than the offline one. To elaborate on this aspect, assume that the resulting offline operation strategy is going to be performed based on a prediction window of the day ahead over T time-slots, e.g., 24-points. In this case, the optimization process will be executed just once per day in order to provide the (optimal) control inputs for the next day, i.e., T time-slots $[\mathrm{k}, \mathrm{k}+1, \mathrm{k}+2, \dots, \mathrm{k}+\mathrm{T}-1]$. Accordingly, the next optimization will be performed over the next prediction window, which is $[\mathrm{k}+\mathrm{T}, \mathrm{k}+\mathrm{T}+1, \mathrm{k}+\mathrm{T}+2, \dots, \mathrm{k}+2\mathrm{T}-1]$ to provide the control inputs for the day after the current horizon. In the online scheme, however, the optimization process will be repeated at every $\mathcal{M}$ points, shorter than the full prediction horizon, i.e., $1 \leq \mathcal{M} \leq \mathrm{T}$, and therefore, the cost function will be consecutively minimized at every $\mathcal{M}$ points over this dynamic horizon. This means that the resulting optimal variables will become effective just for a few time slots from the long horizon $[1,2, \dots, \mathcal{M}]$, and the rest variables in the range $[\mathcal{M}+1, \mathcal{M}+2, \dots, \mathrm{T}]$ will be eventually neglected to start a new optimization process based on the new updates.

In conclusion, the online optimization scheme beats the time-ahead offline optimization one in terms of compensating the deviation resulting from forecasting error, where it can attain the feature of a closed-loop control system by successively updating the resulting control inputs based on the new situation.

Apparently, the deviation between the forecasted and actual measurements increases with time. Therefore, such an approach is promising to handle systems with inacuurate prediction. Figure 3.6 presents a 12-hour wind profile and the assciated sample forecast.

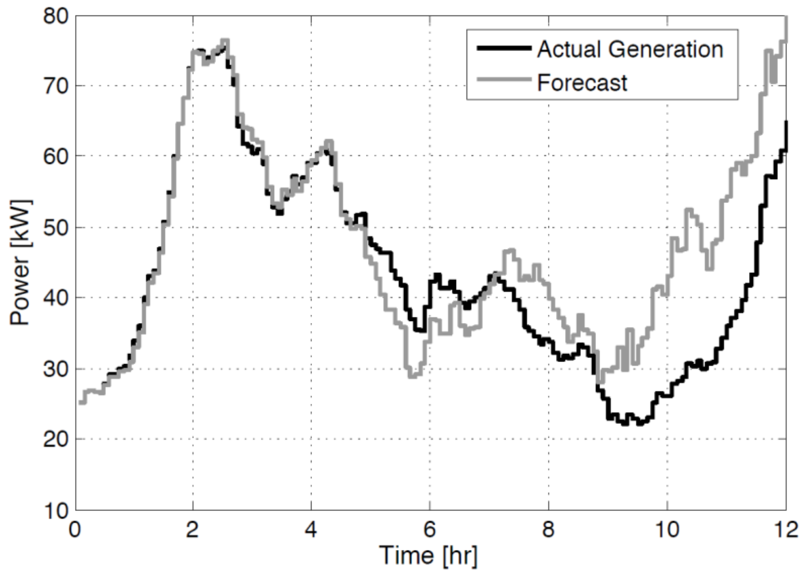


Figure 3.6: Sample forecast generated for a 12-Hr wind profile [SuGD2012]

3.6 Simulation Results

PV-BSS microgrid system used to supply the critical loads in an outpatient clinic in Gaza city is chosen to check the aforementioned approaches except the last one, i.e. Rolling Horizon. The system has been under developing over the past years to lessen the consequences of the severe power outages that Gaza-strip undergoes. The hourly-average prediction and the associated actual values of both solar generation and load demand of a single day are shown below in Figure 3.7. The simulation is firstly performed using the priority-based EMS, followed by the offline-optimization solution and finally the uncertainty is applied to check compare with the adaptation strategy as well.

The former approach, i.e., priority-based EMS, is taken as a baseline to compare the rest approaches with it and highlight the cost savings. Additionally, the net share of PV in is another important key performance factor indicates the real benefit of deploying the RES in the system and gives a better realization of the presented outcomes. It can be described by two values, the penetration level (*PL*) and the utilization factor (*UF*) which both are defined in equations (3.7) and (3.8) as follows:

$$UF = \frac{Net\ energy\ supplied\ by\ RES}{Total\ RES\ production} \times 100\% \tag{3.7}$$

$$PL = \frac{Net\ energy\ supplied\ by\ RES}{Total\ energy\ demand} \times 100\% \tag{3.8}$$

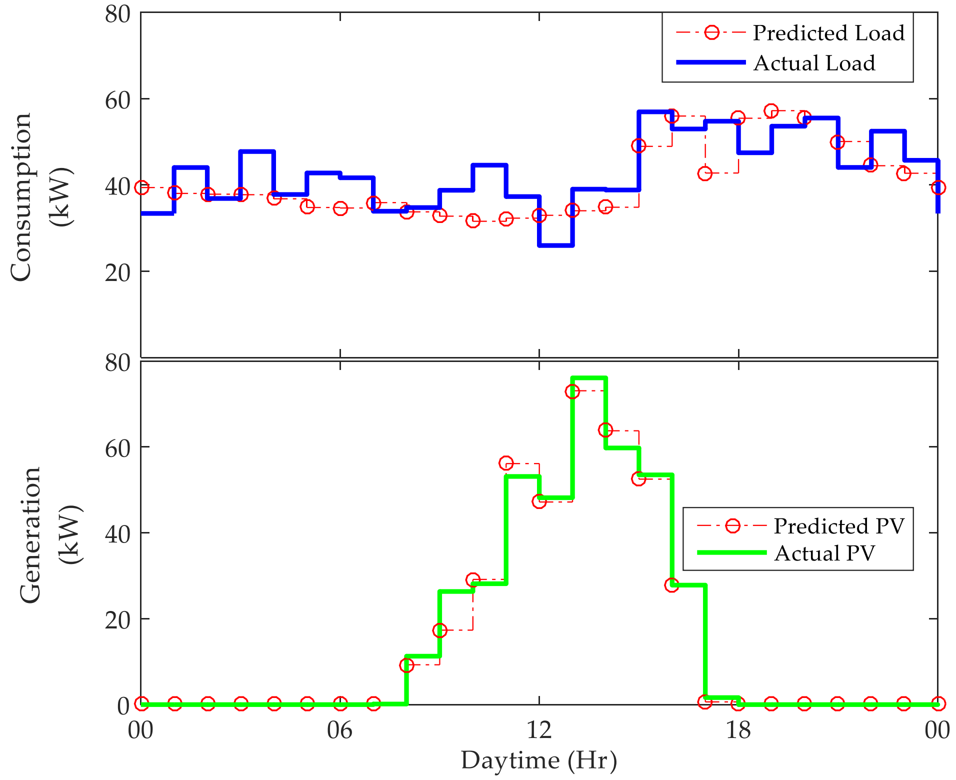


Figure 3.7: Load demand and solar generation of one sample day.

The load has a mean power consumption 41 kW with a standard deviation about 8.5 kW. The solar generation exceeds the demand between 13:00 and 16:00 o'clock. The simulation was performed on MATLAB using a PC with Intel Core i7 processor (2.1 GHz) and 12 GB RAM. All parameters used in simulation with the corresponding nomenclature and values are listed below in Table 3-1.

Table 3-1: Simulation Parameters

Parameter	Nomenclature	Value (s)
$nom.\ P_{PV}$	Nominal maximum solar power	100 kW
C_B	Battery Storage System Capacity	319 kWh
SoC_{int}	Initial state of charge	60 %
SoC_{min}	Minimum allowable state of charge	40 %
SoC_{stp}	Stop charging threshold from GenSet	90 %
SoC_{max}	Stop charging threshold from PV	100 %
η	Inverter and Battery efficiencies	95 %
P_B^{max}	Battery (dis)charging power limit	$\pm C_B/(4h)$
P_{Gen}^{max}	Diesel generator rated power	100 kW
C_f	Diesel fuel cost per liter	1.85 $/L
Δ	Time slot	1 h

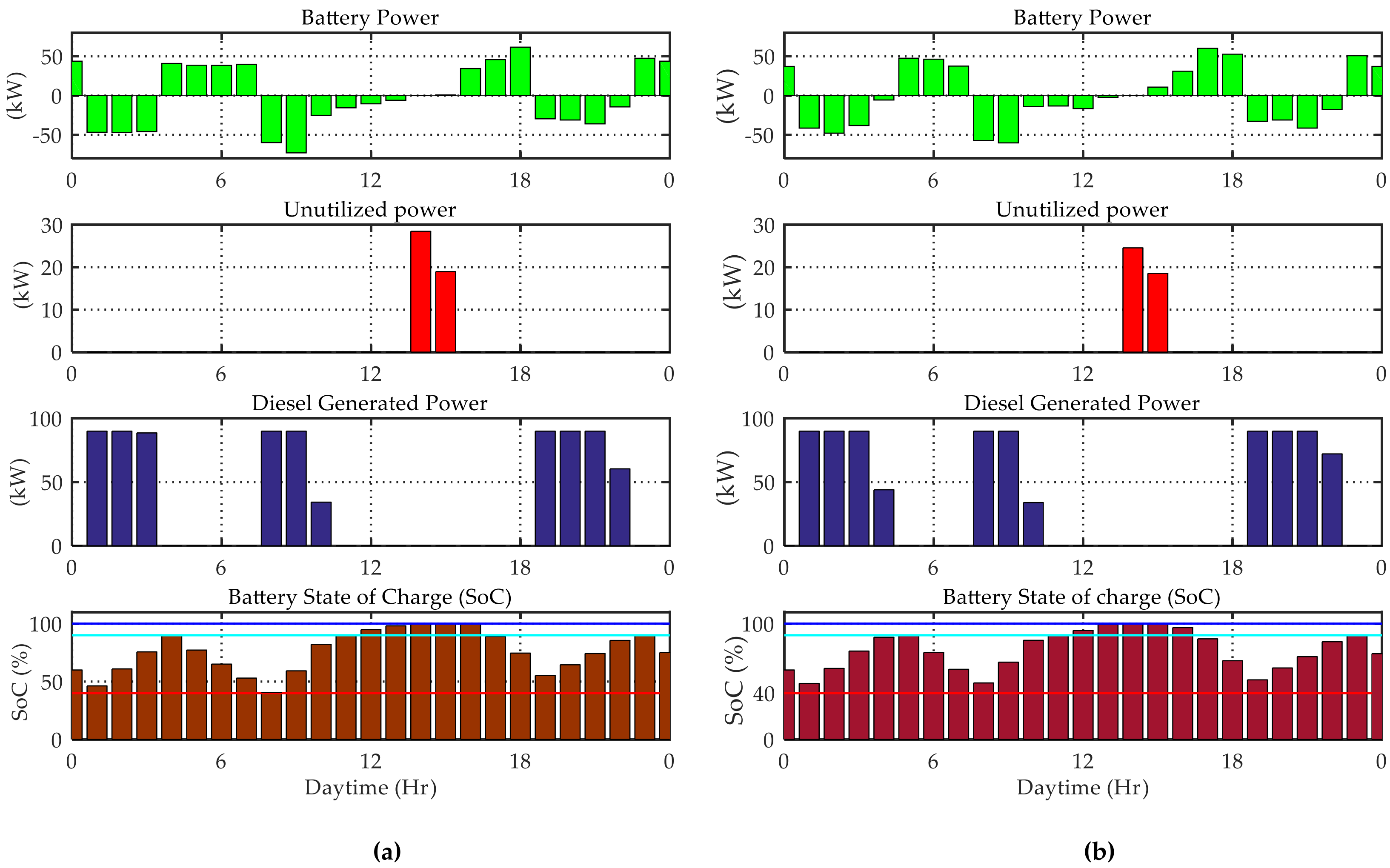


Figure 3.8: Priority-Based EMS: (a) Perfect prediction scenario, (b) Real measurements scenario Detailed power throughputs during a single day: The battery power (top), the unutilized PV power, the power output of the diesel generator w.r.t time and finally the state of charge of the battery bank (bottom)

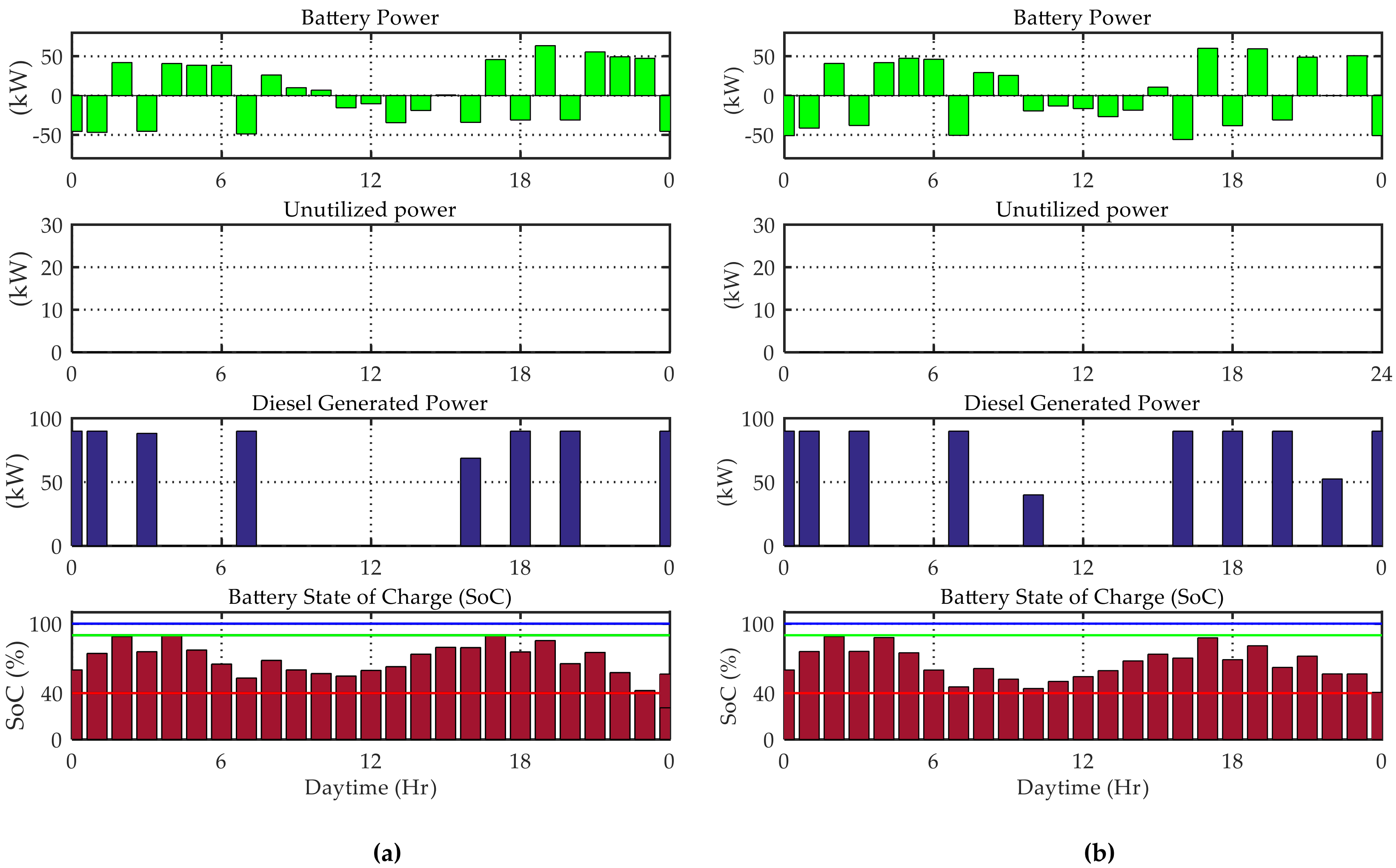
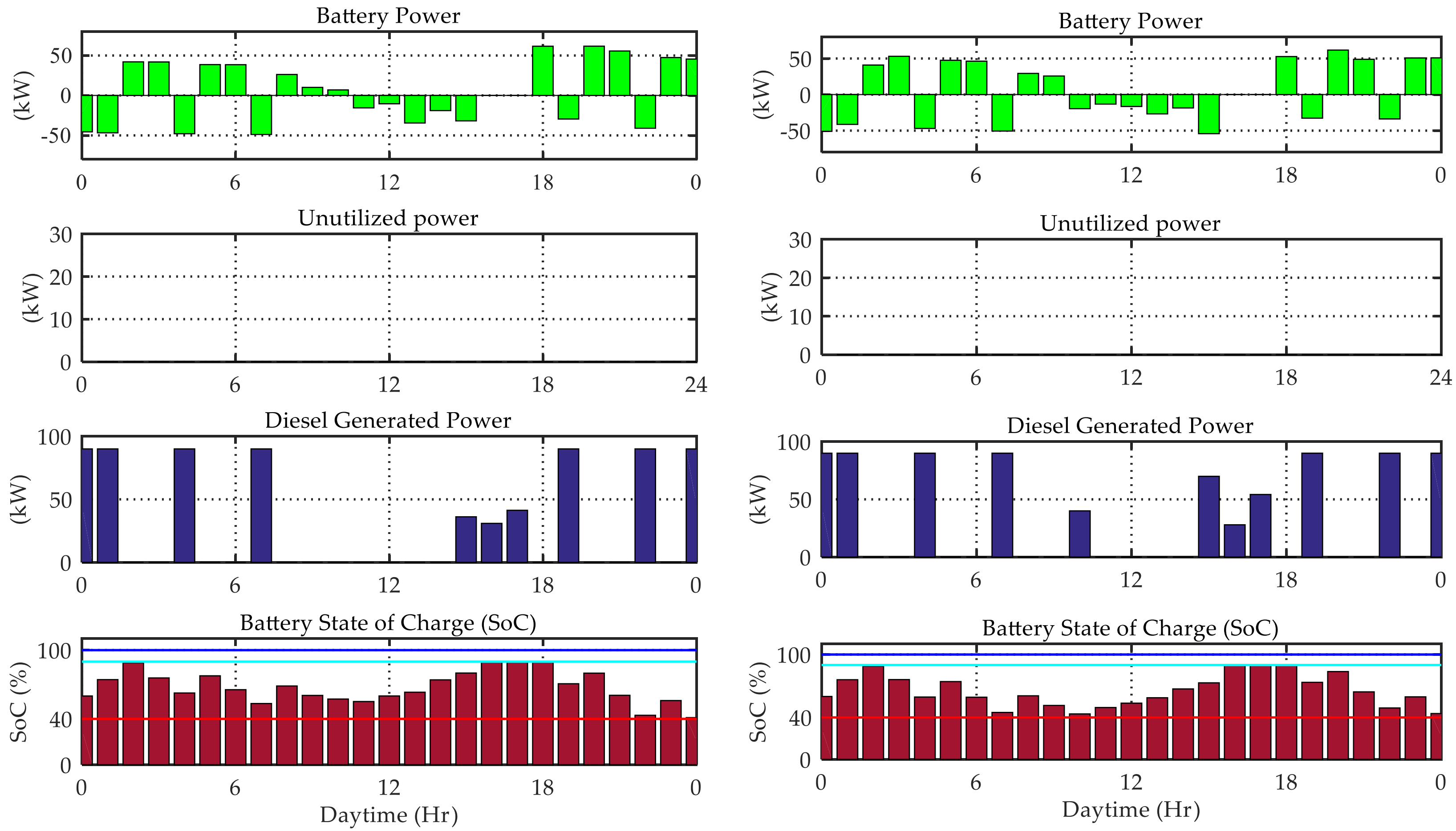


Figure 3.9: Offline-Optimization EMS: (a) Perfect prediction scenario, (b) Real measurements scenario Detailed power throughputs during a single day: The battery power (top), the unutilized PV power, the power output of the diesel generator w.r.t time and finally the state of charge of the battery bank (bottom)



(a) **(b)**

Figure 3.10: Stochastic-Optimization EMS: (a) Perfect prediction scenario, (b) Real measurements scenario Detailed power throughputs during a single day: The battery power (top), the unutilized PV power, the power output of the diesel generator w.r.t time and finally the state of charge of the battery bank (bottom)

Figure 3.8 presents the results of the former priority-based EMS considering the predicted profiles as well as the real measurements. It is noted that the results in both scenarios are similar to a large extent. However, due to the energy difference between the predicted and the real measurements, the unutilized PV energy considering the real scenario is slightly less, namely 43.12 kWh instead of 47.42. In spite of that, this amount of energy was lost during the middle of the day, at 14:00 and 15:00. Observably, at that time, the BESS was fully charged and could not accommodate the surplus PV generation. So, the battery SoC at that time went beyond the SoC_{stp2} threshold and therefore, one can recognize that the oscillation range of the associated SoC takes the interval from SoC_{min} to SoC_{stp1}. Too, in spite of the high demand at midday, it is observed that the battery was exposed to a less stress at noon than at the two ends of the day. Visibly, this can be interpreted by the higher PV production. One additional difference is the operation time of the diesel generator, where it was operated for another hour in the case of real measurements.

Figure 3.9 and 3.10 present the simulation results of the offline-optimization and stochastic-optimization EMS respectively. The simulation considered both scenarios too, the predicted and the real measurements as well. These methods are based on optimization and therefore once can recognize that the unutilized PV energy are zero, which means that only the power conversion losses exist in that case rather than the conventional method which did not benefit from much more energy in addition to the power conversion loss and thus, the battery in the prediction-based EMS is expected to have enough vacancy to absorb the emergence of surplus renewable power during the noon, i.e., between 12:00 to 17:00. However, in both cases, the operation time of the diesel generator considering the real measurements scenario is longer than the counterpart perfect prediction scenario. For instance, the operation time was eight hours considering the perfect prediction by using the offline-optimization method, where this method represent the best case scenario, as shown in Figure 3.9(a). On the other side, the generator was subject to operate at least 10 hours using the stochastic optimization solution, as shown in Figure 3.10(a). However, the increment in case of real measurements was two hours in case of the offline-optimization, and only one-hour in case of the stochastic solution.

Compared to the priority-based EMS method, as in Figure 3.8, it is observed that the oscillation range of the battery SoC was less by using the prediction-based EMS, as in Figure 3.9 and 3.10. Besides, the battery reached the upper threshold SoC_{stp2} but did not go beyond it at the evening time, when the generator was in operation.

From these figures, one can notice how the operation of both diesel generator and BESS are affected. However, the operation in the adaptive-mode was more stable because it could handle the inaccurate prediction. Therefore, there will be no need for load shedding when considering the adaptation algorithm because of the ability of handling the prediction errors.

The fuel consumption using the prediction-based approaches is still less than the consumption using the conventional priority-based method. However, in the adaptive mode, the fuel consumption is a bit greater than its counterpart in the perfect prediction case, and this is expected because the deficit difference between the two cases is about 59 kWh, where the total actual PV generation is 9 kWh lower than the predicted generation and the consumption is about 50 kWh greater than the predicted load. It is expected therefore, that this gap will be covered using the conventional generation. Obviously, the *SoC* of the BESS in both cases is softly ranging between SoC_{min} and SoC_{max}. In addition to that, a sufficient margin is kept up to the fully charged level, 100% SoC, in order to be able to accommodate any unexpected raise in solar generation.

Table 3-2: Simulation results of EMS using the prediction-data

Parameter	RB-EMS	Deterministic Prediction-Based	Stochastic Prediction-Based
Total demand (kWh)	980.54		
Total gross PV energy (kWh)	386.04		
Net utilized PV energy (kWh)	304.76	347.43	347.43
Unutilized PV (kWh)	47.41	0	0
Power conversion loss (kWh)	33.87	38.61	38.61
Total PV energy loss (kWh)	81.28	38.61	38.61
Utilization Factor (UF)	78.95 %	89.99 %	89.99 %
Penetration Level (PL)	31.08 %	35.43 %	35.43 %
Total fuel consumption (Liter)	235.26	173.92	191.25
Total fuel costs ($)	435.23	321.75	353.81
Operation Hours (Hr)	10	7	9

Table 3-3: Simulation results of EMS using the real-data

Parameter	RB-EMS	Deterministic Prediction-Based	Stochastic Prediction-Based
Total demand (kWh)	1040.94		
Total gross PV energy (kWh)	377.02		
Net utilized PV energy (kWh)	300.51	339.32	339.32
Unutilized PV (kWh)	43.11	0	0
Power conversion loss (kWh)	33.40	37.70	37.70
Total PV energy loss (kWh)	76.51	37.70	37.70
Utilization Factor (UF)	79.70 %	89.99 %	89.99 %
Penetration Level (PL)	28.86 %	32.59 %	32.59 %
Total fuel consumption (Liter)	252.76	209.4	215.36
Total fuel costs ($)	467.61	387.4	398.42
Operation Hours (Hr)	11	9	10

4 Demand Side Management

One important key feature of the modern power system paradigm is to have some controllability over the load demand rather than following the ever growing consumption by increasing the generation. ***Demand Side Management*** *as a concept can be simply defined as any actions taken to influence the consumption side in order to be operated in an energy-efficient way. This does not necessarily imply that the consumption must be minimized, but optimized. One drastic solution could be getting completely rid of the unnecessary load. Another intermediate scheme is to adjust the consumption time to take place during the low-price generation time rather than supply-once-plugged scheme. However, these solutions could lead to uncomfortable operation conditions if the users' preferences are not carefully considered. Therefore, a balance should be achieved between the low-price generation time and the operational constraints of these loads in order to achieve the goal of optimization. This chapter presents a Forecast-Driven Power Planning Approach for Microgrids Incorporating Smart Loads.*

4.1 Introduction

Until recently, various approaches have been proposed and applied to coordinate the generation sources in order to meet the varying demand while keeping the electricity cost at optimal levels [Zhu2009]. However, due to ever increasing demand and motivated by the affordable prices of the renewable-energy based systems, a growing desire exists to control or optimize the demand growth in order to facilitate the integration of RES into domestic and industrial sectors. Yet, the fluctuating nature and intermittency of the RES are the still forming a barrier against entirely relying on them as a main power provider or even increasing their penetration level in generation side. In spite of that, this obstacle can be overcome by using a proper energy storage to stabilize the operation and compensate the shortage. This solution is not always affordable, especially in standalone and remote systems, or in buildings subject to severe power outages, where the fluctuating supply cannot be matched by a greater energy storage on all occasions. Otherwise, this will simply add cost and complexity to the system.

A potential alternative solution will be influencing the load demand, totally or partially, in order to lower the need for a larger energy reserve [PaD2011]. A good scheduling of some shiftable loads can improve the reliability of power delivery for customers during (macro)grid blackouts or emergency islanded operation. Once the system is integrated with some smart loads, that can be scheduled in advance, an efficient algorithm could be developed to reallocate these loads in another time, in which, the total energy cost can be minimized and the utilization of RES can be maximized as well.

The need for some controllability over load is not only to assist in accommodating more RES into different power systems around the world, but also there is an important and persistent need to develop and apply such a solution in countries which have weak power systems or suffer from continuously interruption of the utility grid.

Especially in developing countries, a large number of buildings including healthcare facilities, schools and small businesses are suffering from a serious lack of a continuous and stable power supply. This issue has forced the decision makers and the stakeholders to look for some temporary solutions that can alleviate the drawbacks of such a problem.

Conventionally, diesel generators are used to cover the ever increasing demand during the outage time, which are costly and environmentally unfriendly too. The reason behind not using such a forecast-driven approach previously, is the need for efficient forecasting tools that can predict the upcoming load and production accurately.

4.1.1 Related works

A huge work has been done in the context of load scheduling. A heuristic algorithm to schedule a group of smart appliances in a smart building subject to a real-time pricing has been proposed in [LeBa2013]. Another work has been conducted on a smart building environment but using a set of household appliances that allow for a limited interruption time [CaDF2015]. A heuristic-based load shifting optimization approach has been proposed in [LoSh2012], where three adjacent power networks have been chosen to carry out the study. Another load scheduling algorithm based on game theory has been proposed in [MoW2010]. The main objective was to optimize the energy costs by reducing the aggregate peak-to-average ratio of the total energy demand, while respecting the privacy of the customers.

Considering the previously listed literature review and the other ongoing work in this domain; e.g. [HabK2016], [MaR2016], [OBr2016], and [HiFr2018d], it has been realized that the number of studies that have discussed the problem of scheduling dynamic non-preemptive loads from the perspective of standalone microgrids are not much.

Two reasons maybe behind that, which are: *the complexity of solving such a load scheduling problem, which is similar to NP-hard problems* [BaGo2004], and *the difficulties involved in modelling such continuously-operating loads with a non-fixed power consumption*.

4.1.2 Scope of work

As introduced, this chapter takes care of the load scheduling in smart building as an important function of the tertiary level in controlling microgrids. Thus, the scope of the work does not include the voltage stability or power quality at the point of common coupling (*PCC*). However, it tackles the uppermost control level, which has the longest discrete time steps; e.g. ranging from intra-hours to intra-days. To this end, this work offers a proactive scheduling plan for the smart loads which announce their desired operation pattern or the associated consumption profiles in advance; e.g. a day ahead. In other words, the proposed algorithm will attempt to reallocate the aggregated loads to closely follow the low-price available power; e.g. from utility grid or local RES generation.

The load profiles are known in advanced, but they should be reallocated in better time span in order to minimize the total energy cost. Furthermore, the proposed approach will be conducted on a deterministic system, where all load profiles and RES generation as well as the off-peak hours of the utility grid are known in advance. This assumption provides the 'best case' scenario for a stochastic system where the generation/demand profiles are not precisely known ahead of time.

4.2 System Model

4.2.1 Smart Building

A smart building is assumed to conduct this work, where the microgrid model presenting the communication and power network connections is presented in Figure 4.1.

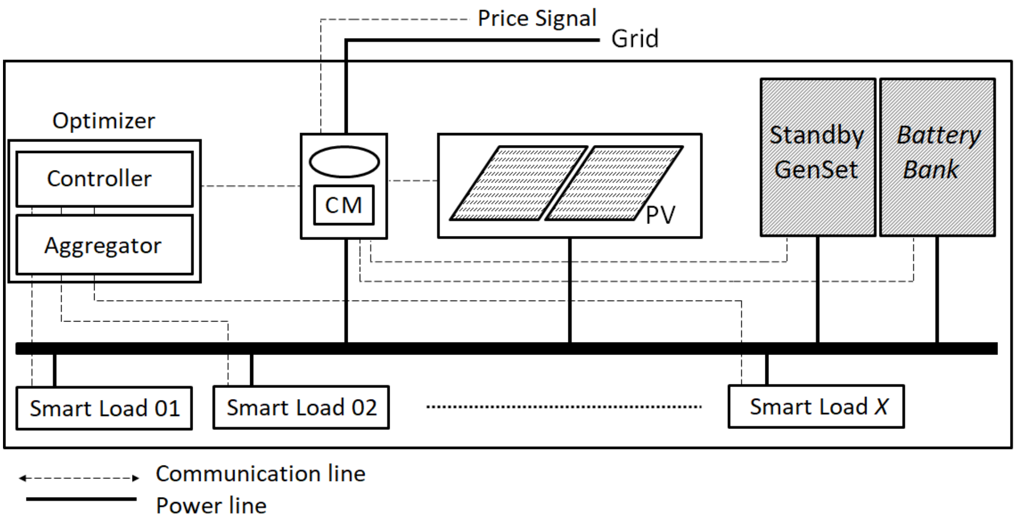


Figure 4.1: Abstract model of the proposed smart building.

In this work, six smart loads are used to model the shiftable electricity consumption. The generation side incorporates PV array and standby generator in addition to the utility grid. Additionally, a battery bank is used to stabilize the operation and facilitate a soft switching between the microgrid's components. The consumption profiles of the smart loads are synthetically created by using a probabilistic model presented in [HiFr2018d], which focuses on non-preemptive loads that have dynamic consumption with multiple modes of operation.

PV solar production profiles are obtained from measurements done in a hospital in Gaza-city, Palestine. A central manager (CM) facilitates the tertiary communication between the optimizer and the production side. Detailed modeling of other components can be revised in Chapter 3.

4.2.2 *Smart Load*

A smart load can be a single appliance or a cluster of devices operate in a particular way to perform a certain function in one of the facilities inside the whole system. Ideally, a shiftable smart load ℓ is modelled by a quadruple: $(e_\ell, d_\ell, L_\ell, A_\ell)$, where e_ℓ, d_ℓ, L_ℓ, and A_ℓ are the earliest possible starting time, the deadline, the duration of the active mode, and the load level during the active mode respectively. In this work, however, an advanced version of this model is introduced, in which, the load can have multiple modes of operation that feature the individual functionalities associated with each smart load. Thus, the resulting model will be modelled as a quintuple.

Specifically, the added element A_ℓ represents another mode of operation, e.g., sleeping mode, in which, the load consumes a much less power than usual to be ready for the normal operation upon request. Furthermore, the stochastic nature of the each individual load is modelled using some statistical properties added to each mode of operation, e.g., means and standard deviations.

Nevertheless, the activation time must be commanded by the system operator (active mode), as depicted in Figure 4.2.

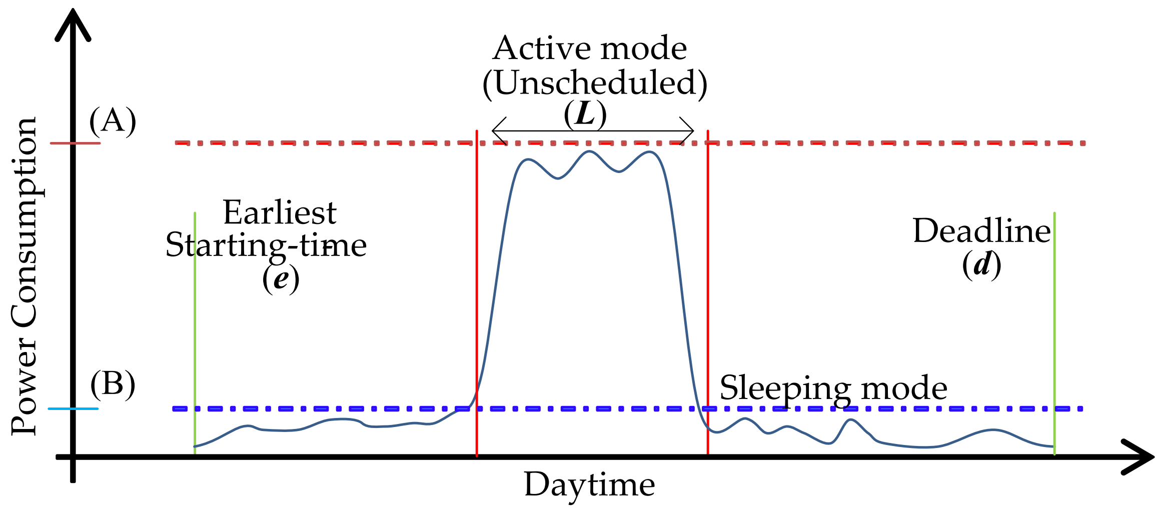


Figure 4.2: Illustrative load profile of a smart shiftable load.

4.2.3 *Scheduling Operator*

Formerly, different penalization functions can be used to measure how far are the scheduled loads from the forecasted available power and thus, find the optimal scheduling plan associated with each smart load in the system [OBr2016]. In our work [HiFr2018d], we chose to penalize the absolute-value norm of the error between the forecasted power signal and the aggregate scheduled load profiles as formulated in Equation (4.1):

$$G(t) = \left\| \Upsilon(t) - \left(\sum_{\ell=1}^{N} P_\ell[t - \tau_\ell] \right) \right\| \quad (4.1)$$

Where $\Upsilon(t)$ is the low-price power signal and $P_\ell[t - \tau_\ell]$ is the shifted version of the smart load ℓ corresponding to the scheduling operator κ, e.g. a typical operator κ may bring the selected load τ time-slots forward or backward, as defined in Equation (4.2):

$$P_\ell \xrightarrow{\kappa} \tilde{P}_\ell = \kappa(P_\ell) = P_\ell[t - \tau_\ell] \quad (4.2)$$

Providing an adequate forecasting tool, an offline solution for this problem can be achieved using the aforementioned formulation. The general overview of the proposed offline load scheduling scheme is shown in Figure 4.3

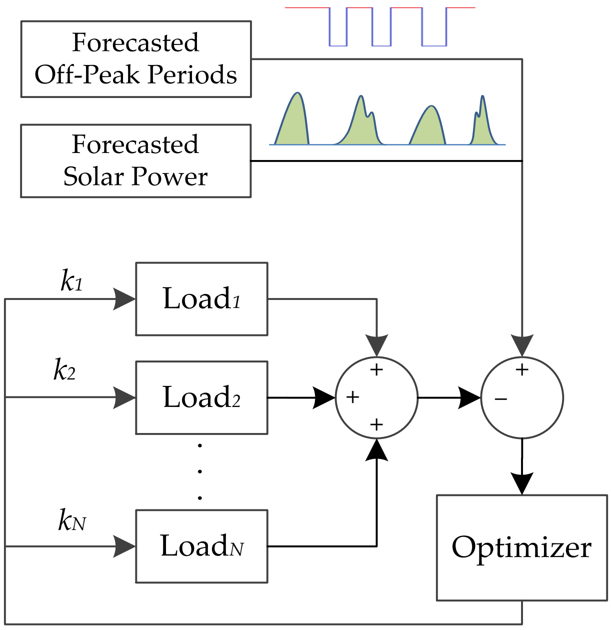


Figure 4.3: Offline Optimization solution for load scheduling problem.

Some key features of the offline optimization approach:

- It targets to reallocate the shiftable loads by minimizing the cost function, i.e. the net difference between the announced low-price power profile and the aggregate scheduled loads, to make use of the maximum possible energy using the available low-price power.
- It does not consider the applied method of routing the power between the microgrid components or in other words, it tracks a given generation profile to minimize the deficit which has to be covered by another source of energy.
- This method might be viable to some anonymous systems that are supplied from a single low-price power source, e.g. solar PV field, which has one cost function at most.

However, in order to realize an optimal power operation for more complex systems such as microgrids adopting hybrid power sources or/and a low-price utility grid, one might need a further detailed scheme that can explain the power transactions among the components of the microgrid. For this reason, the used scheduling operator here is going to be determined based on the involved EMS.

4.2.4 *Microgrid Model*

As presented in Figure 4.1, a grid-connected microgrid is assumed to conduct the work in this chapter. It incorporates PV array, generic battery bank and a diesel generator set (GenSet), all are connected to a unidirectional main grid. The model of each individual component of the system with the corresponding operational constraints was presented earlier in Chapter 3. Here, the focus will be given to the grid model and the electricity price, however.

Due to a frequent power outages, the main grid can have two states: ON (available) and OFF (unavailable). Yet, it can supply the load adequately whenever it is in ON state. The grid outages can be planned in advance or take place unexpectedly due to unpredictable faults. Such a grid can be modeled by means of Time-of-Use tariff (ToU) using a two-level power price, in which, Off-Peak times follow a lower fixed price cl than the peak times which follow a much higher price ch as given in Equation (4.3):

$$U_g(t) = \begin{cases} c_l, & t \in [t_1, t_2] \\ c_h, & otherwise \end{cases} \tag{4.3}$$

The total lower-price power signal $\Upsilon(t)$ is typically resulting from the combination of the grid power during the *ON-times*, $t \in [t_1, t_2]$, which adopts the value c_l, and the generated PV-power which has almost negligible cost of generation.

The higher price level c_h is the price is assumed to be associated with the power withdrawn from the diesel generator. It is assumed that the generation at that period is closer to the maximum loading factor, see Chapter 3 for elaboration.

4.3 Scheduling algorithm

Obviously, the key concept behind scheduling a set of smart loads to track a known power profile is similar to a certain extent to the problem of deciding if objects can fit into a bin, which is classically known as a bin-packing problem [Vaz2003]. The idea is to get the autocorrelation between the aggregate load and the total available power maximized. Nevertheless, the problem of maximizing the profit of minimizing the operational cost of supplying a group of loads is similar to the problem of selecting the most valuable items to carry in a sack, which is known as a knapsack problem [Mm1996].

Although the addressed scheduling problem may seem similar to other classical constraint-based scheduling problems [Wam1996], where the tasks, i.e. the loads, are constant and require a certain share of the resource, it is still harder to solve because of the dynamic nature of the loads which makes it necessary to find a suitable relaxation technique in order to minimize the effect of the fluctuating demand. The existing scheduling problem is a complicated optimization problem, which is NP-hard [BaGo2004]. Therefore, finding an optimal schedule for a large set of schedulable loads is very complicated problem and thus, the exact solution might be hard to find without enumerating all possible schedules and then evaluating them.

To elaborate on this issue, suppose that we have a set of N loads with at least M possible positions for each load to start the active operation, the complexity of the searching space will be M^{N}. Obviously, the complexity of the problem is exponentially increasing with the number of loads and/or the possible schedules of each load. In order to cut down the computation time, the developed optimization approach applies a stochastic optimization technique to solve this problem [Mm1996].

4.3.1 Stochastic Optimization

Recently, the genetic algorithm has become of a great interest to a wide variety of operational research problems, especially, planning and scheduling. However, in order to apply GA to solve a scheduling problem, the problem must be well modeled to be suitable for this kind of approaches. A specific operation periods defining the permissible lower and upper limits (genes) represent the set of chromosomes in the population. To make sure that the candidate schedule is a feasible solution, it must follow the operational constraints.

The candidate solutions are mapped to chromosomes containing genes which are represented using an array of bits. The length of the chromosome is directly related to the number of time steps.

In this Chapter, a preliminary simulation example is used to prove this concept. The default settings of MATLAB-based GAs are applied to conduct the simulation. A population of chromosomes is randomly initialized (i.e., 200) in accordance to the possible number of solutions. The algorithm is then terminated when the stipulated number of generations (i.e., 500) is reached or when the magnitude in the change in fitness value does not vary more than a tolerance limit (i.e., 10-10) for several subsequent generations (i.e., 50).

Due to the complexity of the system, where multiple power sources are sharing the responsibility of supplying the electricity to the aggregate smart loads, the used fitness function here is modeled by embedding the applied EMS, which will result in a specific LCoE. Other assessment factors, e.g. such as the self-consumption (SC) ratio or/and penetration level (P_L), can be imposed to further improve the quality of the resulted schedule. A conceptual model of the proposed EMS-based optimization algorithm is illustrated in Figure 4.4.

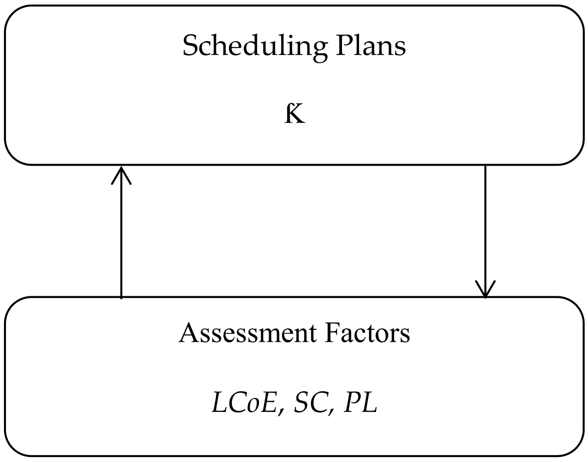


Figure 4.4: The proposed EMS-based optimization for microgrid scheduling.

Suppose that we have a nonempty set $\mathrm{Ƙ} \neq \emptyset$ of finite elements $\mathrm{k_s} \in \mathbb{N}$ representing all possible schedules, where $\mathrm{Ƙ} = \{\mathrm{k_1}, \mathrm{k_2} \dots, \mathrm{k_s}\}$. Thus, each individual operation strategy k_s will obviously result in a different value of *LCoE*, where:

$$LCoE\left(\Upsilon(t), \left(\sum_{\ell=1}^{N} P_\ell[t-\tau_\ell]\right)\middle| k_s\right) \tag{4.3}$$

LCoE is a function of the low-price power signal and the aggregate shiftable loads expressing the applied EMS with respect to the scheduling map $\mathrm{k_s}$. In other words, it uses the forecasted $\Upsilon(\mathrm{t})$ and the announced shiftable loads to provide the LCoE based on the selected scheduling plan. Formerly, such a function is solved based on predefined rules, which is called rule-based method [RifB2009]. However, an optimization-based solution may provide more profitable results, as discussed in our previous work [HiFr2018c].

A simple EMS state-flow diagram for routing the power between the production side and aggregate load is also provided in another work of the authors [HiFr2018b] and [HiFF2017b]. Obviously, the searching space is too huge and resulted from the space of load side, e.g. M^N, and the space of the generation side.

4.4 Simulation Example

A hospital building incorporates a group of six shiftable loads is chosen to conduct this simulation example. Some examples of real loads in the hospitals that can be shifted without affecting the healthcare service are laundry machines, sterilization units, waste incinerator, air conditioning system in some parts of the hospital, and other actions related to the planned maintenance system.

The low-price power signal is generated from the aggregation of the off-peak period from the utility grid in Gaza-city and the onsite solar generation. Other essential loads are assigned to be supplied using the conventional generation as they need a continuous and stable supply without any interruption.

The building is mainly supplied from the utility grid, which has a feeder capacity of 40 kW. However, the grid is interrupting on a daily basis, which makes relying solely on it impossible. Thus, the building was backed recently with a 20 kWp solar array to relieve the stress on the existing standby generator. The used diesel generator has an operative capacity of 20 kW and its associated fuel cost is modelled by fitting the manufacturer data [Dss2018]. The grid price is considered c_l = 0.16 $/kWh during off-peak hours and the price associated with diesel operation under the rated load is c_h = 0.56 $/kWh. Half of the grid capacity is reserved for essential loads and the second half is assigned for the shiftable loads.

The grid-ON times, forecasted PV solar generation, and the notified base and shiftable loads over a three-days period are shown below in Figure 4.5.

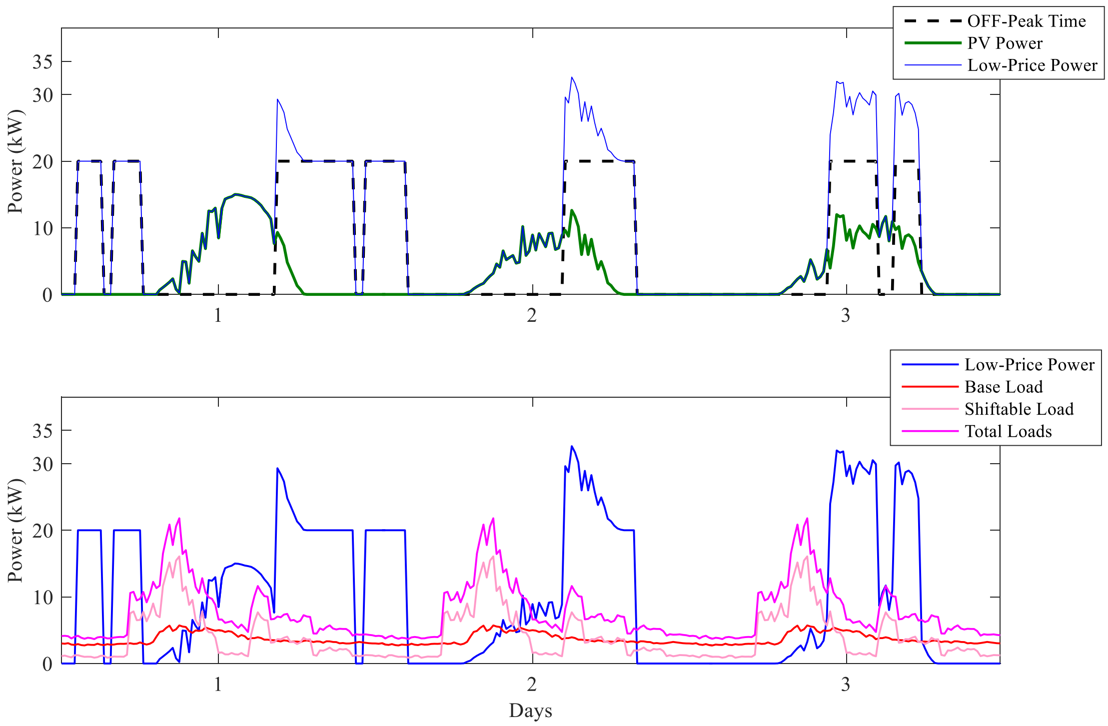


Figure 4.5: An illustrative 3-days window: Generation data (top), Disaggregation load (bottom).

The system is modeled using MATLAB and the optimization algorithm is conducted using the provided optimization toolbox. The optimization window is considered here as a single day and then the optimization process should be repeated in accordance with the new timing constraints for the day after.

The convergence of the optimization process for one sample day is depicted in Figure 4.6, where the searching process is converged after about 100 generation, and then the improvement rate is almost negligible.

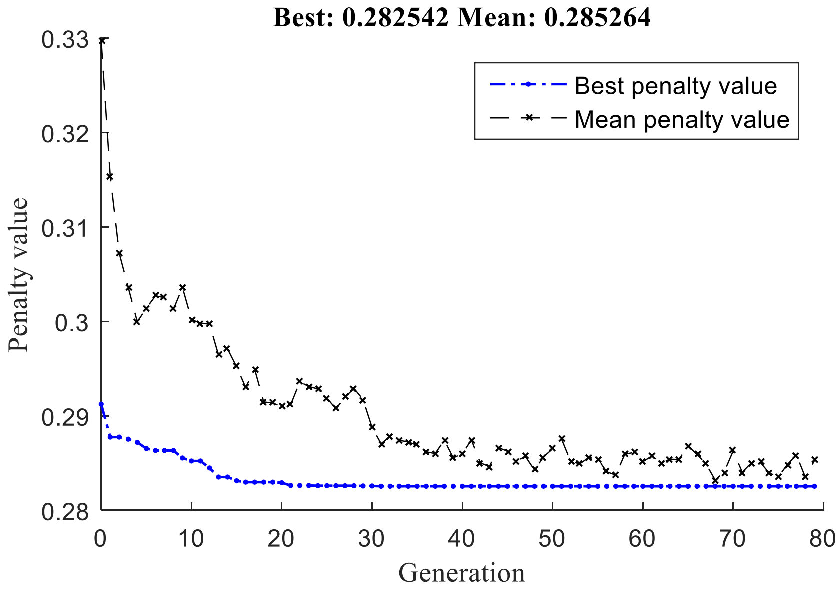


Figure 4.6: Convergence of the proposed GA-Scheduling.

Some performance indices and end results are calculated and concluded in Table 4.1, presenting the net utilization factor of the solar power and *LCoE* as well

Table 4.1: Performance Indices.

Index/Quantity (Unit)	Before Scheduling	After Scheduling
Base Load (kWh)	264.14	
Total Shiftable Loads (kWh)	219.4	
Total Loads (kWh)	555.62	
Total PV production (kWh)	232.73	
Low-Price Available Time (Hr)	24,75	
Purchased Energy from Grid (kWh)	83.1	111.31
Output Energy from Diesel (kWh)	289.29	211.9
Utilized PV Energy (kWh)	183.25	232.41
Utilization Factor (Self Cons. %)	78.74	99.86
Total Cost of Energy ($)	175.3	136.5
LCoE ($/kW)	0.316	0.246

Figure 4.7 shows the final numerical results over a three-days simulation window. It presents the aggregated low-price power (green), i.e. which has to be tracked as well as the total loads before performing the scheduling (red) and finally, the total loads after performing the scheduling (blue).

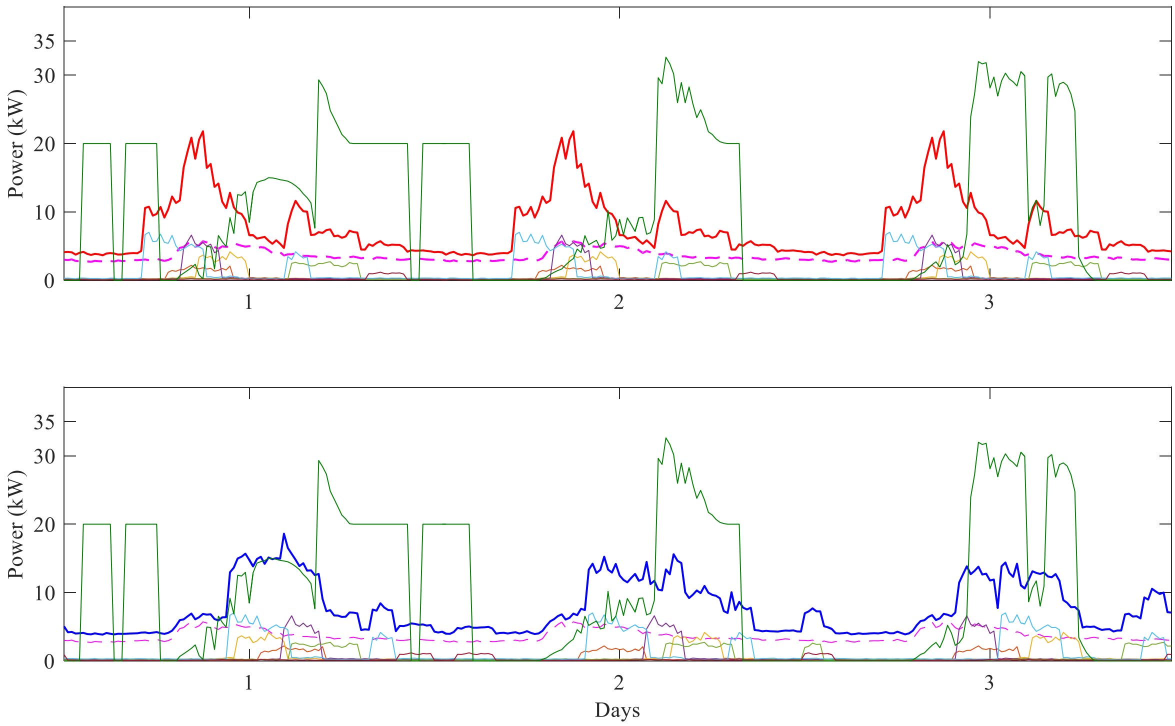


Figure 4.7: Scheduling results of six sample loads: Before scheduling (top), After Scheduling (bottom).

4.5 Discussion and Final Remarks

Unlike other works, such as in [HabK2016], where preemptive loads have been used to reshape the aggregate load, e.g. they can be supplied with interruptions, the proposed contribution in this chapter aims at reallocating each shiftable load to another time interval instead of reshaping them so that the resulting consumed energy after scheduling is similar to their unscheduled counterpart. The reason behind that is to avoid the so-called "rebound effect", because simply switching the loads ON and OFF will not lead to the same desired performance if they work continuously as usual. In such cases, energy is naturally not saved and expectedly another peak will be generated [PaD2011]. The presented model expressed the fluctuating nature of the load that can have multiple operation modes with some variability on the power consumption.

Another addressed aspect is the scheduling window, which is selected here as a single day and then the algorithm is repeated for the next day using the new data. In this regards, one load cannot be requested more than once within the same window.

Otherwise, two or more identical loads with different activation constraints should be used in order not to allow any overlapping of the operation of same load in that facility.

Formerly, the developed scheduling algorithms were adopting some scheduling policies used in real-time processing such as Earliest Deadline First (EDF) and Least Laxity First (LLF) which assign the tasks, e.g. loads, according to their deadlines or the slack times [SuGD2012]. However, in renewable energy systems with versatile loads, such algorithms still need an accurate forecasting tools and systems to handle the fluctuating nature of the RES and the dynamic price of the grid. Therefore, the matter of prioritizing loads should consider both: timings of the loads and their consumption level at each time slot. Obviously, the dominants loads will be those with higher consumption and less timing flexibility than others, which will diminish the effect of other shiftable loads but with lower consumption.

An easy-to-implement load scheduling approach based on the notified nature of the system was proposed. Besides, a straightforward model for smart shiftable loads was introduced in this chapter. The proposed approach has adopted the GAs to cut-down the searching space and find the optimal schedule within a reasonable time budget. Obviously, the net utilization of the installed PV-field is improved by more than 10% and the cost of energy is reduced up to 78% of the original value. As presented in Table 4.1, the reduction in purchased energy from the grid and the output power from diesel generator is substituted after scheduling by increasing the net utilization of the solar energy and the purchased energy from the grid as well.

Yet, there are three important topics that have not been explored and can be the subject of future research:

(a) Reduction the capacity of the diesel generator. The economic basis for this issue should be clearly justified through synthetic examples and much more comprehensive simulations using real data.
(b) The incorporated energy management scheme, which will highlight the power routing between all system components, including the static and the essential loads which cannot be shifted in time.
(c) Online adaptation of the schedules using shorter time window instead of performing the algorithm once per day. Thus, the improvement rate can be further increased according to the recent measurements of the RES generation and the loads as well.

5 Layout Design

Water is known as a lifeblood. Nowadays, ***electricity is the life*** *however. No one can deny how electricity become essential in our daily life. The matter of power provisioning of a system encompasses several challenges starting from selecting the appropriate energy sources and not ending with determining the percentage share of each source to supply the desired load demand. Yet, it would involve a complicated optimization problem, especially when it comes to several components must be managed in a way to cover the instantaneous demand with the least possible price. Furthermore, the capital cost of system should be considered in order to achieve a reasonable Levelized Cost of Energy (LCoE). In this chapter, the traditional min-max designing method will be overviewed firstly with an introductory design example to highlight the most important technical aspects of providing a provisioning power supply system for a specific load profile. Consequently, an optimization-based components' sizing method will be presented and compared with the former method to compare the performance factors and highlight the cost savings.*

5.1 Introduction

As introduced earlier, the concept of hybrid generation is promising from different perspectives, especially to the regions around the world which have an inadequate grid infrastructure or/and an intermittent power from the local grid and mainly depend on backup diesel generators to supply their essential demand. Such examples are widely spread in the Middle East, in Africa and in India with various degrees of power lack [Hi++2016]. Nevertheless, the situation becomes even more complicated when considering the expected extra cost of fuel transportation or a breakdown of the supply chain, which may seriously affect people's life [Hi++2015]. Traditionally, the backup power generation systems are mostly relying on diesel generators which are considered not only huge fuel consumers and environmentally unfriendly, but also economically costly. Recently, with the development in the renewable energy industry, the deployment of renewable energy resources (RES) is expected to be a good alternative of energy at the long term. Moreover, the cooperation between RES and diesel generators can lead to significant synergies compared with legacy systems which are, in fact, depending only on diesel generation in case of power outages. The most appropriate system for such situations is PV-Battery-Diesel, especially where the grid cannot meet the load demand at every time.

5.1.1 Related works

Different search-based method have been applied to solve this problem—considering different constraints—starting from iterative-based or exhaustive searching methods and ending with stochastic searching methods. Regarding the topology of the designed microgrids, the major part of the literature is dedicated to islanded or off-grid applications, such as in [An++2015], [MuKg2011], [CsGW2012], and [Dss2018]. However, a few works presented grid-connected applications, such as [DrBj2005], [AmBa2013], [DjBw2013] and [Mm1996].

Specifically, in [DrBj2005] the authors discuss the sizing of a battery energy storage system (BESS) for a microgrid to maximize the profit of energy trading among the microgrid and the existing power markets. The same objective was searched for in [AmBa2013] and [DjBw2013], but in order to size PV-Battery system considering different energy tariffs and market policies. Other works proposed some flexibility on the demand side, where the systems have been designed based on the worst-case condition of the net demand, such as in [Dss2018] where the system considered was off-grid, and in [Mm1996] where the system was connected to the grid.

5.1.2 *Main Contribution*

It is observed that the most of the previously proposed approaches have not included both the operational constraints of all components and the unutilized RES. However, this work attempts to maximize the net returns of renewable energy resources (RES) by increasing the percentage of their utilization and penetration as well. In addition, it compromises between the expected running costs -resulted by fuel consumption and energy purchased from the grid- and the investment of adding new components. Besides, it makes use of an enhanced version of the developed rule-based energy management strategy, *cf. Ch 3* and integrate it with the design approach to serve as a kernel during the optimization process.

The presented method in this chapter represents an easy-to-implement layout-design method for medium-scale, scalable, and self-sufficient microgrids which are ready to be interconnected with the regional grid (once existed) aiming at healing the weakened grid as far as possible.

The main contribution is the fact that the key factors for selecting the optimum size of the *MG* components cannot be reduced to just the load profile and the available renewable generation, but also how the instantaneous power is routed in the MG. Furthermore, this method tackles also the issue, that the decision parameters do not only concern the sizing of the components—*PV* generation and battery bank (beside the existing diesel generator)—but also the imperial switching criterion among battery, diesel generator and the main grid in case of insufficient *PV* generation: that is, the lower and the upper limit of the state of charge (*SoC*) at which the battery and diesel generator (or the main grid too) are switched on/off. Lastly, the real utilization factor of RES after performing the control strategy is investigated upon different scenarios.

5.2 Enhanced Rule-Based (RB) Operation Policy

The energy management system (EMS) is the core controller which routes the power from different resources to supply the load in an efficient manner. Therefore, an instantaneous power balance must be achieved as depicted in equation (5.1):

$$N_{PV}P_{PV} + N_B P_B + P_D + P_G = P_L + P_{Loss} \tag{5.1}$$

where N_{PV} and N_B are the total number of photovoltaic panels and storage units, respectively, P_D is the generated power by the diesel generator, P_G is the power drawn from the grid utility, P_L is the instantaneous load demand and P_{Loss} is the total unused power, i.e., the lost power due to power conversion, plus the unutilized solar power.

The rule-based operation policy does not require a prediction. However, it only makes use of the real-time measurements and grid status to determine the power route or switching mode of the controllable components of the microgrid, basically the battery storage bank and the generator. The operation policy is general and can be applied on all similar cases. The power set-points for microgrid components are calculated at each time step according to the logic rules or priorities using only the knowledge of current *SoC*, load, RES generation and grid status.

A flow chart diagram of the developed operation policy in this work is shown in Figure 5.1.

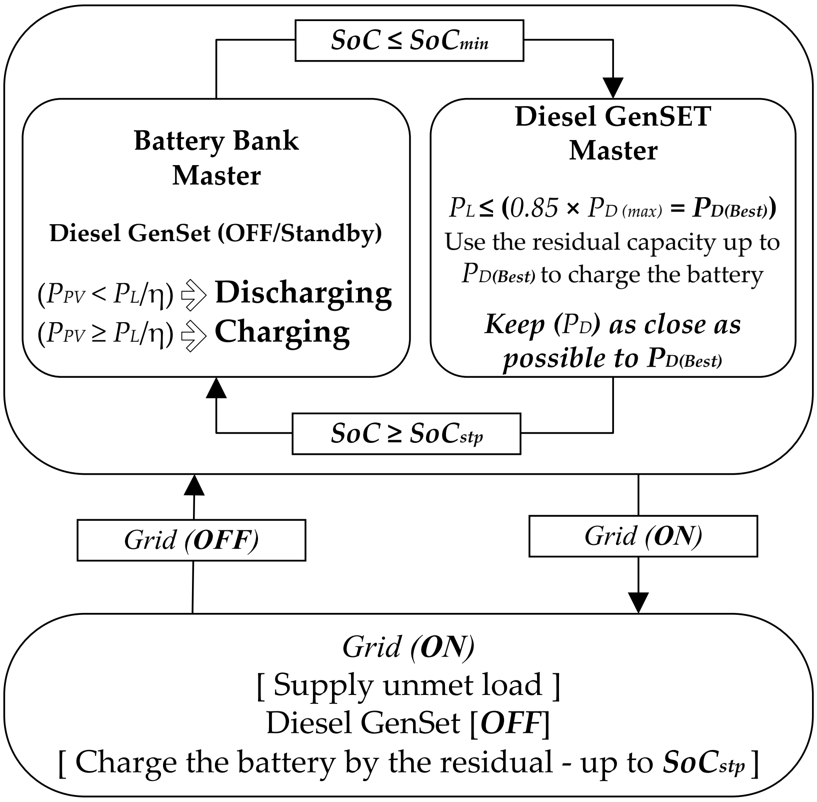


Figure 5.1: Enhanced Rule-based operation policy for the proposed microgrid.

Some key features of this algorithm are:

- RES, i.e. Solar production is utilized in priority order: load >> storage >> dump (unutilized).
- Load is supplied with priority order: PV >> grid >> storage >> generator.
- Battery bank is either charged by the grid during ON-grid hours or by the generator once the load is lower than the best operation point P_{Gen}^{Best}.
- The battery bank and the generator cannot supply the load in the same time, means that the battery cannot operate in the discharging mode during the operation of the generator.

Basically, this operation policy adopts a master/slave operation based on these pre-defined rules, i.e., the highest priority is given to the renewable energy, then to the grid utility, next to the battery storage system and, finally, to the diesel generator. Besides, discharging process of the battery cannot occur with the operation of diesel generator concurrently. On the other hand, the charging process of the battery can occur at times while the diesel generator is ON.

As illustrated in Figure 5.1, P_{PV} takes the highest priority to supply the load. Thus, once it is insufficient, the grid takes the responsibility to supply the residual load if it is ON. In case of insufficient renewable supply and power outage, the battery is imposed to supply the residual load as long as its *SoC* is above a certain threshold SoC_{min}. Finally, the generator is operated to supply the unmet load in case that *SoC* is less than SoC_{min}. To keep a higher fuel efficiency of the diesel generator, its residual power charges the battery up to a certain limit SoC_{stp} if its loading factor is less than P_{Gen}^{Best}.

Such a criterion can be met by solving equation (5.2):

$$P_D(\tau) = min\left\{P_{Gen}^{Best}, netD(\tau) + \frac{1}{\eta\Delta}\left[SoC_{stp} - SoC(\tau)\right]\right\} \tag{5.2}$$

where $netD(\tau)$ is the instantaneous unmet load by PV generation, i.e., $\boldsymbol{N_{PV}P_{PV}}$. Hence, the output power of the diesel generator is kept at its best rate as long as the remaining charge of the battery (to reach its maximum allowable SoC_{stp}) is more than the residual of diesel generator. *This equation applies the concept of a single-slot predictive control, where the output power of the generator is determined based on the current measurement of the SoC and the targeted upper limit of it, if it is going to be charged by the generator.*

An example of the interactions among the microgrid components according to the enhanced RB operation policy is explicitly illustrated in Figure 5.2.

The top figure shows the load profile (blue), available *PV* generation (*green*), and the maximum available power from grid (*yallow*), where these signals represent the main inputs of the EMS to direct the power to the load in an efficient way. The next figure shows the power extracted/injected to the battery (*green*) and the residual amount of PV generation which could not be utilized neither to supply the load nor to charge the battery (*red*). The third figure shows the time-slots in which diesel generator is called to supply the load and how much power it supplies (in total) to cover the unmet demand and charge the battery as well.

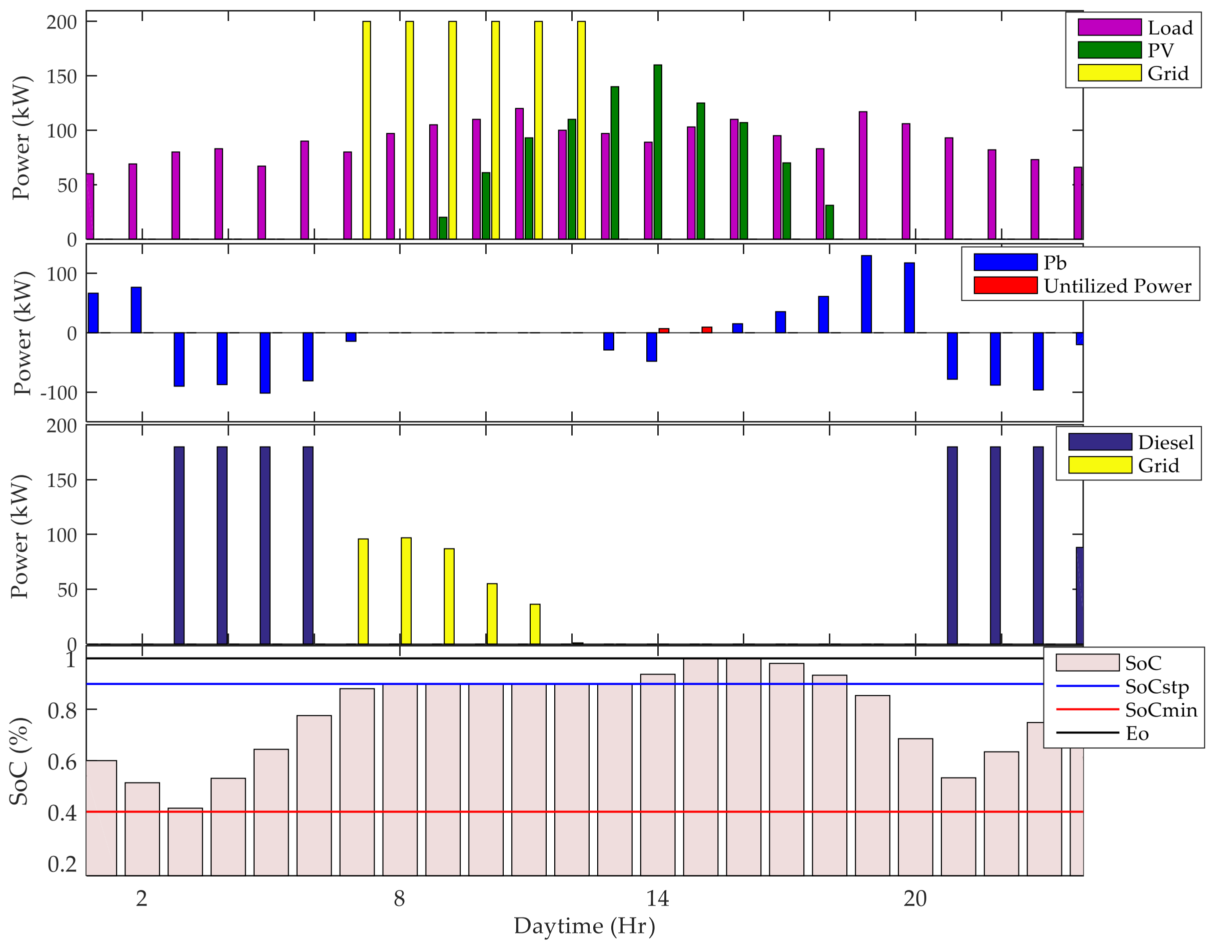


Figure 5.2: Illustration of a one-day operation of the microgrid.

Noticeably, generator operates almost always on its best rate (P_{Gen}^{Best}) except in the last period of operation where the total charge needed to reach SoC_{stp} is less than the residual of its generation capacity up to P_{Gen}^{Best}. The third figure presents also the power supplied from the grid at times when it is available. Lastly, the bottom figure illustrates the *SoC* and how it varies according to the interactions among the load and the power resources.

The simulation of this day uses SoC_{stp} = 90% and SoC_{min} = 40%, and it can be seen that these limits are not violated while the grid and the diesel asset are ON. However, the small margin up *SoC* = 100% is reserved to be covered in the time of plenty ***PV*** generation, hence, *SoC* can reach its maximum limit (100%) and the unutilized power can be minimized.

5.3 EMS-Integrated Design Method

Basically, it is crucial to find a cheaper and cleaner supply than diesel in order to cover the needed demand of a facility at a cheaper price of energy over a long term. Besides, a compromise should be found between the running cost and the investment capital.

The optimization algorithm employs a Genetic Algorithm (GA), which is one of the metaheuristic stochastic optimization techniques that can provide a solution to an optimization problem with less computational effort than iterative ones [Mm1996].

The objective function to be optimized is the total sum of the investment and running cost over the annual cost of the system, where the running cost results mainly from the purchased energy from the grid (in case of a grid-connected case), and the fuel consumption by the diesel generator, and the investment cost depends mainly on the instalment plan or the installation cost of the components (*PV* panels, *Battery bank*, *Diesel Generator* and *the inverter*), plus the maintenance and replacement cost of some components such as batteries.

Equation (5.3) represents the mathematical formulation of the whole cost function, equations (5.4) and (5.5) correspond to the detailed mathematical formulation of the investment and running costs (C_{inv}, C_{run}), respectively.

$$C_{tot} = C_{inv} + C_{run} \tag{5.3}$$

$$C_{inv} = N_{PV} C_{PV} + N_B C_{Bat} + P_{DG}^{Best} C_{DG} \tag{5.4}$$

$$C_{run} = C_f F_c + C_g E_g \tag{5.5}$$

N_{PV} and N_B are the total number of *PV* panels and storage units, P_{Gen}^{Best} is the maximum capacity of diesel generator, C_{PV}, C_{Bat}, C_{DG} are the prices of a single PV panel, a single storage unit and the corresponding diesel generator, respectively.

The parameters C_g, E_g and C_f are the energy price per kWh from the grid, the total energy purchased from grid and fuel price per liter including the costs of transportation and logistics.

In case of isolated ***MG***s, the total purchase from grid E_g will be zero and hence, the run cost will merely be resulted from the diesel generator.

A pseudo-code of the applied GA, including a specific decision on the appropriateness of each candidate 5-tuple $\boldsymbol{C}$ of decision variables (*Step 4*), is depicted in Figure 5.3. Each appropriate candidate is evaluated over a one-year load and weather profile to find out the best fitness function (Equation 5.6).

1. **Inputs:** Weather data, load profile and grid powering states.
2. **Candidate of decision variables:**
   C := (N_{PV} , N_{DG} , N_B, SoC_{min} , SoC_{stp}**)**
3. **Initialization:** randomly seeded possible solutions.
4. **Apply the defined operation policy:** Is candidate **C** appropriate for energy management scheme? If yes, evaluate the penalty function. Otherwise, exclude **C**.
5. **Selection:** Select the best candidate solution among the present generation before step in the next generation.
6. **Crossover and mutation:** The new possible candidate solution is generated from the parents which survived.
7. **Apply the main control strategy again (STEP 4)**
8. **Termination:** after exceeding the time budget or generation limit or satisfying the minimum criteria.
9. **Output:** the values correspond to the best/final solution.

Figure 5.3: Pseudo-code of the optimization algorithm using GA.

Traditionally, a multi-objective optimization problem is reformulated into a single-objective optimization problem using weighted factors and aggregation [KpCk2015]. Here, a weighted sum of the lost or unutilized power is combined with the cost function in order to be minimized.

This adds a new constraint on the problem besides the operational constraints of each component. The final multi-objective penalty function Π can be formulated as in equation (5.6).

$$\Pi := C_T + \left(w \sum_{1\,year} P_{Loss} \Delta \right) \tag{5.6}$$

w is a weighting factor that represents the significance of this additional constraint. The applied searching method is heuristic, however, time-efficient and fully exhaustive as the so-called brute-force.

5.3.1 *Searching Space*

The search space of the problem is obviously very large. Considering N_{PV} solar panels, N_{DG} set of the diesel generators, and N_B battery storage units with N_{SoC} different levels of SoC_{min} and SoC_{stp} (which we declared in advance) to choose from, the number of iterations would reach ($N_{PV} \times N_{DG} \times N_B \times N_{SoC} \times N_{SoC}$) of iterations, each requiring k evaluations of Equ. (5.1) to (5.6) if an iterative method, e.g. brute-force, is chosen to check all possible combinations (as done, e.g., in [An++2015]); $\boldsymbol{k}$ is the number of total time slots among the year (here $k :=$ 6×8760 = 52560). Yet, the checking process includes also the implicit or the integrated operation policy which has been applied to figure out the real efficiency of the system. For that reason, the *GA* is chosen as it enables the exploration of a wide range of allotted elements in a much shorter time.

In our case, less than 80 generations were examined until they converged to a solution (here: just a few minutes of computation time).

5.4 Design Example

The essential load of a building of an outpatient in Gaza city is taken as a case study where daily grid outages are common routine since years [Hi++2015]. A fraction of the load profile is chosen to conduct the simulation where the maximum peak during one year is 71.2 kW and minimum load is 25.3 kW with a mean consumption of 42.8 kW and 10.4 kW of standard deviation [MuKg2011].

A powerful tool to describe the chosen load profile is the load duration curve (LDC), by which, the aforementioned statistical information can be described clearly, where the values of the power profile are sorted in a descending order, as depicted in Figure 5.4.

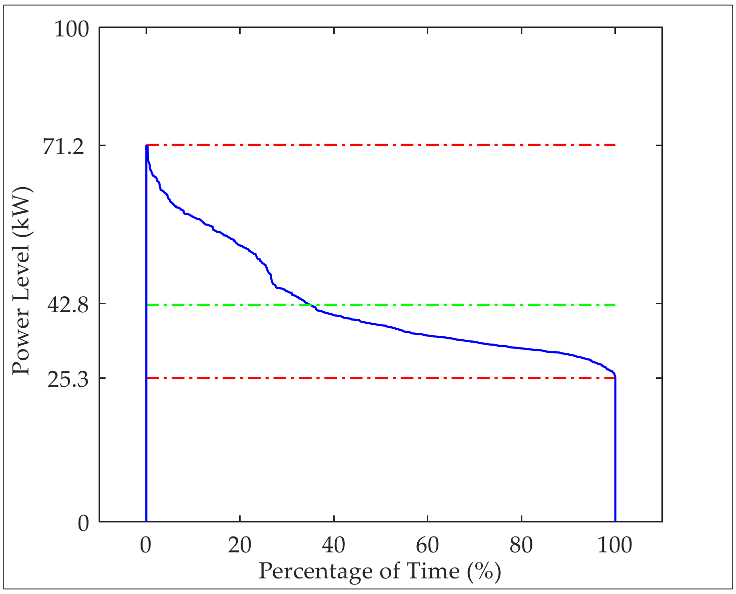


Figure 5.4: Load duration curve (LDC) of the load over one year.

Considering 70% energy deficit in Gaza Strip [OCHA], which can cause daily outages at least 12 hours according to the plan of the distribution company, in which the grid can be ON for 6 hours, at most, and OFF for 12 hours. Generally, the public are notified in advance by such a schedule according to the available resources. More information about the energy deficit in Gaza strip can be found in [HiFF2016b].

A deep cycle lead-acid battery is used as storage unit. Besides, the yearly PV production of a single 250Wp PV panel is calculated using the weather data from the metrological database METEONORM [Meteo]. Extensive simulation for the whole-year data indicates that solar power gained at the site can beat 1750 kWh/kW$_p$ annually.

Figure 5.5 illustrates the average daily power production of a single 250 W$_p$ panel.

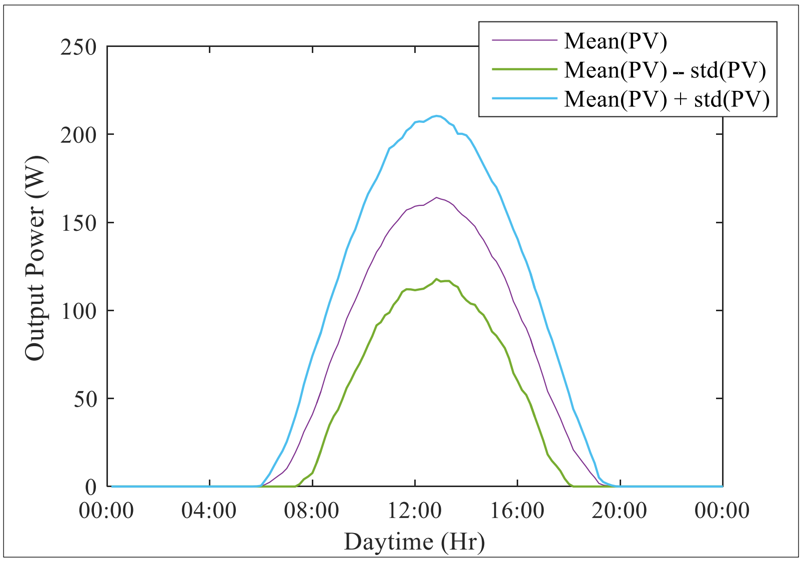


Figure 5.5: Average daily power production of a 250 W_p solar panel.

Further technical data, specifications and associated costs of components are provided in Appendix I.

Four diesel generator candidates to choose from are assumed in this work by fitting their corresponding fuel consumption data [Dss2018].

5.4.1 Predesign Example

In order to give a clear realization of the goodness of the proposed design algorithm and provide an indication of the required system components, a simplified dimensioning approach based on time series analysis is presented here, which is commonly used for the same study purpose. Conventionally, MG systems are designed assuming two prime impractical hypotheses: namely, a full utilization of the generated power from renewable resources, and no losses due to power conversion among DC/AC buses; both hypotheses can lead to specifically optimistic and encouraging results from an economic point of view.

In addition, many approaches do not include the energy management scheme during optimization. By contrast, the proposed design herein is optimized taking into account the applied operation policy and realistic power conversion efficiencies, which together play the key role in determining the realistic percentage of utilized renewable energy.

Obviously, using the integration of equ. (5.1), energy balance of the system must be achieved. By which, capacities of each of diesel generator and the bi-directional inverter can be roughly estimated, as shown in Equ. (5.7):

$$E_{PV} + E_B + E_D + E_G = E_L + E_{Loss} \tag{5.7}$$

Simply, the resulting net power demand, after subtracting available PV power from the load profile should be supplied by either by grid or diesel generator in addition to the assistance of battery storage. Subsequently, by defining the desired penetration level (P_{ℓ} in equ. 5.8) of the renewables, i.e. *PV*, the lower bounds of solar panels can be determined, that is, considering zero losses due to power conversion or/and applied operation policy. After that, other resources can supply the residual load, which has not been supplied by the *PVs*.

$$\int_0^{\tau} P_{PV}(\tau)dt = \mathrm{P}_{\ell} \int_0^{\tau} P_L(\tau)dt \tag{5.8}$$

Besides, maximum power ratings of the battery, diesel generator and power inverter must be able to handle the peak load. Generally, different manufacturers have their different recommendations and preferences of the charging/discharging characteristics. Mostly, in order to assure healthy operating conditions for the battery, maximum throughput rate must not exceed a certain value C/(5 h); C is the battery capacity in Ampere hours (Ah).

Other considerations such as supply of reactive power or fault tolerance considerations, would of course lead to further increased capacities and power ratings.

Findings of the components after a predesign phase are listed below in Table 5-1:

Table 5-1: Predesign Microgrid Components

Parameter	Nomenclature	Value (s)
N_B	Number of storage units	65 Storage units
N_{PV}	Number of PV panels	857 Panels
P_{DG}^{max}	Diesel generator capacity	100 kW
P_{inv}	Ratings of the power inverter	100 kVA

It is worth to mention here, that predesign phase assumes a full penetration of solar energy which can hardly be achieved in such circumstances. In order to verify the actual penetration level of such selected components, the operation policy must be applied. These findings will be presented in details in the next subsection.

5.4.2 *Optimized Design Example*

Simulation results in this section are conducted based on the power outage scenario corresponding to 70% energy deficit in Gaza, with the consideration of some unexpected interruption (as declared in Section II.A). All parameters used in simulation with the corresponding nomenclature and values are listed below in Table 5-2.

Table 5-2: Simulation parameters used in optimized design

Parameter	Nomenclature	Value (s)
N_B^*	Number of storage units	[0, 600]
N_{PV}^*	Number of PV panels	[0, 1000]
SoC_{min}^*	Minimum allowable state of charge	[40, 60] %
SoC_{stp}^*	Stop charging threshold from GenSet	[70, 90] %
CB	Single storage unit capacity	5.55 kWh
SoC_{int}	Initial state of charge	75 %
SoC_{max}	Stop charging threshold from PV	100 %
η_b	(Dis)charging efficiencies	95 %
η_c	Inverter efficiency	95 %
P_B^{max}	Battery (dis)charging power limit	$\pm C_B/(5h)$
P_{Gen}^{max}	Diesel generator rated power	100 kW
C_f	Diesel fuel cost per liter	1.85 $/L
Cg	Utility grid energy price per kWh	0.18 $/kWh
DG^*	Set of available diesel generators	75,100,175,250 kW
Δ	Time slot	(1/6) h
P_{DG}^{max}	Diesel generator capacity	100 kW
P_{inv}	Ratings of the power inverter	100 kVA

(*) parameter to be optimized.

The simulation is carried out using MATLAB optimization toolbox and converged under these circumstances to 0.22 $/kWh as a minimum cost of energy, which is 52% lower than the energy price of diesel-only case, (0.46 $/kWh by 100 kW generator), at average penetration level P_{ℓ} = 70%. These findings are consistent with [Vi2009], that is, the end energy price of the diesel-only systems is very high, though still realistic solution for small island systems, which is similar to a large extent to the case of severe power outages.

The final penalty value is found around 0.22 in case of the declared outage scheme, as depicted Figure 5.6. This value expresses mainly the value of *LCoE* per kWh and the inherent increasing due to the non-utilized *PV* energy as declared previously in equation (5.6).

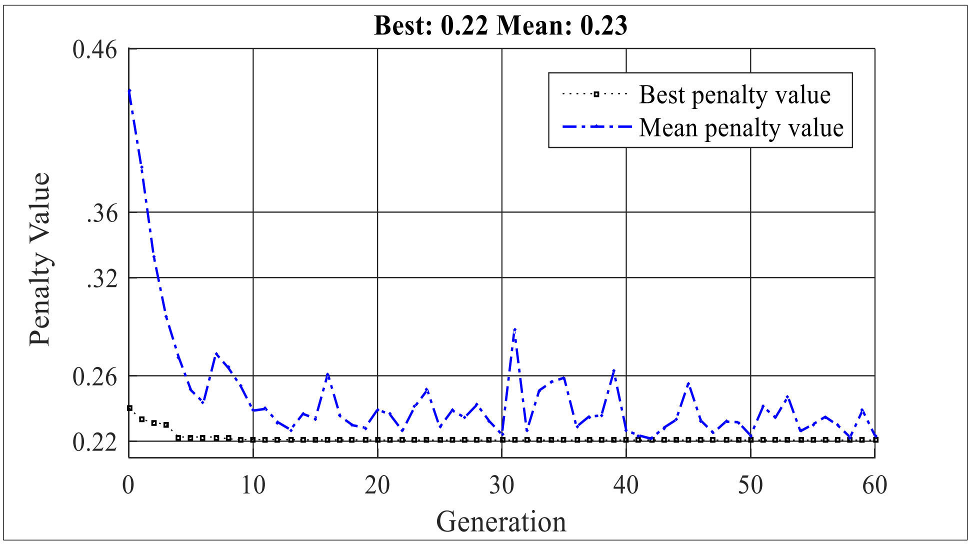


Figure 5.6: Convergence of penalty function over GA generations.

Further advantage of the algorithm that is identifying the optimum operating points of the battery storage where the switching to the generator should be done and vice versa. These findings of the optimized component of the MG under the aforementioned conditions, that minimizes the *LCoE* over the 20-years evaluation period, are listed in below in Table 5-3.

Table 5-3: Optimized Microgrid Configuration

Parameter	Nomenclature	Value (s)
N_B	Number of storage units	140 Storage units
N_{PV}	Number of PV panels	922 Panels
P_{DG}^{max}	Diesel generator capacity	100 kW
P_{inv}	Ratings of the power inverter	100 kVA
SoC_{min}^{*}	Minimum allowable state of charge	40 %
SoC_{stp}^{*}	Stop charging threshold from GenSet	89 %

The annual purchased energy and fuel savings in case of the proposed system is listed below in Table 5-4. The results are then compared with the old baseline configuration, which depends merely on diesel generator as a backup resource in addition to the interrupting grid.

Table 5-4: Annual Purchased Energy and Fuel Savings

Parameter	Legacy System	Microgrid Design
Purchased energy from grid (MWh)	124,98	116,12
Gross purchasing from grid ($×103)	22,45	20,90
Total fuel consumption (L×103)	80,98	3,31
Operation Hours (Hr)	5840	153
Total fuel costs ($×103)	149,8	6,12
Purchased energy from grid (MWh)	124,98	116,12

The supplied energy from each individual resource in both configurations is investigated and listed in Table 5-5. Besides, the annual and utilized energy from all resources in both configurations is presented as well.

Table 5-5: Annual Produced and Utilized Energy

Annual Energy (MWh)	**Legacy System**	**Microgrid Design**
Gross purchased energy from grid	124,98	116,12
Net load supplied from grid	124,98	96,87
Gross produced energy from diesel	249,9	11,50
Net load supplied from diesel	249,9	10,225
Total produced energy from PV	–	404,16
Net load supplied from PV	–	267,78
Total energy of the load	**374,88**	

5.5 Discussion and Economic Assessment

Obviously, the gross and net supply either from grid or diesel in the old configuration are the same. By contrast, with the microgrid, the net supply from any of the resources is less than the gross produced or purchased energy in the system. The main reason of that is the lost energy due to power conversion among the system's components. In addition to that, some non-utilized energy is lost in case of the microgrid because the battery is fully charged and the load is satisfied at the same time.

In addition to the previous indices, the net share of ***PV*** is another important index which accurately indicates the real benefit of deploying the RES in the system and gives a better realization of the presented outcomes. It can be described by two values, the RES utilization factor (λ) and penetration level (P_ℓ) which both are defined in equations (5.9) and (5.10) as follows:

$$\lambda = \frac{Net\ energy\ supplied\ by\ RES}{Total\ RES\ production} \times 100\% \tag{15}$$

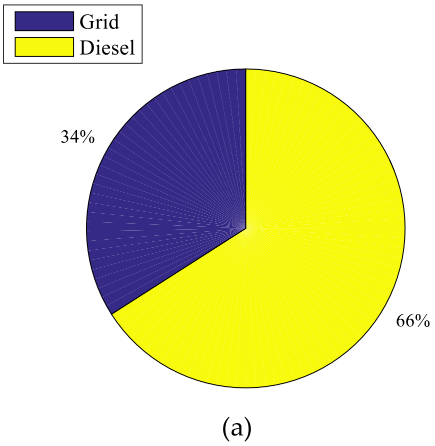
$$P_\ell = \frac{Net\ energy\ supplied\ by\ RES}{Total\ energy\ demand} \times 100\% \tag{16}$$

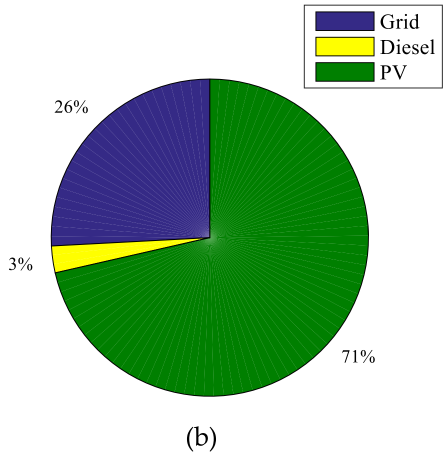
The values λ and P_ℓ can be calculated by dividing the value of the sixth row by the values in the fifth and last row respectively.

$$\lambda = (267.78 / 404.16)\times 100\% \approx 66.25\%$$

$$P_\ell = (267.78 / 374.88)\times 100\% \approx 71.43\%$$

As depicted below in Figure 5.7, a pie chart illustrates the net share of each resource in both situations (Grid-Diesel and Grid-Microgrid). Meanwhile, the penetration level (P_ℓ) of PV array in the new configuration is marked with a green color.





(a) Baseline **(b) Grid-connected MG**

Figure 5.7: The net energy share of each power source.

It is also remarkable that installing less RES, e.g. *PVs* leads to benefit from a plentiful generated energy, meaning that, less rejected or unutilized energy. This is obvious because RES, in that case, lies mostly under the load demand, which allows to be directly taken by the load.

In contrast, seeking a high penetration level leads to a relatively high rejected RES and thus, low utilization factor, because the residual RES will be either redirected to the battery or even rejected. This phenomena can be illustrated using 3-days power profiles of 600 PV panels, grid line and load demand, as shown in Figure 5.8.

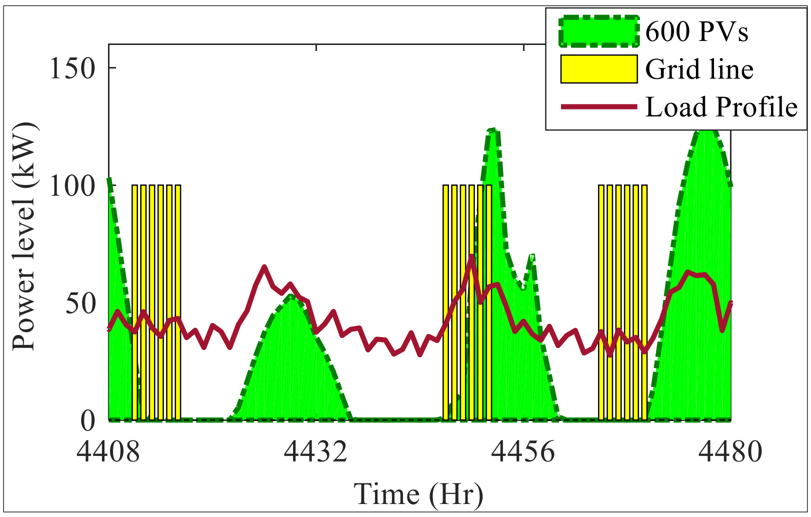


Figure 5.8: Power profiles of 600 PVs, interrupted grid and load.

It is evident that most of the generated PV power can be directly absorbed by the load once it is less than demand. However, in case of residual generation, it will be redirected to charge battery for example.

Of course, this will result in more losses due to power conversion. Thus, oversized *PV* units may lead to higher penetration levels, but not necessarily to more economic designs.

Aside from the technical indices, the net present value (***NPV***) is chosen to analyze the profitability of the proposed project. It indicates the algebraic sum of the net cash flows over a project period. It can be formulated as in equation (5.11).

$$NPV = \sum_{n=1}^{N} \frac{C_n}{(1+r)^n} - C_0 \tag{17}$$

Where: $n \in \{1, 2, 3, \ldots, N\}$ points to the year; $N = 20$ years. C_0 is the first installment of the project (here it is the investment cost of ***PV*** panels and storage units). C_n is the total cash flow over year n, r is the discount rate. The yearly net cash flow is resulted from the revenues minus the running costs and capital investment. Obviously, revenues come from the considered price for supplying the load by RES. Contrariwise, the running costs are dominated by the costs of supplied energy from grid and diesel generator in addition to the replacement costs of the batteries. In addition, extra revenue is added as an incentive to reduce the dependency on the grid and diesel fuel. Considering the resulted components (see Table 5-3) with the corresponding declared prices and two times replacements of the batteries, the *NPV* is described in Figure 5.9.

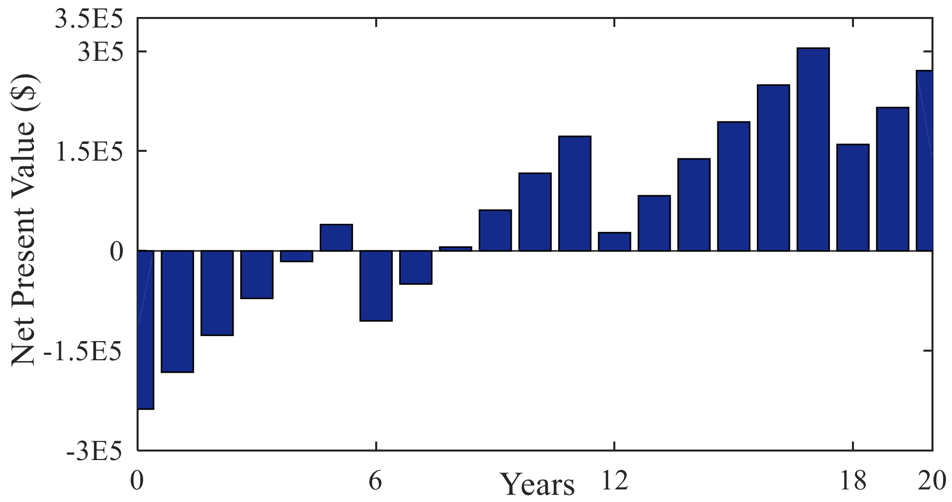


Figure 5.9: Net Present Value of the proposed microgrid.

The graph shows that the net return will beat the payments after the eighth year, which makes the proposed system profitable for the considered case.

5.6 Conclusion and Final Remarks

This chapter presents a straight-forward method to provide an optimal layout design of a microgrid including *PV* array, *ESS* and *Diesel* asset. The presented method is general and can be applied for deigning a grid-connected or an isolated microgrid, considering a complete power outage. The method is appropriate for societies and communities subject to frequent grid outages where, in times of grid outage, the load is supplied merely by diesel generators, which consume a huge amount of fuel. A case study of a hospital building subject to severe power outages has been presented.

However, with the microgrid, the annual payments of installation and replacement count 75×10^3 US-$, but the long-term annual savings will be 145×10^3 US-$, which means that the net annual saving will be about 70×10^3 US-$, that is half the fuel cost in the old configuration. In addition, a very reasonable utilization of RES can be achieved with microgrid (UF = 66.25%). Besides, a high RES penetration level can be achieved (P_ℓ = 71.43%).

Furthermore, it is noticed that the optimal selection of components depends primarily on the adopted operation policy in addition to the gross energy produced by RES rather than on the initial prices of the components only. Installing such RES in microgrids can be done gradually, and expectedly, the savings will increase progressively.

6 Conclusion and Outlook

This work addressed in the first place the PV-Battery-Diesel Microgrid system as a resolution for one of the most emerging electrification problems, especially in the developing countries where the operational costs of conventional alternatives are unimaginable.

Mainly, two important topics were comprehensively covered in the course of this work. The first one was on the developing of an efficient EMS based on the basic modeling of each system component. For this topic, three different EMSs were presented and discussed with a real-case scenario. A former rule-based was discussed firstly and the enhancement potential to increase the efficiency of the system was successfully highlighted. Afterwards, two optimization-based EMS using the prediction of were presented. The offline solution is firstly conducted assuming a perfect prediction and then the adaptation was carried out by imposing some errors on the predicted data. The optimization goal aims at not only minimizing the running costs but also maximizing the net utilization of the clean solar energy. The proposed solution adopted the former Dynamic Programming method for tracking the least cost operation strategy. However, a relaxation technique was proposed to speed up the optimization process and reduce the search space. Besides, another form of energy management was presented in this work concerning the demand side in the smart grid environment, where the loads can be predicted or notified in advance. An optimization-based load scheduling approach was presented assuming the predictability of a group of shiftable load. The scheduling approach considers the involved EMS of the generation side and seeks to minimize the *LCoE* in accordance with the permissible operation time of the considered loads.

The second topic of this thesis discussed the issue of selecting the capacity of each component of the MG that will lead to the least cost of energy. The need for a hybrid system was elaborated using a practical power outage scenario. This approach differs from other predecessor methods in particular with the consideration of the applied EMS, by which the effective utilization of solar energy can be varied and thus, the resulted capacity might be oversized. It was observed that the components' sizing depends primarily on the adopted EMS in addition to the gross energy produced by PV rather than on the initial prices of the components only.

The percentage of fuel reduction using the optimization-based EMS exceeded 25% in case of accurate prediction and was about 18% in case of uncertain prediction. Depending on the accuracy of the prediction, the proposed optimization-based approaches could maximize the net utilized PV energy up to about 90% and thus, it can be concluded that such methods can result in not only economic benefits but also in a more efficient operation in terms of solar energy utilization.

Additionally, simulation results could clearly indicate the advantage of performing such analyses before developing such EMS for microgrid systems or deploying new components for the purpose of solving electrification problems to assist the legacy backup power systems, e.g. in this case PV and Battery assist diesel Generator).

As a future prospect, it can be said that some further studies for the systems could be carried out. First of all, it would be interesting to apply the results of the research on a specific battery models and PV modules. Moreover, as with the aging mechanism of the considered battery units, further investigation might be helpful for complicated strategies with dynamic load behavior. Additionally, further operational scenario of the future microgrid systems including Electric Vehicles and responsive loads could be an interesting research area, especially when considering the matter of scheduling different energy sources jointly with this kind of demand.

Appendix

A.1 Diesel Generator Fuel Consumption Characteristics

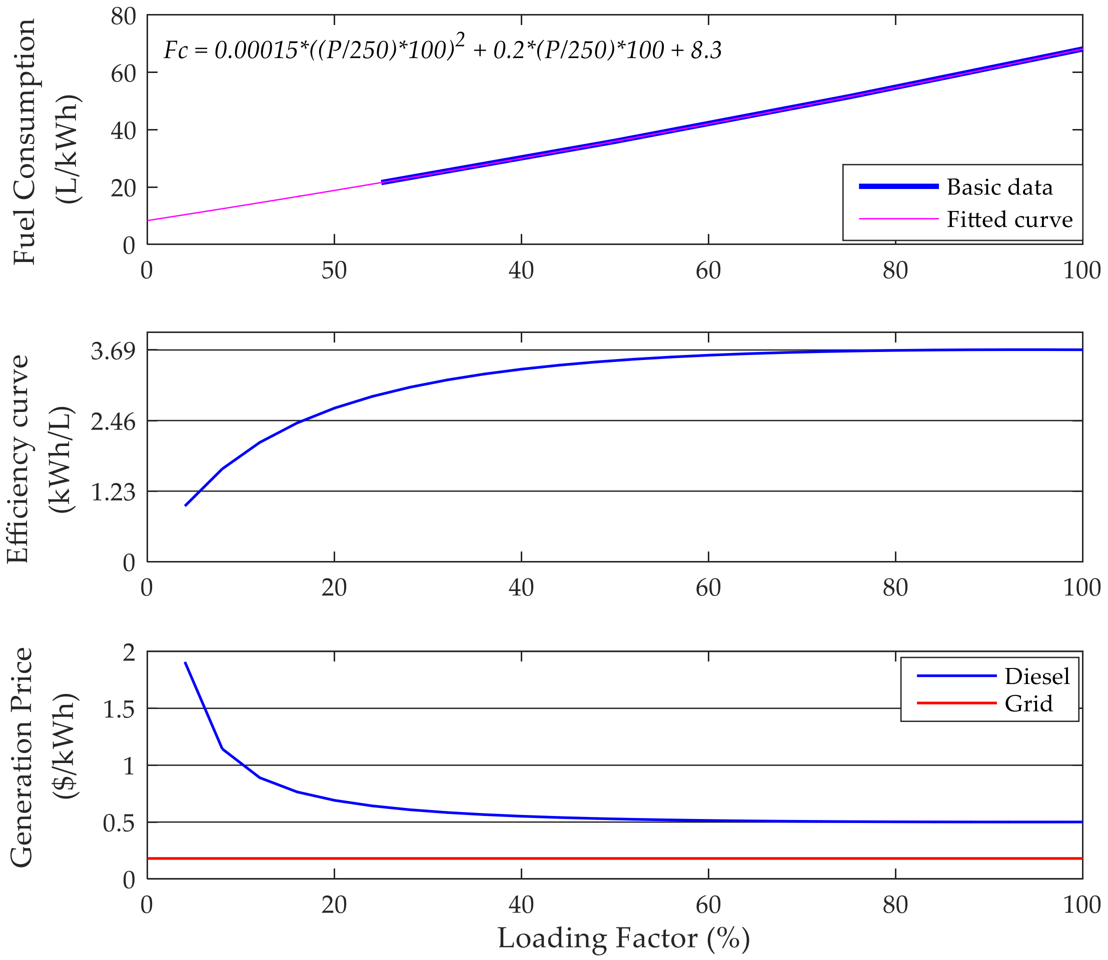


Figure A.1: Fuel Consumption Curves of 250 kW Diesel Generator
Consumption chart (uppermost), Generation efficiency (middle), Generation Price (bottom)

A.2 Components' Initial Costs and Specifications

The deployed battery storage unit is a Trojan battery model IND17-6V adopted from [Yu++2014]. It has a 5.55 kWh capacity at 20-h discharging rate and a relatively long lifetime under a low *SoC*, i.e. 2200 cycles at 40% *SoC* with a nominal price of 1400 \$. Its maximum (dis)charging is considered 1/5 of the capacity within 1 h to keep healthy operating conditions. Considering one cycle per day, its annual capital cost is:

1430 (\$) × [365 (cycles/yr) / 2200 (cycles)] = 237 (\$/yr).

The used solar generator is a 250Wp PV panel which is the kernel of the *PV* array and has a price of 1.9\$/Wp including the installation, corresponding power electronics, and converters for voltage regulation and adaption among power bus bars. Assuming a 20-years warranty over the project lifetime, the annual price of each panel is:

[1.9 (\$/Wp) × 250 (Wp)] / 20 (yr) = 24 (\$/yr).

A.3 Elaboration on the battery-only backup systems

The illustration below is used to show how fast the depletion of the battery charge can be just during an eight hours of power outages occurring in different times during a single day. A generic battery model is used with a nominal capacity 500 kWh and (dis)charging efficiency 0.9. Other operational constraints are imposed in order not to discharge it below 40% of its nominal capacity, i.e. 200 kWh. Obviously, the depletion time due to the first outage, i.e. occurring during the peak time as in the middle figure, is much faster than its counterpart second outage which occurs during the off-peak time, as in the bottom figure. One can recognize that the recovery time needed to recharge the battery is highly dependent with the grid capacity and the battery capability of fast charging, i.e. in less than 5 hours to be completely recharged. Thus, such a model, using battery-only backup systems is not a feasible solution for communities under prolonged power outages. Consequently, once can observe how numerous the battery size at least can be due to the variation of the demand and the interval of power outage.

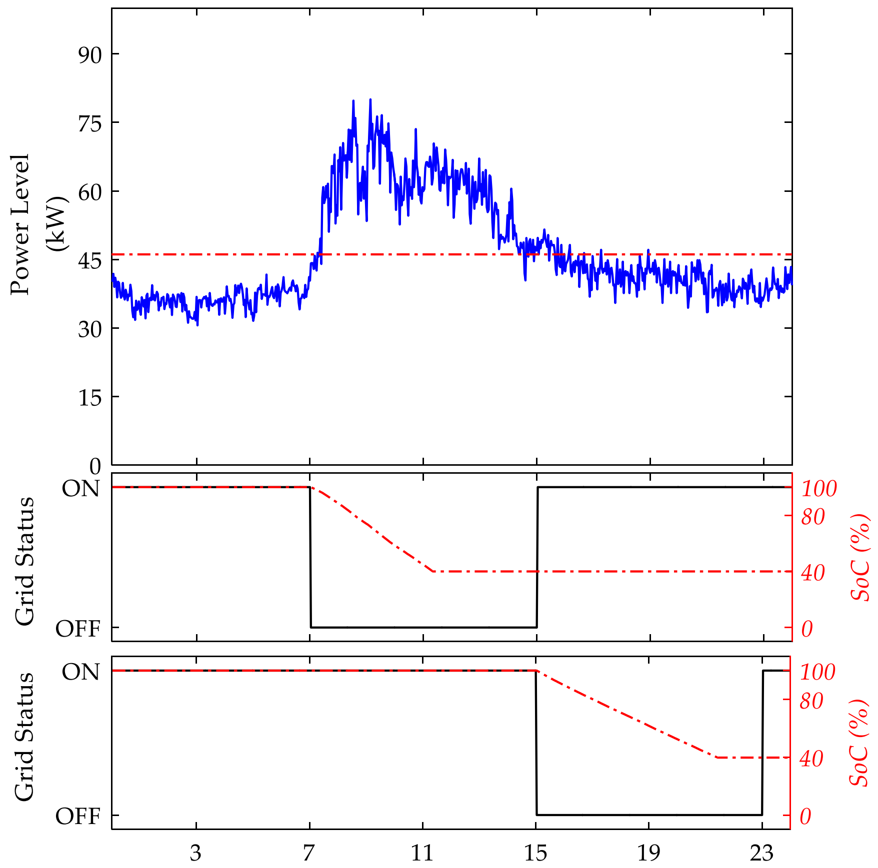


Figure A.3: Trajectories of battery *SoC* in battery-only backup system during power outages Load profile (uppermost), trajectories correspond to outage period 1 and 2: (middle) and (bottom)

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