

**EFFECTIVE ENERGY MANAGEMENT OF MICROGRIDS USING  
INTERIOR POINT ALGORITHM**

**A Thesis Submitted**

*In partial fulfillment of the requirements for the award of the degree of*

**MASTER OF ENGINEERING**

In

**ELECTRICAL ENGINEERING**

By

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**CERTIFICATE**

This is to certify that this dissertation titled “EFFECTIVE ENERGY MANAGEMENT OF MICROGRIDS USING INTERIOR POINT ALGORITHM” is being submitted by **SOUMIK GHOSH**, with Roll No. 002210802006 in partial fulfillment of the requirements for the award of the degree of **Master of Engineering in Electrical Engineering** from JADAVPUR UNIVERSITY, KOLKATA, WEST BENGAL, INDIA has been carried out by him under my guidance and supervision. The project, in my opinion, is worthy of its acceptance.

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**CERTIFICATE OF APPROVAL\***

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**DECLARATION**

*I certify that the work shall be performed exclusively by the applicant, unless it has been recognized in good time. This thesis constitutes a summary of my previous research, which was never fully or partly presented in order to qualify for the next academic award. Moreover, the content of this thesis is based on work that has been accomplished since the entry into force of the approved research program.*

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## **ABSTRACT**

This study uses an optimization-based technique to investigate microgrid energy management systems. Specifically, it optimizes the operating costs associated with energy purchased from the utility grid and the money generated from selling energy to the utility grid. To solve the confined optimization problem presented in micro-grid energy management, the research employs an interior point method and a Linear Program-Based Optimization technique. The interior point method is quite adept in handling both equality and inequality constraints. In comparison to the linear programming method, simulation results show the improved performance of the interior point method algorithm.

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## List of Abbreviations

RES	Renewable Energy Sources
DER	Distributed Energy Resources
LP	Linear Programming
GA	Genetic Algorithms
PCC	Point of Common Coupling
MPC	Model Predictive Control
PSO	Particle Swarm Optimization
ESS	Energy Storage Systems
DG	Distributed Generation
MPPT	Maximum Power Point Tracking
BESS	Battery-based Energy Storage System
STC	Standard Test Conditions
EMS	Energy Management System
SOC	State of Charge

## List of Symbols

$\psi(x)$	Logarithmic Barrier
$\nabla f(x^*(t))$	Divergence of a function $f(x^*(t))$
$I(f_i(x))$	A penalty term representing the violation of constraints
$f_o(x)$	Given objective function
$f_i(x)$	Inequality constraint functions
$\epsilon$	Tolerance
$\mu$	Scaled improvement of the variable $t$
$c^T$	Transpose of coefficient matrix
$K_i$	Short circuit current coefficient of solar cell
$I_{sc}$	Short circuit current of solar cell
$G_{STC}$	Nominal irradiance
$P_{solar}$	Solar system's power output
$T_{amb}$	Ambient temperature
$T_{cell}$	Cell temperature
$\eta_{solar,t}$	Efficiency of Solar Cell at time $t$
$A_{solar}$	Area of the solar module in square meter
$P_{grid,min}$	Minimum grid power
$P_{grid,max}$	Maximum grid power
$P_{grid,t}$	Grid power at time, $t$
$C_{grid,t}(P_{b,t})$	Cost of electricity at time $t$
$E_{b,min}$	Minimum energy stored in the battery
$E_{b,max}$	Maximum energy stored in the battery

$\eta$	Charging or discharging efficiency
$C_{reserve,b}$	Stored energy coefficient of battery
$P_{b,t}$	Battery power at time $t$
$X$	Vector representing all the control variables
$C_{TOU,t}$	Price of electricity at time $t$
$C_{norm}$	Normal capacity of ESS
$V_{var,L}$	Variable load voltage
$P_{var,L}$	Variable load power
$V_{stat,L}$	Static load voltage
$P_{stat,L}$	Static load power



## **Chapter 1**

### **Introduction**

#### **1.1 Overview**

The increasing use of renewable energy sources (RES) for power generation is a result of growing concern over the world's escalating energy consumption and reliance on fossil fuels in recent years. The power system encounters obstacles when integrating renewable energy sources, which demands novel solutions to enhance system performance. Microgrids and distributed energy resources (DERs), which provide flexibility and control to the power system, have grown to be appealing concepts for power systems [29].

Insufficient energy sources can make it difficult for micro-grids to meet demand. The unpredictable nature of loads and renewable energy sources is the cause of this difficulty. Thus, an energy management system is needed to solve this issue [4]. Scheduling Energy Storage Systems (ESS) power dispatch under the unpredictable nature of solar PhotoVoltaic(PV) power generation and load is one of the study's primary goals in order to improve microgrid operating performance. Although the ideal combinations of renewable generation and load are not always apparent, they can be predicted using past statistical data or empirical judgments. These aid in solving the problem of energy dispatch [29].

Scholars have investigated a range of optimization techniques like adaptive particle swarm optimization, robust scheduling techniques, multi-objective genetic algorithms, linear programming and many more to tackle energy management issues in microgrids. In microgrid systems, these initiatives seek to lower expenses, improve dependability, and cut emissions [29].

This study presents an interior point-based optimization method for energy management in microgrids. Its performance has been compared with a conventional linear programming algorithm. The suggested approach seeks to optimize energy flow, save operating costs, and enhance overall system performance when compared with the conventional linear programming algorithm. The interior point-based optimization method algorithm plays a crucial role in improving energy storage scheduling efficiency in micro-grid systems, as demonstrated by the sections that follow, which detail the system model, optimization methods, simulation outcomes, and study conclusions.

## **1.2 Microgrids**

A collection of electrical sources and loads that may function both independently and in tandem with the larger power grid is known as a microgrid. Distributed energy resources (DERs) like solar panels, wind turbines, batteries, and backup generators are usually included. A neighborhood, college, or industrial complex can receive dependable and resilient power supply via microgrids, which can also facilitate effective energy management and the integration of renewable energy sources [29].

There are two primary modes of operation for microgrids: islanded mode and grid-connected mode. When in islanded mode, the microgrid powers its immediate area without relying on the main grid in the event of an emergency or grid failure. The utility also provides adaptability in the control of energy supply and demand [29].

When in grid-connected mode, the microgrid can interchange electricity with the utility and is linked to the main grid, providing flexibility in managing energy supply and demand. Control and management of microgrids are essential for preserving system stability, maximizing energy flow, and guaranteeing dependable operation. Microgrids are connected to the utility grid by Point of Common Coupling (PCC) [29]. To improve the effectiveness and efficiency of microgrid operations, advanced control strategies like Model Predictive Control (MPC) and optimization algorithms like Particle Swarm Optimization (PSO) are frequently used. In general, microgrids contribute significantly to energy independence, increased integration of renewable energy, improved energy efficiency, and enhanced resilience of the grid against disturbances or variations in the main power system [29].

## **1.3 Energy Management in Microgrids:**

Microgrid management is the process of regulating and coordinating the various parts of a microgrid to provide reliable, economical and effective operation. To meet the energy needs of its users, microgrid management is crucial for optimizing energy generation, storage, distribution, and consumption inside the microgrid [33].



Fig.1: Microgrid Systems[31]

Important facets of energy management in microgrids consist of:

**Energy Storage:**

To store extra energy for later use, microgrids frequently employ energy storage devices, such as batteries. In order to balance the supply and demand of energy, microgrid management involves planning the charging and discharging of energy storage devices. Effective control of energy storage devices, such as batteries, to release stored energy as required and store extra energy when generation exceeds load are important aspects of energy management [32].

**Load management:**

Load balancing is the process of adjusting the microgrid's energy supply and demand to make sure that there is always enough electricity to fulfill the demands of the linked loads [32].

**Demand Response:**

Microgrid management systems can modify energy output and consumption to ensure system stability in response to variations in energy supply or demand. This could entail reducing load during times of high demand or moving energy use to off-peak hours [32].

**Grid Interaction:**

Being able to function independently in islanded mode during grid failures, as well as interacting with the main grid to import or export electricity as needed [33].

**Energy Optimization:**

By coordinating the functioning of dispersed energy resources, microgrid management seeks to maximize energy utilization and minimize waste. This entails limiting dependency on the main power grid and optimizing the usage of renewable energy sources [32].

Energy management issues can be resolved by applying optimization methods including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Model Predictive Control (MPC), and Linear Programming (LP). Operators can optimize energy efficiency, lower costs, and improve system reliability by skillfully controlling the microgrid's energy generation, distribution, and consumption [28,29].

In this work, integrated microgrids have been considered, hence our main objective have been to optimally use the energy storage system, the solar energy to reduce the energy drawn from the grid (grid usage) and thus reduce the cost of energy.

#### **1.4. Optimization Techniques in Energy Management of Integrated Microgrid:**

Any attempt to minimize the energy cost or grid usage of an integrated microgrid using optimization techniques makes the problem complex. So, advanced optimization techniques can be used in dealing with these problems. Traditionally, optimization techniques like Linear Programming (LP), Heuristics, and Particle Swarm Optimization (PSO) have been widely used in these problems. But for large and complex optimization problems, the Interior point method is supposed to provide better results. Unlike LP, which goes on looking for the solution in the vertices of a simplex, the interior point method, tries to find the solution in the interior of the simplex, which has a better chance of finding the optimized solution.

These optimization techniques help to better manage the microgrid by determining to charge and discharge the ESS, buy or sell power to the grid, and respond to variations in electricity cost, load demand, and other parameters.

#### **1.4. Literature Review**

Numerous studies have been carried out using novel and effective energy management techniques as well as optimization models. Numerous scholars have tackled issues related to energy management by employing diverse optimization methodologies to attain the most optimal and efficient functioning of the microgrids. In order to meet the economic and emission reduction goals for microgrid management involving fuel cells, wind turbines, battery storage, solar arrays, and micro-turbines, Deng et al. [7] suggested multi-objective offline scheduling. The authors applied a multi-objective genetic algorithm to the resulting optimization problem. In this multi-objective problem,

both cost and environmental impacts were considered as objective function. In this work the tariff details, equipment performance, weather conditions and its forecast, load details and their forecasts and other necessary information were considered as the basis of the onstraints considered [7].

In [8] Mohammadi et al. presented a robust optimal scheduling strategy that accounts for generation and pricing variations in micro-grid management with storage and renewable energy sources. This work proposed a probabilistic Energy Management system based on an effective Point Estimate Method to optimize Micro-Grid operation. The market prices, load needs, and the unpredictability in the electricity generation of photovoltaic and wind farms were all modeled using this technique.

In order to control micro-grids powered by renewable energy and backup hybrid turbine/fuel cell/battery power, Moghaddam et al. [9] employed a multi-objective adaptive modified particle swarm optimization; the optimization problem in this study was nonlinear. This work presented the optimal operation of a typical microgrid with a backup energy storage to balance the power mismatch or store excess energy. An expert multi-objective Adaptive Modified Particle Swarm Optimization algorithm was used in this work [9].

To accommodate for the uncertainty in projected parameters, Chaouachi et al. [10] scheduled battery consumption using a multi-objective linear program with fuzzy logic. Using artificial intelligence approaches in conjunction with multiobjective optimization based on linear programming, a generalized formulation for intelligent energy management of a microgrid was developed. The goal of the suggested multi-objective intelligent energy management is to reduce a microgrid's operational costs and environmental effect while accounting for preoperational factors like load demand and the availability of renewable energy sources in the future [10]. To forecast solar power generation twenty-four hours in advance, wind power generation one hour in advance, and load demand, an artificial neural network ensemble was developed [10].

A Mixed-Integer-Linear-Program (MILP) was utilized by Morais et al. in [11] to create an offline, non-robust optimization for power dispatch management. Through the use of mixed-integer linear programming in General Algebraic Modeling Systems, the optimized operation for a wind turbine, solar unit, fuel cell, and storage battery was investigated. In order to ensure optimal performance of the generation units, proper maintenance, good equipment functioning, lower operating costs, and improved generation monitoring and control, a Virtual Power Producer was employed A Virtual Power Producer was able to handle the best generation and load control with the usage of a central control system. The authors assessed a microgrid that ran solely on electricity and had fuel cells, PV panels, wind turbines, battery storage, and an adjustable load.

Boonbumroong et al. [12] employed PSO to lower the life-cycle cost of a standalone PV/wind/diesel system intended to supply a particular load. Like most of the related works, in this work also, the

generated energy was used to meet the hourly energy requirement as per the constraint of optimization. The primary goal of this work was to provide a method for optimizing the setup of a standard stand-alone hybrid power system with an AC coupling. The design was presented as an optimization problem, and its solution enabled the stand-alone hybrid power system to be configured in a way that minimized overall costs over the system's useful life [12]. An existing PV/wind/diesel hybrid power system at Chik Island, Thailand, was chosen as a reference system, and the simulation results were compared with the in-situ monitoring data in order to validate the system component models.

Wang et al. [13] optimized a hybrid PV/wind/battery energy system according to cost, reliability, and emission requirements without considering load management using a multi-objective PSO algorithm. In this study, hybrid generation systems that were ideal in terms of cost, dependability, and emissions were constructed using wind turbine generators, solar panels, and storage batteries. The decision maker was assisted in making more logical decisions by the use of multicriteria design. To obtain these nondominated solutions, a better particle swarm optimization algorithm was created in this work. Time-series models are used to represent the stochastic features of wind speed, solar insolation, and random load change because of their unpredictability. Time-dependent sources were included in the sufficiency evaluation process. Sensitivity experiments were also conducted to investigate the effects of various system factors on the overall performance of the design.

Sufian et al. [28] employed LP and Heuristics both for minimizing cost and grid usage. Their work clearly showed that the LP outperforms Heuristics in all aspects. Their work considered both the cases for clear day and cloudy day and in both the cases LP outperforms Heuristics. The measurement parameters like microgrid voltage profile, cost of energy, State of Charge of the Energy Storage System (SOC) were also graphically shown in this work.

Gbadega et al. [29] uses Constrained PSO using Deb's rule for constraint handling and LP for cost minimization. This work used Model Predictive Control (MPC) for the forecasting of solar irradiation, cost of electricity and load.

As for a large and complex convex optimization problem, interior point method gives better results than LP, hence in this work, interior –point method has been used. Hence, the main contributions of this work are the following:

1. An interior –point based energy management technique is developed and applied using constraint handling methodology to obtain better results than the previously discussed works. Specifically it outperforms the results obtained in [28] clearly in terms of cost and grid usage reduction.
2. The constrained optimization problem formulated in micro-grid energy management is solved

using interior point method and linear program-based optimization approach. Their optimization results are compared.

3. The optimization strategies employed in this study satisfied the generation-demand balance and the associated limitations while minimizing the microgrid's operating costs and grid energy consumption.

### **1.5 Organization of the Thesis:**

This thesis is organized into five chapters. In Chapter 1 a brief overview of the microgrid along with the previous works on the energy management aspect of the microgrid has been discussed. Chapter 2 describes the microgrid under study. It elaborates on how the renewable energy sources, loads and the energy management system are integrated into the microgrid. In Chapter 3, the convex optimization techniques, namely the linear programming and interior point method, are discussed for the energy management of this integrated microgrid. The simulation model, its results and discussions of the superiority of the interior point method over the linear programming optimization method for microgrid energy management have been discussed in Chapter 4. Further, Chapter 5 provides the conclusion and gives information regarding the future scope of this work.

## **Chapter 2**

### **Microgrid Systems**

#### **2.1. An Introduction to Microgrid Systems:**

Distributed generation resources (DER), energy storage systems (ESS), and different kinds of electrical load demands are all combined to form a microgrid. The microgrid functions as a solitary unit in relation to the main grid, which is controlled via control signals. Any conventional or non-traditional power source, including fuel cells, solar cells, wind turbines, and micro turbines, can be used as DERs in the microgrid. A microgrid is characterized as a group of load units, distributed energy resources (DERs), energy management systems and energy storage systems that work together to provide reliable electricity. The microgrid is connected to the host power system i.e. utility grid at the consumption level at a single point of connection called the Point of Common Coupling (PCC) [2][3]. Usually, it is on the power distribution system's low voltage side. The goal of microgrids is to provide energy in a cost-effective, secure, and sustainable manner through intelligent control, monitoring, and self-healing technology. Microgrids appear to be a new kind of small-scale, local grid that minimizes losses while maximizing local resources available in a given area. There are two ways that microgrids can function: island mode and grid connected mode [4].

##### **(i) Island Mode:**

The condition when the power quality of the main grid poses a risk to the operation and quality of the microgrid the microgrid island's itself from the main grid. This ability to island itself reduces outages and enhances dependability, quality, and service of the electricity. Islanding may occur accidentally or on purpose for example during scheduled repair, planned islanding may take place. Unplanned islanding may occur as a result of any disturbance on the main grid and other unplanned, microgrid events [34].

##### **(ii) Grid Connected Mode:**

In this mode of operation, the microgrid is linked to the electrical grid. This operation can also be defined by two instances: (1) The microgrid supplies excess electricity to the utility grid while

remaining connected to the grid and, (2) it may draw power from the grid when there is deficiency of supplied power from the connected DERs of the microgrid. For proper synchronization operation of the microgrid along with the main utility grid various methods, including droop control, artificial intelligence approaches like fuzzy logic, neural networks, genetic algorithms, and particle swarm optimization (PSO), are available for control of the various parameters of the microgrid. Whenever there is a peak demand and DER is unable to meet the load demand, the main grid, meets the requirement. This mode guarantees a continuous supply of power because the main utility grid can step in as a backup power source. Therefore, this method leads to minimal load shedding [5].

The forming blocks of the Microgrid Systems are discussed below:

### **1. Energy Sources:**

Electric power sources connected to the distribution network are referred to as distributed energy resources, distributed generation (DG), dispersed generation, embedded generation, and decentralized generation [44]. DER has several benefits, such as minimizing transmission losses by consuming electricity at the generating point and supplying power to inaccessible areas [45]. There are two types of distributed energy resources: dispatchable (such hydroelectricity, natural gas, pumped storage power plants, biomass, geothermal, and ocean thermal energy) and non-dispatchable (which cannot change their output power in response to changing conditions i.e. wind, solar, tidal, wave etc.). DERs provide both reactive and active power [46]. They can control the flow of both reactive and active power to control both voltage and frequency respectively.

### **2. Energy Storage Systems or Batteries:**

Renewable energy sources (RES) are intermittent in nature, meaning that they cannot produce power when needed. Energy storage systems are utilized to get over this problem by storing the excess energy from these sources. This increases the reliability of the microgrid. Hence it necessitates more detailed studies on the types of energy storage systems and their control strategies [48][49].

### **3. Electrical Loads in the Microgrid:**

In a power system, a microgrid acts as an electric load and functions similarly to an electrical "Slack Bus," supplying or absorbing power from the utility grid in accordance with operational plans or contractual duties. Various categories of electrical loads can be linked to the microgrid. Heating, ventilation, and air conditioning (HVAC), dishwashing, dryers, washing machines, refrigerators, light loads, fans, plug-in hybrid electric vehicles (PHEVs), plug-in electric vehicles (PEVs), commercial and residential buildings, schools, hospitals, and so on are examples of small industrial or domestic loads. Depending on the customer, these loads can be defined as basic, shiftable, programmable, interruptible, continuous, critical, etc. [51][52].

### **4. Energy Management Systems:**

Microgrids need to meet a number of objectives pertaining to the environment, technology, and economy. The major goals of an energy management system are to import/export of power in accordance with the microgrid's needs, manage forecasted/actual load demand, generation, and electric grid as well as to minimize or balance transients or disturbances in the power system, and manage real/reactive power flow[54][55][56].The energy management system in a microgrid has the following purposes:

#### **(i) Maximizing the Generation output:**

As most of the DERs employed in microgrid like Solar PV and wind generators, generate power intermittently hence it is becoming necessary to extract the maximum possible power from these DERs. There are several different kinds of Maximum Power Point Tracking (MPPT) technologies, available in literature to maximize the power output of these DERs. Few examples of them are artificial neural network, fuzzy logic control, load matching, learning algorithm, lookup table, ripple correlation control technique etc. [34].

#### **(ii) Forecasting of Power Output Generation:**

It is extremely difficult to predict the energy produced from RES as it varies according on the geographic area. However, an accurate projection of generation is necessary for power balance. There are various kinds of methods available in literature. One may use historical data from prior

hours, months, or years, while others may use model approaches like numerical weather prediction, etc. The output power is projected after certain parameters have been estimated [34].

### **(iii) Forecasting of the Electrical Load:**

The electric load forecasting is indispensable procedure for the planning of power system industry, which plays an essential role in the scheduling of electricity and the management of the power system. Many factors are taken into account while forecasting load, including weather (temperature, humidity, cloud cover, rainfall, etc.), economics (consumer earnings, location, population, etc.), and load consumption trends during a certain time period. Load forecasting is necessary for energy procurement, transmission and distribution, operation and maintenance, economical dispatch and fuel scheduling [34].

For economical and effective energy management of microgrids, sophisticated forecasting technique is required. Techniques like moving average forecasting, autoregressive forecasting, sliding window forecasting, rolling window forecasting becomes very important tools for this forecasting.

Different techniques exist for load forecasting, namely Artificial Neural Network, Genetic Algorithm, Fuzzy logic, Support vector machine, Adaptive Neuro fuzzy inference, self-organizing map, extreme learning machines, etc. and Analytical methods like Linear Regression method, Box-Jenkins method, non-parametric regression, etc. [34].

### **(iv) Demand Side Management:**

The primary goal of Demand side management is to schedule deferrable loads to reduce the amount of energy that must be supplied by the electric grid. It attempts to modify the maximum load in accordance with the power supply from the RES. It reduces the ESS's cycles of charging and discharging. Although the peak demand only lasts for 5% of the total time, certain power plants that are mostly operated during the peak demand period and are idle during the rest time must be used to meet the demand. Demand side management involves a number of different operations, such as strategic load growth, flexible load shaping, peak clipping, valley filling, shifting of different loads, reshaping of the load profile, overall cost reduction, emission reduction, and storage element capacity [34].

It is possible to deploy demand side management with the aid of inexpensive sensors and two-way communication between the grid and the consumer. This would result in a win-win situation for the utility and the customer and enhance the system's dependability, transparency, and efficiency [34].

(v) **Meeting the Constraints and Minimizing the Cost:**

In many cases, the energy management system in a microgrid is generally modeled as a constrained optimization problem. Hence, minimizing the total operating cost and meeting the given constrained becomes of utmost importance.

**5. Microgrid Control Systems:**

A utility grid connection is necessary for DERs to function to their fullest potential. Because DERs span a wide geographic region, centralized control systems demand a greater deal of processing and communication, while decentralized control is likewise impractical because of the high connection between various controllers. Three control layers, or primary, secondary, and tertiary, can be used to create a control hierarchy that achieves the benefits of both methods. These levels differ in terms of their speed of reaction, operating time, and infrastructure requirements [40][41].

**2.2 The Microgrid System under Consideration:**

Fig. 2 depicts the model-based design in a MATLAB/Simulink environment of the micro-grid system under consideration. Using the suggested optimization strategies, the system model is used to look into the micro-grid's system performance. PV panels, loads, a battery-based energy storage system (BESS), and the utility grid make up this system. The loads are made up of a static load (basic load) that is constant across time and a variable load that represents the residential property. The energy management system block receives input from the ESS, and the solar array is linked to the irradiance profile block. The two distinct optimization strategies taken into consideration in this study are integrated into the energy management system. In this study, the micro-grid system under consideration functions in grid-connected mode. When operating in this mode, the micro-grid trades electricity with the utility grid, which also controls the micro-grid's frequency and voltage. Only when operating in stand-alone mode, the conventional diesel

production is regarded as a component of the micro-grid and is mostly employed in emergency or contingent situations. The diesel generator can be integrated into the system to provide reliable operation in the event that mandatory maintenance is needed or the electrical network is experiencing an unplanned outage. Nevertheless, it is absent from the micro-grid arrangement examined in this research.[29]



Fig.2: The Microgrid System under Consideration [29]

### 2.3 Solar Photo Voltaic System:

The output power of the solar array fluctuates depending on the temperature and amount of irradiation. It is possible to express the solar panel current as a function of temperature and irradiance input as follows [14]:

$$I_{ph} = (I_{sc} + K_i \Delta T) \frac{G}{G_{STC}} \quad (1)$$

Where,  $K_i$  is the short circuit current coefficient, often supplied by the manufacturer, and  $I_{sc}$  is the short circuit current under standard test conditions (STC).  $\Delta T$  is the change in temperature from the nominal temperature.

$G$  is the cell's surface irradiance, while  $G_{STC}$  is the nominal irradiance under STC (1000W/m<sup>2</sup>). The solar system's power output is expressed as  $P_{solar}(t)$ . At the maximum power point (MPP), the output power of the solar PV generator can be expressed as follows [15]:

$$P_{solar} = [P_{solar,STC} \times \frac{G_t}{1000} \times [1 - \gamma \times (T_{cell} - 25)]] \times N_{solar} \quad (2)$$

$$T_{cell} = T_{amb} + [\frac{NOCT-20}{800}] \times G_t \quad (3)$$

Wherein, The solar PV generator's output power is denoted by  $P_{solar}$ . The number of PV panels is  $N_{solar}$ . The irradiance level at MPP is represented by  $G_t$ , the power temperature coefficient at MPP by  $\gamma$ , the cell temperature at MPP by  $T_{cell}$ , and the rated power at the standard test condition (STC) by  $P_{solar,STC}$ .  $T_{cell,STC}= 25$  °C,  $G_{T,STC}=1000$  W/m<sup>2</sup>, and a wind speed of 1 m/s are the STC measure conditions. The  $N_{OTC}$  measurement parameters are as follows:  $T_{amb,NOCT}=20$ °C,  $G_{T,NOCT}=800$  W/m<sup>2</sup> and the wind speed is 1m/s.

The value provided by the panel's manufacturer determines the temperature coefficient. Fig. 3 displays the solar predicted power used in this investigation over a total of 24 hours for the month of July at Jadavpur Police Station location .

$P_{solar,t} = \eta_{solar,t} \times A_{solar} \times G_t$  is the expression used to compute the power output of the PV modules based on their area  $A_{solar}(m^2)$  and the PV efficiency  $\eta_{solar,t}$  of the panel from [29].

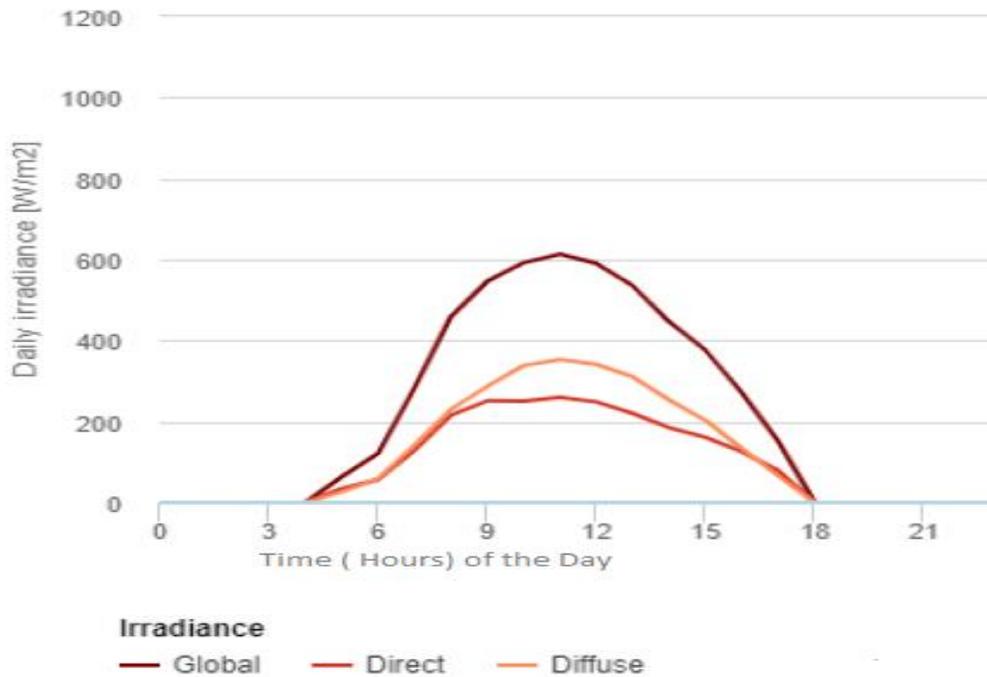


Fig.3: Irradiance Profile for July (Cloudy Day) in Jadavpur Police station Location [30]

As we know that there are mainly three types of irradiance data available in European Commission website e.g. Global, Direct, Diffuse. For this work though, we have used the data for global irradiance on two axis tracking plane from [30]. We have taken the month of July as cloudy season and march as clear sky season. Fig.3 shows the solar irradiation profile for cloudy day (month of July). Irradiance data for both the seasons have been collected from European Commission website [30] for Jadavpur Police Station location. Fig. 4 shows the solar irradiation profile for clear day (month of March).

#### 2.4. Point of Common Coupling:

By the Point of Common Coupling (PCC), the microgrid is actually connected to the utility grid. The purpose of this connection can be described as when the solar power generation in the grid is more (like in the noon), then the surplus power should be sold to the utility grid and when the solar power generation is almost zero, then the power is to be drawn or purchased from the grid. For a particular algorithm, it may also be possible that the power is sold to the utility grid at the night from the ESS because at that point of time, the cost of power is high. Due to the transmission line's limit, power exchange between the microgrid and utility grid is limited in this



Fig.4: Irradiance Profile for June (Clear Day) in Jadavpur Police station Location [30]

study to a specific range in order to prevent line congestion and voltage sags or swells [16].

$$-P_{grid,min} \leq P_{grid,t} \leq P_{grid,max} \quad (5)$$

As seen in Fig. 3, the projected energy price fluctuates over time. The peak hours of the day, which are from 4:00 to 10:00 p.m., are when the price of energy is highest. The energy passes through the PCC in both directions for simplicity's sake, and this can be expressed by a single variable  $P_{grid,t}$ . Value of it might represent the buy or sale price in either a positive or negative value. So, the cost of buying or selling electricity from the utility grid can be expressed as follows [29]:

$$C_{grid,t}(P_{b,t}) = C_{TOU,t}P_{grid,t} \quad (6)$$

Where,  $C_{grid,t}(P_{b,t})$  is the cost of electricity at time  $t$  and  $C_{TOU,t}$  is the price of electricity at time  $t$ .

## 2.5. The Energy Storage System:

A crucial micro-grid element, particularly in the islanded system, is the ESS. It is essential to keeping the micro-grid system operating with stability and dependability. Because renewable energy sources behave erratically, the ESS is utilized to offset the mismatch between generation and demand.

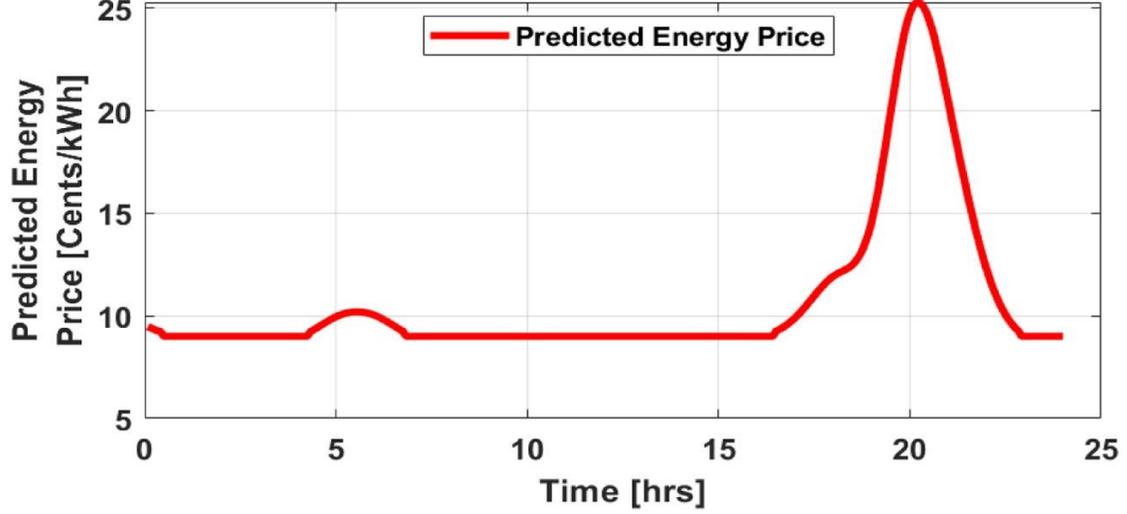


Fig. 5: Predicted Cost of Power throughout 24 hour [29]

This storage system raises the degree of RES penetration in the electrical system and helps outfit RESs with dispatch capabilities. The energy management system installed in the energy storage system (ESS) must be able to monitor its state of charge, estimate its energy storage state, set physical restrictions, and other functions. The energy storage capacity, which is limited by the maximum and minimum bounds ( $E_{b,min}, E_{b,max}$ ), charging and discharge efficiency ( $\eta_{\text{charg}}, \eta_{\text{discharg}}$ ), and maximum charging and discharging power ( $P_{b,min}, P_{b,max}$ ) are the primary parameters of the energy storage system. Because of this, the ESS must meet the following operating requirements in order to limit physical capacity at any given time [3]:

$$0 \leq E_{b,min} \leq E_{b,t} \leq E_{b,max} \quad (7)$$

$$-P_{b,min} \leq P_{b,t} \leq P_{b,max} \quad (8)$$

With the assumption that there is a constant ratio of energy to power at each interval due to the constant sampling time step, the ESS dynamic model is taken into consideration to update the laws of storage energy level. This is expressed as the following expression [29]:

$$E_{b,t+1} = E_{b,t} - \eta P_{b,t} \Delta t \quad (9)$$

Where  $\eta$  is the charging or discharging efficiency, and  $E_{b,t}$  is the amount of energy stored and taken into consideration, the system's status variable;  $P_{b,t}$  is the power exchange with the storage unit, the choice or control variable; and  $\eta$  is  $\eta_{\text{chrg}}$  for charging and  $\eta_{\text{dischrg}}$  for discharging.

Likewise, in order to schedule the subsequent time horizon, the ultimate stored energy in the ESS is likewise bounded, that is [29]:

$$E_{b,t=T} \geq E_{b,min} \geq 0 \quad (10)$$

## 2.6. Description of Loads:

The suggested EMS is effective for household or domestic appliances. Home EMS is linked to a load-carrying microgrid. Fig.5 provides an illustration of how the smart home EMS operates i.e. specifically its load profile. First, the prediction process is finished with the help of rolling window forecasting method, and the forecast data is sent to EMS optimization by the prediction analysis. Next, the forecasted data is used. The system's constraints from the prediction analysis are used to carry out the EMS optimization. Lastly, the EMS provides an automatic, ideal method of utilizing each of those all [29].

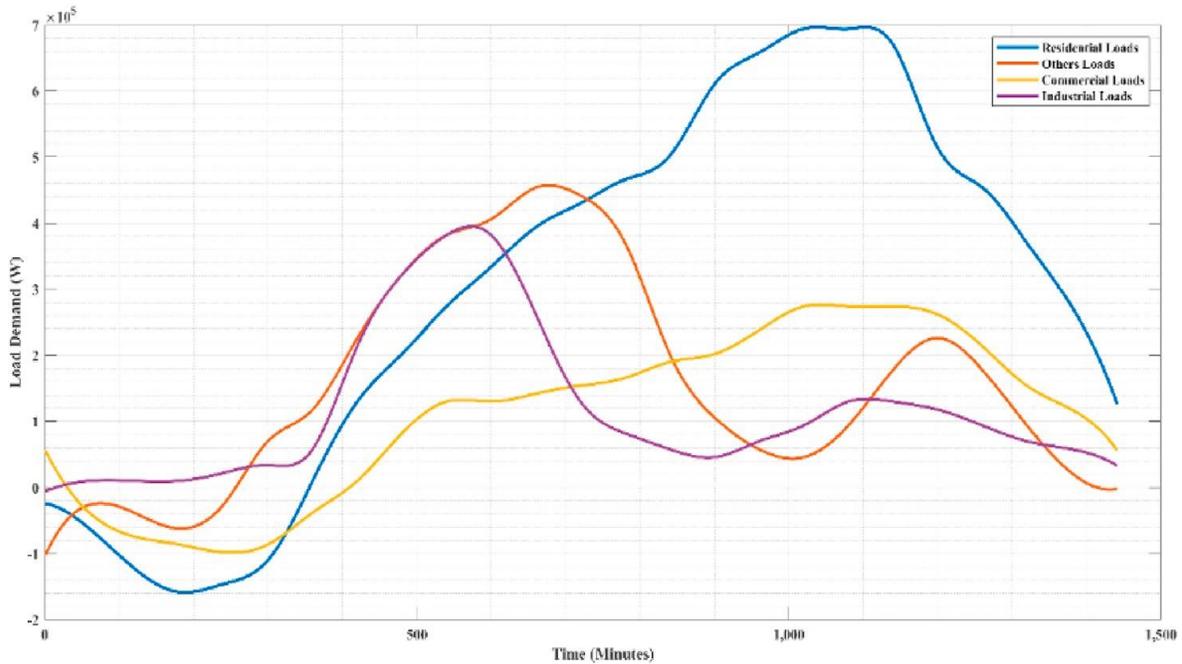


Fig.6: Load Profile [29]

## 2.7. Description of Problem Statement:

The goal of the optimization method employed in this study is to satisfy the generation-demand balance and related constraints while minimizing the microgrid's operating costs and grid energy

consumption. Under the uncertainties of RESs generation and demand, the key is to guarantee the correct operation of all micro-grid components and prevent breaking the operation requirements and physical restrictions [29].

### 2.8. Objective Function:

The cost function comprises of the DGs' cost and the penalty cost incurred to represent already stored energy in the ESS. Optimizing the performance of the micro-grid system and the overall cost of variable-priced power are the goals. Generally speaking, the objective function is built as follows:

$$\text{Min } f = \sum_{t=1}^T (C_{T\text{OU},t} P_{grid} - C_{reserve,b} E_{b,T}) \quad (11)$$

Subject to inequality constraints (5) and (7) to (10) and equality constraint

$$P_{grid} + \eta P_{b,t} + P_{solar,t} = P_{L,t} \quad (12)$$

Where,  $X = (P_{grid,t}, P_{b,t}, E_{b,t})$  is the array or vector representing all the control/ decision variables[29]. Depending on the objective function used to describe a particular goal to be achieved by an optimization problem, the optimal combination of decision variables obtained can lead to the smallest objective function value for minimization problems [29].

## Chapter 3

### Optimization Techniques

#### 3.1. Introduction

Innumerable optimization techniques are available for the maximization or minimization of an objective function [57]. The problem statement considered in this work is a minimization problem because the fundamental aspect of this research is to minimize the grid usage and overall, per-day cost of the power used in the integrated microgrid [28][29]. The application of convex optimization techniques to minimize the objective function has proved to be quite a helpful tool in getting the desired results. The convex optimization techniques used in this work are the following: (1) Linear Programming, and (2) Interior-Point Method. In this chapter, these two convex optimization techniques will be discussed in detail.

#### 3.2. Linear Programming

##### 3.2.1. Introduction

A field of applied mathematics known as "linear programming" is dedicated to deal with specific types of optimization problems. In linear programming, a linear cost function with a given number of variables is minimized or maximized while taking into account a set of restrictions. The cost function's variables' linear inequalities serve as the restrictions. The objective function is another name for the cost function. The most obvious distinction between linear algebra and linear programming is that the former frequently employs equalities in the problem formulation, whereas the latter frequently includes inequalities [57][58].

##### 3.2.1. Mathematical Representation

When a linear programming issue is expressed as follows, it is considered to be in "standard form"[58]:

$$\text{Maximize } \sum_{j=1}^n c_j x_j \quad (13)$$

Subject to

$$\left. \begin{aligned} \sum_{j=1}^n a_{ij} x_j &\leq b_i, & i = 1, 2, \dots, m \\ x_j &\geq 0, & j = 1, 2, \dots, n \end{aligned} \right\} \quad (14)$$

There are  $n$  variables and  $m$  constraints in the problem. It might be expressed as follows in vector terminology [57]:

$$\begin{array}{ll}
 \text{Maximize} & \mathbf{c}^T \mathbf{x} \\
 \text{Subject to} & \mathbf{Ax} \leq \mathbf{b} \\
 & \mathbf{x} \geq \mathbf{0}
 \end{array} \quad (15)$$

As in the energy management problem described in this work, the cost and grid usage minimization are the main objectives, hence the cost function can be considered as a minimization problem. In the simplex method of linear programming, a maximization problem can be converted to a minimization problem by taking the negative of the cost/objective function. The simplex method is explained as a maximization problem for the ease of understanding. A plausible solution to a linear programming issue is any vector  $x$  that satisfies the problem's constraints [58]. There are three types of linear programming problems that all problems belong to:

1. Infeasible:

If there is no feasible solution to a linear programming problem—that is, no vector  $x$  for which all the constraints of the issue can be satisfied—then the problem is not feasible [57].

2. Unbounded:

If the restrictions on the cost function are not tight enough to prevent future improvement of the cost function for any given feasible solution, then the issue of linear programming is said to be unbounded [57].

3. Offers an ideal resolution:

If a linear programming problem is not unbounded or infeasible, then it has an optimal solution, meaning that the cost function has a unique value for its minimum or maximum. Yet, this does not imply that the combinations of the variables that produce that ideal result are exclusive. The simplex method is the fundamental algorithm that is most frequently utilized to resolve linear programming issues [57][58].

Almost any bounded, workable linear programming problem of a reasonable size may be solved by computer programs utilizing the simplex technique and its relative, the revised simplex method and the network simplex method, in a reasonable period of time. It has only been in the last decade that alternative approaches to tackling linear programming problems known as interior point methods, have advanced to the point that they may be applied to real-world issues [58].

### 3.2.2 The Simplex Method

There are two fundamental phases, or steps, in the simplex technique. The first step is to identify a workable remedy for the issue. This is not at all difficult for little problems, or larger problems of particular kinds. As in the case of the production planning problem previously discussed, a simple answer like  $x = 0$  is frequently a workable option. For the time being, we shall discover a workable solution by skipping over the complexities of addressing the first phase. The simplex technique operates by iteratively increasing the value of the cost function once a workable solution to the problem has been identified. This is achieved by identifying a variable in the issue that can be raised while lowering another variable to have an enhancement of the overall cost function. This can be represented graphically as travelling from corner to corner around the borders of a viable set. Below is an example in two dimensions [59].

### 3.2.3 Geometric Representation of Simplex Method

For an example, consider the following problem [59]:

$$\text{Maximize } (x + y) \tag{16}$$

$$\text{Subject to } 2x + y \leq 14$$

$$-x + 2y \leq 8$$

$$2x - y \leq 10 \tag{17}$$

$$x \geq 0, y \geq 0$$

Fig.6 illustrates a two-dimensional graph of the feasible set for this problem. The feasible set is restricted to the first quadrant by the non-zero constraints  $x \geq 0$  and  $y \geq 0$ . As seen, the last three constraints are lines in the x-y plane. One way to visualize the cost function,  $x + y$ , is as a line with an intercept of any slope,  $-1$ . Any solution that falls along the cost function line has a cost function equal to the value of the intercept of the cost function line. Since the heavy line in Fig.6 crosses the feasible set and has a slope of  $-1$  and a maximum intercept of 10, it is the best possible solution to the problem. The cost function's value for the cost function line  $x + y = 10$  has exactly one point in the feasible set,  $x = 4, y = 6$ , and the optimal answer is 10 [59].

The simplex approach operates by first locating a viable solution, after which it moves to any feasible set vertex that maximizes the cost function. There comes a point at which further movement is ineffective in improving the cost function. This is the best course of action. The trivial viable solution in this case is  $x = 0$  and  $y = 0$ , and its cost function value is 0. In Fig.6, this is vertex A. It is required to proceed to point B or point E from here. The cost function is increased to 4 at point E (0, 4), whereas at point B (5,0), it is increased to 5. It is required start with point B because it offers us the greatest improvement. While y stays at 0, the value of x increases from 0 to 5 [59].

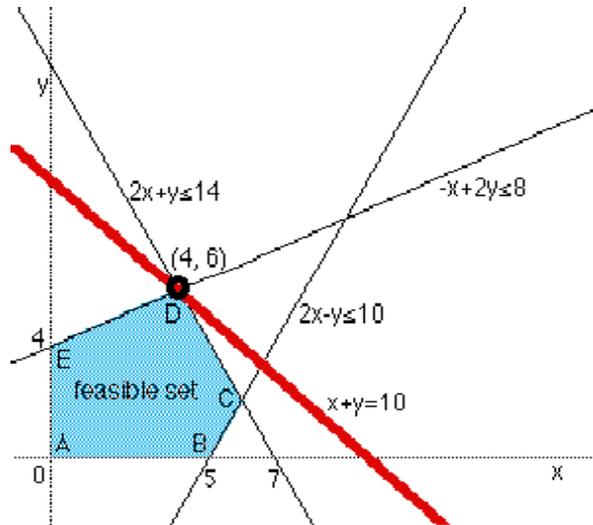


Fig. 7: Graphical Representation of Simplex method [59]

Determination of whether a move to point C is favorable is done from point B. The cost function value at point C (6, 2) is 8, indicating an improvement. Raising value of x from 5 to 6 is done, which necessitates an increase in value of y from 0 to 2 due to the constraints  $2x - y \leq 10$  and  $-x + 2y \leq 8$ . The fact whether the movement from C (6,2) to D(4,6) does an improvement to the cost function has to be considered. It is quite clear that this movement improves the cost function to 10. For this movement, it is required to raise the variable y from 2 to 6. This indicates that due to the limitations, x must drop from 6 to 4. The point D is the best answer to this issue because moving to either point E (cost function value of 4) or point C (cost function value of 8) lowers the cost function [59].

### 3.2.4 The Simplex Algorithm

1. *Initialization.* Finding a workable first solution to launch the simplex approach is the issue at hand [59][61].
2. *Iteration.* Selecting an entering or leaving variable is the work to be done here [59][61].
3. *Termination.* This is the process of stopping the algorithm itself making sure the simplex method ends and doesn't just keep going through an infinite series of iterations without ever arriving at the best solution[59][61].

### 3.3 Interior-Point Method

#### 3.3.1 Introduction

In 1984, Narendra Karmarkar introduced a novel approach for effectively resolving large-scale linear programming issues. Since it only finds better search paths inside the feasible space, the method is known as an interior-point method. This is not the case for the simplex technique, which moves from one feasible vertex to an adjacent one along the feasible space's boundary until it finds the optimal point. Since there will be a lot of vertices in large LP problems, the simplex method will become quite costly in terms of computing time. It was discovered that, for large problems, interior-point method can be up to 50 times faster than the simplex method [57]. Though, Karmarkar introduced and advocated interior-point method for the first time, but still the entire research on interior-point method has evolved extensively since its introduction. In this work, 'Logarithmic Barrier' type interior method is used [60].

#### 3.3.2 Mathematical Representation

The following problem is being considered [58]:

$$\begin{aligned} &\text{Minimize } f_o(x) \\ &\text{Subject to } f_i(x) \leq 0; i = 1, 2, \dots, m \\ &\text{And } Ax = b \end{aligned} \quad \left. \vphantom{\begin{aligned} &\text{Minimize } f_o(x) \\ &\text{Subject to } f_i(x) \leq 0; i = 1, 2, \dots, m \\ &\text{And } Ax = b \end{aligned}} \right\} \quad (23)$$

Where,  $m$ =No of inequality constraints.

$A$  is a coefficient matrix of order  $p \times n$ .

$x$  is a matrix of order  $n \times 1$

$b$  is a matrix of order  $p \times n$

#### 3.3.3 Modification of the Problem Statement for Application of Newton's Method

As it is observed in equation (23) that, this equation contains inequality constraints. Hence, Newton's Method cannot be applied to solve this problem. In order to apply Newton's Method, the inequality constrained problem of (22) should be roughly formulated as an equality constrained problem [60]. So, the inequality constraint is converted into an approximate equality constraint so that the problem statement remains almost same even without the inequality constraint.

Hence, the modified problem with implicit inequality constraints is the following [58][62]:

$$\begin{aligned} &\text{Minimize } f_o(x) + \sum_{i=1}^m I(f_i(x)) \\ &\text{Subject to } Ax = b \end{aligned} \tag{24}$$

$$\text{Where, } I(u) = \begin{cases} 0; & u \leq 0 \\ \infty; & u > 0 \end{cases}$$

Hence, obviously,

$$I(f_i(x)) = \begin{cases} 0; & f_i(x) \leq 0 \\ \infty; & f_i(x) > 0 \end{cases}$$

It is quite evident in equation (24), that the term  $I(f_i(x))$  is actually a penalty term representing the violation of the given inequality constraints.

### 3.3.4 An Approximation of the Penalty Term

The main drawback in resolving the problem described in (24) is that this function is not differentiable and is discontinuous at  $x = 0$ . Therefore, Newton's method is inapplicable to this particular case. Because, Newton's Method is applicable to differentiable functions only. Thus, we use the following function to approximate the additional non-differentiable term,  $I(f_i(x))$  in the equation (24) [58][60]:

$$I_-(u) = -\left(\frac{1}{t}\right) \log(-u) \tag{25}$$

It is needless to mention that  $u = f_i(x)$  is assumed for the ease of understanding. For high value of  $t$ , the approximation becomes more accurate.  $I_-(u)$ , in contrast to  $I(u)$ , is differentiable and yields a finite value across a somewhat larger range [62].

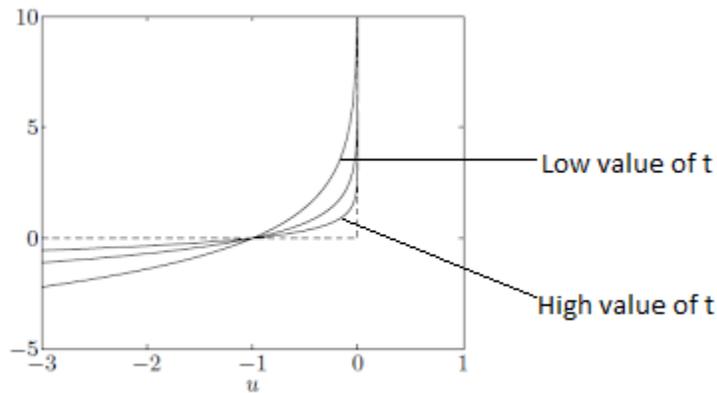


Fig.8: The approximated  $I_-(u)$  function for different values of  $t$  [58]

It can be clearly understood from Fig. 7, and equation (25), that for higher values of  $t$ , the approximation of the inequality constraint becomes more accurate. Graphs for higher and lower values of  $t$  have been indicated in the Fig. 7.

Ultimately, the obtained overall approximated objective function (with an explicit equality constraint and an implicit approximated inequality constraint) is stated as the following [58][62]:

$$\begin{aligned} & \text{Minimize } f_o(x) + \sum_{i=1}^m -\left(\frac{1}{t}\right) \log(-f_i(x_i)) \\ & \text{Subject to } Ax = b \end{aligned} \tag{26}$$

Assume,  $\psi(x) = -\sum_{i=1}^m \log(-f_i(x_i))$

### 3.3.5 Logarithmic Barrier

$\psi(x)$  is known as ‘Logarithmic Barrier’ or ‘Log Barrier’ for the optimization problem of equation (23). The set of points or the vectors  $x$  those strictly satisfy the inequality constraints of the equation (23) are defines as the domain of this ‘Log barrier’. Since, all this term ‘Log Barrier’ is an approximation; hence its domain also may vary a little with the actual discontinuous term of equation (24).

The problem of equation (26) is the approximate representation of the original problem of equation (23).As it is evident from Fig.7, that the approximation gets better with larger value of  $t$ .

### 3.3.6 Methodology and Visualization

Conversely, the function of (27) becomes difficult to minimize via Newton's method when  $t$  approaches a large value because its Hessian rapidly varies around the feasible set limit [58][62]. By going through a series of iterations of the equation (26) and beginning each Newton’s Method minimization iteration for the problem assuming larger value of  $t$  than that of previous iteration [60], we will demonstrate that this difficulty can be resolved. This enables us to raise the parameter  $t$  at each stage, increasing the accuracy of the approximation as a result [58][60]. Hence, it is advisable to increase the value of  $t$  slowly in each iteration. As this process continues for some number of iterations (increasing the value of  $t$  without much fluctuation in Hessian), the approximation becomes better.

The equation (26) can now be represented as the following:

$$\text{Minimize } f_o(x) + \left(\frac{1}{t}\right)\psi(x) \tag{27}$$

Because it is equivalent to the following problem:

$$\text{Minimize } f_o(x) + \sum_{i=1}^m -\left(\frac{1}{t}\right) \log(-f_i(x_i))$$

The problem of (26) will simplify if we multiply the objective by  $t$  and consider the equivalent problem [58].

$$\begin{aligned} & \text{Minimize } tf_o(x) + \psi(x) \\ & \text{Subject to } Ax=b \end{aligned} \tag{28}$$

For  $t > 0$ , we define  $x^*(t)$  as the solution of (28). The central path associated with problem (23) is defined as the set of points,  $x^*(t); t \geq 0$ , that satisfy the equation (28) and is bounded within the simplex defined by the implicit inequality constraints [58]. The points on the central path are characterized by the following necessary and sufficient conditions [58]:

$$\begin{aligned} Ax^*(t) &= b; \\ f_i(x^*(t)) &< 0; i = 1, 2, \dots, m \end{aligned} \tag{29}$$

The problem stated in (28) is modified in the following form considering the equality constraints:

$$\text{Minimize } tf_o(x(t)) + \psi(x(t)) + \hat{v}(A^T x(t) - b)$$

And there exists a  $\hat{v}$  such that [58],

$$0 = t\nabla f(x^*(t)) + \nabla\psi(x^*(t)) + A^T \hat{v}$$

$$\text{Or, } 0 = t\nabla f(x^*(t)) + \sum_{i=1}^m (1/(-f_i(x^*(t)))) \nabla f_i(x_i(t)) + A^T \hat{v} \tag{30}$$

The equation (30) is solved by Newton's Method [58]. Then for next iteration, the value of  $t$  is increased and the same method is repeated.

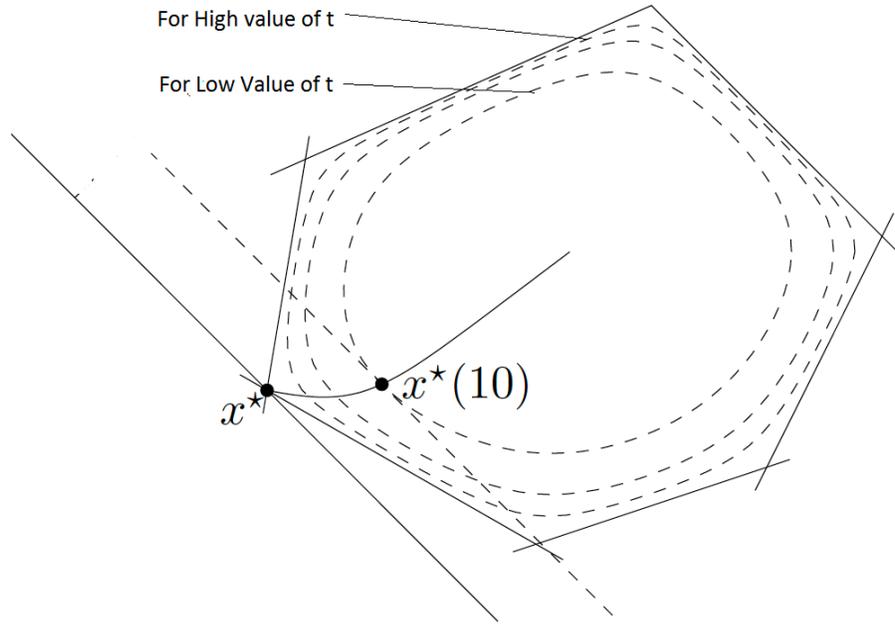


Fig.9:Central path for problem with 2 dimensions ( $n = 2$ ) and 6 inequality constraints ( $m = 6$ )[58].

In the fig.8, the central path for two dimensions and six inequality constraints are shown. Because of the six inequality constraints, the structure formed is a hexagon and the central path lies in the interior of the hexagon. The dotted lines represent the logarithmic barrier,  $\psi(x(t))$ . As the value of  $t$  increases, then the approximation of logarithmic barrier,  $\psi(x(t))$  becomes more accurate. As we can observe from the diagram, that for very large values of  $t$ , the logarithmic barrier comes very close to the lines representing the inequality constraints and almost entirely approximates the hexagon. The central path converges to  $x^*(t)$  i.e. actual solution as  $t$  tends to infinity [60].

The Simplex method looks for solutions in a simplex's vertices. Therefore, looking for answers at the vertices of larger, more complex problems just makes them more difficult to solve [57]. Conversely, interior point techniques such as the one mentioned above look for workable solutions inside the simplex [57].

### 3.3.7 The Algorithm

The algorithm for the interior-point method, is the following:

Given feasible  $x(t)$ ;  $t := t^{(0)} > 0$ ,  $\mu > 1$ , tolerance,  $\epsilon > 0$

Repeat

{

- (1) Centering Step: Compute  $x(t)$  by minimizing  $tf_o(x) + \psi(x)$  ; subject to  $Ax=b$ , starting at  $x$ .
- (2) Update:  $x := x^*(t)$
- (3) Stopping Criterion: quit if  $\left(\frac{m}{t}\right) < \epsilon$
- (4) Raise the value of t,  $t := \mu t$

} [58][62]

It will be observed in Chapter 4 that interior-point method out performs the Linear Programming method in terms of result. The reason for this is that a Linear Programming method like Simplex method tries to find the solutions in the vertices of a simplex. Hence, as discussed before as well, that for larger and more complicated problems the technique of searching the solutions only in the vertices increases the difficulty to find an optimal solution [57]. On the contrary, interior point method discussed above, searches feasible solutions within the simplex itself [57]. Hence, the results are better but the search space is more random.

## Chapter 4

### Simulation and Results

#### 4.1 Simulation Model

The simulated model of the microgrid system is shown in the Fig.9. The Loads, battery-powered ESS units, and solar PV panels make up the PV-based microgrid [29]. The performance of the micro-grid configuration with LP and the interior point method are compared using storage scheduling optimization. Based on the projected statistics of solar irradiance, load needs, and electricity pricing over a 24-hour period, the optimization algorithm determines the working schedule for the ESS while meeting the operational and physical restrictions of the system [29]. Additionally, using the suggested optimization algorithms, simulations are run to examine the system's performance under various external variables (demand and weather variations). For a 24-hour simulation period, two different generation scenarios—cloudy and clear days—are thus implemented. The simulations are implemented and executed using MATLAB/Simulink. [29].

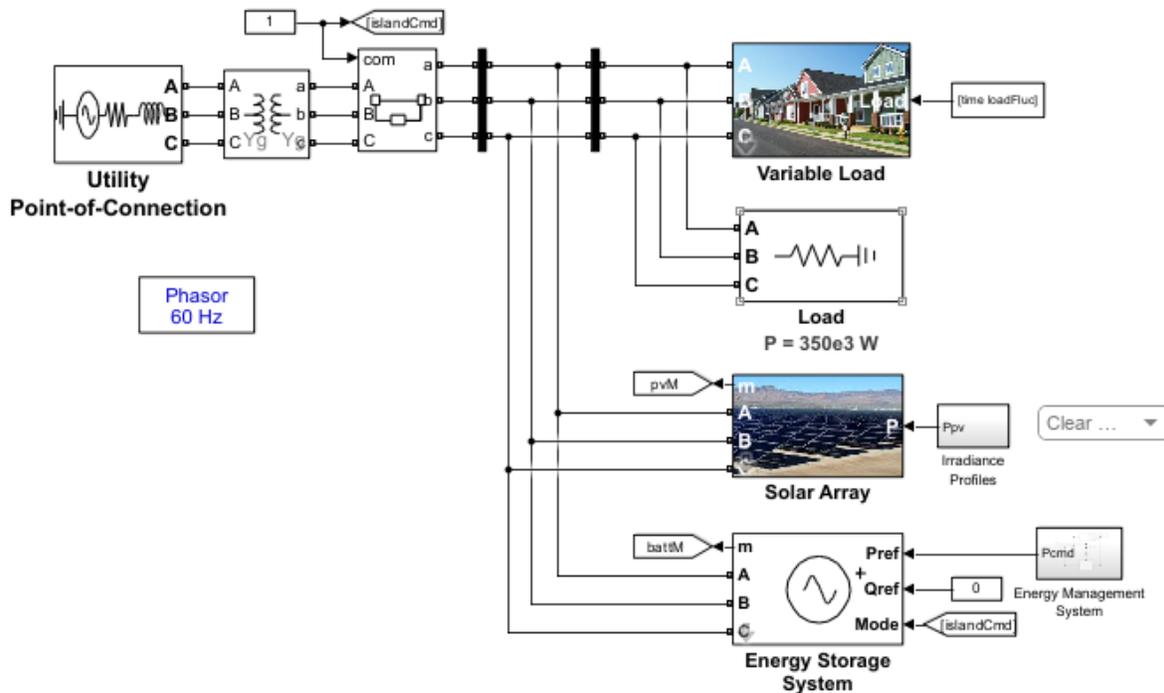


Fig.9: The Simulated Microgrid System under Consideration [29]

It can be observed in Fig.9, that the microgrid system consists of a base load, a variable load, a solar array for power generation, and energy storage systems which are important parts of the EMS (it's representation is also shown in the diagram). It is also easily understood from Fig.9

that this integrated microgrid is connected to the utility grid to draw power from the utility grid whenever required. In the same way during the noon, when the solar power generation is surplus, the generated power can also be fed back or sold to the utility grid.

The system parameters are given in table 1.

Table 1: System parameters [29]

Parameter	Value
$A_{solar}$	2500 m <sup>2</sup>
$\eta_{solar,t}$	0.3
$f$ (System frequency)	60 Hz
$V_{rms}$	5000 V
$P_{solar}$	500 kW
$C_{norm}$ (Normal capacity of ESS)	2500 kWh
$E_{b,min}$	20% of $C_{norm}$
$E_{b,max}$	20% of $C_{norm}$
$P_{b,min}$	-400 kW
$P_{b,max}$	400 kW
$P_{grid,min}$	-500 kW
$P_{grid,max}$	1500 kW
$V_{var,L}$ (Variable load voltage)	5000 V
$P_{var,L}$ (Variable Load power)	200 kW
$V_{stat,L}$ (Static load voltage)	5000 V
$P_{stat,L}$ (Static load power)	350 kW

The most crucial aspect of any energy management system is knowing when and how much energy will be stored. At the same time, when and how much power is to be fed into the grid during peak solar radiation, whether or not to sell energy and how much to sell to the grid when electricity costs are high, whether or not to consume energy and how much to consume when electricity costs are low, how much stored energy to be used from the battery storage when there is a lack of solar power generation. These issues should be adequately considered and decided by the optimization-based EMS. Since cost reduction is the ultimate goal of any optimization-based energy management system (EMS), the most crucial metric by which we assess an optimization algorithm's performance in controlling the system's energy flow is the reduction of overall cost [36][37][38].

The energy from the solar PV panel powers the load and recharges the battery at midday when solar irradiance is at its highest. When load demand and electricity prices are particularly high in the evening, the energy stored in the battery is used to serve the load [29].

In the next section of this chapter, the following performance profiles of several parameters of the microgrid system of Fig.9 are discussed: The voltage profile of the microgrid system, Solar PV profile, ESS power profile, grid power profile, load profile, and state of charge (SOC) of the Energy Storage System. It can be understood that the Battery and Cost of Electricity are the main parameters that are concentrated upon. Among them, the load profile and cost of electricity are the same for all the cases. It can be observed that for all the cases, the load is low in the morning and early forenoon sessions. The load significantly increases in the late forenoon and noon sessions. In the afternoon and evening sessions, a rapid increment of load profile is observed. Hence, it can be concluded that in the evening session, the load increases and therefore the price of electricity is also at its peak during this period which can be observed quite clearly in the Price profiles of Fig.10-13.

## **4.2 Results**

### **4.2.1 Results of Linear Programming Method for Clear Day:**

Fig.10 shows the characteristics of all the important microgrid parameters involved in this case of LP-based energy management of integrated microgrids for a clear day. The graphs of the parameters indicated below for the Linear programming method in the case of the clear day are discussed in the following section.

#### **(i) Microgrid Voltage Profile:**

It is observed that the voltage profile is quite smooth. There are voltage fluctuations in the morning and forenoon sessions and the voltage is relatively low in those times of the day, but from noon onwards, the voltage profile follows the PV output power and after PV is not there it follows the grid voltage.

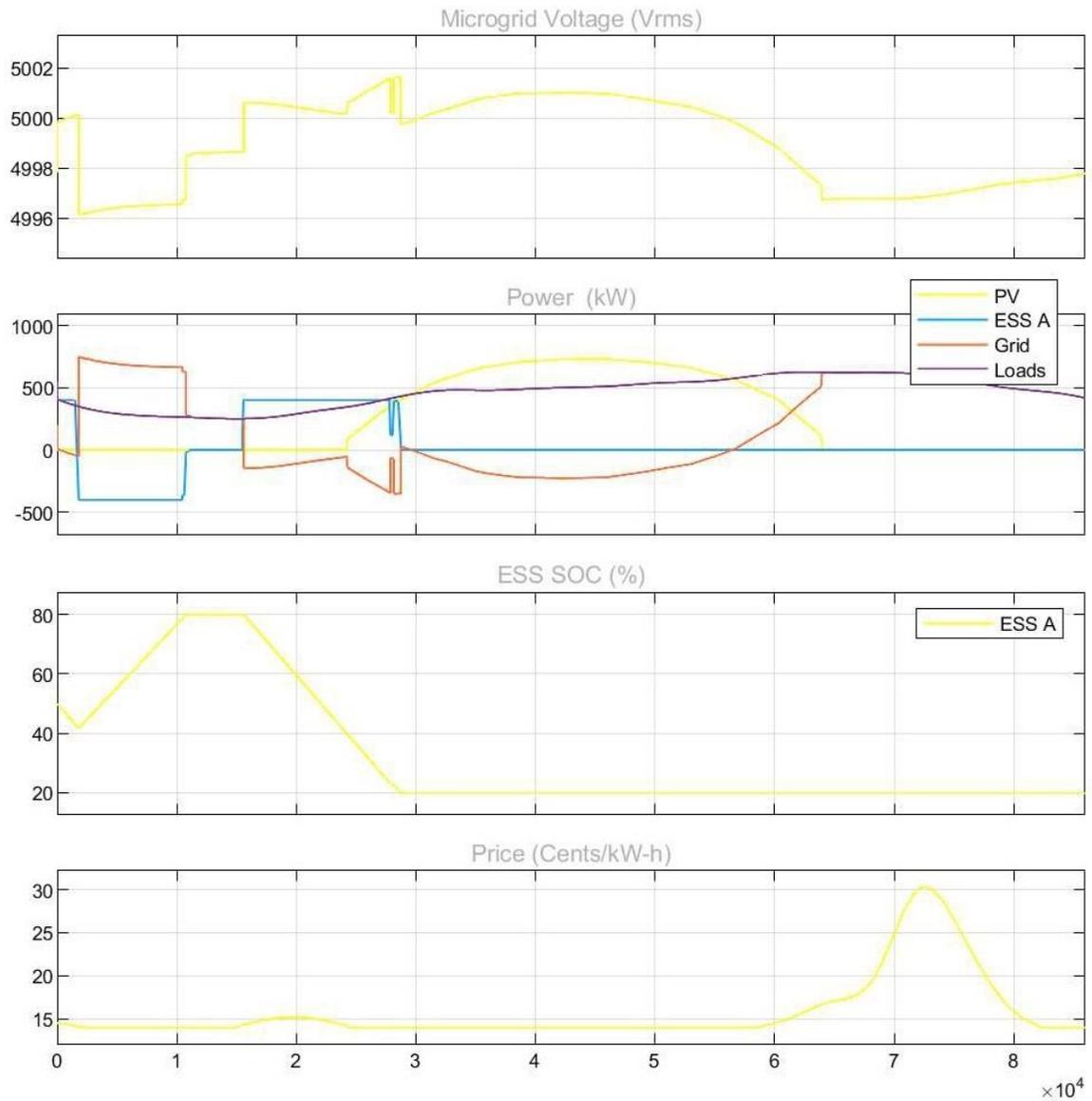


Fig.10 : Graphs for various parameters of the system using Linear Programming for Clear Day

(ii) ESS Power Profile:

In the early morning, the ESS is charged from the grid. Because at that time, the price of electricity is low. Hence, it is profitable to store some energy at that time. In the forenoon session, the ESS delivers the power to the load. The ESS line lies flat afterwards.

(iii) Grid Power Profile:

In the early morning, the grid power is required to charge the battery, because solar irradiation is not available. During this time, the price of electricity is low. So, it is profitable to store an adequate amount of energy at that time to be used when electricity cost is high. During the forenoon, the sun becomes available. Hence, solar power meets most of the load demand and the battery also discharges power. During this time, the grid also receives power from the battery and solar irradiation-based generation. During the noon, solar-based generated power is fed to the grid but the battery is not charged, which may be treated as the main disadvantage of this algorithm. From the late afternoon and evening, the load receives power directly from the grid.

(iv) ESS SOC Profile:

During the early morning, when the ESS is charged directly from the grid, the SOC increases. In the forenoon session, when the ESS is discharged, the SOC is decreasing. Quite justifiably, the graph of ESS SOC is an approximate integration of the ESS graph.

#### **4.2.2 Results of Linear Programming Method for Cloudy Day:**

Fig.11 shows the characteristics of all the important microgrid parameters involved in this case of LP-based energy management of integrated microgrids for cloudy days. The graphs for the linear programming approach on a cloudy day are discussed below:

(i) Voltage Profile of Microgrid:

The voltage profile is seen to be fairly smooth. While there are variations in voltage and relatively low voltage during the morning and afternoon sessions, the voltage profile is noted to be rather reliable starting at midday.

(ii) ESS Power Profile:

The grid charges the ESS in the early morning period. This is because the electricity is inexpensive at that time. Therefore, it makes sense to reserve some energy throughout that period. The ESS provides the load with power during the forenoon session. After that, the ESS line is flat.

(iii) Grid Electricity Profile:

Because solar radiation is not available in the early morning, grid electricity is needed to charge the battery. Considering that electricity is cheap at that time. It makes financial sense to reserve some energy during that period. In the afternoon, the sun gets a little bit more accessible. Thus, the majority of load demand is satisfied by solar power, and battery power is also released. In this period, battery and solar radiation-based generation also supply power to the grid. This algorithm's primary drawback is that in this case of a cloudy day, the solar-generated power is not fed into the utility grid during the midday and even the batteries are not charged. Loads get power straight from the grid in the late afternoon and evening.

(iv) Profile of ESS SOC:

The SOC rises in the early morning when the ESS is charged straight from the grid. When the ESS is discharged in the forenoon session, the SOC decreases. It makes perfect sense that the ESS SOC graph is an approximation of the ESS graph integration.

#### **4.2.3 Results of Interior-Point Method for Clear Day:**

Fig.12 shows the graphs of the microgrid parameters involved in this case of Interior point-based energy management of integrated microgrids for a clear day. The relevant profiles of the parameters for this case of clear day are discussed below:

(i) Microgrid Voltage Profile:

It is observed that the voltage profile in this case is a bit unsmooth. There are voltage fluctuations in the early morning and morning session and the voltage is having relatively low variations afterwards.

(ii) ESS Power Profile:

In the early morning, the ESS stores energy directly from the utility grid. Storing energy at this hour makes sense as the cost of electricity is cheap at this specified hour. In the forenoon session of the day, the ESS is discharged and this energy is fed back to the grid. After some time, the energy is again stored in the ESS from the grid. During this energy storing period, load demand is partially met by the grid power and solar-based generation. In the evening, the load demand is met by the battery and the grid.

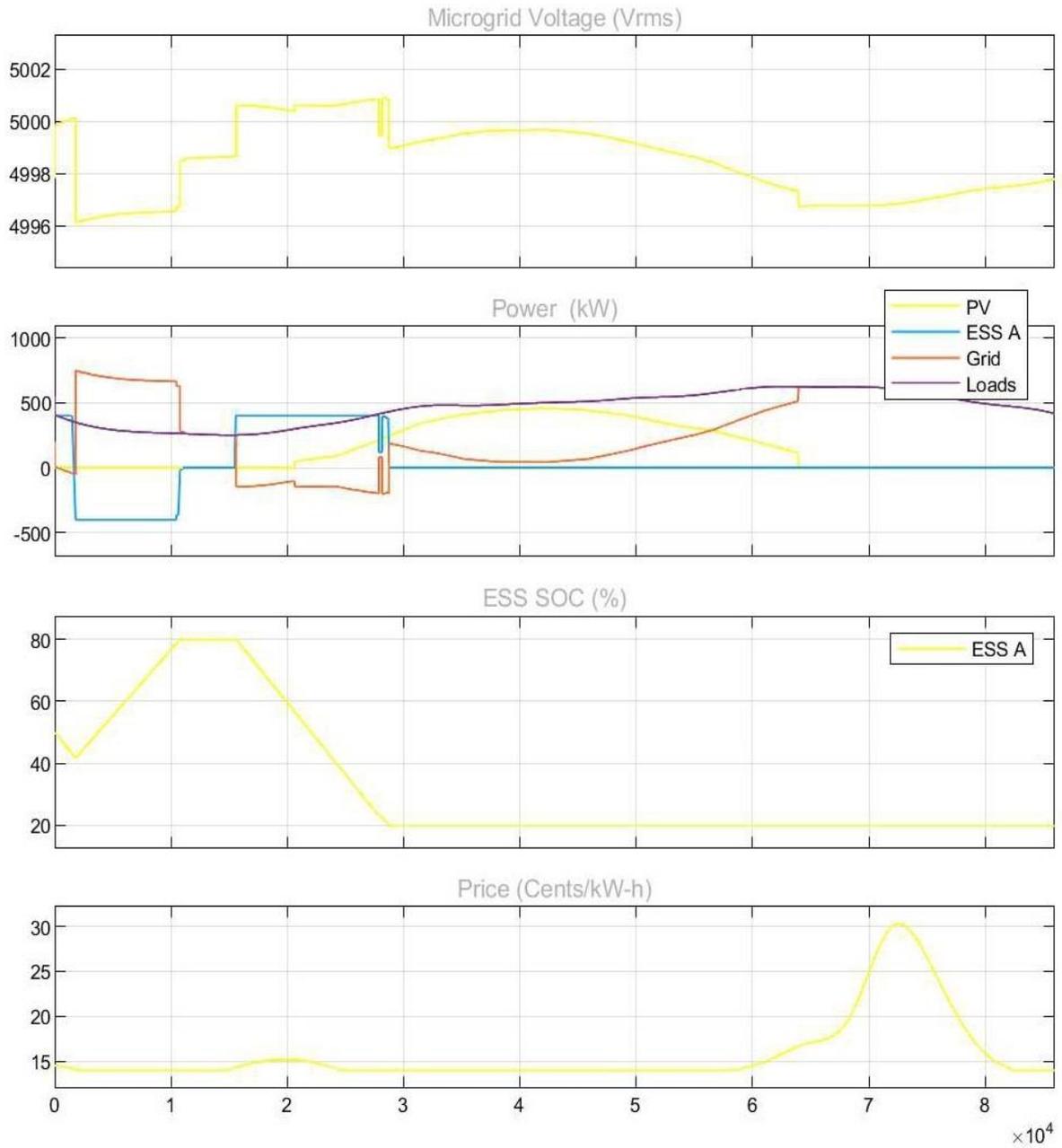


Fig.11 : Graphs for various parameters of the system using Linear Programming for Cloudy Day

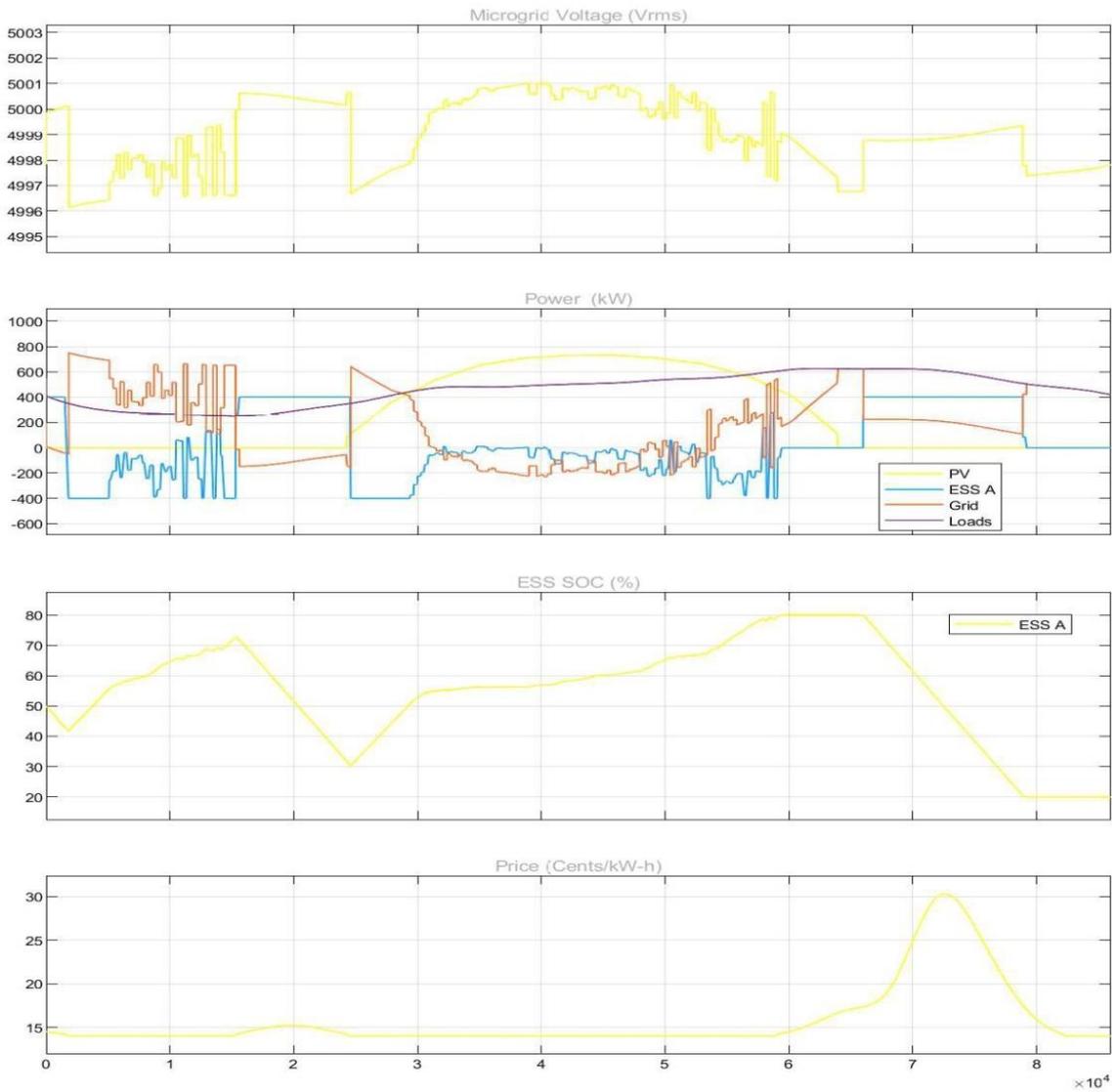


Fig.12 : Graphs for various parameters of the system using Interior Point Method for Clear Day

(iii) Grid Power Profile:

During the early morning, power is consumed from the grid to charge the ESS. Hence, power is stored in the ESS during this period as the electricity is cheap at that time. During the next phase, power is fed to the grid from the ESS. In the next part of the day, power is taken from the utility grid and solar irradiation-based generators as the sun becomes available. At that time ESS also is charged from the utility grid and solar-based generators. This partial charging from the utility grid is also done because of the low electricity cost at that time. During the noon, as the solar power generation is high, hence, the power is fed to the grid and the ESS is charged to some

extent, which is quite evident from the graphs shown in Fig.12. During the evening, the power is taken from both the utility grid and ESS to meet the load demand.

(iv) ESS SOC Profile:

During the early morning, when the ESS is charged directly from the grid, the SOC is increased. During the following phase when ESS is discharged, the SOC is decreased followed by another increment in SOC for another charging. In the evening though, SOC only steeply reduces due to its rapid discharging. Quite justifiably, the graph of ESS SOC is an approximate integration of the ESS graph.

#### **4.2.4 Results of Interior-Point Method for Cloudy Day:**

Fig.13 shows the characteristics involved in this case of interior point-based energy management of integrated microgrids for cloudy days. These are similar to the graphs of the results of the Interior-Point Method for a clear day. The relevant points of the graphs of the parameters for this case of a cloudy day are the following:

(i) Microgrid Voltage Profile:

The voltage profile in this instance is shown to be a little uneven. Early in the morning and during the morning session, there are voltage fluctuations; after that, the voltage variation is less.

(ii) ESS Power Profile:

The ESS stores energy straight from the electric grid in the early morning. Since electricity is cheap at that time, thus, it makes sense to store some energy during that period. The ESS discharges and returns energy to the grid throughout the day's forenoon session. This is followed by another ESS power consumption from the grid and storing in the ESS. Grid electricity and solar-powered generation help to partially meet load demand during this energy-storing phase. The ESS feeds power to the utility grid and saves energy from the grid during noon. The grid and batteries work together to meet the load requirement in the evening.

(iii) Grid Power Profile:

To charge the ESS, power is taken from the grid in the early morning. Power is therefore stored in the ESS during this time. As the electricity is cheap at that time hence it makes sense to reserve some energy during that period. Power from the ESS is injected into the grid during the next stage. When the sun comes out later in the day, power is taken both from the utility grid and solar irradiation-based generators. Fig.13 clearly illustrates how power is supplied into the grid and how much the energy storage system (ESS) is charged at midday when solar power generation is at its highest. To meet load demand throughout the evening, power is drawn from both the utility grid and ESS.

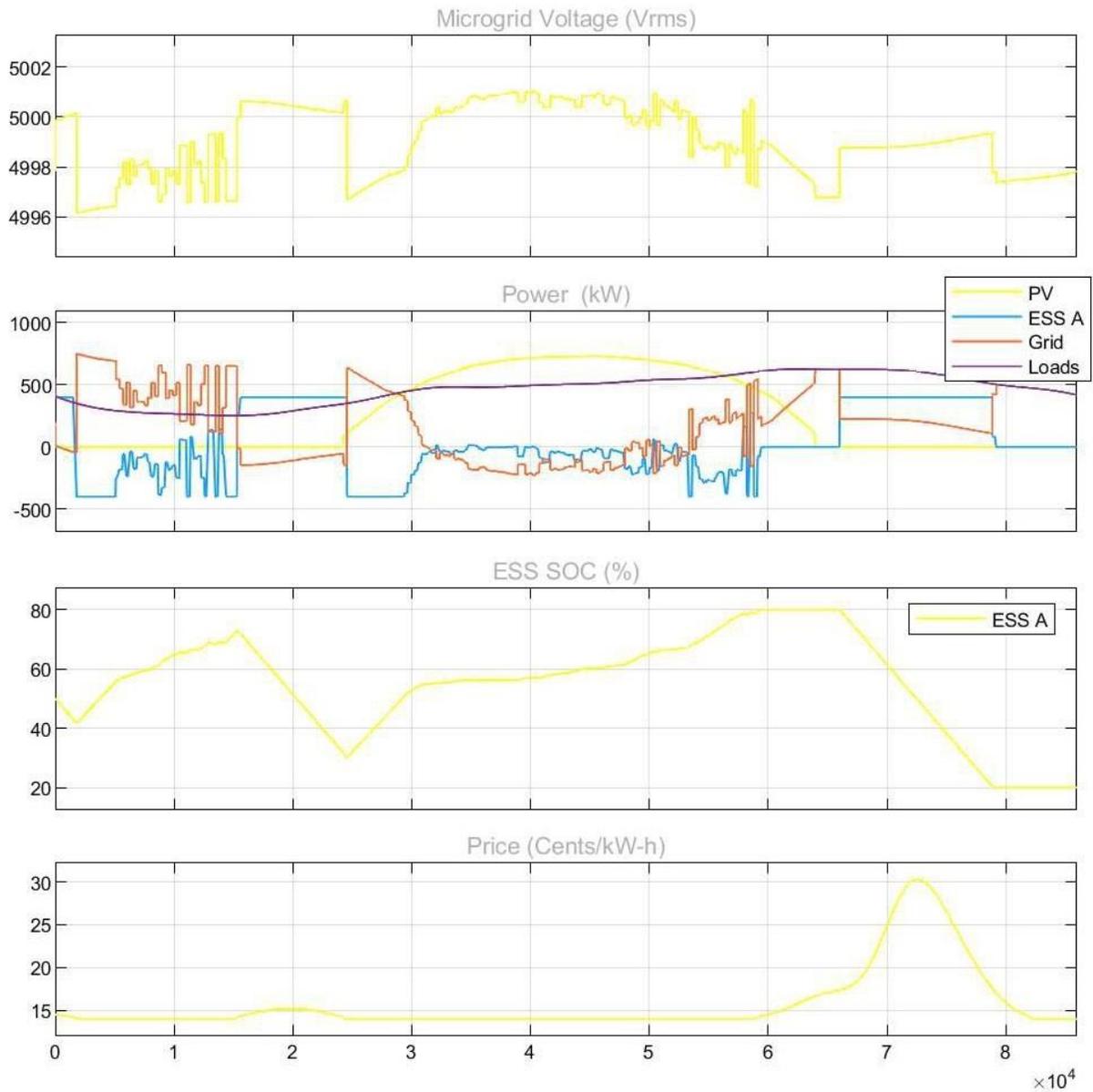


Fig.13 : Graphs for various parameters of the system using Interior Point Method for Cloudy Day

(iv) ESS SOC Profile:

The SOC is raised in the early morning when the ESS is charged directly from the grid. The SOC is lowered during the subsequent phase of ESS discharge, and it is then increased again for more

charging. But in the evening, because of its quick discharge, SOC drops dramatically. It makes perfect sense that the ESS SOC graph is an approximation of the ESS graph's integration.

### 4.3 Comparison of Cost and Grid usage for Different Algorithms:

Table 2 shows the comparison between the LP method and Interior-Point method in terms of cost and grid usage.

Table 2: Cost and Grid Usage using Different Algorithms.

		LP	Interior-Point Method	Without Storage
Cost	Clear Day	\$ 818.0468	\$ 690.4595	\$ 916.8345
Cost	Cloudy Day	\$ 1162.5495	\$ 1034.962	\$ 1261.3399
Grid Usage	Clear Day	4194.251 kWh	4290.7353 kWh	4836.4242 kWh
Grid Usage	Cloudy Day	6648.7078 kWh	6744.8741 kWh	7290.8994 kWh

This study aims to minimize energy costs. Table 1 shows clearly that the interior-point method optimization technique has a lower cost, though there is a slight increase in the grid usage from the LP method.

It can be observed that though the grid usage is more in the case of the Interior-Point method, the cost is lower. This is because while using the Interior-Point method, the microgrid sells more energy than that of the LP method. The overall cost of electricity is reduced in the case of the Interior-Point method. This is because a linear programming technique, such as the simplex method, looks for solutions in a simplex's vertices. Therefore, as was previously mentioned, looking for answers at the vertices of larger, more complex problems just makes them more difficult to solve [57]. Conversely, interior point techniques look for workable solutions inside the simplex [57]. Because of this, although the search space is more random, the results for cost reduction are better.

## **Chapter 5**

### **Conclusion and Future Scopes**

#### **5.1 Conclusion**

The primary objective of this work is to reduce the per-day operating cost of the considered integrated microgrid. The proposed optimization technique which uses the Interior-Point method has lesser computational complexity because of its search space within the simplex rather than the vertices of the simplex. The overall operating cost for both Linear Programming (LP) and Interior-Point Method was made. The Interior-Point Method outperforms the Linear Programming (LP) method in terms of cost. The overall operating cost is reduced in the case of the Interior-Point method approximately by 18.55% in the case of clear day and 12.38% in the case of cloudy day than its counterpart i.e. Linear Programming (LP) method. Hence, it can be concluded that for this type of large and complex problem, Interior-Point Method is preferable.

Additionally, it is to be understood that, though Linear Programming (LP) is widely regarded as one of the most important optimization tools for finding global optimum, still it has a limitation in handling non-linear problems. Through this research work, it is understood that the Interior-Point Method deals with non-linearity better.

Meanwhile, because of trying to find the solution inside of the simplex rather than the vertices, the search space becomes random. This randomness ultimately results in voltage fluctuations in the new and more cost-effective system. This may be seen as the main drawback of this algorithm.

Finally, it can be concluded that this research reduces the total per day operating cost of an integrated microgrid by allowing the randomness of the variables involved.

#### **5.2 Future Scopes**

The reduction in per day operating cost of an integrated microgrid by the Interior-Point Method was modelled in MATLAB/Simulink environment. Hence, this whole optimized improvement can be replicated in the physical and real-time implementation. Apart from that practical implementation, the future path of research based on this work is the following:

- (i) More advanced optimization algorithms could be applied to investigate further reduction of the operating cost. Deep Learning algorithms like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deep Belief Networks could be implemented for the same purpose.
- (ii) The same algorithm (Interior-Point Method) could be used to deal with more complex energy management problems with more non-linearity and a greater number of constraints.

## **References**

- [1] Bidram A, Lewis FL, Davoudi A. Distributed control systems for small-scale power networks: Using multiagent cooperative control theory. *IEEE Control Syst Mag* 2014; 34(6):56–77.
- [2] Bordons C, Gracia-Torres F, Ridao MA. *Model predictive control of microgrids*, vol. 358. Berlin/Heidelberg, Germany: Springer; 2020.
- [3] Gbadega PA, Saha AK. Model-based receding horizon control of wind turbine system for optimal power generation. In: *Advanced engineering forum*, vol. 40. Trans Tech Publ; 2021, p. 83–98.
- [4] Zheng Y, Jenkins BM, Kornbluth K, Kendall A, Træholt C. Optimization of a biomass-integrated renewable energy microgrid with demand side management under uncertainty. *Appl Energy* 2018;230:836–44.
- [5] Gracia CE, Prett DM, Morari M. Model Predictive control : Theory and practice-A survey. *Automatica* 1989;25(3):335-48.
- [6] Polimeni S, Meraldi L, Moretti L, Leva S, Manzolini G. Development and experimental validation of hierarchical energy management system based on stochastic model predictive control for off-grid microgrids. *Adv Appl Energy* 2021;2:100028.
- [7] Deng Q, Gao X, Zhou H, Hu W. System modeling and optimization of microgrid using genetic algorithm. In: *2011 2nd international conference on intelligent control and information processing*, vol. 1. IEEE; 2011, p. 540–4.
- [8] Mohammadi S, Mozafari B, Solimani S, Niknam T. An adaptive modified firefly optimisation algorithm based on Hong's point estimate method to optimal operation management in a microgrid with consideration of uncertainties. *Energy* 2013;51:339–48.
- [9] Moghaddam AA, Seifi A, Niknam T, Pahlavani MRA. Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy* 2011; 36(11):6490–507.
- [10] Chaouachi A, Kamel RM, Andoulsi R, Nagasaka K. Multiobjective intelligent energy management for a microgrid. *IEEE Trans Ind Electron* 2012;60(4):1688–99.
- [11] Morais H, Kádár P, Faria P, Vale ZA, Khodr H. Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. *Renew Energy* 2010;35(1):151–6.
- [12] Boonbumroong U, Pratinthong N, Thepa S, Jivacate C, Pridasawas W. Particle swarm optimization for AC-coupling stand alone hybrid power systems. *Sol Energy* 2011;85(3):560–9.
- [13] Wang L, Singh C. Multicriteria design of hybrid power generation systems based on a modified particle swarm optimization algorithm. *IEEE Trans Energy Convers* 2009;24(1):163–72.
- [14] Gbadega PA, Saha AK. Effects and performance indicators evaluation of PV array topologies on PV systems operation under partial shading conditions. In: *2019 Southern African universities power engineering conference/robotics and mechatronics/pattern recognition association of South Africa (SAUPEC/RobMech/PRASA)*. IEEE; 2019, p. 322–7.
- [15] Gbadega PA, Saha AK. Electrical characteristics improvement of photovoltaic modules using two-diode model and its application under mismatch conditions. In: *2019 Southern African universities power engineering conference/robotics and mechatronics/pattern*

- recognition association of South Africa (SAUPEC/RobMech/PRASA). IEEE; 2019, p. 328–33.
- [16] Zhang Y, Gatsis N, Giannakis GB. Robust energy management for microgrids with high-penetration renewables. *IEEE Trans Sustain Energy* 2013;4(4):944–53.
- [17] Koutroulis E, Kolokotsa D, Potirakis A, Kalaitzakis K. Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms. *Sol Energy* 2006;80(9):1072–88.
- [18] Gbadega PA, Akindeji KT. Linear quadratic regulator technique for optimal load frequency controller design of interconnected linear power systems. In: 2020 IEEE PES/IAS PowerAfrica. IEEE; 2020, p. 1–5.
- [19] Ang KM, Lim WH, Isa NAM, Tiang SS, Wong CH. A constrained multi-swarm particle swarm optimization without velocity for constrained optimization problems. *Expert Syst Appl* 2020;140:112882.
- [20] Runarsson TP, Yao X. Stochastic ranking for constrained evolutionary optimization. *IEEE Trans Evol Comput* 2000;4(3):284–94.
- [21] Mezura-Montes E, Coello CAC. Constraint-handling in nature-inspired numerical optimization: past present and future. *Swarm EvolComput* 2011;1(4):173–94.
- [22] Banks A, Vincent J, Anyakoha C. A review of particle swarm optimization part II: hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications. *Nat Comput* 2008;7(1):109–24.
- [23] Deb K. An efficient constraint handling method for genetic algorithms. *Comput Methods Appl. Mech. Eng.* 2000;186(2-4):311–38.
- [24] El-Sherbiny MM. Particle swarm inspired optimization algorithm without velocity equation. *Egypt Inf J* 2011;12(1):1–8.
- [25] Gbadega PA, Saha AK. Impact of incorporating disturbance prediction on the performance of energy management systems in micro-grid. *IEEE Access* 2020;3(8):162855-162879.
- [26] Gbadega PA, Saha AK. Predictive control of adaptive micro-grid energy management system considering electric vehicles integration. *Int J Eng Res Afr* 2022;59.
- [27] Gbadega PA, Saha AK. Load frequency control of a two-area power system with a stand-alone microgrid based on adaptive model predictive control. *IEEE J Emerg Sel Top Power Electron* 2020;9(6):7253–63.
- [28] Sufian A, Mohammad N. Modeling and analysis of cost-effective energy management for integrated microgrids. *Cleaner Engineering and Technology*, 13 May 2022, Elsevier, DOI:<https://doi.org/10.1016/j.clet.2022.100508>
- [29] Gbadega PA, Yanxia Sun, A hybrid constraint particle swarm optimization – model predictive control(CPSO-MPC) algorithm for storage energy management optimization problem in microgrid. 2022 International Conference on Energy Storage Technology and Power Systems (ESPS 2022), February 25–27, 2022, Guilin, China, Elsevier Ltd.
- [30] [https://re.jrc.ec.europa.eu/pvg\\_tools/en/](https://re.jrc.ec.europa.eu/pvg_tools/en/) (Accessed on 26 April, 2024)
- [31] <https://nsci.ca/2019/11/08/microgrids-what-are-they-and-how-do-they-work/> (Accessed on 3 April, 2024)
- [32] Hassan Bevrani, Masayuki Watanabe, and Yasunori Mitan, *Microgrid Dynamics and Control*, 2017, John Wiley & Sons, Inc., pp:36 -38.
- [33] Lawrence E. Jones, *Renewable Energy Integration: Practical Management of Variability, Uncertainty, and Flexibility in Power Grids*, 2017, Academic Press, ISBN978-0-12-809592-8
- [34] Vijay Kumar Garg, Sudhir Sharma, Overview on Microgrid System, *Proceedings of Fifth*

- International Conference on Parallel, Distributed and Grid Computing (PDGC) 2018 ,IEEE,DOI: 10.1109/PDGC.2018.8745849.
- [35] C. Phurailatpam, B.S. Rajpurohit and N.M. Pindoriya, "Embracing Microgrids: Applications for Rural and Urban India", *Reserachgate*, pp. 1-10, 2011.
- [36] F. Nejabatkhah and Y.W. Li, "Overview of Power Management Strategies of Hybrid AC/DC Microgrid", *IEEE Trans. Power Electron.*, vol. 30, no. 12, pp. 7072-7089, 2015.
- [37] A. Hirsch, Y. Parag and J. Guerrero, "Microgrids: A review of technologies key drivers and outstanding issues", *Renew. Sustain. Energy Rev.*, vol. 90, pp. 402-411, 2018.
- [38] F. Katiraei and M.R. Iravani, "Power management strategies for a microgrid with multiple distributed generation units", *IEEE Trans. Power Syst.*, vol. 21, no. 4, pp. 1821-1831, 2006.
- [39] G.K. Venayagamoorthy, "Potentials and promises of computational intelligence for smart grids", *IEEE Power Energy Soc. Gen. Meet.*, pp. 1-6, 2009.
- [40] Eghtedarpour and E. Farjah, "Power control and management in a hybrid AC/DC microgrid", *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1494-1505, 2014.
- [41] S. Monesha, S.G. Kumar and M. Rivera, "Microgrid Energy Management and Control: Technical Review", *IEEE Int. Conf. Autom.*, pp. 1-7, 2017.
- [42] B.M. Eid, S. Member, N.A. Rahim, S. Member, J. Selvaraj and A.H. El Khateb, "Control Methods and Objectives for Electronically Coupled Distributed Energy Resources in Microgrids: A Review", *IEEE Syst. J.*, vol. 10, no. 2, pp. 446-458, 2016.
- [43] A.M.R. Lede, M.G. Molina, M. Maximiliano and M. P. E, "Microgrid Architectures for Distributed Generation: A Brief Review", *IEEE PES Innov. Smart Grid Technol. Conf.*, pp. 1-6, 2017.
- [44] T. Ackermann, G. Andersson and L. Soder, "Distributed generation: a definition", *Electr. Power Syst. Res.*, vol. 57, pp. 195-204, 2001
- [45] S. Pradhan, D. Mishra and M.K. Maharana, "Energy Management System for Micro Grid Pertaining to Renewable Energy Sources: A Review", *Int. Conf. Innov. Mech. Ind. Appl.*, pp. 18-23, 2017.
- [46] S.I. Gkavanoudis and C.S. Demoulias, "A control strategy for enhancing the Fault Ride-Through capability of a microgrid during balanced and unbalanced grid voltage sags", *Sustain. Energy Grids Networks*, vol. 3, pp. 1-11, 2015.
- [47] D. Arcos-Aviles, F. Guinjoan, P.M. Marietta, J. Pascual, L. Marroyo and P. Sanchis, "Energy management strategy for a grid-tied residential microgrid based on fuzzy logic and power forecasting", *IECON 2016 — 42nd Annu. Conf. IEEE Ind. Electron. Soc.*, pp. 4103-4108, 2016.
- [48] E.R. Sanseverino, M.L. Di Silvestre, G. Zizzo and G. Graditi, "Energy efficient operation in smart grids: Optimal management of shiftable loads and storage systems", *SPEEDAM 2012 — 21st Int. Symp. Power Electron. Electr. Drives Autom. Motion*, pp. 978-982, 2012.
- [49] A. Khodaei, M. Shahidehpou and J. Choi, "Optimal hourly scheduling of community-aggregated electricity consumption", *J. Electr. Eng. Technol.*, vol. 8, no. 6, pp. 1251-1260, 2013.
- [50] K. Thirugnanam, S.G. Kerk, C. Yuen and S. Member, "Battery Integrated Solar Photovoltaic Energy Management System for Micro-Grid", *Innov. Smart Grid Technol. Asia*, pp. 1-7, 2015.
- [51] G. Graditi, M.L. Di Silvestre, R. Gallea and E.R. Sanseverino, "Heuristic-based shiftable loads optimal management in smart micro-grids", *IEEE Trans. Ind. Informatics*, vol. 11, no. 1, pp. 271-280, 2015.

- [52] Y. Hamdaoui and A. Maach, "Smart islanding in smart grids", *2016 4th IEEE Int. Conf. Smart Energy Grid Eng. SEGE 2016*, pp. 175-180, 2016.
- [53] Y. Yan, Y. Qian, H. Sharif and D. Tipper, "A Survey on Smart Grid Communication Infrastructures: Motivations Requirements and Challenges", *IEEE Commun. Surv. Tutorials*, vol. 15, no. 1, pp. 5-20, 2013.
- [54] M.F.M. Yusof and A.Z. Ahmad, "Power Energy Management Strategy of Micro-grid System", *IEEE Int. Conf. Autom. Control Intell. Syst.*, pp. 107-112, 2016.
- [55] C. Rat, C. Vasar, O. Gana and O. Prostean, "Microgrid supply management", *Procedia - Soc. Behav. Sci.*, vol. 238, pp. 46-52, 2018.
- [56] M. Fahad, E. Elbouchikhi and M. Benbouzid, "Microgrids energy management systems: A critical review on methods solutions and prospects", *Appl. Energy*, vol. 222, pp. 1033-1055, 2018.
- [57] S.S. Rao, *Engineering Optimization: Theory and Practice*. 4th Edition, John Wiley & Sons, Inc., Hoboken, New Jersey, 2009.
- [58] Stephen Boyd and Lieven Vandenberghe, *Convex Optimization*. Cambridge: Cambridge University Press, 2004.
- [59] Mark Schulze, *Linear Programming for Optimization*, Perceptive Scientific Instruments, Inc., 1998,  
[https://www.researchgate.net/publication/2420905\\_Linear\\_Programming\\_for\\_Optimization](https://www.researchgate.net/publication/2420905_Linear_Programming_for_Optimization) (Accessed on 9 May, 2024)
- [60] <https://in.mathworks.com/help/optim/ug/constrained-nonlinear-optimization-algorithms.html#brnpd5f> (Accessed on 9 May, 2024).
- [61] <https://in.mathworks.com/help/optim/ug/linprog.html> (Accessed on 9 May, 2024).
- [62] Florian A. Potra, Stephen J. Wright, Interior-point methods, *Journal of Computational and Applied Mathematics*, Elsevier Ltd., Volume 124, Issues 1–2, 2000, Pages 281-302, ISSN 0377- 0427, [https://doi.org/10.1016/S0377-0427\(00\)00433-7](https://doi.org/10.1016/S0377-0427(00)00433-7).