Energy Management System of a Microgrid with Distributed Generation

by

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Examining Committee

Chair of Examining Committee	Dr. Ying Wang
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Abstract

An Energy Management System (EMS) is required to control the flow of power and match generation with the load within a microgrid during grid-connected and islanded modes of operation. In grid-connected mode, a microgrid draws/supplies power from/to the main grid, depending on the generation and load requirements, and with suitable market policies to maximize the efficiency/cost etc. Likewise, it can separate itself from the main grid whenever a drastic power quality event (such as a fault occurs in the main grid) and continues to supply power to critical loads. An optimization algorithm is needed to minimise the cost of the energy drawn from the grid, generated within the grid and consumed by the loads. In this thesis, two optimization techniques namely Particle Swarm Optimization (PSO) and Differential Evolution (DE) are used to optimize an EMS for a generic MG comprised of Combined Heat and Power (CHP) plant, Diesel generator, Natural gas-fired generator, Photovoltaic (PV) generator and Wind generator. The EMS is tested for both grid-connected and islanded modes of operation to demonstrate the effectiveness of the optimization algorithms. In grid connected mode, the comparison of the most optimal utilization of grid during on- and off-peak hours and achieve the lowest operational cost. Likewise, for islanded mode of operation the comparison between the utilization of the three generators to match the load demand and achieve the lowest operational cost.

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to public.

Statement of Contribution

- Energy Management System from chapter 3, is published as:

    - M. Y. Ali, F. Khan and V. K. Sood, "*Energy Management System of a Microgrid using Particle Swarm Optimization and Wireless Communication System,*" *2018 IEEE Electrical Power and Energy Conference (EPEC)*, Toronto, ON, 2018, pp. 1-7.

I established an Energy Management System for a generic Microgrid Model, to achieve optimal operation of the system.

- Optimization Algorithms from chapter 4, are published as:

    - Faizan. Khan, Ali. Sunbul, Mohammad. Y. Ali. Haytham. AbdEl.-Gawad, Shahryar. Rahnamayan, Vijay. K. Sood, "*Maximum Power Point Tracking in PV Farms Using DE and PSO Algorithms: A Comparative Study," in IEEE CEC* 2018, Brazil, 2018, pp 1-9.

I established a PSO model for an optimize Maximum Power Point Tracking, for photovoltaic array.

Dedication

This thesis is dedicated to my family without their continuous love and support, this work would have not been possible to complete.

Acknowledgements

I would like to express my deep appreciation for my supervisor, Dr. Vijay Sood, who is leading the electrical power engineering program at UOIT. Without his supervision and consistent guidance, completing this thesis would not have been possible.

I am also thankful to my colleagues who have inspired me and make me laugh at critical phases during the entire study period.

Finally, acknowledge funding received from NSERC for this research work.

Abbreviations

ACL	Agent Communication Language
ADP	Approximate Dynamic Programming
AC	Alternating Current
BESS	Battery Energy Storage System
CHP	Combined Heat and Power
DERs	Distributed energy resources
DE	Differential Evolution
DGs	Distributed Generations
DR	Demand Response
DSO	Distribution System Operator
ED	Economical Dispatch
EMS	Energy Management System
EPS	Electric Power System
ESSs	Energy Storage Systems
EVs	Electric Vehicles
GA	Genetic Algorithm
HMI	Human Machine interfaces
I/O	Inputs/Outputs
kW	Kilo-Watts
LCs	Local Controllers
MASs	Multi-Agents Systems
MGs	Microgrids
MG	Microgrid
MGMS	Microgrid Management System
MILP	Mix-integer linear programing
MINLP	mix-integer nonlinear programing
MW	Mega-Watts
NNs	Neural Networks
O&M	Operation and Maintenance
P2P	Point to Point
PCC	Point of Common Coupling
PSO	Particle Swarm Optimization
PV	Photovoltaic
RESs	Renewable Energy Systems
REED	Reactive Export Error Detector
ROCOF	Rate of Change of Frequency
SCADA	Supervisory Control and Data Acquisition
SOC	State of charge
UC	Unit Commitment
UOF	Under/over frequency
UOV	Under/over voltage
VSIs	Voltage Source Inverters
VPP	Virtual Power Plant

Table of Contents

List of Figures

List of Tables

1.0 Introduction

Traditionally, power systems have been structured as one-way power flow systems with centralized generation sources, radial long-distance transmission systems, distribution systems and power demand [1]. Fossil fuels-based generation sources have been deployed widely. However, Government policies, technological advancement, economic and environmental incentives, are changing the features of the system while the presence of distributed energy resources (DERs) is on the increase. Power outages during extreme weather conditions have also exposed the vulnerability of a centralized power system and highlighted the benefits of DERs. Many key industrial players have developed energy saving strategies and are investing in renewable energy infrastructure. Federal and provincial authorities in Canada have introduced programs and plans to reduce greenhouse gas emissions and encourage investment in renewable energy. Particularly, the provincial government of Ontario introduced a carbon levy or tax as part of its climate action plan for 2006 to 2012. Ontario later joined the Western Climate Initiative and introduced a carbon cap and trade system as the centerpiece of the province's climate action plan for 2013 to 2020 to further reduce its greenhouse gas emissions [2].

Nowadays, the distribution system is evolving into a more complex and interacting set of systems at multiple levels by means of the development of new technologies, along with innovations in business models and policies. In this way, the whole system tends to be a conglomerate of smarter grids that interconnect hardware, software and communication technologies [3].

Accordingly, distributed solutions are becoming an integral part of the electricity system, providing improvements in energy efficiency, generation, and demand-side flexibility, as well as integrating diverse distributed energy resources such as Renewable Energy Systems (RES), Energy Storage Systems (ESS), Electric vehicles (EVs), smart devices and appliances, among others [4].

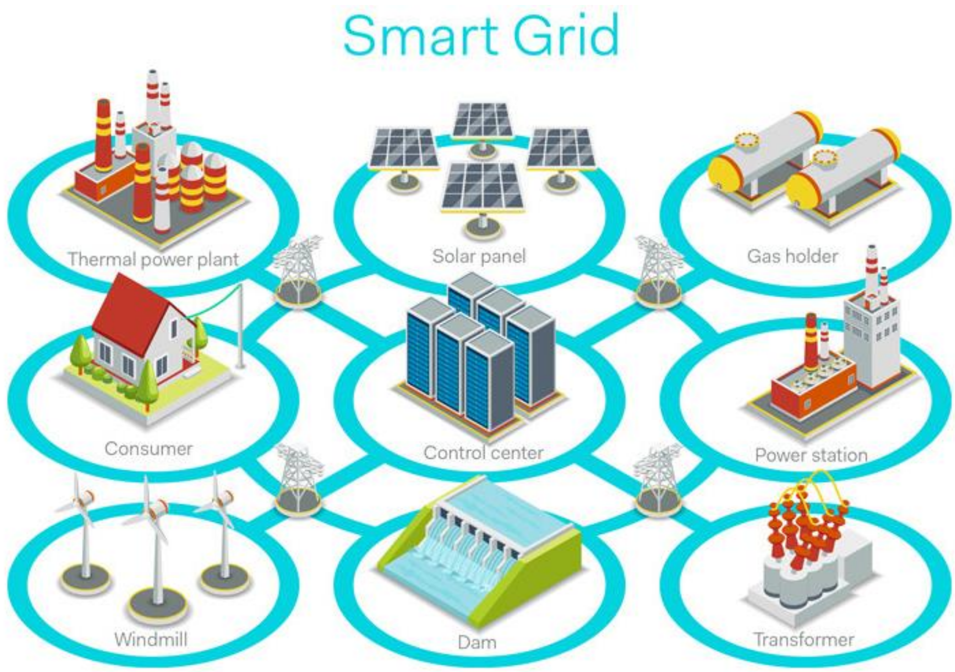

Figure 1.0: Smart Grid

In this context, distributed autonomous systems known as MGs have appeared as a natural component of the smart grid in order to provide it with controllability and management to local power areas and enhance the power system with resiliency properties [5]. As well, provide major incentive to move towards a carbon-free energy future.

MGs encompass both heat and electric loads and are tailored towards the integration of distributed energy resources (DERs), such as generators, Renewable energy sources (RESs), Energy storage systems (ESSs) and a cluster of critical and non-critical loads. They provide stability to the main grid and offer optimal integration of these sub-systems into the distribution system [6]. Based on the standard IEEE 1547.4, a distributed islanded resources system (considered as MG) fulfills four conditions: (i) integrate Distributed Energy Resources (DERs) and loads, (ii) have the capability of being disconnected (in parallel) from the area Electric Power System (EPS), (iii) contain the local EPS and (iv) be intentionally planned [7]. Therefore, an MG can operate in an interconnected mode linked to the main grid at the Point of Common Coupling (PCC) or in islanded (autonomous) mode when it is disconnected from the main grid [8]. In grid-connected mode, a MG draws/supplies power from/to the main grid, depending on the generation and load requirements, and respecting certain suitable market policies to maximize the efficiency/cost etc. Likewise, it can separate itself from the main grid whenever a fault occurs in the main grid and continues to supply power to connected critical loads. Furthermore, to ensure that the MG operates in an economical and reliable manner, it is equipped with a supervisory control and data acquisition (SCADA) system. The control system is responsible for scheduling and controlling of all DERs to warrant the stability, reliability and economical operation of the MG.

1.1 Evolution of Microgrids

The idea of MG and its technology has evolved over the years to fully realize its benefits of providing optimal integration of RESs, energy cost saving, improvement in reliability and resiliency to the grid. Similarly, MG applications have advanced to becoming a large industrial and commercial system with critical need for reliable energy source. Researchers in the early days of MGs viewed it as the epitome of the move towards a distributed power system, where DERs will coordinate to serve the needs of local distribution networks and provide services to the main grid [9-13]. Since then, the term has changed its meaning within the power system community, where some researchers consider it one of the major building blocks of the smart grid [9]. Nevertheless, MG functionalities are embodiment of that of the smart grid concept, which states to the integrated array of technologies, devices and systems that provide and utilize digital information, communications and controls to optimize the efficient, reliable, safe and secure delivery of electricity [14]. The modern concept of an EMS is discussed in [15]. It presents the newly developed EMS strategy for a rapidly growing power grid in China. The new system is designed to improve the traditional EMS that was not able to meet the requirements of the new system. The major areas of concerns before developing this system were on security and stability; effective accommodation of large-scale RESs, an ability to handle major natural disasters, and cyber and terror attacks.

1.2 Protection and Control of Microgrids

As mentioned, in recent decades, more attention has been given to the MG framework from the aspects of the market, control, management, reliability, etc. due to the active role of both the energy producers and consumers. A MG, which is a product of smart grid, provides us with more flexibility and reliability for control and protection of a power system. Constant interaction between private commercial generators and controllable consumers is an inseparable part of smart grids that makes the power system more and more complex to handle. Thus, it is evident that conventional protection and control systems will not effectively work in a MG because they cannot satisfy all the control and protection requirements of such a dynamic and variable grid. The importance of the inescapable integration of RESs, communication devices and the physical energy network (i.e. the power system) needs to be considered as a way to reach an advanced and developed management system for grid-connected/Islanded MGs.

1.2.1 Protection of Microgrid

MG protection poses some serious challenges in the area of the power system protection due to the two-way flow of power and information in the system. One of the major areas of concern in MG protection is the effect of islanding on the system. Islanding occurs in the system when the MG that includes distribution generation, energy storage and local loads, is separated from the power grid due a fault at the grid side.

In islanded mode, the DGs supply the power to the local loads only while maintaining the voltage and frequency (V/F mode) within acceptable operating limits. Seamless transition between grid connected and islanded modes of operation is challenging at best and can result in power quality problems, and islanding protection issues. Many islanding detection methods have been proposed in the literature and they have been divided into passive or active methods [16-18]. The passive method includes under/over voltage (UOV) and under/over frequency (UOF) relays. The rate of change of frequency (ROCOF) relay is generally accepted as the standard method for islanding protection schemes [19]. The most recognized active methods utilise the Reactive Export Error Detector (REED) [20].

1.2.2 Control of Microgrid

A crucial unit that controls the operation of the MG is the MG Management System (MGMS) that operates the system autonomously, connecting it to the utility grid appropriately for the bi-directional exchange of power and providing support to components within the MG. It enables the interplay of components and different controllers to operate the EMS in a controlled manner. This approach will allow customization of the system to enhance optimization to improve the overall efficiency without sacrificing the plug-and-play functionality. MGMS is broken down into three different subsystems i.e. Primary, Secondary and Tertiary Control layers that manage the entire MG operation (Figure 1.2).

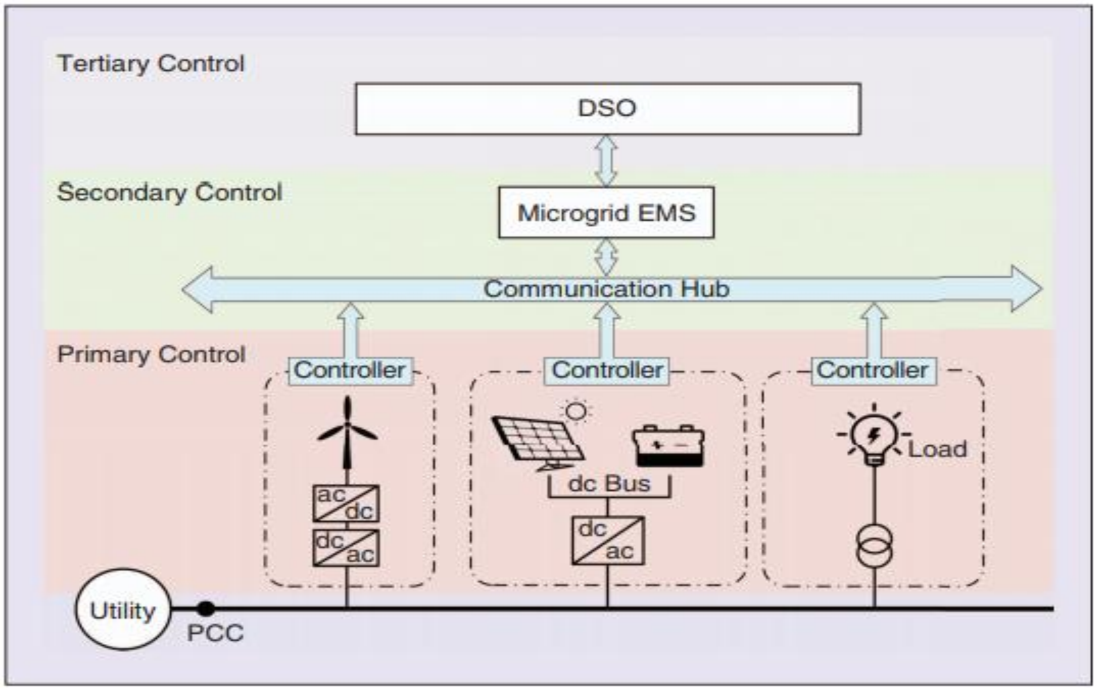

Figure 1.2: Microgrid Management System (MGMS) [21]

The MGMS controls the DGs to maintain the balance between generation and load demand during islanded mode, grid-connected mode or the transition period between the two modes. The three control layers are described next.

Primary Control Layer

This is the base layer that has the fastest response time (typically, in the region of milliseconds to minutes), and is also known as the local or internal controller. This control is based exclusively on local measurements and requires no communications. The function of this control includes islanding detection, converter output control, frequency regulation, voltage regulation and power-sharing control. In the MG, the voltage source inverters (VSIs) are the common interface between the DERs and the MG. VSIs controller requires a specially designed control to simulate the inertia characteristic of synchronous generators and provide appropriate frequency regulation. The VSI has two stages of control: inverter output control and power-sharing control. The inverter typically consists of an outer control loop for voltage control and an inner loop for current regulation. The power sharing control is used for the sharing of the active and reactive power in the system.

Secondary Control Layer

This is the central layer (Figure 1.2) and is responsible for the reliable and economical operation of the MG. Its main function includes an Energy Management System (EMS) and automatic generation control. The secondary control also helps reset the frequency and voltage deviations of the droop-controlled VSIs and generators, then assigns to them new optimal long-term set points calculated from the MG EMS. The EMS minimizes the MG's operation cost and maximizes its reliability in grid-connected or islanded modes of operation. The objective of the EMS consists of finding the optimal Unit Commitment (UC) and Economical Dispatch (ED) of the available DER units, to achieve load and power balance in the system. The cost function is designed in terms of economic tolls such as fuel cost, power bill, maintenance cost, shutdown and start-up cost, emissions, and social welfare and battery degradation cost and cost of loss load. The reliability indices are formulated as constraints such as load forecast, forecasted power availability RES, the generation and demand balance, energy storage capacity limits and power limits for all controllable generations. The EMS resolves a multi objective optimization problem with complex constraints and falls under mixed-integer linear/non-linear programing. The output of the optimizer is the schedule energy import/export and DGs power output. The EMS system is illustrated in Figure 1.2.

Tertiary Control Layer

This is the highest control layer and provides intelligence for the whole system. It is responsible for buying and selling of energy between consumers and transmission system, as well as providing active and reactive power support for the whole distribution system. Tertiary control layer is not a part of MGMS as it is recognized as a subsystem of the utility Distribution System Operator (DSO). Nevertheless, due to the increase of MGs in the distribution system, the tertiary control layer is evolving into a concept called Virtual Power Plant (VPP). The objective of a VPP is to coordinate the operation of multiple MGs interacting with one another within the system and communicate needs and requirements from the main grid. The VPP can provide transmission system primary frequency support, reactive power support and energy market participation. The control layer response time is typically of the order of several minutes to hours. It provides signals to secondary controls at MGs, and other sub-systems that form the full grid.

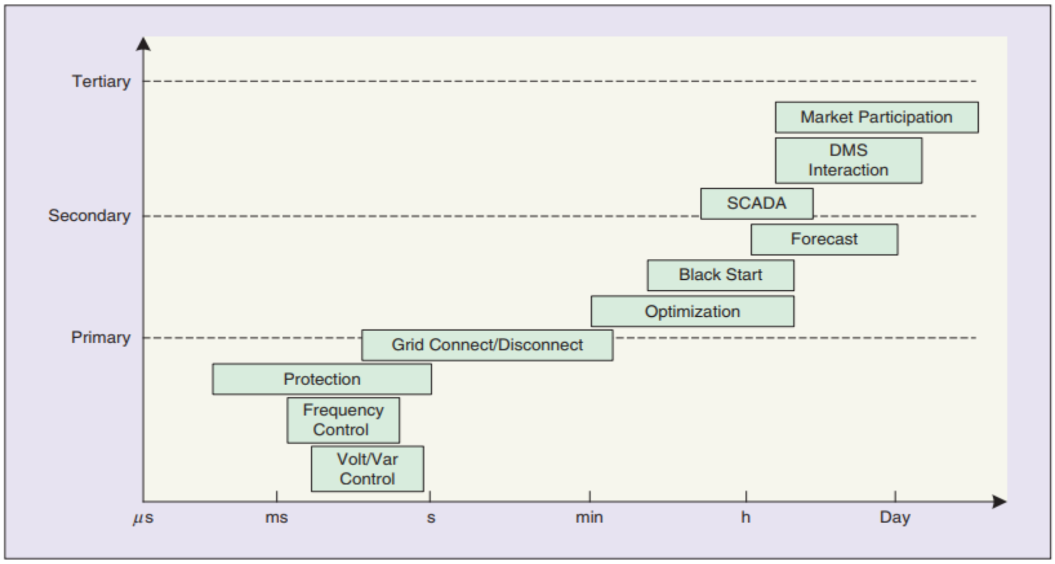

Figure 1.3: Response time of various layers in MGMS [21]

Figure 1.3 shows the time-scales of the three MGMS control layers where the lower (Primary) layer controls devices with fastest response times, and whereas higher (Secondary and Tertiary) layers controls tend to have slower response times.

1.3 Literature Review

This thesis focuses on the secondary control of a MG where it looks at designing an optimized EMS for a generic MG to reduce operation cost. Hence, the literature review mainly relates to work done in that area.

Many researchers have used different approaches to achieve optimal and efficient operation of MGs. This section presents a literature review on some of the popular methods used by researchers to solve the EMS application.

1.3.1 Linear and Non-linear Programming

An optimal EMS using mix-integer linear programing (MILP) of residential MG is presented in [22] to help minimize the operation cost. The objective cost function was derived from: Grid tariffs, EV battery maintenance cost, adjustable load shedding cost and EV range anxiety cost. The author conducted three case studies using different types of loads, namely: critical, adjustable, and shift able loads. Similarly, in [23] an optimal EMS using MILP to minimize the operational cost of a MG in grid connected mode of operation. The objective function is formulated by using operational and maintenance (O&M) costs, start-up and shutdown cost, energy trading cost, and load shedding cost. The system was to determine the optimal cost of operation while efficiently trading power from the grid. In [24] the authors proposed MILP optimization model for a MG EMS to maximize daily revenue with main grid peak-shaving application by introducing demand responsive loads. For this system, the load demand used will always be more than generation for each time interval. First, the EMS was tested using one-bus MG model. Afterwards, the EMS was analyzed with an IEEE 14-bus MG system.

The authors in [25] presented an EMS of an islanded MG with demand response (DR) using mix-integer nonlinear programing (MINLP) to minimize the operation cost of the generators. Furthermore, droop controlled active and reactive power dispatch of AC side CGs, and operation of water desalination units are also included as a constraint in the proposed model. A centralized EMS of a grid connected MG using sequential quadratic programing method is proposed in [26]. The system is designed to optimize production of the local DGs and power exchanges with the main distribution grid. A min-max objective function used, where the author aims to minimize the operation cost and maximize the profits considering energy transactions with the main grid. Likewise, in [27] the author introduces an EMS of a grid-connected MG based on MINLP. In which the system is constrained by an operation window of transformer nominal operation and voltage security. The model helps minimizes MG operational cost using modified gradient descent solution method. The forward backward sweep algorithm determines power flow solution of MG. Three scenarios are considered in the objective function with respect to customer benefits, network losses, and load levelling.

1.3.2 Dynamic Programming and Rule-based

Another solution of MG EMS is presented in [28]. In which the author used approximate dynamic programming (ADP) for a grid connected system and compared to myopic optimization and dynamic programming methods. The objective function (cost) was calculated using receptive field weight regression and lookup table. The EMS was tested under various external constraints (wind speed, load demand, and ambient temperature). Overall the proposed system had a higher operation cost but lower computational time.

1.3.3 Meta-Heuristic Algorithm

Various authors have used Meta-Heuristic Approaches to solve the MG EMS. In [29] the authors proposed a genetic algorithm (GA) and rule-based approach to solve an economic load dispatch and battery degradation cost-based multi-objective EMS for a remote MG. The proposed system was used for both day-head and real time operation to examine the operation of all diesel generators, better supply and load shedding to match the load demand. In [30] the author used and other meta-heuristic algorithm called PSO to design an optimal EMS for grid-connected MG that considers uncertainties of RESs, load demand, and electricity price. The results achieved from the PSO algorithm is shown to be better in comparison with GA, combinatorial PSO, fuzzy self-adaptive PSO, and adaptive modified PSO. Likewise, in [31] the author proposed an EMS for a grid connected MG using differential evaluation (DE) algorithm. In which the system was design to minimize the operation cost and the emission of MG. Cost function is derived from bidding cost of DERs, DR incentives, and energy trading cost with main grid. The result obtained from system were compared to PSO based results, which showed DE algorithm performed better than the PSO based EMS with lower operation cost and faster convergence speed. Another EMS designed using meta-heuristic algorithm is proposed in [32], the researchers designed an EMS for grid connected MG. the objective of the EMS to determine the energy scheduling of the MG while minimizing the operation cost. The economic objectives are profit on selling energy to load-end and main grid, energy-purchasing cost with main grid, and battery ageing cost. The proposed approach is more efficient than rule-based method in achieving best economic operation of MG. In [33], an ant colony optimization-based multi-layer EMS model for an islanded MG is proposed to minimize its operational cost. The objective function is comprised of bidding cost of RERs, DGs and battery, penalty cost on load shedding, and DR incentives in both day-ahead scheduling and five minutes' interval real-time scheduling layers. Three case studies were used to analyze the system:

operation, sudden high requirement of load demand, and plug and play ability. The proposed approach reduces operational cost of MG by almost 20% and 5% more than the modified conventional EMS and PSO-based EMS, respectively.

1.3.4 Artificial Intelligent

In [34] the authors presented a fuzzy-based MG EMS. The algorithm utilized two GAs to optimize its day-ahead MG scheduling and built a fuzzy expert system to control the power output of the storage system. The first GA determined MG energy scheduling and fuzzy rules, while the second GA tuned fuzzy membership functions. Ref. [35] proposed an intelligent adaptive dynamic EMS for a grid-connected MG. It maximized the utilization of RERs and minimized carbon emissions to achieve a reliable and self-sustainable system. It also improved battery lifetime. The proposed EMS was modeled using evolutionary adaptive dynamic programming and reinforcement learning concepts and solved by use of two NNs. An active NN is used to solve the proposed EMS strategy, while a critical NN checks its performance with respect to optimality. The new defined performance index evaluates the performance of dynamic EMS in terms of battery lifetime, utilization of renewable energy, and minimum curtailment of controllable load. The performance of the proposed approach is better as compared to decision tree approach-based dynamic EMS.

1.3.5 Multi-Agents Systems (MAS)

In [36] the author introduced a decentralized EMS for a grid connected MG using MAS. The objective function is derived using all the consumers, storage units, generation units, and grid cost. The algorithm was able to find the optimal way to reduce the power balance and improve customer satisfaction. Furthermore, in [37], multi-objective hierarchical MAS-based EMS for a grid-connected MG system is presented to minimize its operational cost, emission cost, and line losses. The MAS is split into three levels: upper, middle and lower level. The upper level is designed to work as an EMS for the MG to minimize the operation cost. The middle level is designed to operate the local controls is an optimal manner. Lastly, the lower level is designed to control f/V and PQ-based control strategies for unit agents to manage real-time operation of DERs.

1.4 Motivation

As the transformation towards a low carbon and more decentralised energy grid continues, the flexibility requirements for the electrical grid system are increasing. MGs are now seen as a key enabler in the transition towards a smarter, cleaner energy system. The control of the MG system is a really important aspect to help improve reliability and efficient operation of the system. Hence, EMS becomes a crucial part of the MG system and great area for research.

The motivation of this work is to develop EMS for generic MG model for both the grid connected and islanded modes of operation. The objective of the EMS consists of finding the optimal Unit Commitment (UC) and Economical Dispatch (ED) of the available DER units, to achieve load and power balance in the system, while minimizing the operation cost.

1. The objective function for the system is derived using the variable cost function for each DG in the MG model. These cost functions are described later in the thesis in Chapter 4.
2. To optimize the EMS system, two different optimization algorithms are used and compared. The algorithms used are Particle Swarm Optimization (PSO) and Differential evolution (DE); they both belong to the stochastic, population-based algorithms. Recently, both PSO and DE have emerged as a promising algorithm in solving various optimization problems in the field of science and engineering. The algorithms are tested for both grid connected and Islanded mode operation.

1.5 Problem Statement

Currently, a new challenge is growing in the energy power systems field, which is the increase of distributed generation in from of renewable energy sources (RESs). One of the main drawbacks is the intermittency in power generation from these sources. Therefore, for a better use of the variable power production from renewable energy, these systems are integrated with energy storage (for off-grid applications) and the utility grid [38].

The storage systems associated with photovoltaic and wind energy are a promising solution for future MGs, in maximizing consumption, reducing the operation costs, powersmoothing and peak-shaving. The system could be viable in areas with high solar/wind penetration level and high retail electricity prices or areas where there is no access to the power grid [39].

The power variations in PV generation emerge when instantaneous passage of clouds covers the solar arrays. The PV output is difficult to predict, due to the PV performance being reliant on cloud shadowing, solar irradiance, temperature, wind etc. [40]. Unlike solar power, where the power is generated only during the daylight hours, wind turbines can produce power also during the night. Therefore, in some regions or during some periods of the year, the peak output from wind could be in the night when the demand is low [41].

Therefore, with increasing adoption of renewable energy sources by individual home owners and commercial business owners in the form of isolated MG system. The produced energy is usually injected into the utility grid without considering demand. Most renewable energy sources, e.g. solar and wind, are not controllable sources. A MG with renewable energy sources, provides a degree of control to maximize the benefit of electricity consumer by lowering the overall cost of energy. A simple optimization-based energy management system is proposed in this thesis for finding the optimal way to dispatch the available DERs to achieve lowest operational cost by complying to system constraints. This is achieved by taking advantage of time-of-use pricing and non-linear cost function of the various generation in the system.

1.6 Thesis Overview and Organization

The focus of this work is to evaluate the performance of optimized EMS for a MG in grid connected and islanded modes of operation, to reduce the operational cost for a day-ahead predicted operation.

This thesis is arranged as follows: the breakdown of the MG EMS is presented in **Chapter 2**. This chapter explains the two different types of EMS that are used in literature and real-world systems. The concepts introduced in chapter 2 are essential to the analysis and optimization performed in the thesis.

Chapter 3 presents the model of the MG used for the EMS along with power limits for the DGs, forecasted power with RESs and the grid tariffs used for the system.

In **Chapter 4**, the two optimization techniques used for the EMS are presented in detail. The complete design and configuration of both PSO and DE is explained in detail. These algorithms are coded and simulated in MATLAB. The flow diagram of the EMS is presented and explained.

In **Chapter 5**, begins by presenting the simulation and analysis of applying the two optimization techniques to the EMS. The simulation results for both PSO and DE are shown separately and also compared for both the grid connected and islanded modes of operation.

In **Chapter 6**, concludes the thesis with summary of the contributions and suggestions for future research.

2.0 Microgrid Energy Management Systems

This chapter focuses on the secondary level which is responsible to operate and coordinate a variety of DGs, energy storage and loads in order to provide high-quality, reliable, sustainable and environmentally friendly energy in a cost-effective way. This is done through the MG EMS. The International Electrotechnical Commission in the standard IEC 61970, defines an EMS as "a computer system comprising a software platform providing basic support services and a set of applications providing the functionality needed for the effective operation of electrical generation and transmission facilities so as to assure adequate security of energy supply at minimum cost" [44]. Hence, the MG EMS is a product of these features. It is usually equipped with decision-making algorithms, load and power forecasting, Human Machine interfaces (HMI) and supervisory control and data acquisition (SCADA) system. These functions help the EMS in optimizing MG operation, while satisfying the technical constraints.

MG EMS can be sub-divided into two types, namely, centralized and decentralized:

- In a Centralized system, a control center receives all measured values from all the DGs in the MG and outputs the operating points of each DG based on the objectives and constraints, which can be minimizing system operation and maintenance costs, environmental impact, maximizing system efficiency.
- In a Decentralized system, a communication bus is used to exchange data among DGs' controllers. In this energy management system, each local control system knows the operation point of other converters. This information is used to determine the DGs' operating points according to different optimization objectives.

This section will be going more in-depth about the two different control methods, also the advantages and disadvantages of both.

2.1 Centralized Energy Management

In the centralized EMS system, data information and collection are usually required from the Tertiary control and Primary control layers such as operating cost, weather forecast, load demand, voltage and current readings from each component etc. Based on the gathered information, an appropriate unit commitment and economical dispatch optimization algorithm is executed to achieve efficient, economical operation, and maintain power quality as well as match generation with load demand. The MG relies on the Secondary Layer, where a Master Controller with a high computing performance and a dedicated communication network is utilized for the operation. Usually the Master Controller supports EMS and SCADA functions with an HMI which allows the System Operator to control and monitor the MG. A centralized configuration is shown in Figure 4.

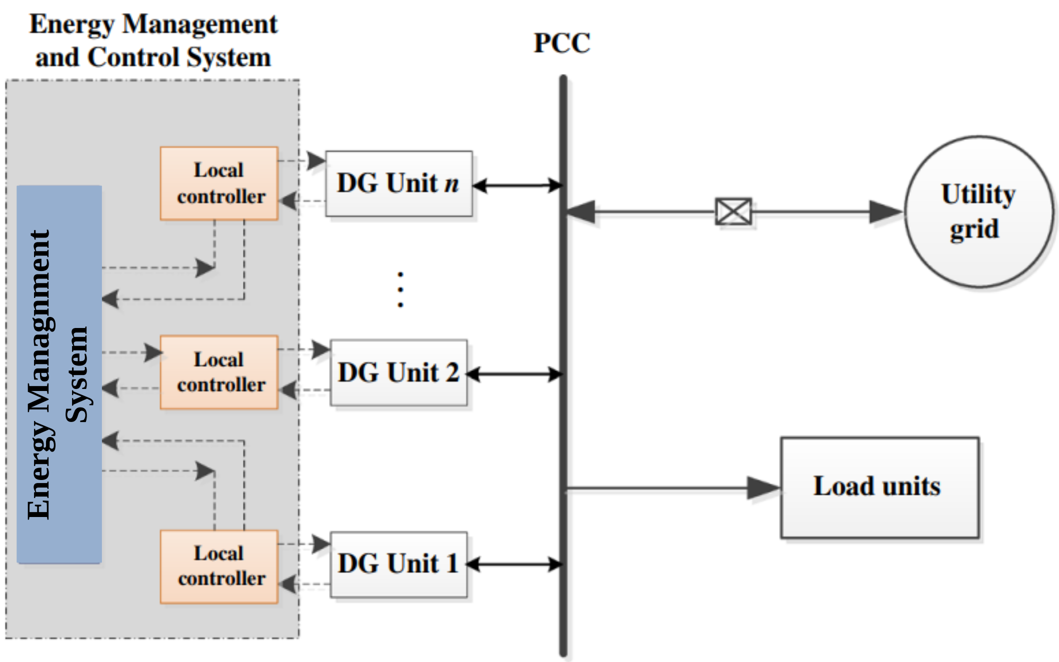

Figure 2.1: Centralized EMS Configuration

In Figure 2.1, the centralized configuration requires a two-way communication channel between the Primary Control (local controllers) and Secondary Control (EMS) for the exchange of information. This configuration is called a Star connection topology and a master/slave technique is established. The communication channels can be either wired or wireless depending on its requirements. Some of the available technologies are based on power line carriers, telephone lines or a wireless medium.

In centralized EMS, operation is in real-time where the Secondary controller frequently observes the entire system and samples the critical generation/demand information from each component. This frequent communication may cause a computational burden; therefore, a high-performance computing unit is required where the

EMS can execute accurate decisions by processing the data read through the communication channel. Moreover, a high bandwidth communication is required to meet the growing demands of EMSs.

Centralized EMS is a comparatively straightforward implementation but can also endanger the overall performance as any single point failure or any fault at a unit can cause the entire system to breakdown. Therefore, it is considered to have a low expandability and flexibility. Considering its structure and functionality, the following options can be more desirable for the MG cases [45]

- A small scale MG, with low communication and computational cost where centralized information can be processed
- Unity between the components is required which can operate the MG with a common goal for generation/demand balances
- Must operate with a high security that keeps the data information secure.

The EMS optimizes the MGs power flow distribution, resulting in maximizing the DG's production depending on the various parameters, constraints, variables and market prices provided as an input to the EMS controller. Some commonly used data, provided as input information to the controller to process and provide the reference values to the Primary Control layer, include:

- Forecasting of the grid electricity prices
- Status of interconnection of utility grid
- Reliability and security constraints of the MG
- Operational limits of DG to be discharged
- State of Charge (SOC) of the Battery Energy Storage System (BESS)
- Load day-ahead forecast values
- RESs generation forecasted power output

Centralized EMS enables all the relevant information to be gathered at a single point for the controller to perform its function. The following steps are involved in a centralized framework for the EMS to perform its tasks [21].

1. Performing a RESs generation and load day-ahead forecast
2. Performing a day-ahead energy scheduling calculation by collecting information from all the components
3. Executing an optimization algorithm to calculate the optimal day-ahead schedules
4. Assigning optimal day-ahead schedules to the corresponding components
5. Acquiring real-time system information, as there might be unexpected events or forecast errors
6. Generating short-term forecasts during the operation
7. Re-executing the optimization algorithm and rescheduling the dispatch of RESs (15 min)
8. Finally, sending the EMS the most updated and optimal set points to the Primary Control

When the EMS order is executed, a set of information is dispatched to the local controllers at the Primary Control level to operate the DG's in a cost-effective manner and simultaneously maximize the reliability of the MG. The set of information dispatched are [46]:

- Set points for DG's to dispatch the production of power
- Set points for Local loads to be shed or to be served
- Market prices to serve as the input for EMS

2.2 Decentralized Energy Management

In the Decentralized EMS scheme (Figure 2.2), local controllers are interfaced with each DG unit to communicate amongst each other through a communication channel within the MG. Each unit is controlled by its local controller where data for each of the DG controllers is exchanged. Local controllers communicate with each other to request/offer a service, exchange information, communicate expectations and share knowledge, which is relevant to the MG operation. These controllers have advanced algorithms to make their own decisions or to process information and execute commands from the upper level.

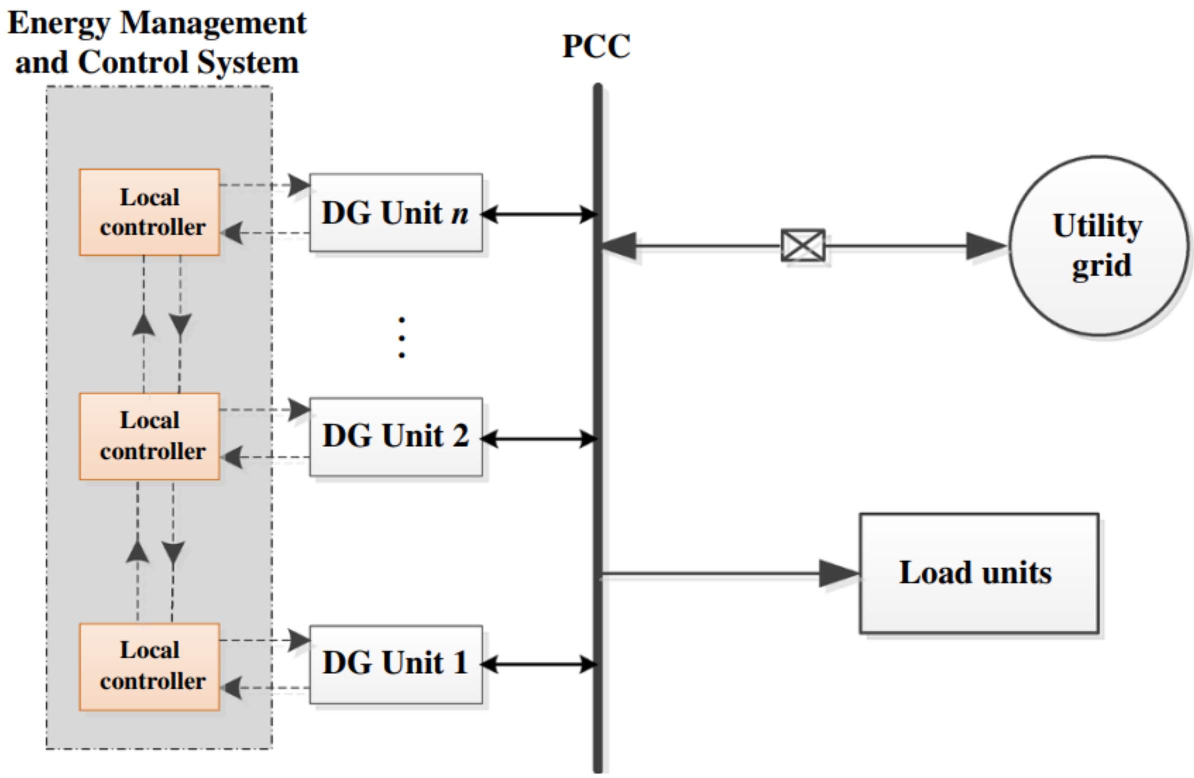

Figure 2.2: Decentralized EMS Configuration

In Figure 2.2, the decentralized configuration illustrates a two-way communication channel between the local controllers for the exchange of information. This configuration is called a peer-to-peer (P2P) communication topology and is established within the Primary Control layer. The EMS is implemented locally in each of its Local controllers connected to either DGs or the loads within the MG to allow the interaction of each unit to enable a decision-making process to optimally solve the energy management problem while providing flexibility within the MG to provide autonomy for all DG's and loads.

In a decentralized EMS operation, the need for Secondary Control layer is eliminated as the collaboration at the Primary Control layer between the local controllers which work jointly to achieve local goals to meet generation and demand of the entire MG. This can reduce the computational burden to some degree, as the customers no longer need to report their current or historical generation and demand data to EMS at the Secondary Control layer. Processing of information such as weather forecast, operating cost, load demand etc. can be optimized by the local controllers, which reduces the use of hierarchical levels in the MG.

Implementation of EMS in a Decentralized control architecture can increase the overall complexity of the entire MG. When looking at other perspectives, this configuration in terms of its flexible operation and avoidance of a single point failure can still maintain the normal operation of EMS. Another advantage is that it can allow interaction of various other DG units, like a plug-and-play functionality, without the need to make continuous changes to the local controller settings. Considering its structure and functionality, the following options can be more desirable for the MG cases [45]:

- Large scale MGs, or the consumption, storage and generation are widely isolated which can make data acquisition costly or difficult when using centralized EMS
- Requirement of local decision making, when the resources are owned by multiple owners
- Adding or removing of DG

When modeling the MG using the decentralized approach, the concept of Multi-Agent System (MAS) has been primarily addressed in the literature. MAS has evolved from a classical distribution control system which is specially designed for automated control systems with capabilities to control large and complex entities or groups of entities by dedicated controllers. Distributed control and MAS have a similar structure but what distinguishes them is the level of intelligence that the agents are embedded with. The MAS relies on a framework to achieve multiple local and global objectives autonomously, where two or more agents or intelligent agents are provided with local information. The characteristics of the local information, responsibilities and functionalities assigned to each agent and information shared by the agents between each other, plays a vital role in the overall performance of the system for the enhanced robustness, reliability and flexibility of MG. An intelligent agent is distinguished from a hardware or a software automated system and can be described as an agent which possess the characteristics such as [43]:

- **Reactivity:** ability to show reaction and reach to the changes in the environment in a timely manner
- **Pro-activeness:** seeking initiatives to achieve goals
- **Social-ability:** interaction with other agents through a communication channel

These characteristics in local controllers work towards improving the performance of the system and not have the main objective to maximize the revenue of the corresponding unit. This means that the intelligent agents can interact with other intelligent agents to react to environmental changes and establish a goal-oriented behaviour.

Overall operation of MAS is to control objectives, such as: economy, reliability, energy market participation and MG operation. Although this is an overall global goal for the MG to operate in a reliable manner, in MAS only local goals are defined and not global goals. When intelligent agents cooperate among themselves and work towards local goals, the targeted global goal may be achieved with local goals responding to sub-parts of the global goal. The design of MAS algorithms is a complex process that requires a great deal of expertise to decompose global goal task by modeling the agent's interactions and classifying agents. Intelligent agents working together to achieve various local goals is a multi-objective problem, where the complexity of the MAS algorithm is structured in a rigorous manner for the agents to communicate autonomously.

2.3 Comparison between Centralized and Decentralized EMS

Table 2.1: Comparison of Centralized and Decentralized

Controls	**Advantages**	**Disadvantages**
Centralized	• Simple to implement • Easy to maintain • Relatively low cost • Widely used and operated. • Wide control over the entire system	• Computational burden. • Requires high-bandwidth links. • Single point of failure • Not easy to expand. • Weak plug-and-play functionality.
Decentralized	• Easier plug-and-play (easy to expand) • Low computational cost • Avoid single point of failure • Suitable for large-scale complex, heterogeneous systems.	• Need synchronization • May be time-consuming for local agents to reach consensus • Convergence rates may be affected by the communication network topology • Upgrading cost on the existing control and communication facility • Needs new communication structure.

In conclusion, with regard to the architecture of the energy management system (EMS), two main approaches have been proposed to date in the technical literature: Centralized and Distributed EMS. The CEMS architecture consists of a central controller provided with the relevant information of every distributed energy resource within the MG and the MG itself (e.g., cost functions, technical characteristics/limitations, network parameters and mode of operation), as well as the information from forecasting systems (e.g., local load, wind speed, solar radiation) in order to determine an appropriate UC and dispatch of the resources according to the selected objective. On the other hand, DEMS provides a market environment through the use of Multi-Agent Systems (MAS) where each MG agent sends buying and/or selling bids to a Distributed System Operator (DSO) according to their particular needs and cost structures; the DSO then performs a binding process to determine the operation of the MG for the next period. In this case, a separated UC process must be realized to determine the agents that will operate in each particular period. Also, the table above shows the advantages and disadvantages of both configurations of an EMS. As can be seen, the centralized EMS is easy to implement and is widely used and operated for standalone MG system. Therefore, the EMS implemented in this thesis is be based on the Centralized EMS configuration.

3.0 Mathematical Modeling of the System

A MG includes distributed energy resource (DER) (photovoltaics, small wind turbines, fuel cells, internal combustion engines, micro turbines, etc.), distributed energy storage devices (flywheels, superconductor inductors, batteries, etc.), and loads. DERs can be divided into two main groups: (i) DER directed-coupled conventional rotating machines (e.g., an induction generator driven by a fixed-speed wind turbine), and (ii) DER grid coupled with the inverter (e.g. Photovoltaic, fuel cells, etc.). Distributed energy storage devices can be charged with the power excess and discharged to cover the power deficit. Thus, they help to enhance the reliability of MG as well as making it efficient and economical. Furthermore, energy storage (e.g. Batteries, Flywheels, etc.) is known for its fast response devices. Therefore, they also provide means to damp out transient instabilities and participate to control the voltage and the frequency of the MG.

3.1 Generic Microgrid

The MG of interest for this part of the thesis correspond to an integrated system near a community which is locally operated, and where the system is connected to main grid with the ability to buy/sell power and increase reliability. Thus, the schematic diagram of the MG model used for the EMS is shown in Figure 3.1. A typical MG model is used which includes different DGs, such as: Combined Heat and Power (CHP) plant, Diesel generator, Natural gas-fired generator, Photovoltaic (PV) generator and Wind generator. The DGs are connected and integrated at the point of common coupling (PCC) to provided power to a cluster of loads. The rated power for DGs are shown in Table 3.1. The MG is capable to operate in two different modes:

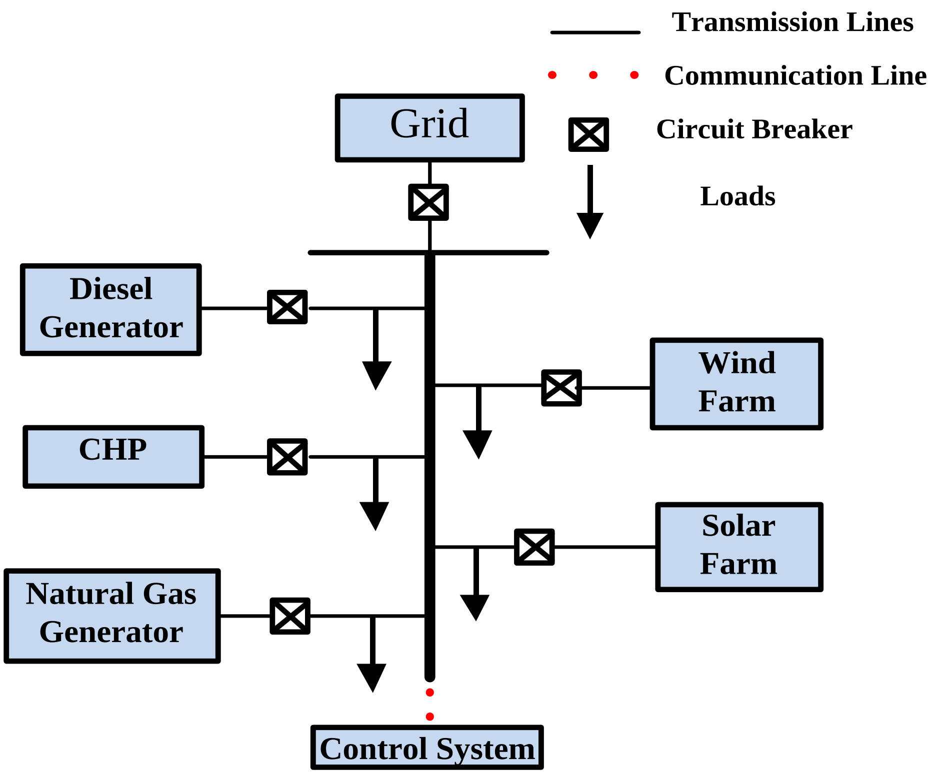

Figure 3.1: Overall system

- **Grid-connected mode** where the MG is able to buy power from the grid if demand exceeds available power or sell power back to the grid if production exceeds demand. The load demand in this mode is 4.35 MW.
- **Islanded mode** where it supplies power to only the critical loads. The load demand in this mode is 2.50 MW.

Table 3.1: Rating of all the DGs in the system

Distribution Generations	Minimum Power (MW)	Maximum Power (MW)
Combined Heat and power	0.2	1.5
Diesel Generation	0.1	1.0
Natural Gas Generation	0.1	1.0
Solar Farm	0.0	0.5
Wind Farm	0.0	0.5
Grid	-1.0	1.0

3.2 Mathematical model of system

The optimization model for the MG requires the objective function formulation subjected to the constraints. The objective function in this optimization model is the total operating and maintenance cost of the power consumed by the load of the MG. The cost function of the various generation units of the MG are modeled next

3.2.1 Generators Cost Functions

The generator cost is typically represented by four curves: fuel cost, heat rate, input/output (I/O) and incremental cost. Generator curves are generally represented as cubic or quadratic functions and piecewise linear functions. The fuel cost function for the CHP, diesel generator and natural gas generator are typically approximated by a quadratic function, as stated in Equation (3.1):

$$F_j\left(P_j(t)\right) = \alpha_j + \beta_j P_j(t) + \gamma_j P_j^2(t) \tag{3.1}$$

Where j= generating source; P = power output of a source j; F = operation cost of source j in \$/hr; α, β, γ are the cost coefficients in \$/hr (shown in Table 3.2) [28]. The fuel cost curve allows us to look at a wide range of economic dispatch practice such as total operating cost of a system, incremental cost and minute by minute loading of a generator. The fuel cost function becomes more nonlinear when the actual generator response is considered. Quadratic and naturally, cubic cost functions more accurately model the actual response of conventional thermal generators where fuel is oil, coal and gas, but also diesel generators, gas micro turbines, biomass power plants, fuel cells, etc. [5]. Energy sources such as solar, wind and hydro are not included because the fuel that drives its power generation is free.

Table 3.2: Cost figures for various generators

	CHP	**Diesel Generator**	**Natural Gas**
***α* ($/hr)**	15.30	14.88	9.00
***β* ($/hr)**	0.210	0.300	0.306
***γ* ($/hr)**	0.000240	0.000435	0.000315

3.2.2 Solar Generation Cost function

PV systems are one of the fastest growing renewable energy sources. Although both are based on non-dispatch able energy sources, the PV panels usually have a more easily predicted power production. Different levels of penetration, real solar radiation profiles and PV panel characteristics should be considered. The solar generation cost function is given by:

$$F(P_s) = aI^P P_s + G^e P_s \tag{3.2}$$

$$a = \frac{r}{[1-(1+r)^{-N}]} \tag{3.3}$$

where:

F	operation cost of source
P_s	Solar generation (kW)
a	Annuitization coefficient (dimensionless)
r	Interest rate
N	Investment lifetime (taken as N = 20 years)
I^P	Investment costs, per unit installed power ($/kW)
G^E	Operation and Maintenance (O & M) costs, per unit generated energy ($/kW)

Equations (3.2) & (3.3) are used to calculate the total generating cost of the solar energy considering the depreciation of all the equipment for generation. In this system, the values for the investment costs per unit of installed power (I^P) and O & M costs per unit of generated energy (G^E) are assumed to be equal to $4000 and 1.6 cents per kW respectively. Therefore, the final cost function can be derived, represented in Equation (3.4) [29].

$$F(P_s) = 505.016\ P_s(t) \tag{3.4}$$

Figure 3.2 depicts the forecasted power for the solar farm for this study over an aggregated 24-hour period. This data is not based on any one particular season or geographical area; however, it is a typical curve, and is used here for discussion purposes.

The seasonality over the year of particular geographical regions can also be accommodated, if desired.

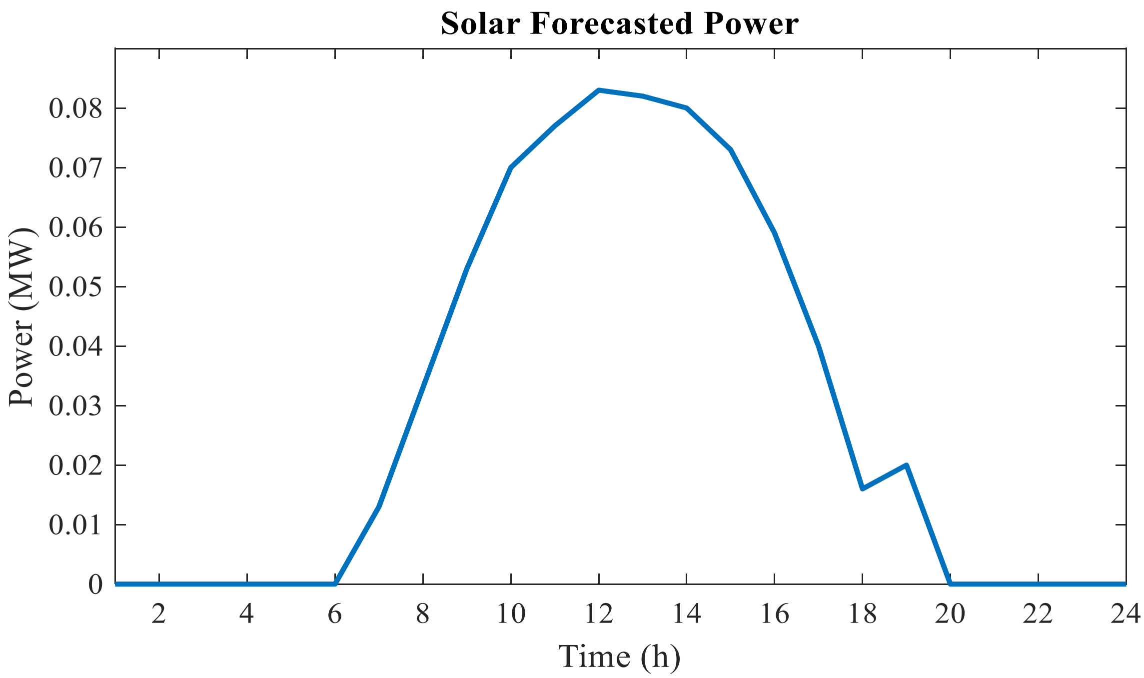

Figure3.2: Forecasted Power for Solar Farm [27]

3.2.3 Wind Generation Cost function

A wide range of levels of penetration of wind power can be observed in existing MGs; however, only wind turbines with a significant share of the MG peak load are relevant for the operation of the EMS. Different levels of penetration, wind speed profiles and wind turbine characteristics should be considered.

The cost function for wind generation is derived from Equations (3.3) & (3.5), and is similar to solar generation. However, the investment costs per unit installed power (I^P) and O & M costs per unit generated energy (G^E) are assumed to be equal to \$2000 and 1.6 cents per kW. Therefore, the final cost function can be derived, and is represented in Equation (3.5) [29].

$$F(P_w) = 185.616 P_w\ (t) \tag{3.5}$$

Figure 3.4 depicts the forecasted aggregated power for the wind farm for this study over a 24-hr period. Again, this data is not based on any particular season or geographical area; however, it is typical, and it is just assumed here for test purposes.

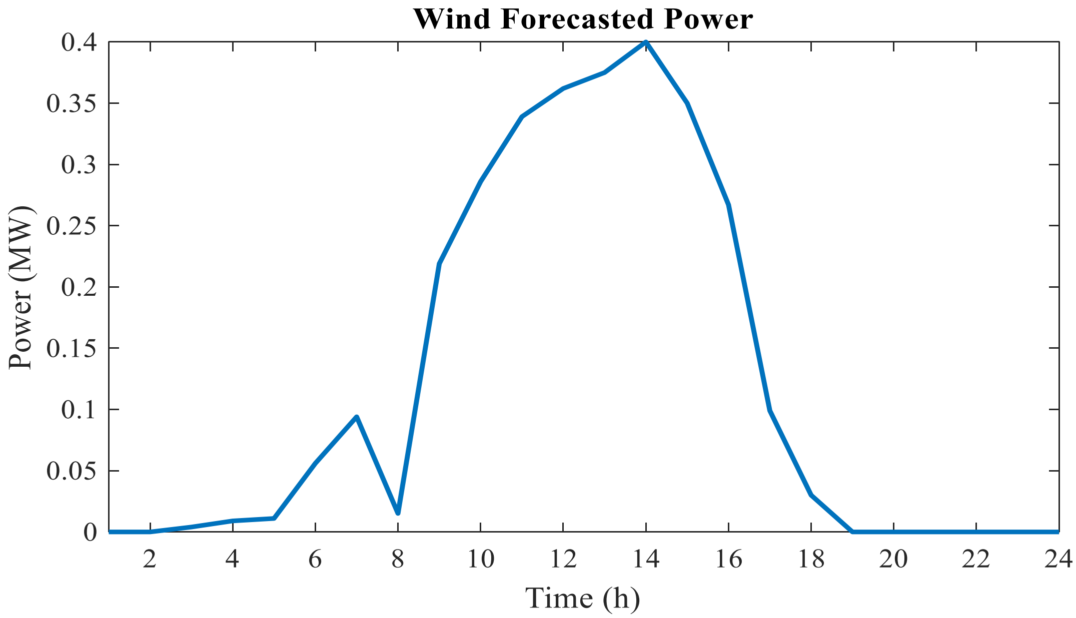

Figure 3.4: Forecasted Power for Wind Farm [27]

3.2.4 Grid

As seen in the Figure 3.1 the MG is connected to a distribution grid, which is considered as an infinite bus. In grid connected mode, the MG has ability to purchase power from the grid if the demand is more than the generation. It also has the ability transfer power back or sell back to grid if the generation is more than the demand at time interval *(t).* Therefore, tariffs have to be put in place for the system to operate by. The grid tariffs are designed based on peak and off-peak demand hours. When the system in operating on-peak hours the purchasing price is high and selling price is low. Then when the system is operating in off-peak hours the purchasing price in low and selling price is high. The grid tariffs used for this system are shown in the table below.

Table 3.3: Electricity Tariff Periods

Time of Use *(Hours)*	**Off-Peak 00:00–05:00**	**On-Peak 05:00–10:00**	**Off-Peak 10:00–17:00**	**On-Peak 17:00–21:00**	**Off-Peak 21:00–23:59**
Purchasing price ($/MWh)	*87.5*	*180*	*132*	*180*	*87*
Selling price ($/MWh)	*43.5*	*90*	*66*	*90*	*43.5*

Figure 3.5 depicts the forecasted aggregated load demand for this study over a 24-hr period. The graph in red represents the load profile of the system in grid-connected

mode, where it has two major peaks. First, the morning peak from 05:00 to 10:00 hrs. and a late evening peak between 17:00–21:00 hrs. The graph in blue represents the load profile during Islanding mode. As can be observed, the total demand is much lower than what it was during grid-connected mode. That is due to the fact during the islanding mode the system only supply's power to the critical loads. Again, this data is not based on any one particular season or geographical area; however, it is typical, and it is assumed here for test and demonstration purposes.

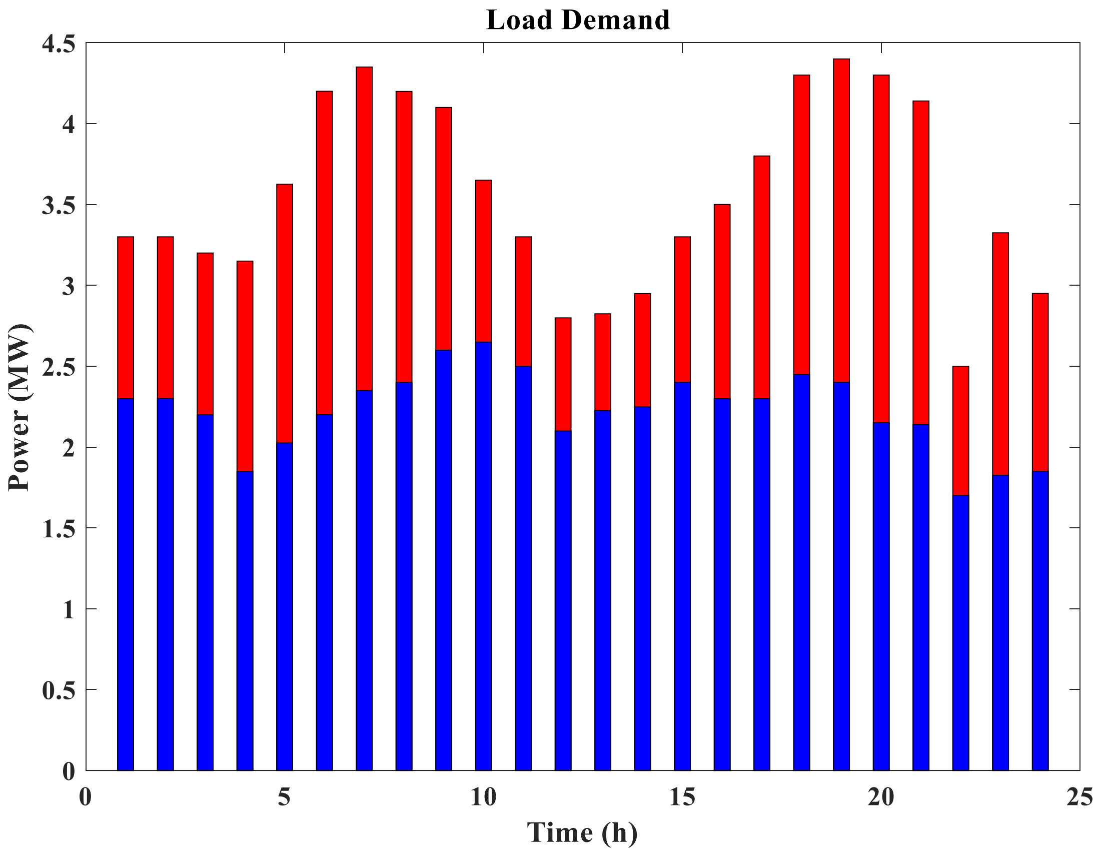

Figure 3.5: Load demand

3.3 Objective Function

The objective function for this EMS to minimize the total operation cost for the day. The cost function is calculated by the summation of all the cost function of DGs, and the grid. The cost function for grid-connected mode is a little different from the islanded-mode, due to the fact during islanded-mode, the grid is not available. The formulation of the cost function for both in grid-connected and islanding modes is presented below.

3.3.1 For Grid Connected mode

The object function for the EMS in grid-connected mode is formulated as:

$$Min \sum F\ (P_{dispatch}(t)) = \ Min \sum [F_j\big(P_j\big)(t) + \ F\big(P_w(t)\big) + F(P_S(t)) + F(P_b(t)) + \ F(P_{grid}((t))] \tag{3.6}$$

In grid-connected mode, the MG has an ability to buy/sell power from the grid. That depending on the total power available from the DGs and ESS at each time interval (*t*). Thus, $\sum F\ (P_{dispatch}(t))$ is the total cost of power for the day.

3.3.2 For Islanded mode

The objective function for EMS in Islanded mode is formulated as:

$$Min \sum F\ (P_{dispatch}(t)) = \ Min \sum [F_j(\big(P_j\big)(t)) + \ F\big(P_w(t)\big) + F(P_S(t)) + F(P_b(t))] \tag{3.7}$$

In Islanded mode, since the MG is disconnected from the main grid, the total load has to be satisfied by the remaining DGs and ESS. Thus, $\sum F\ (P_{dispatch}(t))$ is the total of the all the DGs and ESS for a 24-hour day period.

3.4 Constraints Functions

In real life, the optimal EMS for MG is affected by a number of constraints. The constraints functions are used to help keep the system within set limits and helps guide the system to achieve the desired results. This section presents constraints related to the objectives discussed earlier.

3.4.1 Grid connected mode

As mentioned before, in grid-connected mode, the MG is able to buy/sell power from/to the main grid depending on the load demand. Hence, to decide how much power is bought from or sold to the grid, the following equation is applied.

$$P_{generation}(t) = \ \sum P_j(t) + \ P_w(t) + P_S(t) + \ P_b(t) \tag{3.8}$$

$$P_{generated}(t) \neq \ P_{Demand}(t) \tag{3.9}$$

If Equation (3.8) is true, then

$$P_{grid}(t) = P_{generated}\ (t) - P_{Demand}(t) \tag{3.10}$$

$$P_{Demand}(t) = \ P_{generated}(t) + P_{grid}(t) \tag{3.11}$$

Therefore, if P_{grid} is positive, then MG is purchasing power from the grid and if P_{grid} is negative then microgrid is selling power to the grid.

3.4.2 Islanded Mode

Since, in islanded mode, the MG is disconnected from the main grid, there cannot be any buying/selling of power. Therefore, the power generated must always be equal to the demand.

$$P_{generation}(t) = \ \sum P_j(t) + \ P_w(t) + P_S(t) + \ P_b(t) \tag{3.12}$$

$$P_{generated}(t) = \ P_{Demand}(t) \tag{3.13}$$

Thus, Equation (3.13) must always be true.

3.4.3 Power generation limits.

Power generation capacity limits. The power generated by each unit should be within its lower limit and upper limit, so that each generator has a power rating as shown in Table 3.1.

$$P_j^{min}(t) \le P_j(t) \le P_j^{max}(t) \tag{3.14}$$

4.0 Details of PSO and DE Algorithms

Various optimization techniques have been used by researchers to tackle the problem of energy management in MGs. Section 1.3 presents a review for all the different types of optimization algorithms used to solve the problem of EMS. The preceding section discusses the two optimization techniques used for the EMS system in this thesis.

Particle swarm optimization (PSO) and Deferential Evolution (DE) are two of the most popular optimization algorithms developed. Since their development, many variants have also been developed for solving practical issues related to optimization. Recently, both PSO and DE have emerged as promising algorithms in solving various optimization problems in the field of science and engineering. As mentioned in the literature review, both algorithms have been used to solve the EMS. In this section, an overview of the two P-metaheuristics algorithms, namely PSO and DE, is given.

4.1 Particle Swarm Optimization (PSO)

PSO belongs to the swarm intelligence family of stochastic, population-based algorithms, first proposed by Kennedy and Eberhard in 1995. In swarm intelligence, intelligent behaviour is shown by some agents like birds, ants or fish. Without collaboration, this level of intelligence is absolutely unattainable for a stand-alone member of the swarm; but, with collaboration amongst the particles of the swarm, it can be possible. The technique is based on particle movements in the search space; each particle flies around in the search space with an adaptable velocity that is dynamically adapted according to its own flying experience and to the flying experience of other particles. It takes the advantages of its peers as each particle tries to improve itself by imitating traits from their successful peers. Furthermore, each particle is capable of remembering the best position in the search space ever visited by itself. Main characteristics of the PSO algorithm are the ability to escape from local optimum, fast convergence and easy implementation [47].

4.1.1 Algorithm

PSO algorithm works by simultaneously maintaining several candidate solutions in the search space. During each iteration of the algorithm, each member of the population is evaluated by the objective function being optimized, determining the fitness of that solution. Each candidate solution can be thought of as a particle "flying" through the fitness landscape finding the maximum or minimum of the objective function. Initially, the PSO algorithm chooses candidate solutions randomly within the search space [48].

Figure 4.0 depicts an example PSO algorithm with four particles in search space trying to find the global maxima. The x-axis represents all possible solutions in the search space. The sinusoidal curve is the objective function. Since, the PSO algorithm has no knowledge of the behaviour of the objective function, thus, the algorithm simply uses the objective function to evaluate its candidate solutions and operates upon the resultant fitness values.

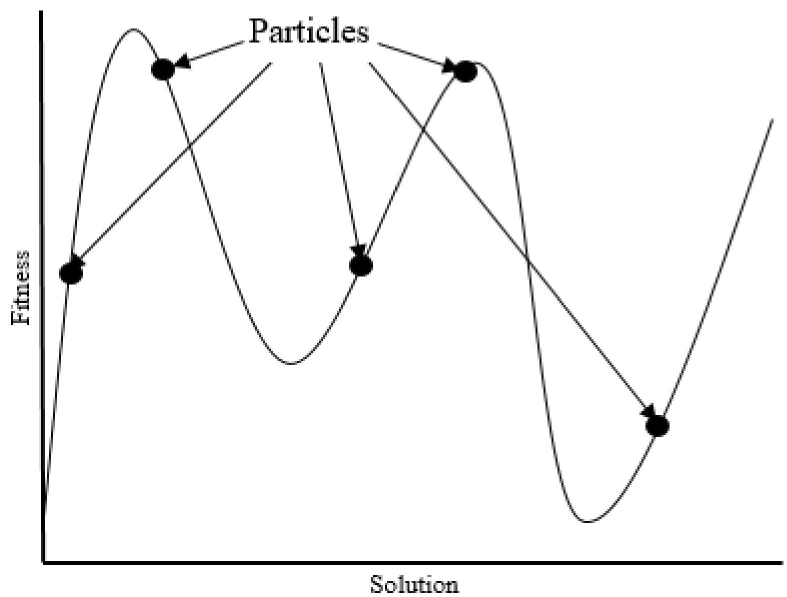

Figure 4.0: Initial PSO State [49]

Each particle maintains its position, composed of the candidate solution and its evaluated fitness, and its velocity. Additionally, it remembers the best fitness value it has achieved thus far during the operation of the algorithm, referred to as the individual best fitness, and the candidate solution that achieved this fitness, referred to as the individual best position or individual best candidate solution. Finally, the PSO algorithm maintains the best fitness value achieved among all particles in the swarm, called the global best fitness, and the candidate solution that achieved this fitness, called the global best position or global best candidate solution [49].

4.1.1.1 Updating the velocity

Using the personal best (p_i) and global best (p_g) of each particle, the particle velocity is updated according to equation (4.1),

$$v_i(t) = [w * v_i(t-1)] + \left[c_1 * r_1 * \left(p_i - x_i(t-1)\right)\right] + [c_2 * r_2\left(p_g - x_i(t-1)\right)] \quad (4.1)$$

The first term i.e. $[w * v_i(t-1)]$, acts as the particle's memory, causing it to explore the search space at a similar velocity as before. The inertia weight coefficient w controls the influence of the previous velocity on the movement of the particle.

The second term i.e. $[c_1 * r_1 * \left(p_i - x_i(t-1)\right)]$, called the *cognitive component*, acts as the particle's memory, causing it to tend to return to the regions of the search space in which it has experienced high individual fitness. The cognitive coefficient c_1 is usually close to 2 and affects the size of the step the particle takes toward its individual best candidate solutionp_i.

Then, the third term i.e. $[c_2 * r_2 * \left(p_g - x_i(t-1)\right)]$, called the *social component*, causes the particle to move to the best region the swarm has found so far. The social coefficient c_2 is typically close to 2 and represents the size of the step that the particle takes toward the global best candidate solution p_g the swarm has found up until that point.

The random values r_1 in the *cognitive component* and r_2 in the *social component* cause these components to have a stochastic influence on the velocity update. This stochastic nature causes each particle to move in a semi-random manner heavily influenced in the directions of the individual best solution of the particle and global best solution of the swarm.

The Figure 4.1 depicts the movement of a single particle. For particle i, the position of the particle is denoted by the vector $x_i(t-1)$. In addition to the position, there is a velocity for each particle which is denoted by $v_i(t)$. The dimensions of x and v are the same. The velocity describes the movement of particle i, in the sense of direction. Particles interact and learn from each other and obey some simple rules to find the solution. In addition to the position and velocity, every particle has a memory of its own best position so far, which is denoted by personal best (p_i) and a common best experience among the members of swarm, which is denoted by global best (p_g). At each iteration, position and velocity of each particle are updated, using the equations mentioned above [48].

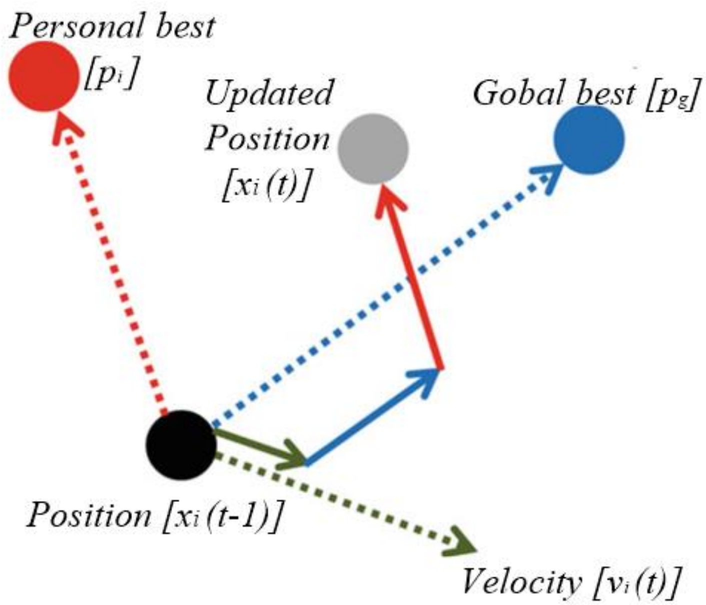

Figure 4.1: PSO system

4.1.1.2 Updating the position

Based on the updated velocity, each particle will change its position in the search space according to equation (11). The term $x_i(t-1)$ represents the location of the particle in the pervious iteration

$$x_i(t) = x_i(t-1) + v_i(t) \tag{4.2}$$

4.1.1.3 Updating the best-found particle so far, local and global

Then, the fitness of each particle is evaluated. If the fitness is less than its personal best (for a minimization problem), then each particle updates it's personal best solution according to equation (4.2). However, if the fitness is less than its global best, then the best global solution of the swarm is updated accordingly, as shown in equation (4.1c). The whole process is defined in Algorithm 1.

$$if \quad f(x_i) < \; p_{best_i}, then \; p_i = \; x_i \tag{4.3}$$

$$if \quad f(x_i) < \; g_{best_i}, then \; g_i = \; x_i \tag{4.4}$$

4.1.2 PSO flow diagram

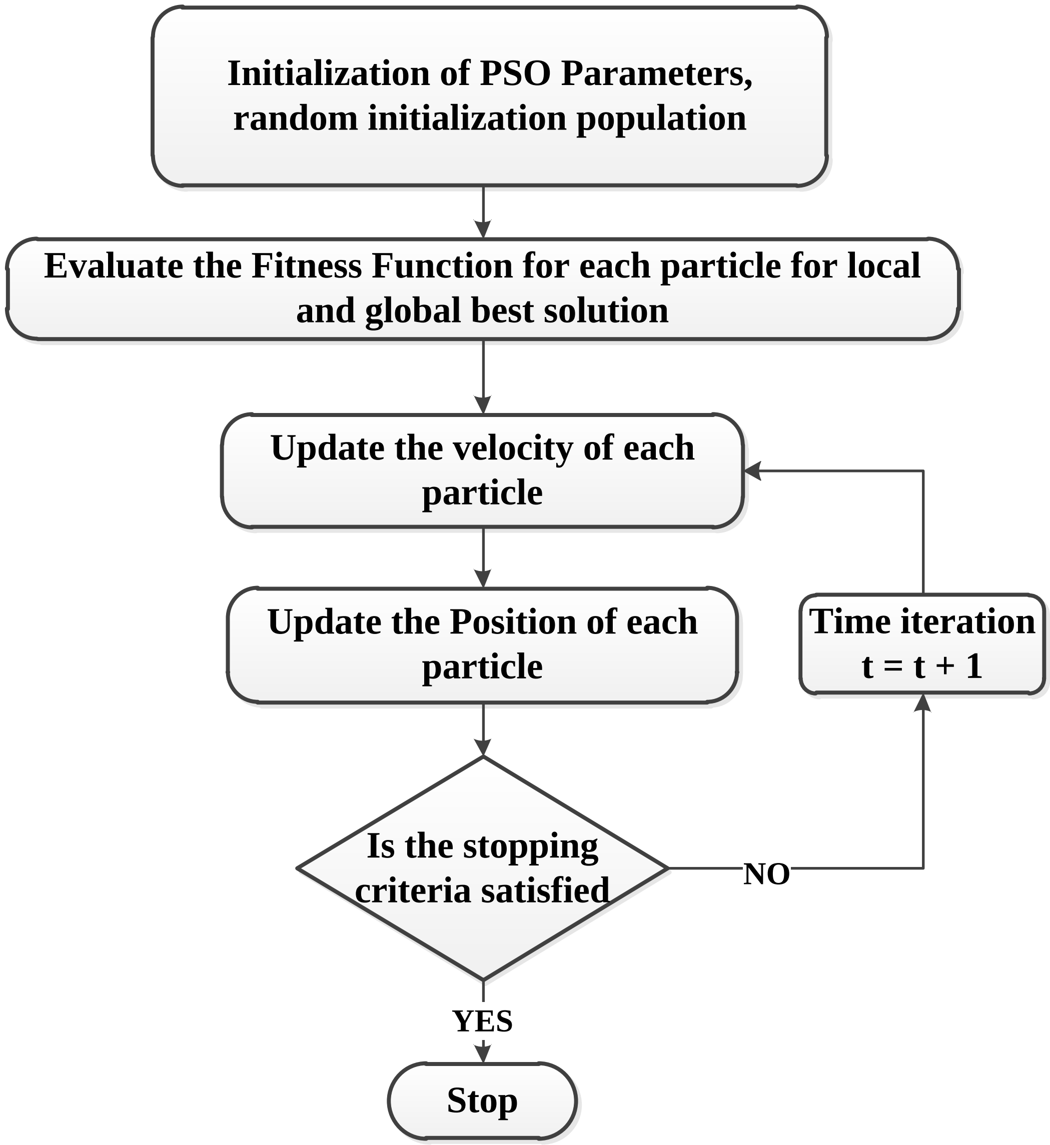

Figure 4.3: PSO Flow Diagram

4.1.3 PSO Pseudo Code

Algorithm 1: Particle Swarm Optimization
1: Start Procedure
Inputs:
c_1: Cognitive coefficient
c_2: Social coefficient
NP: Population size
w: inertia weight
2. *Initialize whole swarm using Randomly uniformly distributed and evaluate fitness*
3. While (ite ≤ ite_{max})
4. *Evaluate each particle $f(x_i)$*
5. For (i=1, i ≤ NP, i++) Do
6. ***//Update particle velocity:***
7. $v_i(t) = w * v_i(t-1) + c_1 * r_1 * \left(p_i - x_i(t-1)\right) + c_2 * r_2 * \left(p_g - x_i(t-1)\right)$
8. *//**Move to new position:***
9. $X_i(t) = X_i(t-1) + v_i(t)$
10. ***If*** *($f(x_i) \leq f(Pbest_i)$) then $Pbest_i = x_i$*
11. ***If*** *($f(x_i) \leq f(gbest_i)$) then $gbest_i = x_i$*
12. ***Update (x_i, v_i);***
13. End For
14. End While
15. ***Output:*** *Best Solution*
16. End Procedure

4.2 Differential Evolution (DE)

Differential Evolution *(DE)* is a stochastic, population-based optimization algorithm which was introduced in 1996. DE has emerged as one of the techniques most favored by engineers for solving continuous optimization problems. DE has several attractive features. Besides being an exceptionally simple evolutionary strategy, it is significantly faster and robust for solving numerical optimization problems and is more likely to find the function's true global optimum. Also, it is worth mentioning that DE has a compact structure with a small computer code and has fewer control parameters in comparison to other evolutionary algorithms. Originally, Price and Storn proposed a single strategy for DE, which they later extended to ten different strategies [3].

4.2.1 Algorithm

The DE algorithm is divided into 4 different modes of operation, as shown in Figure 4.4. The algorithm starts from the initialization stage, where an initial population is generated. Second, the algorithm applies mutation to the initial population. Third, a crossover is performed and lastly, a selection is made to generate a population. The system is repeated from mutation again until the termination condition is met.

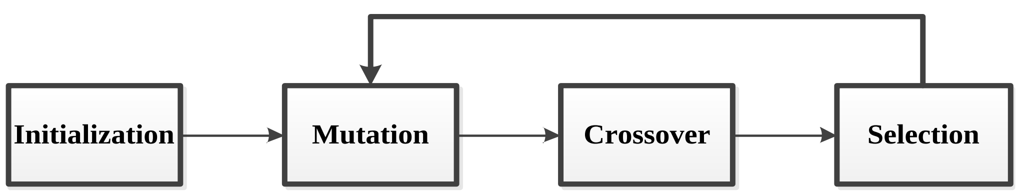

Figure 4.4: DE Algorithm

4.2.1.1 Initialization

Initially, in DE, the initial population size (NP) a D-dimensional parameter vector generates a uniformly distributed random variable, where each decision variable x_j is defined to be within its upper and lower limits $[l_j, u_j]$. Therefore, the candidate solution x_{ij} is initialized, as follows [19]:

$$x_{ij} = l_j + rand_j[0,1] * \left(u_j - l_j\right), \; i \in [1, np], j \in [1, D] \tag{4.5}$$

Where $rand_j$ is a uniformly distributed random variable in the range [0, 1]. After the initialization of population, the following operators are applied next: mutation, crossover, and selection. These are explained next in the following subsections [47].

4.2.1.2 Mutation

Once initialized, DE mutates and recombines the population to produce a population of NP trial vectors. In particular, differential mutation adds a scaled, randomly sampled, vector difference to a third vector. Equation (4.6) shows how to combine three different, randomly chosen vectors to create a mutant vector, V_{iG}:

$$V_{iG} = X_{best^i G} + F * (X_{r_1{}^i G} - X_{2^i G}) \tag{4.6}$$

The indices $r_1{}^i$ and, $r_2{}^i$ are randomly chosen from the range [1, NP]. The parameter F represents the mutation scaling factor (F ∈ [0,1]) which controls the amplification of the difference vectors to avoid stagnation of the search process. X_{best} is the best individual vector with the best fitness in the population at generation G. The whole process is defined in Algorithm 2 [50].

4.2.1.3 Crossover

To complement the differential mutation search strategy, DE also employs uniform crossover. Sometimes referred to as discrete recombination, (dual) crossover builds trial vectors out of parameter values that have been copied from two different vectors.

$$Ui,j(t+1) = \begin{cases} Vij(t+1) & \textbf{\textit{if}}\ (rand(0,1) \leq Cr\ ) \\ Xij(t) & else \end{cases} \tag{4.7}$$

The crossover probability, Cr ∈ [0,1], is a user-defined or a random value that controls the fraction of parameter values that are copied from the mutant. To determine which source contributes a given parameter, uniform crossover compares Cr to the output of a uniform random number generator, *rand* (0,1). If the random number is less than or equal to Cr, the trial parameter is inherited from the mutant, V_{ij}. Otherwise, the parameter is copied from the vector, X_{ij}. In addition, the trial parameter with randomly chosen index, rand, is taken from the mutant to ensure that the trial vector does not duplicate X_{ij} [51].

4.2.1.4 Selection

Based on a greedy selection scheme, the offspring (which is the vector generated after crossover), would replace the target vector X_i if its fitness value is better or equal to the target vector to be a member of the population in the next generation.

$$Xi(t+1) = \begin{cases} Ui(t+1) & \boldsymbol{if}\ (F(Ui(t+1)) \le F(Xi(t))\ ) \\ Xi(t) & else \end{cases} \tag{4.8}$$

Where *F()* is the objectives function to be minimized. Therefore, based on the greedy selection scheme, if the objective function value (fitness) of the trial vector $[Ui(t+1)]$ created after crossover is lower than that of the target vector, then $Ui(t+1)$ will be the individual going into the next generation. Likewise, if $Xi(t)$has a lower fitness value, then $Ui(t+1)$, $Xi(t)$ will remain and moved into the next generation [47].

4.2.2 DE Flow diagram

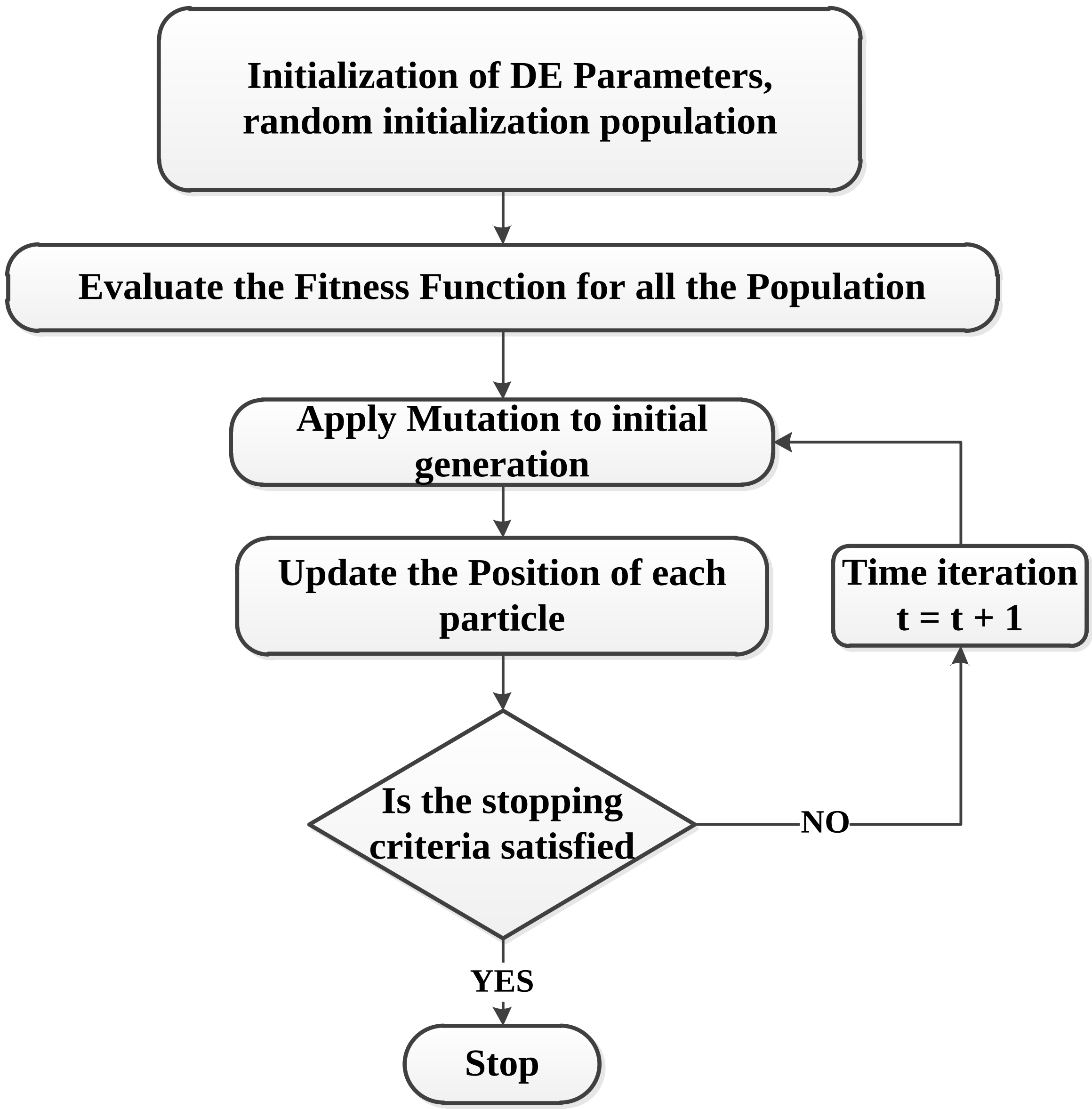

Figure 4.5: DE Flow Diagram

4.2.3 DE Pseudo Code

Algorithm 2: Differential Evaluation Algorithm, *DE/best/1 scheme*

1: Start Procedure
        Inputs:
        F: Mutation Factor
        Cr: Crossover rate
        NP: Population size
        D: Problem dimension
2. *Initialize population using Randomly uniformly distributed and evaluate fitness*
3. While $(NFC \leq NFC_{max})$
4.   ***For*** $(i=1, i \leq NP, i{+}{+})$ ***Do***
5.   ***//Mutation:***
6.   *Select the best particle* (X_{best})
7.   *Select the parent*
8. $V_{iG} = X_{bestG} + F * (X_{r_1{}^{i}G} - X_{2^{i}G})$
9.   ***For*** *j=1* ***to D***   ***// Crossover***
10.   ***if (****rand(0,1)* $\leq$ *Cr* ***) Then***
11. $U_{i,j}(t+1) = V_{ij}(t+1)$
12.   ***else***
13. $U_{i,j}(t+1) = X_{ij}(t)$
14.   ***End if***
15.   ***End For***
16.   ***// Selection***
17.   ***Evaluate*** $U_{i,}(t+1)$
18.   ***End For***
19. End While
20.   ***Output:*** *Best Solution*
21. End Procedure

4.3 Parameters Selection

There are two different approaches for parameter value selection: off-line parameter initialization and online parameter tuning. In off-line parameter initialization, the values of different parameters are fixed before the execution of the algorithm. These values are usually decided upon through empirical study. In online parameter tuning, function is built-in to change the parameters while the algorithm is being executed. Online approach can be classified into two main groups, dynamic and adaptive. In a dynamic parameter updating approach, the change of the parameter value is performed without considering the search progress. The adaptive approach changes the values according to the search progress [52].

Hence, for this thesis, the parameters for both algorithms were decided using the off-line parameter initialization where the parameters were adjusted one by one until optimal results were achieved.

4.3.1 PSO parameters

The parameters fir PSO algorithm were manually tuned one by one as mentioned above. This helped achieve close to best setting possible for this application. But to achieve the most optimal parameters for PSO algorithm this application all the possible setting has to be run and compared as shown in the Table 4.1. Due lack of computational power available all the possible could evaluated.

Table 4.1: All the possibilities

Parameters	***Range***	***Step-size***	***Possibilities***
Cognitive coefficient c_1	0 to 2.6	0.1	27
Social coefficient c_2	0 to 2.6	0.1	27
Pop. Initialization	*UniR, LHS, CLHS*	-	3
Population Size (*NP*)	5, 10, 50, 100	-	4
Inertia Coefficient (*w*)	0 to 1	0.1	11
Total Number of Combinations			**96,228**

Hence, the parameters used for the PSO algorithm are shown in Table 4.2 below. These parameters are chosen on the basis of previous work done by different researchers and some testing done offline [47].

Table 4.2: Parameters used for PSO algorithm

PSO Parameters	Values
w	*w (1 -alpha)*
alpha	0.05
c_1	2.2
c_2	2.2
r_1, r_2	random
Population Size	500

4.3.2 DE Parameters

The parameters for DE algorithm were manually tuned one by one as mentioned above. This helped achieve close to best setting possible for this application. But to achieve the most optimal parameters for DE algorithm this application all the possible setting have to be run and compared As shown in the Table 4.3. Due to lack of computational power available all the possible could not be evaluated.

Table 4.3: All the possibilities

Parameters	***Range***	***Step-size***	***Possibilities***
Crossover rate (Cr)	0 to 1	0.05	21
Mutation Factor (*F*)	0 to 1	0.05	21
Pop. Initialization	*UniR, LHS, CLHS*	-	3
Population Size (*NP*)	5, 10, 50, 100	-	4
Mutation Schemes (DE/x/y/z)	DE/rand/1, DE/best/1, DE/rand-to-best/1	-	3
Total Number of Combinations			**15,876**

Hence, the parameters used for the DE algorithm are shown in Table 4.4 below. These parameters are chosen on the basis of previous work done by different researchers [47].

Table 4.4: Parameters used for DE algorithm

DE Parameters	Values
F	0.8
CR	0.5
Population Size	500

4.4 EMS system flow diagram

The layout of the EMS is presented below. The flow chart in Figure 15 illustrates the main procedure of the system. The various steps in the procedure are discussed next.

4.1 Flow Diagram

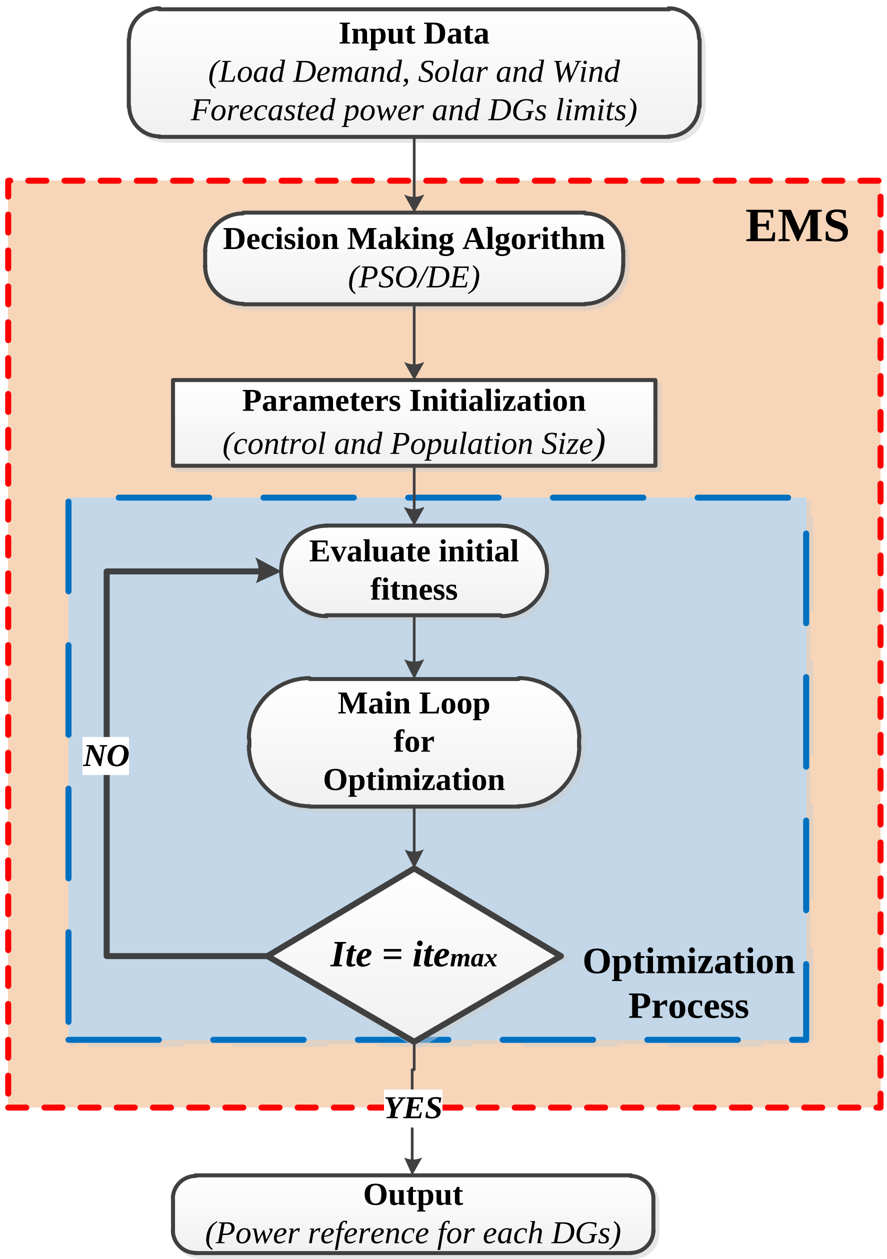

Figure 4.4: PSO Algorithm Flow chart

Step 1 (Input data): Forecasted Data such as load demand, Power available from Wind and Solar, and Power limits for generators are inputted in the system.

Step 2 (Decision making algorithm): Since in this work we are using two different optimization algorithms, therefore, before we start, we have to select which algorithm to apply.

Step 3 (Parameters Initialization): Both PSO and DE have optimization parameters that need to be set before starting the optimization process. For PSO, parameters that need to be set are *(c1, c2, w and population size).* And for DE, parameters that need to be set are *(F, CR, and population size).* This help with the initial population generation.

Step 4 (Optimization Process): PSO/DE algorithm is applied to find the optimum way to dispatch all available DGs to satisfy the load demand, while minimizing the operating cost for the MG.

Step 5 (Output): The termination condition is checked, and if it is satisfied, the system would output the power reference signal for each DG at each time interval. If the termination condition is not satisfied, the system would go back to Step 3

5.0 Results & Discussion

In this section, the results of both PSO and DE based EMS are presented and analyzed. The optimal dispatch of the DGs and main grid is investigated for a 24-hour operation period. Two different case studies of MG system are presented:

- **First case study**: The optimization model of EMS is analyzed for a ***grid connected*** MG. The load demand used for this case study is presented in Figure 3.1 in red. In this case study, the main area of focus is the ability of the algorithms (PSO and DE) to economically optimize the purchasing/ selling power from/to the grid to reduce the MG operation cost.
- **Second case study**: This presents the optimization model of EMS for MG in ***islanded mode*** suppling only to critical loads. The load demand used for this case study is presented in Figure 3.1 in blue. In this case study, the main area of focus is the ability of the algorithms to utilize the ramping feature of the three generators (CHP, Diesel generator and Natural gas) and optimize them for an economically and stable operation of the MG.

5.1 Grid Connected Mode

In this case study, the optimization of the EMS for the installed capacity of the CHP, Diesel generator, Natural gas generator, Wind, Solar and main grid is investigated for a 24-hour operation period. The optimized EMS model considers the load demand, main grid tariff, and available power from wind and PV. Additionally, all generators are assumed to be in operating mode and the algorithm aimed to find the minimum operating cost while satisfying load demand. All the results achieved from both PSO and DE for this case study are presented below.

5.1.1 PSO Based EMS (Grid Connected)

Performance Based on different Population Size

Before the optimal result can be analyzed from PSO algorithm, the ideal population size has to determine by the test shown in Figure 5.1. The figure below depicts the performance of PSO algorithm with different population sizes (NP = 50, 100, 300, 500).

To achieve accurate results for comparison, the system was averaged over 100 iterations. As can be observed, different population sizes have a clear impact on the performance of the algorithm. Each population size produced a different convergence point with a different number of runs required. From this result, it was determined that the algorithm performed best for the highest population size of 500. The breakdown of the results is presented in Table 7, which shows the convergence point in terms of number of Runs and the most optimal cost achieved.

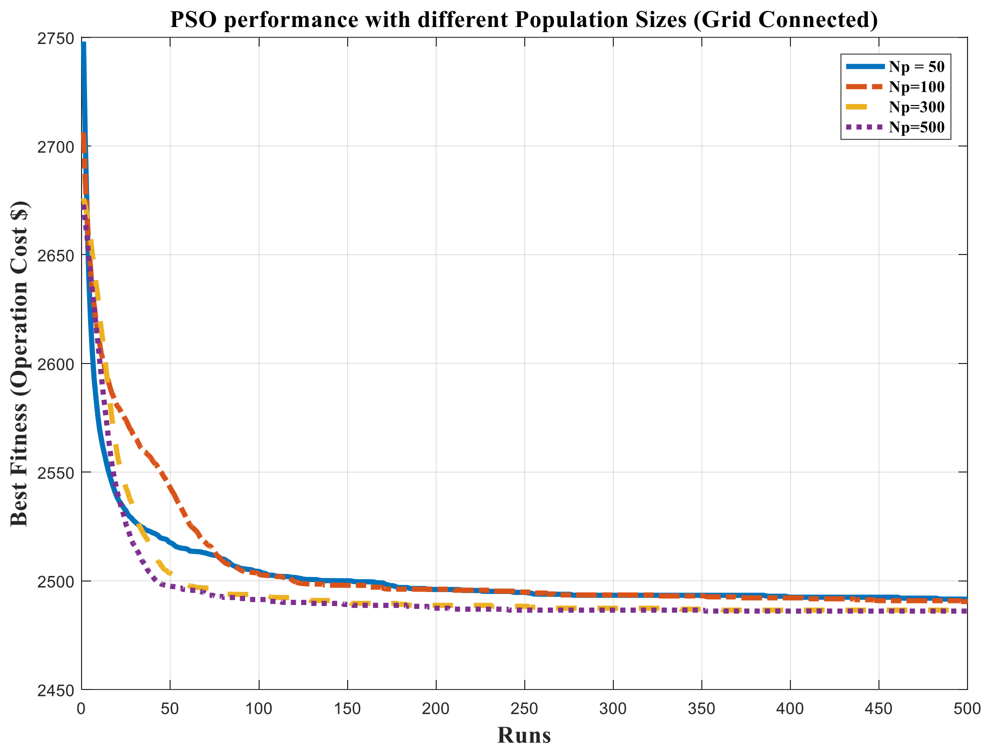

Figure 5.1: PSO performance with Different Population Size (Grid Connected)

Table 5.1: Optimal Operation Cost with different Population Size (PSO)

Population Size (NP)	Convergence Point (Runs)	Best Operation Cost ($/day)
50	486	2491.610
100	451	2490.900
300	362	2486.526
500	352	2486.103

Best Solution by PSO (Grid Connected)

Figure 5.2, depicts the best output achieved from the PSO EMS for grid-connected mode. The algorithm was able to find the optimal solution to dispatch all available DGs to satisfy the given load demand for the 24 hours time period. It can be observed that the system is able to buy and sell power from the grid during off-peak and peak hours (Red line). Likewise, it can be seen in the output three generators are being operated at full capacity at almost all time because for the system is more cost effective if the system buys and sells power rather than ramping the generators up and down to match the demand at each time interval. The optimal cost of operation during the 24-hour period achieved by the PSO algorithm is $2486.103.

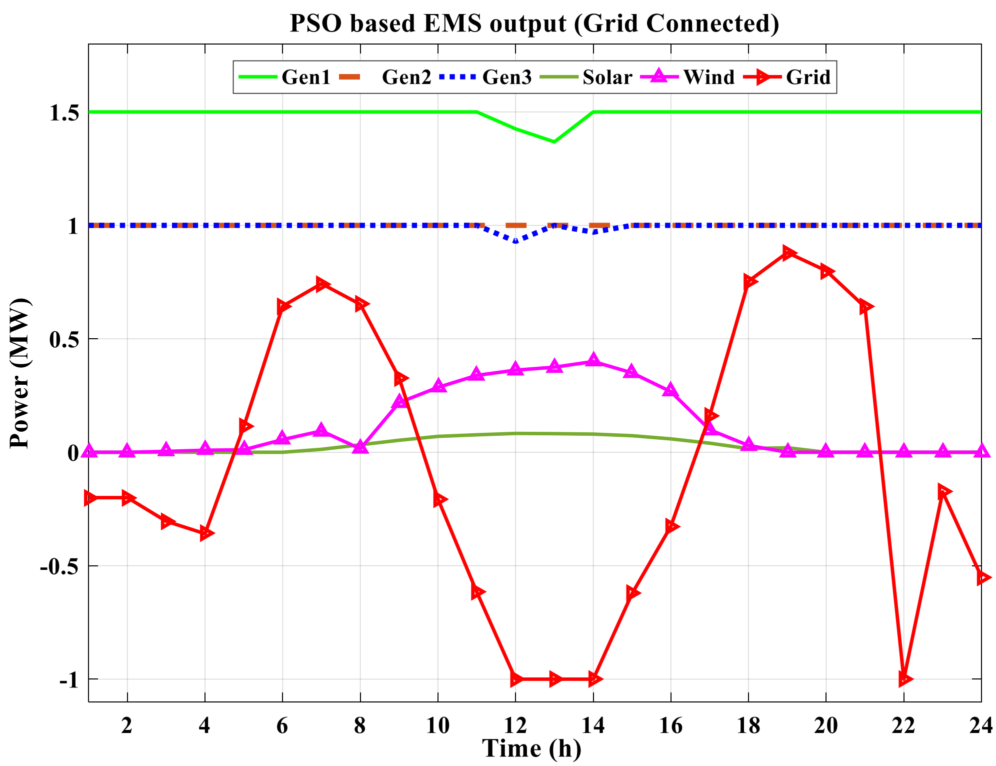

Figure 5.2: PSO based EMS output for Grid connected mode (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Table 5.2: EMS output for PSO Grid connected mode breakdown (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Time	Gen 1	Gen2	Gen 3	Solar	Wind	Grid	Sum	Demand
1	1.500	1.000	1.000	0.000	0.000	-0.200	**3.300**	**3.300**
2	1.500	1.000	1.00	0.000	0.000	-0.200	**3.300**	**3.300**
3	1.500	1.000	1.000	0.000	0.004	-0.304	**3.200**	**3.200**
4	1.500	1.000	1.000	0.000	0.009	-0.359	**3.150**	**3.150**
5	1.500	1.000	1.000	0.000	0.011	0.114	**3.625**	**3.625**
6	1.500	1.000	1.000	0.000	0.056	0.644	**4.200**	**4.200**
7	1.500	1.000	1.000	0.013	0.094	0.743	**4.350**	**4.350**
8	1.500	1.000	1.000	0.033	0.0151	0.651	**4.200**	**4.200**
9	1.500	1.000	1.000	0.053	0.219	0.328	**4.100**	**4.100**
10	1.500	1.000	1.000	0.070	0.286	-0.206	**3.650**	**3.650**
11	1.500	1.000	1.000	0.077	0.339	-0.616	**3.300**	**3.300**
12	1.425	1.000	0.929	0.083	0.362	-1.000	**2.800**	**2.800**
13	1.368	1.000	0.999	0.082	0.375	-1.000	**2.824**	**2.824**
14	1.500	0.999	0.970	0.080	0.400	-1.000	**2.949**	**2.949**
15	1.500	1.000	1.000	0.073	0.350	-0.623	**3.300**	**3.300**
16	1.500	1.000	1.000	0.059	0.267	-0.326	**3.500**	**3.500**
17	1.500	1.000	1.000	0.040	0.099	0.161	**3.800**	**3.800**
18	1.500	1.000	1.000	0.016	0.030	0.754	**4.300**	**4.300**
19	1.500	1.000	1.000	0.020	0.000	0.880	**4.400**	**4.400**
20	1.500	1.000	1.000	0.000	0.000	0.800	**4.300**	**4.300**
21	1.500	1.000	1.000	0.000	0.000	0.640	**4.140**	**4.140**
22	1.500	1.000	1.000	0.000	0.000	-1.000	**2.500**	**2.500**
23	1.500	1.000	1.000	0.000	0.000	-0.175	**3.325**	**3.325**
24	1.500	1.000	1.000	0.000	0.000	-0.550	**2.950**	**2.950**
Total	**35.79337**	**23.99993**	**23.8997**	**0.699**	**2.9161**	**-**	**84.54**	**84.54**

The results obtained by the algorithm in Figure 5.2 are presented in Table 5.2. The table shows the optimal way to dispatch the DGs based on the availability of the units to match the load demand in Figure 3.1 by the PSO algorithm for individual time intervals. With a closer look, it can be seen that the output of the algorithm is accurate for all time intervals. The dispatch power matches the load demand, which is acceptable for the selected system. Therefore, the system is able to find an optimal solution for the scenario presented with a minimal cost.

Table 5.3: Operation Cost breakdown for each time interval (PSO)

Time (h)	Cost ($)	Time (h)	Cost ($)
1	55.202	***13***	132.34
2	55.202	***14***	120.29
3	27.507	***15***	107.25
4	73.486	***16***	99.625
5	84.457	***17***	91.315
6	122.69	***18***	142.88
7	126.45	***19***	233.20
8	117.15	***20***	109.70
9	155.40	***21***	95.782
10	137.59	***22***	44.202
11	108.02	***23***	65.214
12	145.73	***24***	34.027

Table 5.3 shows the breakdown of the operating cost of the MG per hour for the results shown in Figure 5.2 and Table 5.2. It can be observed from the table that the operation cost during off-peak hours (when demand is lower than generation) is noticeably lower than the operating during peak hours (5-9 & 17-21). This is due to fact that MG is able to the cost of operation when the generation is higher than load demand by selling power back to the main grid. Likewise, when generation is lower than demand, it has to pay extra by buying excess power from the main grid. This shows that the algorithm is capable of making decisions for when to buy/sell power to/from main grid and this is very beneficial for the overall system.

5.1.2 DE Based EMS (Grid Connected)

Performance Based on different Population Size

Before the optimal result can be analyzed from DE algorithm, the optimal population size has to determine by the test shown in Figure 5.3. The figure depicts the performance of DE algorithm with different population size (NP = 50, 100, 300, 500). To achieve accurate results for comparison the system was averaged over 100 iterations. As can be observed, the starting point for each graph is different; this is due to the fact that the system is using uniform random population initialization. Likewise, different population size has a major impact on the performance of the DE algorithm. Each population size produced a different convergence point for the algorithm or for this system different optimal operation cost. From this result, is was determined that the algorithm performed best for the highest population size of 500. The breakdown of the results is presented in Table 5.4, which it shows the convergence point in number of Runs and the optimal cost achieved.

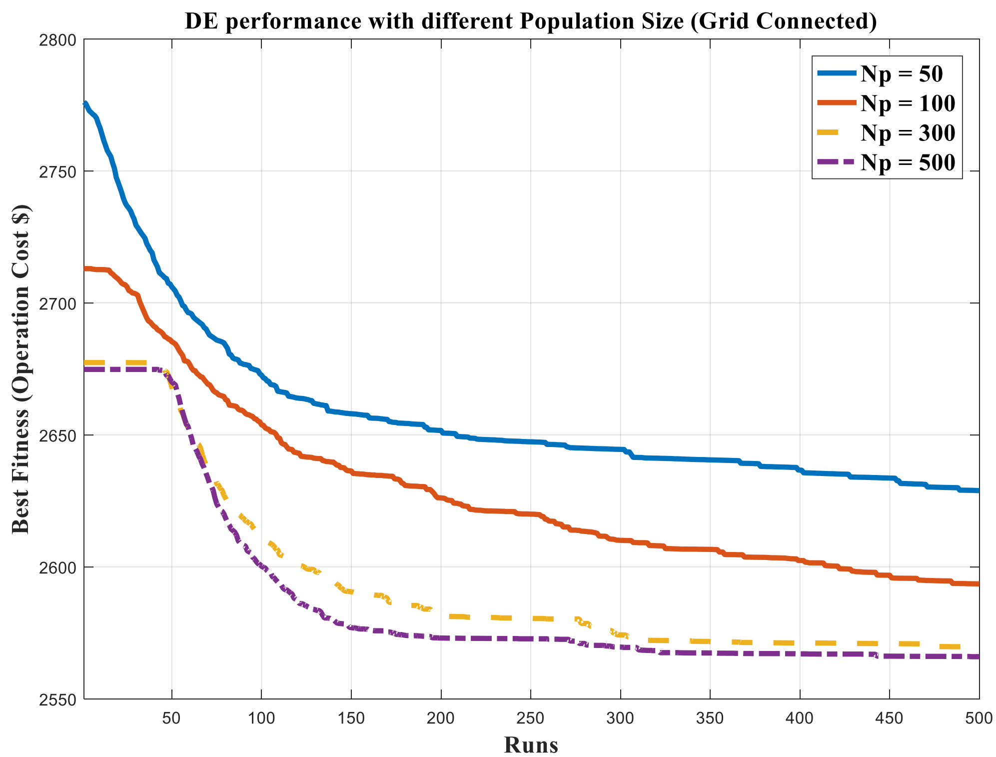

Figure 5.3: DE performance with Population Size for Grid Connected Mode

Table 1.4:Optimal Operation Cost with different Population Size (DE)

Population Size (NP)	Convergence Point (Runs)	Best Operation Cost ($/day)
50	No Convergence	2628.900
100	No Convergence	2593.510
300	475	2569.800
500	450	2566.100

Best Solution by DE (Grid Connected)

Figure 5.4, depicts the best output achieved from the DE EMS for grid-connected mode. The algorithm was able to find the optimal solution to dispatch DGs to satisfy the given load demand for the time period. It can be observed that the system is able to buy and sell power from the grid during off-peak and peak hours. Similarly, to PSO output in Figure 5.2 the DE output has all three generators operating at full capacity at almost all time because for the system is more cost effective if the system buys and sells power rather than ramping the generators up and down to match the demand at each time interval. The total cost of operation during the 24-hour period achieved is $2540.14.

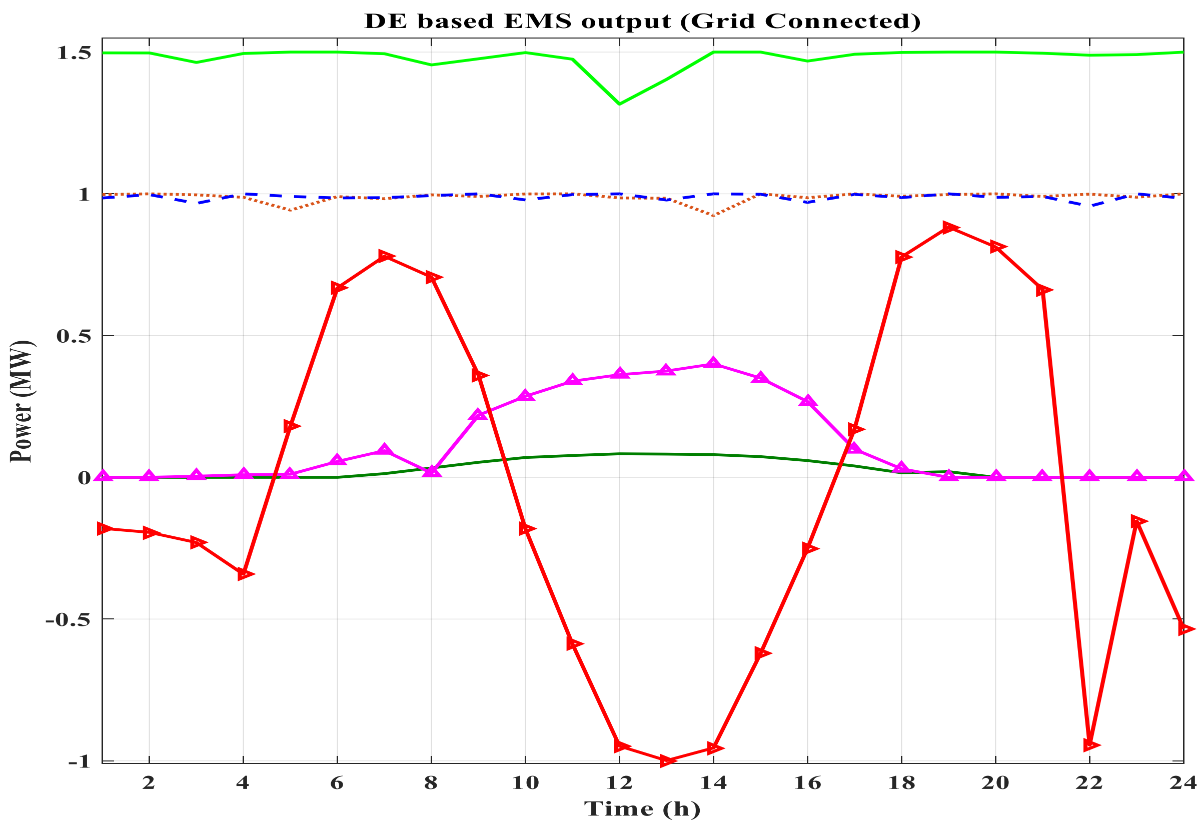

Figure 5.4: EMS output for DE Grid connected mode (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Table 5.5: EMS output for DE Grid connected mode breakdown (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Time	Gen 1	Gen2	Gen 3	Solar	Wind	Grid	Sum	Demand
1	1.500	1.000	1.000	0.000	0.000	-0.200	**3.300**	**3.300**
2	1.500	0.896	0.996	0.000	0.000	-0.092	**3.300**	**3.300**
3	1.500	1.000	1.000	0.000	0.004	-0.304	**3.200**	**3.200**
4	1.425	1.000	1.000	0.000	0.009	-0.284	**3.150**	**3.150**
5	1.488	0.999	1.000	0.000	0.011	0.125	**3.625**	**3.625**
6	1.483	1.000	1.000	0.000	0.056	0.660	**4.200**	**4.200**
7	1.500	0.998	0.995	0.013	0.094	0.749	**4.350**	**4.350**
8	1.494	1.000	0.998	0.033	0.015	0.658	**4.200**	**4.200**
9	1.500	1.000	0.999	0.053	0.219	0.328	**4.100**	**4.100**
10	1.500	0.994	0.995	0.070	0.286	-0.195	**3.650**	**3.650**
11	1.475	1.000	1.000	0.077	0.339	-0.591	**3.300**	**3.300**
12	1.413	1.000	0.879	0.083	0.362	-0.938	**2.800**	**2.800**
13	1.483	0.878	0.999	0.082	0.375	-0.993	**2.824**	**2.824**
14	1.406	1.000	0.958	0.080	0.400	-0.895	**2.949**	**2.949**
15	1.500	0.989	1.000	0.073	0.350	-0.612	**3.300**	**3.300**
16	1.490	1.000	0.997	0.059	0.267	-0.313	**3.500**	**3.500**
17	1.393	1.000	0.999	0.040	0.099	0.267	**3.800**	**3.800**
18	1.500	1.000	1.000	0.016	0.030	0.754	**4.300**	**4.300**
19	1.500	1.000	1.000	0.020	0.000	0.880	**4.400**	**4.400**
20	1.500	1.000	0.991	0.000	0.000	0.808	**4.300**	**4.300**
21	1.500	1.000	0.995	0.000	0.000	0.644	**4.140**	**4.140**
22	1.400	0.	0.969	0.000	0.000	-0.900	**2.500**	**2.500**
23	1.470	1.000	1.000	0.000	0.000	-0.145	**3.325**	**3.325**
24	1.500	1.000	1.000	0.000	0.000	-0.550	**2.950**	**2.950**
Total	**35.52448**	**23.75624**	**23.77731**	**0.699**	**2.9161**		**84.54**	**84.54**

The results obtained by the algorithm in Figure 5.4 are presented in Table 5.5. The table shows the optimal way to dispatch the DGs based on the availability of the unit to match the load demand in Figure 3.1 by the DE algorithm for individual time intervals. With a closer look, it can be seen that the output of the algorithm is accurate for all time intervals. The dispatch power matches the load demand, which is acceptable for the selected system. Therefore, the system is able to find an optimal solution for the scenario presented with a minimal cost.

Table 5.6: Operation Cost breakdown for each time interval (DE)

Time (h)	Cost ($)	Time (h)	Cost ($)
1	57.202	***13***	132.62
2	59.831	***14***	124.80
3	33.500	***15***	107.72
4	76.728	***16***	100.14
5	90.486	***17***	100.55
6	124.15	***18***	142.88
7	127.03	***19***	233.20
8	119.74	***20***	110.45
9	157.40	***21***	96.187
10	138.03	***22***	50.050
11	109.08	***23***	66.483
12	148.40	***24***	34.027

Table 5.6 shows the breakdown of the operating cost of the MG per hour. It can be observed from the table that the operation cost during off-peak hours (when demand is lower than generation) is noticeably lower than the operating during peak hours (5-9 & 17-21). This is due to fact that MG is able to save money when the generation is higher than load demand by selling power back to the main grid. Likewise, when generation is lower than demand, it has to pay extra by buying excess power from the main grid. This shows that the algorithm is capable of making decisions for when to buy/sell power to/from main grid and this is very beneficial for the overall system.

5.1.3 Comparison between PSO & DE *(Grid connected mode)*

Performance

Figure 5.5, shows the comparison between the best performance system of PSO and DE. As it can be observed both systems start from the same initialization point even though both systems used uniform random initialization technique. But the DE has a slow start as where PSO drop moves towards the convergence point faster. This shows that PSO is able explore the search space faster and towards the optimal solution faster than the DE algorithm. Therefore, it is clear from the result shown below, that the PSO algorithm was able to converge faster and find the most optimal solution for the application.

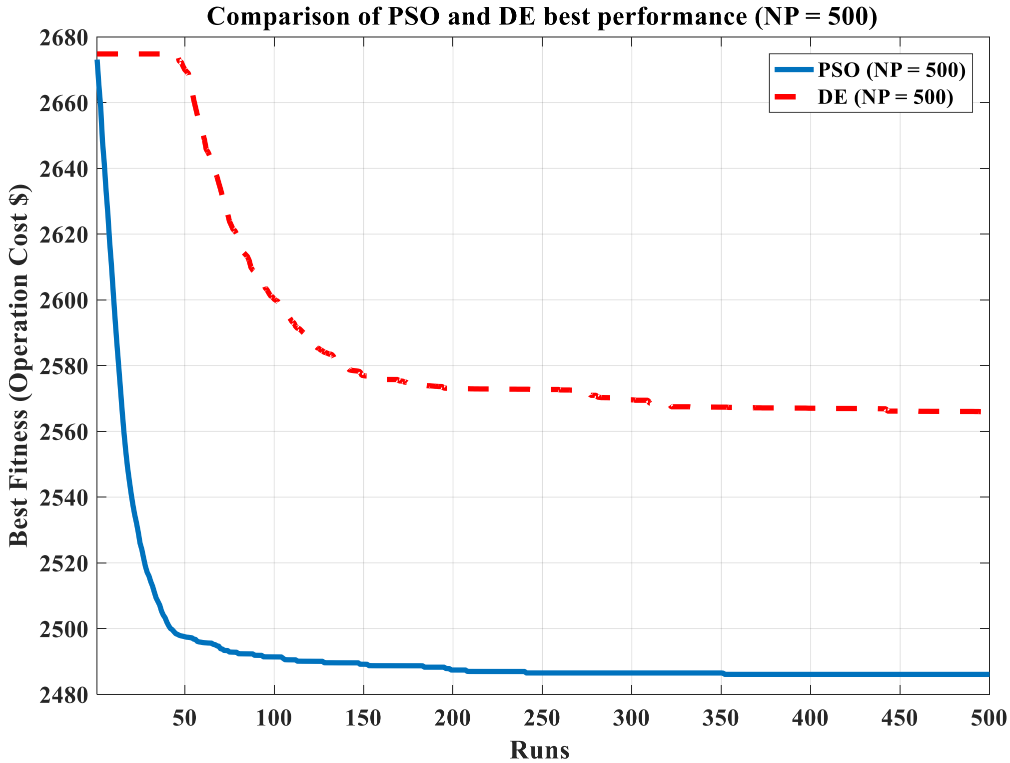

Figure 5.5: Comparison of PSO and DE best performance

Table 5.7: Optimal Cost for PSO and DE (NP = 500)

Algorithm	Convergence Point (Runs)	Best Operation Cost ($/day)
PSO	352	2486.103
DE	450	2540.100

Operational Cost ($/hr)

Figure 5.6 depicts the comparsion between the most optimal operation cost ($/hr) achieved by PSO and DE. As can be observed for most part of the 24 hour period the PSO and DE output the same or very similar results for the operational cost with an approximate offset of -5 $/hr. But for a some time interval the PSO algorithm is able to produce a lot lower operational cost than the DE algorithm. For example at time (T =17) the PSO produced a hourly operational cost of $91.315/hr and the DE produced $100.553/hr, is a difference of approximatly 10$. Then the second major difference is hourly operational cost is at (T = 22), where the difference between the PSO and DE algroithm of approximatly 6 $.

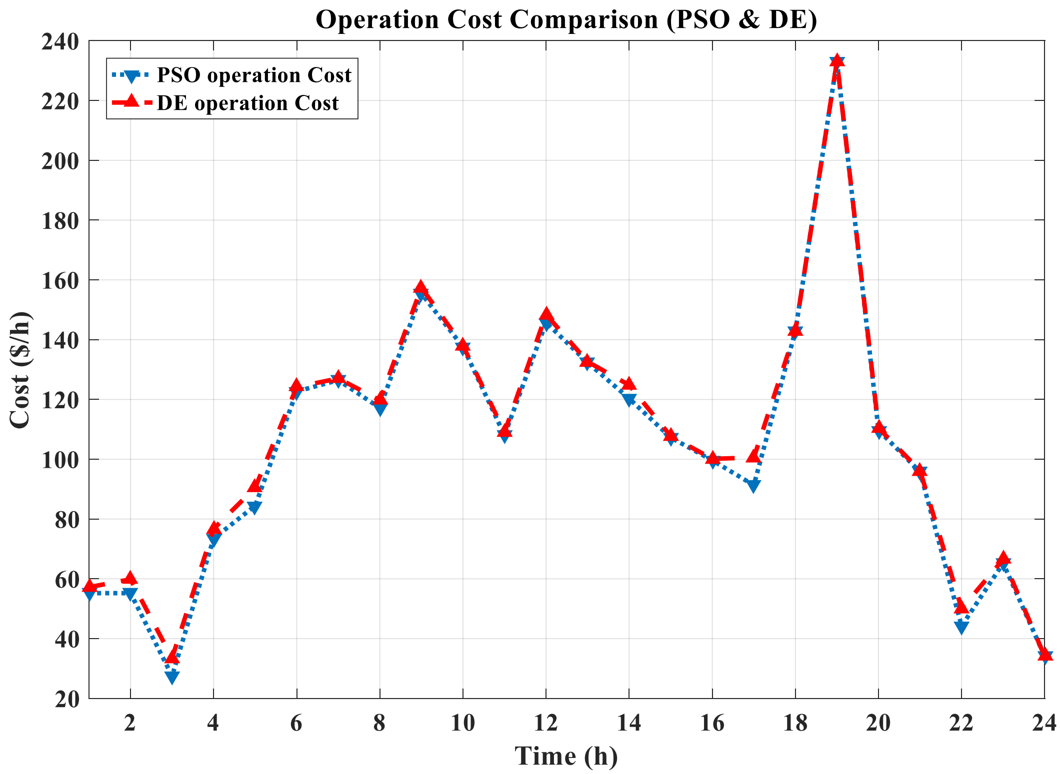

Figure 5.6: Operation Cost Comparison for Grid connected system (PSO & DE)

Therefore, based on this result PSO algroithm performed better than DE by producing lower full day operational cost of $2484.10 compare to $2540.65 The result shown in Figure 5.6 above it is further broken down in Table 5.8.

Table 5.8: Operation Cost Comparison for Grid connected system (PSO Vs DE)

Time (h)	Cost ($) (PSO)	Cost ($) (DE)	Time (h)	Cost ($) (PSO)	Cost ($) (DE)
1	55.20229	57.202	***13***	132.3468	132.62
2	55.20229	59.831	***14***	120.2908	124.80
3	27.50076	33.500	***15***	107.2536	107.72
4	73.48633	76.728	***16***	99.62671	100.14
5	84.45707	90.486	***17***	91.31591	100.55
6	122.6948	124.15	***18***	142.889	142.88
7	126.4564	127.03	***19***	233.2026	233.20
8	117.1529	119.74	***20***	109.7023	110.45
9	155.404	157.40	***21***	95.7823	96.187
10	137.5986	138.03	***22***	44.20229	50.050
11	108.0263	109.08	***23***	65.21479	66.483
12	145.7343	148.40	***24***	34.02729	34.027

Utilization of Grid

The main objective of the Grid connected EMS is to opimize the utilization of the Grid to help minimize the operational cost. Therefore, the the comparison between the grid utlizational of both algorithm is made in the Figure 5.7. As it can be observed in the figure below that PSO and DE grid power output fairly similar for alomost all time intervals, excluding few time slots. At time equal 3 hours, the PSO grid power is optiomzed to be –0.31 MW and for DE grid power is optimized to be -0.22 MW. At time equal 22 hours, the PSO grid power is optiomzed to be -1.000 MW and for DE grid power is optimized to be -0.9 MW. This shows that at time interval 22 the PSO EMS id selling power to main grid and the DE EMS is buying power from the main grid, therefore this descision reduced the operating cost at this time interval from $55.42 to $44.20 which a difference of $11.21.

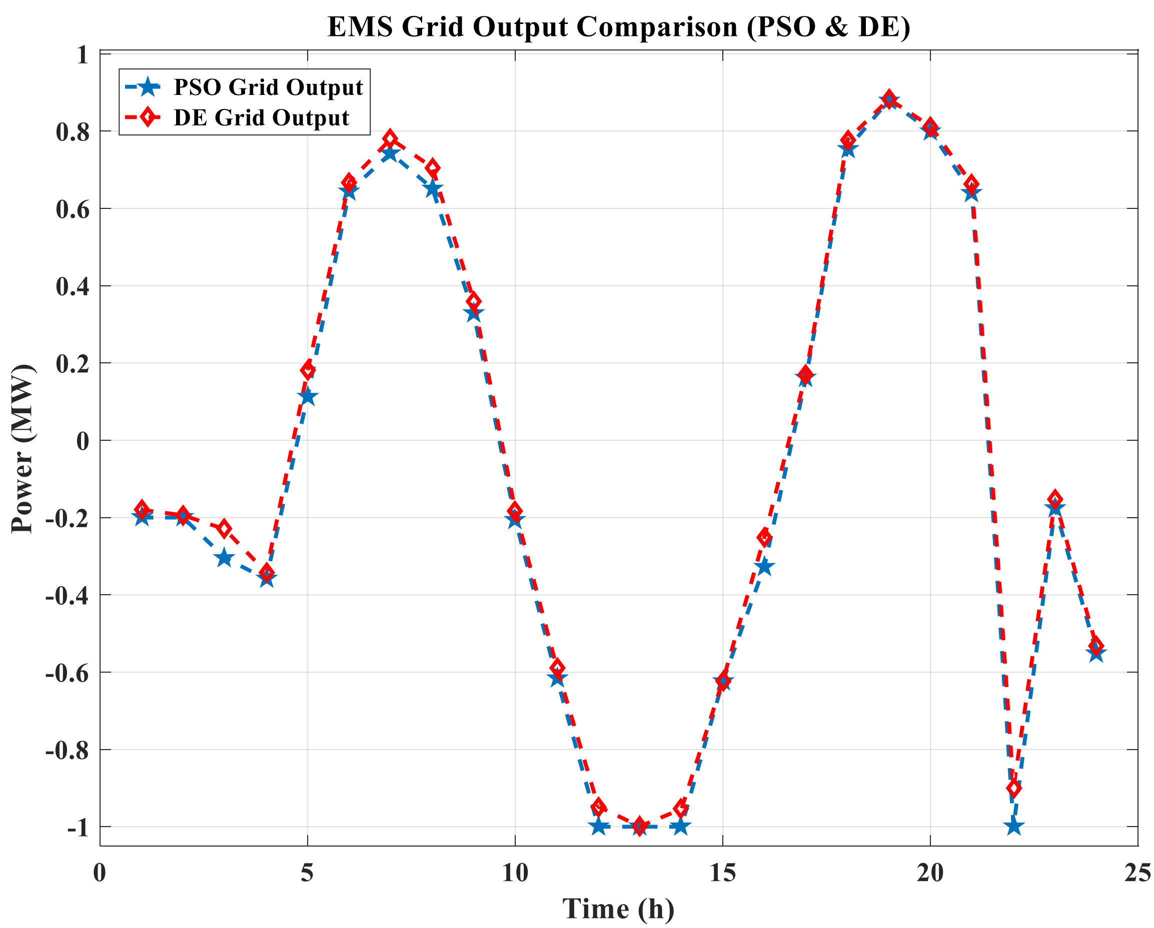

Figure 5.75: EMS Grid output Comparison (PSO& DE)

Table 5.8: Grid output Comparison PSO Vs DE

Time (h)	**Grid Power (PSO)**	**Grid Power (DE)**	**Time (h)**	**Grid Power (PSO)**	**Grid Power (DE)**
1	-0.200	-0.179	**13**	-1.000	-0.999
2	-0.200	-0.194	**14**	-1.000	-0.954
3	-0.304	-0.229	**15**	-0.623	-0.621
4	-0.359	-0.341	**16**	-0.326	-0.250
5	0.114	0.180	**17**	0.161	0.170
6	0.644	0.668	**18**	0.754	0.777
7	0.743	0.779	**19**	0.880	0.882
8	0.651	0.706	**20**	0.800	0.812
9	0.328	0.360	**21**	0.640	0.662
10	-0.206	-0.182	**22**	-1.000	-0.900
11	-0.616	-0.588	**23**	-0.175	-0.154
12	-1.000	-0.947	**24**	-0.550	-0.534

5.2 Islanded Mode

Similar to the pervious case study, the optimized EMS is implemented to solve the energy consumption problem for a MG for 24-hour operation period. Except, in this case, the MG is disconnected from the main grid and is running in islanded condition. The load demand used for this case is presented in Figure 3.5. In this study, the system does not have the option to buy/sell power, therefore the algorithm will have to decide the optimal way to dispatch the three available generators. Since it is assumed that the PV and Wind generators will run on full available power for each time interval.

7.2.1 PSO

Performance based on different Population Size

Figure 5.8, depicts the performance of PSO algorithm with different population size (NP = 50, 100, 300, 500) in islanded mode. Similar to grid connected system to achieve accurate results for comparison, the system was averaged over 100 iterations. As can be observed, different population size has a small impact on the performance of the PSO algorithm in islanded mode of operation. Each population size made the system convergence at a different optimal solution. From this result, it was determined the algorithm performed best for the highest population size of 500. The high population size made the system converge faster compared to the other population size and it also produced the most optimal solution for the system. The breakdown of the result is presented in Table 5.9, which shows the convergence point in number of Runs and the optimal cost achieved for system.

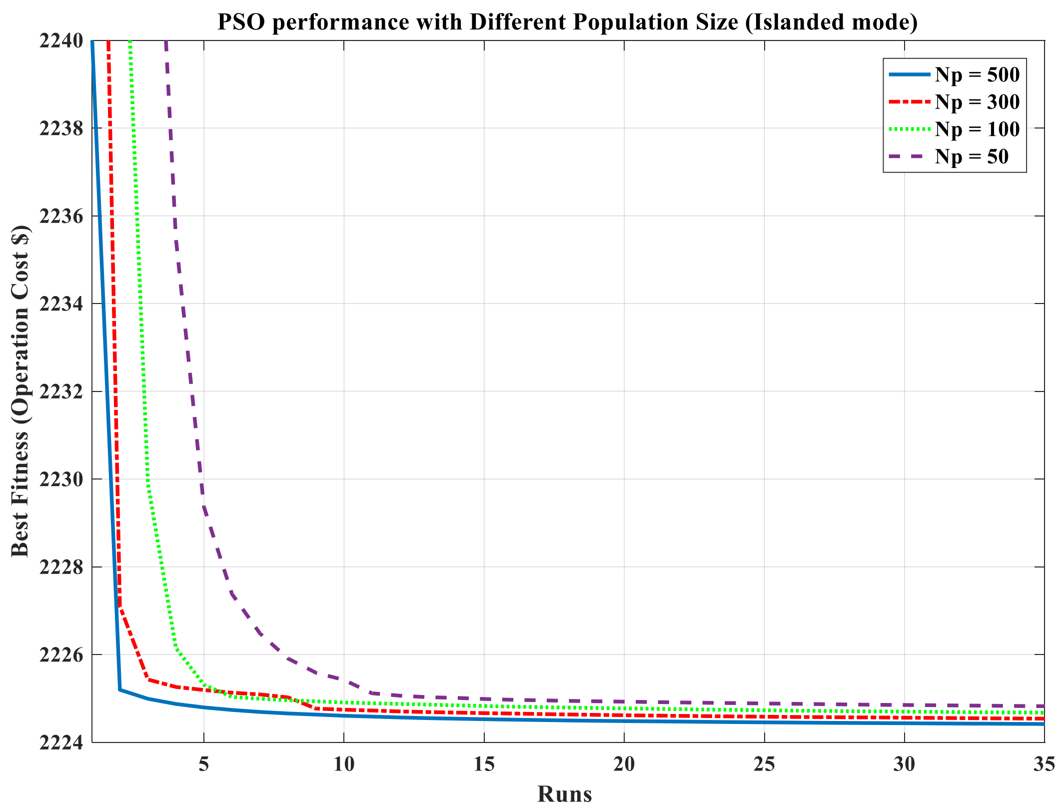

Figure 6: PSO performance with Population Size (Islanded mode)

Table 2: PSO performance with Population Size (Islanded mode)

Population Size (NP)	Convergence Point (Runs)	Best Operation Cost ($/day)
50	350	2225.652
100	329	2224.563
300	195	2224.336
500	192	2224.226

Best Solution (PSO Islanded Mode)

Figure 5.9 depicts the best output achieved from the PSO based EMS for islanded mode of operation. The algorithm was able to find the optimal solution to dispatch every generator to satisfy the given load demand for each time interval. As can be observed, power from the three generators CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3) are being rapidly ramped up/ down for each time interval to help satisfy the load demand. This ramping in the generator powers has to be controlled by adding a ramp rate constraint in the algorithm, but for the present study the ramp rate has been ignored due to the use of a one-hour time step. The total operation cost achieved during the 24-hour period for case is $2224.226.

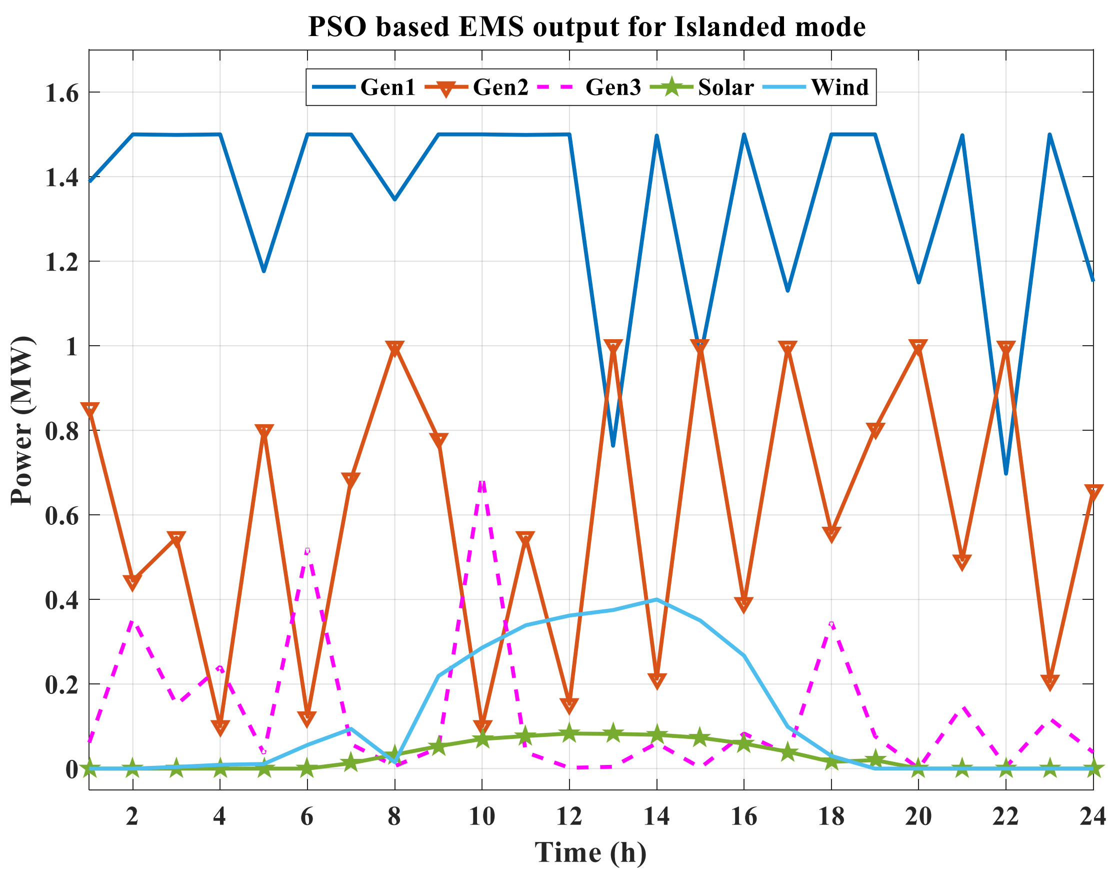

Figure 5.9: PSO based EMS output for Islanded mode (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Table 5.10: EMS output for PSO Islanded mode breakdown (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Time	Gen 1	Gen2	Gen 3	Solar	Wind	Sum	Demand
1	1.387	0.851	0.061	0.000	0.000	**2.300**	**2.300**
2	1.500	0.444	0.355	0.000	0.000	**2.300**	**2.300**
3	1.498	0.546	0.151	0.000	0.004	**2.200**	**2.200**
4	1.500	0.100	0.240	0.000	0.009	**1.850**	**1.850**
5	1.176	0.801	0.035	0.000	0.011	**2.025**	**2.025**
6	1.500	0.122	0.521	0.000	0.056	**2.200**	**2.200**
7	1.499	0.685	0.057	0.013	0.094	**2.350**	**2.350**
8	1.345	0.999	0.005	0.033	0.015	**2.400**	**2.400**
9	1.500	0.779	0.048	0.053	0.219	**2.600**	**2.600**
10	1.500	0.100	0.694	0.070	0.286	**2.650**	**2.650**
11	1.498	0.546	0.038	0.077	0.339	**2.500**	**2.500**
12	1.500	0.153	0.001	0.083	0.362	**2.100**	**2.100**
13	0.763	1.000	0.004	0.082	0.375	**2.225**	**2.225**
14	1.497	0.212	0.060	0.080	0.400	**2.250**	**2.250**
15	0.974	1.000	0.002	0.073	0.350	**2.400**	**2.400**
16	1.500	0.391	0.082	0.059	0.267	**2.300**	**2.300**
17	1.130	0.997	0.033	0.040	0.099	**2.300**	**2.300**
18	1.500	0.557	0.346	0.016	0.030	**2.450**	**2.450**
19	1.500	0.803	7.66E-02	0.020	0.000	**2.400**	**2.400**
20	1.149	1.000	0.002	0.000	0.000	**2.150**	**2.150**
21	1.497	0.493	0.148	0.000	0.000	**2.140**	**2.140**
22	0.697	0.998	0.004	0.000	0.000	**1.700**	**1.700**
23	1.499	0.206	0.118	0.000	0.000	**1.825**	**1.825**
24	1.152	0.659	0.038	0.000	0.000	**1.850**	**1.850**
Total	**32.26983**	**14.4514**	**3.128672**	**0.699**	**2.9161**	**54.74**	**53.477**

The results obtained by the algorithm in Figure 5.9 are presented in Table 5.10. The table shows the optimal way to dispatch the DGs based on the availability of the unit to match the load demand in Figure 3.1 by the PSO algorithm for individual time intervals. With a closer look, it can be seen that the output of the algorithm is accurate for all time intervals. The dispatch power matches the load demand, which is acceptable for the selected system. Therefore, the system is able to find an optimal solution for the scenario presented with a minimal cost.

Table 5.11: Operation Cost breakdown for each time interval (PSO islanded mode)

Time (h)	Cost ($) (PSO)	Time (h)	Cost ($) (PSO)
1	63.5384	***13***	188.7163
2	63.53771	***14***	175.3562
3	40.33024	***15***	163.2768
4	88.60498	***16***	133.8951
5	74.09269	***17***	113.3472
6	66.25696	***18***	76.90222
7	61.43464	***19***	76.95668
8	60.08828	***20***	74.46201
9	126.5115	***21***	39.69226
10	146.1939	***22***	39.69276
11	134.3949	***23***	87.16381
12	63.5384	***24***	72.32373

Table 5.11, shows the breakdown of the operating cost of the MG in islanded mode for each time interval. For this case study, the load demand did not have peak and off-peak hours because during islanded mode the system only provides power to the critical loads. From the data provided, it can be observed that from periods 10 to 17 hrs, the cost is noticeably greater than at other periods. This is due to the fact the load demand is near maximum critical load of 2.5 MW and all DGs, PV and Wind are in operation at the same time near their peak capacities.

5.2.2 DE

Population Size

Figure 5.10, depicts the performance of DE algorithm with different population size (NP = 50, 100, 300, 500) in islanded mode. To achieve accurate results for comparison the system was averaged over 100 iterations. As it can be observed different population size has a small impact on the performance of the DE algorithm. Each population size made the system convergence at a different optimal operation cost shown in Table 19. From this result it was determined the algorithm performed best for the highest population size of 500. The high population size helped the algorithm converge faster and output the most optimal solution for the system. The breakdown of the results is presented in Table 5.12, which shows the convergence point in number of Runs and the optimal cost achieved.

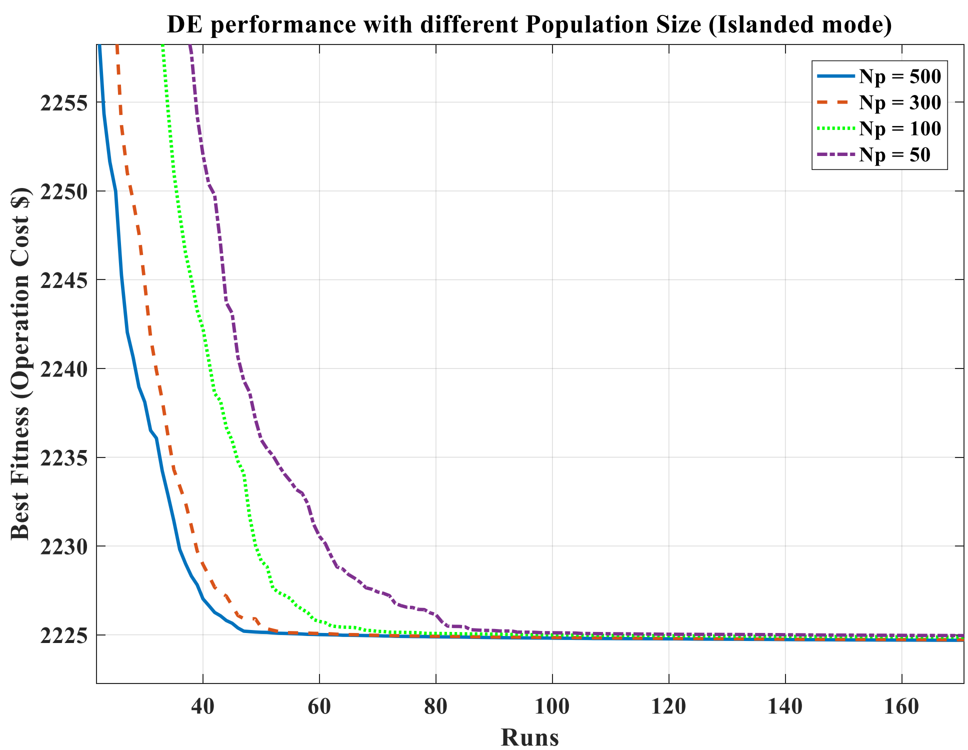

Figure 5.10: DE performance with Population Size (Islanded Mode)

Table 5.12: DE performance with Population Size for Islanded mode

Population Size (NP)	Convergence Point (Runs)	Best Operation Cost ($/day)
50	315	2225.101
100	321	2224.987
300	322	2224.652
500	258	2224.593

Best Solution (DE Islanded Mode)

Figure 5.11 depicts the best output achieved from the DE based EMS for islanded mode of operation. The algorithm was able to find the optimal solution to dispatch every generator to satisfy the given load demand for each time interval. As it can be observed, power from the three generators CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3) are being rapidly ramped up/ down for each time interval to help satisfy the load demand. This ramping in the generator powers has to be controlled by adding a ramp rate constraint in the algorithm, but for the present study the ramp rate has been ignored due to the use of a one-hour time step. The total operation cost achieved during the 24-hour period for case is $2224.593.

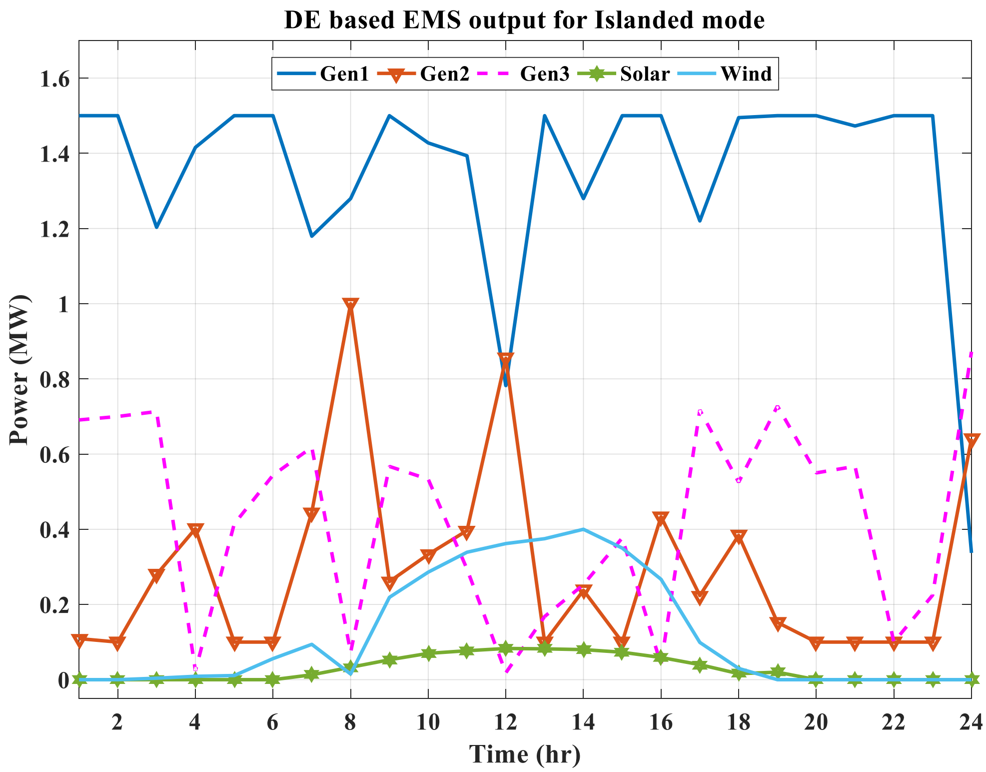

Figure 5.11: DE based EMS output for Islanded mode (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Table 5.13: EMS output for DE Islanded mode breakdown (Case study 1, CHP (Gen1), Diesel generator (Gen2) and Natural gas generator (Gen3))

Time	Gen 1	Gen2	Gen 3	Solar	Wind	Sum	Demand
1	1.500	0.109	0.690	0.000	0.000	**2.300**	**2.300**
2	1.500	0.100	0.700	0.000	0.000	**2.300**	**2.300**
3	1.203	0.279	0.713	0.000	0.004	**2.200**	**2.200**
4	1.415	0.401	0.023	0.000	0.009	**1.850**	**1.850**
5	1.500	0.100	0.414	0.000	0.011	**2.025**	**2.025**
6	1.500	0.100	0.544	0.000	0.056	**2.200**	**2.200**
7	1.179	0.445	0.618	0.013	0.094	**2.350**	**2.350**
8	1.279	1.000	0.072	0.033	0.015	**2.400**	**2.400**
9	1.500	0.260	0.567	0.053	0.219	**2.600**	**2.600**
10	1.427	0.333	0.533	0.070	0.286	**2.650**	**2.650**
11	1.393	0.396	0.294	0.077	0.339	**2.500**	**2.500**
12	0.782	0.854	0.018	0.083	0.362	**2.100**	**2.100**
13	1.500	0.100	0.168	0.082	0.375	**2.225**	**2.225**
14	1.279	0.237	0.252	0.080	0.400	**2.250**	**2.250**
15	1.500	0.100	0.377	0.073	0.350	**2.400**	**2.400**
16	1.500	0.433	0.040	0.059	0.267	**2.300**	**2.300**
17	1.220	0.223	0.717	0.040	0.099	**2.300**	**2.300**
18	1.494	0.383	0.525	0.016	0.030	**2.450**	**2.450**
19	1.500	0.152	7.28E-01	0.020	0.000	**2.400**	**2.400**
20	1.500	0.100	0.550	0.000	0.000	**2.150**	**2.150**
21	1.472	0.100	0.567	0.000	0.000	**2.140**	**2.140**
22	1.500	0.100	0.100	0.000	0.000	**1.700**	**1.700**
23	1.500	0.100	0.225	0.000	0.000	**1.825**	**1.825**
24	0.337	0.640	0.872	0.000	0.000	**1.850**	**1.850**
Total	**32.48491**	**7.053462**	**10.31153**	**0.699**	**2.9161**	**54.74**	**54.74**

The results obtained by the algorithm in Figure 5.11 are presented in Table 5.13. The table shows the optimal way to dispatch the DGs based on the availability of the unit to match the load demand in Figure 3.1 by the DE algorithm for individual time intervals. With a closer look, it can be seen that the output of the algorithm is accurate for all time intervals. The dispatch power matches the load demand, which is acceptable for the selected system. Therefore, the system is able to find an optimal solution for the scenario presented with a minimal cost.

Table 5.14: Operation Cost breakdown for each time interval (DE islanded mode)

Time (h)	Cost ($) (DE)	Time (h)	Cost ($) (DE)
1	63.55372	***13***	175.3708
2	63.54986	***14***	163.2964
3	40.34741	***15***	133.9153
4	88.62072	***16***	113.3669
5	74.10577	***17***	76.91885
6	66.27602	***18***	76.96894
7	61.44523	***19***	74.47484
8	60.10193	***20***	39.71133
9	126.5223	***21***	39.70307
10	146.2068	***22***	87.18027
11	134.4097	***23***	72.33552
12	188.7384	***24***	57.47315

Table 5.14 shows the breakdown of the operating cost of the MG in islanded mode for each time interval. For this case study, the load demand did not have peak and off-peak hours because during islanded mode the system only provides power to the critical loads. From the data provided, it can be observed that from periods 10 to 17 hrs, the cost is noticeably greater than at other periods. This is due to the fact the load demand is near maximum critical load of 2.5 MW and all DGs, PV and Wind are in operation at the same time near their peak capacities.

5.2.3 Comparison (PSO & DE Islanded mode)

Performance of PSO and DE

Figure 5.12, shows the comparison between the best performance of both PSO and DE EMS for islanded mode of operation. As it can be observed both systems start from a different initialization point because of uniform random initialization technique used for initialization of population. Hence, the DE algorithm initialized far away from the solution and was not able to catch up with the PSO algorithm. Where as, the PSO initial start point was fairly close to the optimal solution and was able to drop move towards the convergence point faster. Therefore, it is clear from the result shown below, that the PSO algorithm was able to converge faster and find the most optimal solution (Operation Cost) for the application. The results are further explained in Table 5.15.

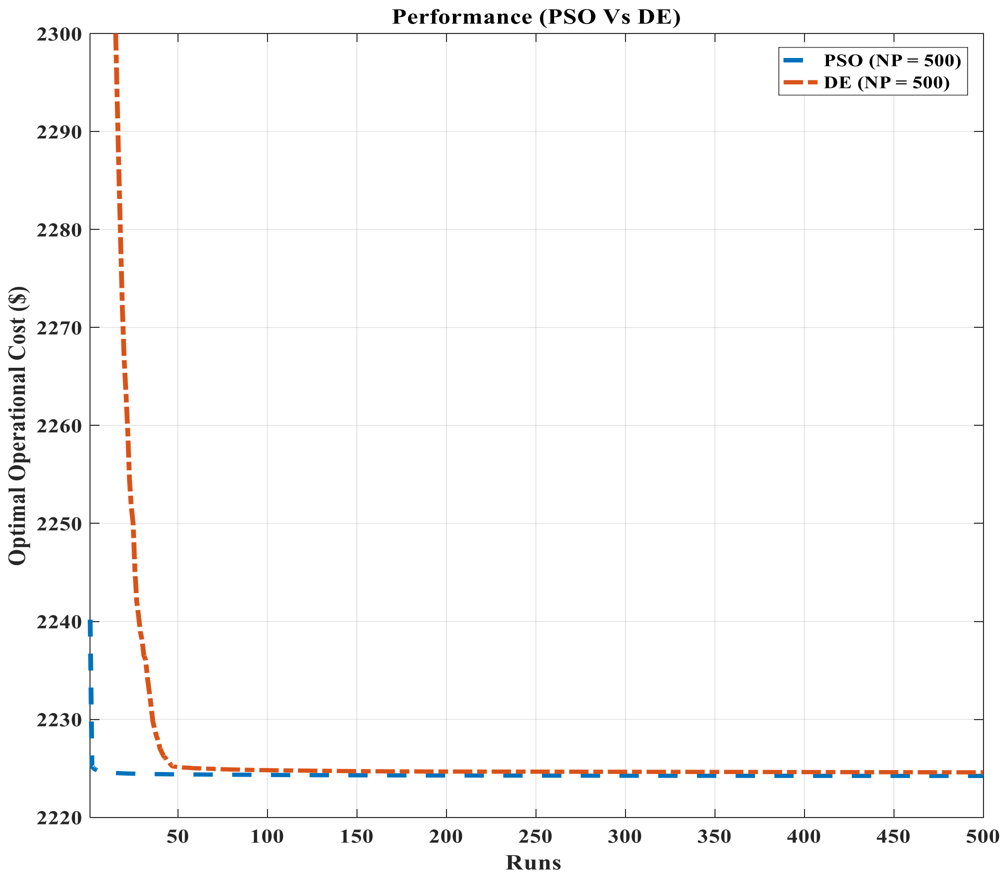

Figure 5.12: Comparison of PSO and DE best performance (Islanded Mode)

Table 5.15: Optimal Cost for PSO and DE for Islanded Mode (NP = 500)

Algorithm	Convergence Point (Runs)	Best Operation Cost ($/day)
PSO	192	2224.226
DE	258	2224.593

Operational Cost ($/hr)

Figure 5.13 depicts the comparsion between the most optimal operation cost ($/hr) achieved by PSO and DE for the solution shown in Figure 24 & 26. As it can be observed for the 24 hour period the PSO and DE output the same or very similar results for the operational cost with an approximate offset of -1 $/hr. This results shows that both algorithms are able to find a similar convergence point and are performing very well. To show the similarity in the results, the output is shown in a Table 5.16.

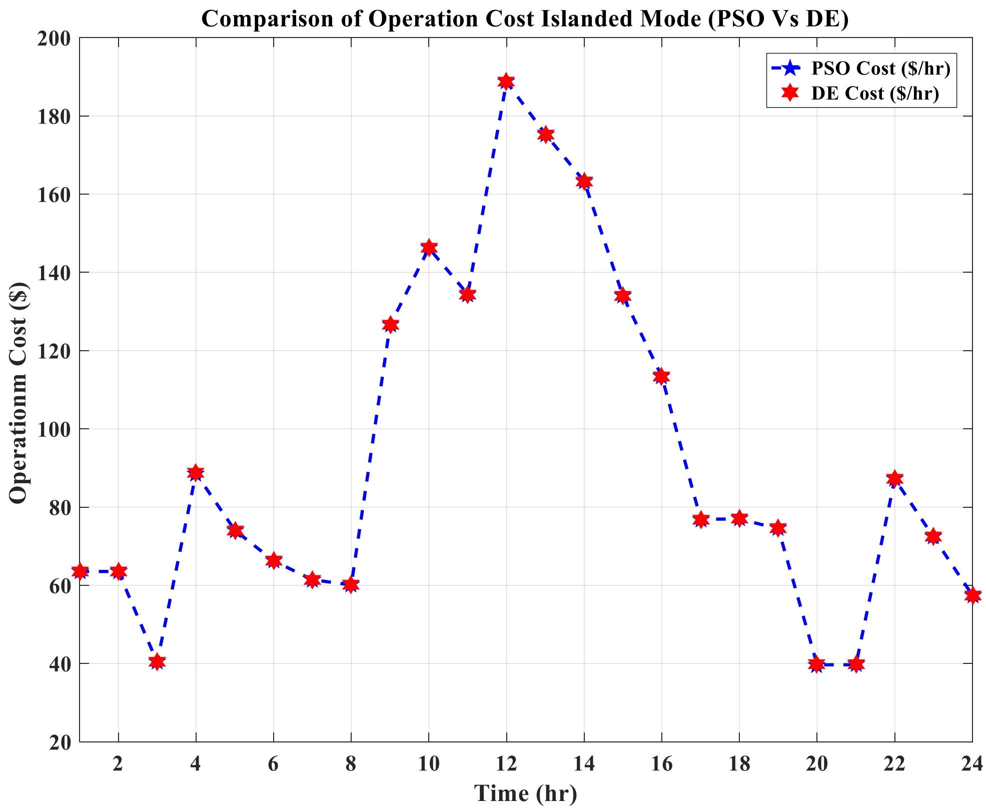

Figure 5.13: Operation Cost Comparison for Islanded mode (DE&PSO)

Table 5.16: Operation Cost Comparison for Islanded mode (DE&PSO)

Time (h)	Cost ($) (PSO)	Cost ($) (DE)	Time (h)	Cost ($) (PSO)	Cost ($) (DE)
1	63.5384	63.55372	***13***	175.3562	175.3708
2	63.53771	63.54986	***14***	163.2768	163.2964
3	40.33024	40.34741	***15***	133.8951	133.9153
4	88.60498	88.62072	***16***	113.3472	113.3669
5	74.09269	74.10577	***17***	76.90222	76.91885
6	66.25696	66.27602	***18***	76.95668	76.96894
7	61.43464	61.44523	***19***	74.46201	74.47484
8	60.08828	60.10193	***20***	39.69226	39.71133
9	126.5115	126.5223	***21***	39.69276	39.70307
10	146.1939	146.2068	***22***	87.16381	87.18027
11	134.3949	134.4097	***23***	72.32373	72.33552
12	188.7163	188.7384	***24***	57.45677	57.47315

The table shows the output comparsion between the optimal operation cost ($/hr) achieved by PSO and DE in the figure above. As mentioned the both algorithm are performing very similar to each other with a offset of ±1 *$/hr*. Therefore, for islanded mode both algorithms perfored equally well, but in comparison the PSO algorithm performed slightly better than DE algorithm.

Utilization of Generator

The main objective of the islaned mode EMS is to opimize the operation of three different generators to help minimize the operational cost and match the load deamd. Therefore, the the comparison between the utlizational of the generators of both algorithm is made in the following sections.

Generator 1: Combine Heat and Power (CHP)

As it can be observed in Figure 5.14, that PSO and DE generator 1 (CHP) power output are very different from each other at almost each time interval. The PSO have optimizded the CHP to operate by ramping up and down for alomost every time interval to to help satisfy the load demand at optimal operating cost. Where as, the DE algorithm has optimized the operation of the CHP system differently. The CHP has been optimized to operate close to full capacity for almost every time interval (between 1.5 to 12 MW) with minimal ramping, except at T= 12 and T= 24 where the genertor in being down to 0.78 MW amd 0.33 MW to help minimize the operational cost and match the load demand. Further breakdown the of results are presented in Table 24.

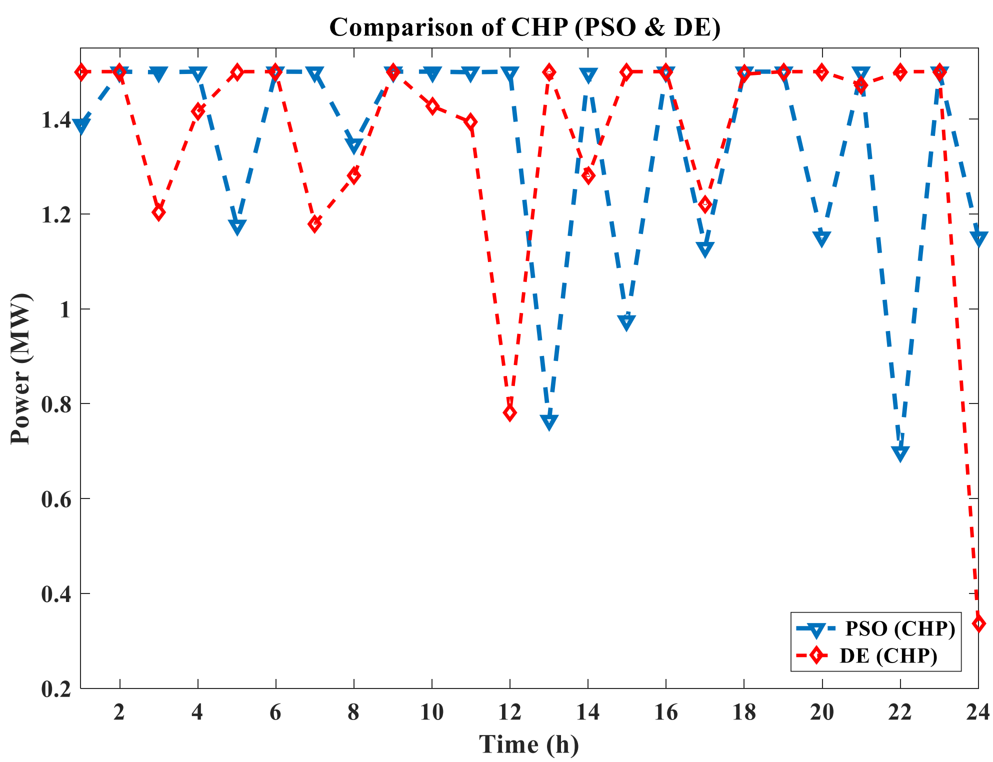

Figure 5.14: CHP Output Power Comparison for Islanded mode (PSO & DE)

Table 5.17: Generator 1 Cost Comparison for Islanded mode (DE&PSO)

Time (h)	Power (MW) (PSO)	Power (MW) (DE)	Time (h)	Power (MW) (PSO)	Power (MW) (DE)
1	1.387	1.500	**13**	0.763	1.500
2	1.500	1.500	**14**	1.497	1.279
3	1.498	1.203	**15**	0.974	1.500
4	1.500	1.415	**16**	1.500	1.500
5	1.176	1.500	**17**	1.130	1.220
6	1.500	1.500	**18**	1.500	1.494
7	1.499	1.179	**19**	1.500	1.500
8	1.345	1.279	**20**	1.149	1.500
9	1.500	1.500	**21**	1.497	1.472
10	1.500	1.427	**22**	0.697	1.500
11	1.498	1.393	**23**	1.499	1.500
12	1.500	0.782	**24**	1.152	0.337

Generator 2: Diesel generator

The Figure 5.15 depicts the output power of the Diesel generator during the Islanding condition for both PSO and DE. As it can be observed both PSO and DE optimized the DG very differently from each other at almost each time interval. The PSO have optimizded the diesel generator to operate at a very high ramping rate, the generator is being ramped up or down for every time interval. This is due the fact that system is being optimized with any ramping constraint, which are neglected because of one hour time intervals. However, the DE algorithm has optimized the operation of the diesel generator a little differently, where for the most part the genertor in being opreated at powers below 0.5MW. But at time 6 , 12 and 24 the power of the generator exceeds 0.5 MW of power (1MW, 0.9MW and 0.6 MW). Further breakdown the of results are presented in Table 5.18.

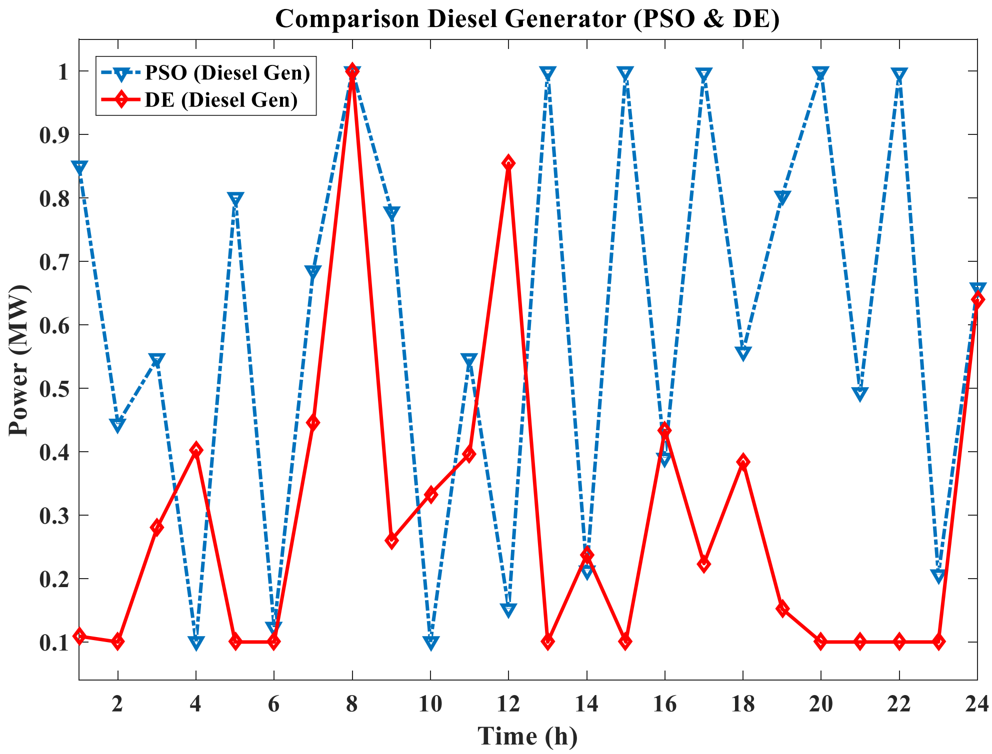

Figure 5.15: Diesel Generator Output Power Comparison for Islanded mode (PSO & DE)

Table 5.18: Generator 2 Cost Comparison for Islanded mode (DE&PSO)

Time (h)	Power (MW) (PSO)	Power (MW) (DE)	Time (h)	Power (MW) (PSO)	Power (MW) (DE)
1	0.851	0.109	***13***	1.000	0.100
2	0.444	0.100	***14***	0.212	0.237
3	0.546	0.279	***15***	1.000	0.100
4	0.100	0.401	***16***	0.391	0.433
5	0.801	0.100	***17***	0.997	0.223
6	0.122	0.100	***18***	0.557	0.383
7	0.685	0.445	***19***	0.803	0.152
8	0.999	1.000	***20***	1.000	0.100
9	0.779	0.260	***21***	0.493	0.100
10	0.100	0.333	***22***	0.998	0.100
11	0.546	0.396	***23***	0.206	0.100
12	0.153	0.854	***24***	0.659	0.640

Generator 3: Natural Gas generator

As it can be observed in the figure below that PSO and DE Natural Gas generator power output are different from each other at almost each time interval. The PSO have optimizded the Natural gas generator to operate at a very high ramping rate, the generator is being ramped up or down for every time interval. This is due the fact that system is being optimized with any ramping constraint, which are neglected because of one hour time intervals. But, the DE algorithm has optimized the generator very differently. DE algorithm used the Natural gas generator in a form of a back up power supply. It operated the generator at the minimum power level for mijority of the 24 hours time period, but at some time interval such as 6 and 10 the generator is ramped up to 0.5 MW and 0.7 MW to help match the load demand. Further breakdown the of results are presented in Table 5.19.

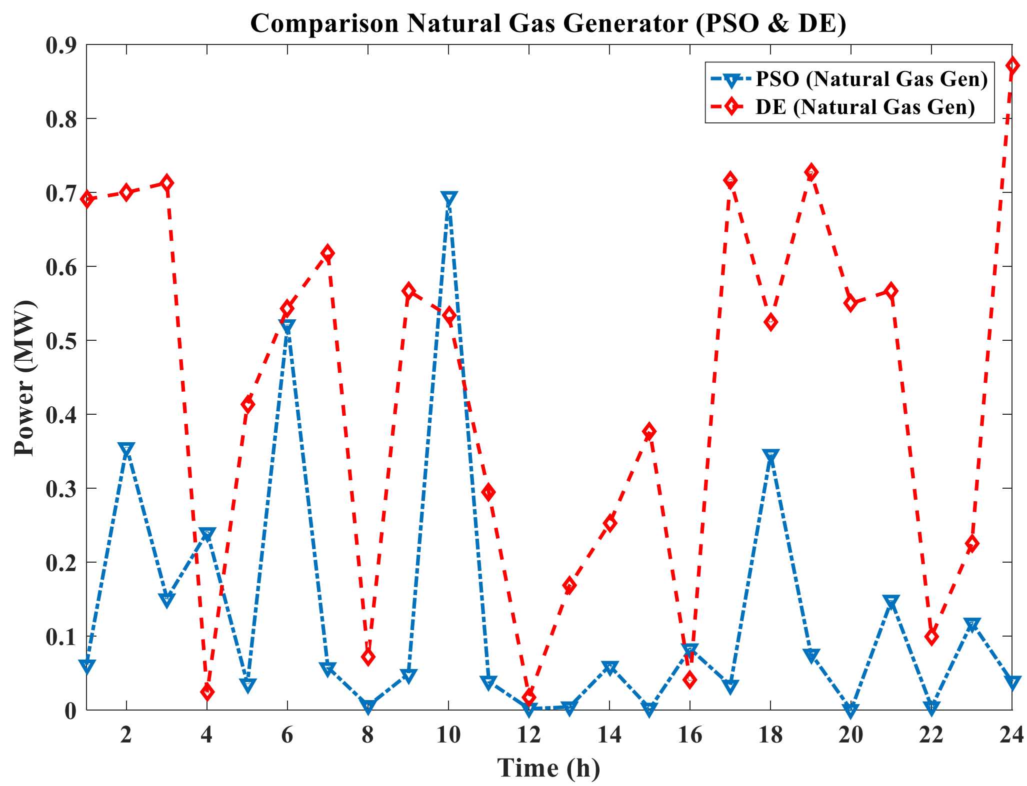

Figure 5.16: Natural Gas Generator Output Power Comparison for Islanded mode (PSO & DE)

Table 5.19: Generator 3 Cost Comparison for Islanded mode (DE&PSO)

Time (h)	Power (MW) (PSO)	Power (MW) (DE)	Time (h)	Power (MW) (PSO)	Power (MW) (DE)
1	0.061	0.690	***13***	0.004	0.168
2	0.355	0.700	***14***	0.060	0.252
3	0.151	0.713	***15***	0.002	0.377
4	0.240	0.023	***16***	0.082	0.040
5	0.035	0.414	***17***	0.033	0.717
6	0.521	0.544	***18***	0.346	0.525
7	0.057	0.618	***19***	0.076	0.727
8	0.005	0.072	***20***	0.001	0.550
9	0.048	0.567	***21***	0.148	0.567
10	0.694	0.533	***22***	0.004	0.100
11	0.038	0.294	***23***	0.118	0.225
12	0.001	0.018	***24***	0.038	0.872

6.0 Conclusion and Future work

6.1 Conclusion

The area of EMS in the last decade has generated tremendous research interest in its MG applications. An EMS is required to control the flow of power and match generation with the load within a MG during grid-connected and islanded modes of operation. An optimization algorithm is needed to minimise the cost of the energy drawn from the grid, generated within the grid and consumed by the loads. In this thesis, two optimization techniques - namely PSO and DE - are used to optimize an EMS for a generic MG for both grid-connected and islanded modes of operation to demonstrate the effectiveness of the optimization algorithms. The results show that PSO algorithm operated the MG in the most optimal way compared to DE, while minimizing the operational cost in either grid-connected and islanded modes of operation. In grid connected mode, the PSO based EMS was able to find the most optimal solution to dispatch all available DGs and buy/sell power to/from main grid while minimizing operation cost as shown in Table 13. Similarly, in Islanded mode, the PSO based EMS was able to utilize three independent generators by ramping up or down to satisfy the load demand, while minimizing operation cost for MG and shown illustrated in Table 22.

The major contributions of this thesis are as follows:

- Development of an EMS for a MG comprised of Combined Heat and Power (CHP) plant, Diesel generator, Natural gas-fired generator, Photovoltaic (PV) generator and Wind generator, for both the grid connected and islanded modes of operation in MATLAB (coding).
- Development of the objective function for the system using the variable cost function for each DG in the MG model. These cost functions are described in Chapter 4.
- Implementation of EMS using two different optimization algorithms: Particle Swarm Optimization (PSO) and Differential evolution (DE). Both belong to the stochastic, population-based algorithms.

The optimization of the system was done with two different algorithms, namely PSO and DE. The algorithms were investigated and the performance was tested under both modes of operations for the MG, i.e. grid connected and islanded mode. Results for grid connected mode show that the PSO algorithm is able to utilize the selling and buying power to and from the main grid better than the DE algorithm, to help reduce the total operation cost while satisfying the day ahead load demand. The optimal operation cost output by PSO was $2486.10 and optimal cost outputted by DE was $2564.14. The cost difference between the two algorithms is $78.03. Based on this result, it can be concluded that for grid connected mode, PSO-based EMS performed better than DE-based EMS.

Unlike the grid-connected mode results achieved for islanded mode show that PSO performed slightly better than the DE algorithm. PSO algorithm is able to utilize the three generators independently by ramping up or down to satisfy the load demand, while minimizing operation cost a touch better than the DE algorithm. As shown in Tables 5.17, 5.18 and 5.19, both algorithms optimized the three generators differently but achieved a very similar operation cost. The PSO was $2224.226 and optimal cost outputted by DE was $2224.593. The cost difference between the two algorithms is only $0.367. Based on this result, it can be concluded that for islanded mode, PS based EMS performed equally well as the DE system.

6.2 Future work

The following topics emanating from this research are considered for future work:

Efficient EMS design:

In this thesis the study was conducted for 24-hrs time period with one-hour intervals. Due to the large interval size, some constraints (such as, ramping of the generators and startup/shutdown cost of generators) are neglected. This was due to the lack of access to suitable computational resources. Therefore, for future work this can be extended to propose a MG EMS model with a smaller time interval (i.e. every 15 min). This will help to bring this study to be a more realistic implementation of an EMS, with that many more constraints being added to the model i.e.: ramping cost for all the generators to help control the rapid ramping of the generators in islanded mode of operation and to smooth out the operation.

Power Forecasting

The power variations in solar and wind turbine generation emerge when clouds cover the solar arrays and wind speeds change abruptly. The PV and wind power output is difficult to predict, due to the performance being reliant on cloud shadowing, solar irradiance, temperature, wind etc. Design of better Power forecasting algorithms for both Wind and Solar, for a better understanding of the uncertainty of power is required. This will help build a stronger algorithm with is adaptable to dynamic changes experienced in the real world.

Energy Storage System

Energy storage is normally used in the system to provide stability for the system. For instance, energy storage within a power system can help optimize generation, transmission, and distribution, from integration of renewable energy generation to demand response programs improving distribution losses and performance of the system. In recent years, the use of renewable sources such as wind power into the power system network has been increasing. Therefore, power systems have faced serious concerns over their operation in terms of reliability. Integrating energy storage system devices into the power system is one of the solutions being proposed to overcome this concern in power systems. The profit margins of wind farm owners could also be increased by using these storage devices in the future.

ESS present possibilities for the distribution system to have better performance in case of failure or outage in the system. In previous chapters, the necessity to have an ESS in today's MGs and the optimal allocation of the battery have not been studied. The optimal sizing and placement of the battery in the system have been defined as another challenge in this area. In the case of a failure in a distribution system, i.e. when the system is temporarily being disconnected from the main grid, considering the location of the failure the whole system may be shut down. The distribution system normally has a radial architecture. So, based on the location of the battery, the loss of load could be controlled. To obtain an economical ESS, a battery sizing strategy has to be developed focusing on decreasing the peak load in the power distribution system.

Publications

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2. Faizan Khan, Ali Sunbul, Mohammad. Y. Ali, Haytham AbdEl-Gawad, Shahryar Rahnamayan, Vijay. K. Sood, "Maximum Power Point Tracking in PV Farms Using DE and PSO Algorithms: A Comparative Study", 8-13 July 2018 – IEEE World Congress on Computational Intelligence (WCCI) 2018, Rio de Janeiro, Brazil.

3. Mohammad. Y. Ali, Faizan Khan, Vijay. K. Sood, "Energy Management System of a Microgrid using Particle Swarm Optimization and Wireless Communication System", IEEE EPEC 2018, Toronto, Canada. Oct 2018.

4. Vijay. K. Sood, Mohammad. Y. Ali, Faizan Khan "Energy Management System of a Microgrid using Particle Swarm Optimization (PSO) and communication system" Microgrid: Operation, Control, Monitoring & Protection edited by: Papia Ray, Monalisa Biswal, Elsevier Publishing, 2019

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Appendix (a)

PSO based EMS (Matlab Code)

```
%% parameters setting
 Answer=zeros(24,6);
 nvar=6; % number of variable

 % Load Demand
data1=[3.3
3.3
3.2
3.15
3.625
4.2
4.35
4.1991
4.1
3.65
3.3
2.799
2.824
2.949
3.3
3.5
3.8
4.3
4.4
4.3
4.14
2.5
3.325
2.95
];


lb=[0.2 0.1 0.1 0 0 -1
   0.2 0.1 0.1 0 0 -1
   0.2 0.1 0.1 0 0.004 -1
   0.2 0.1 0.1 0 0.009 -1
   0.2 0.1 0.1 0 0.011 -1
   0.2 0.1 0.1 0 0.056 -1
   0.2 0.1 0.1 0.013 0.094 -1
   0.2 0.1 0.1 0.033 0.0151 -1
   0.2 0.1 0.1 0.053 0.219 -1
   0.2 0.1 0.1 0.07 0.286 -1
   0.2 0.1 0.1 0.077 0.339 -1
   0.2 0.1 0.1 0.083 0.362 -1
   0.2 0.1 0.1 0.082 0.375 -1
   0.2 0.1 0.1 0.08 0.4 -1
   0.2 0.1 0.1 0.073 00.35 -1
   0.2 0.1 0.1 0.059 0.267 -1
   0.2 0.1 0.1 0.04 0.099 -1
   0.2 0.1 0.1 0.016 0.03 -1
   0.2 0.1 0.1 0.02 0 -1
```

```
   0.2 0.1 0.1  0 0 -1
   0.2 0.1 0.1 0 0 -1
   0.2 0.1 0.1 0 0 -1
   0.2 0.1 0.1 0 0 -1
   0.2 0.1 0.1 0 0 -1]; % lower bound

ub=[1.5 1 1 0 0 1
    1.5 1 1 0 0 1
    1.5 1 1 0 0.004 1
    1.5 1 1 0 0.009 1
    1.5 1 1 0 0.011 1
    1.5 1 1 0 0.056 1
    1.5 1 1 0.013 0.094 1
    1.5 1 1 0.033 0.0151 1
    1.5 1 1 0.053 0.219 1
    1.5 1 1 0.07 0.286 1
    1.5 1 1 0.077 0.339 1
    1.5 1 1 0.083 0.362 1
    1.5 1 1 0.082 0.375 1
    1.5 1 1 0.08 0.4 1
    1.5 1 1 0.073 0.35 1
    1.5 1 1 0.059 0.267 1
    1.5 1 1 0.04 0.099 1
    1.5 1 1 0.016 0.03 1
    1.5 1 1 0.02 0 1
    1.5 1 1 0 0 1
    1.5 1 1 0 0 1
    1.5 1 1 0 0 1
    1.5 1 1 0 0 1
    1.5 1 1 0 0 1];%upper bound


NP=500;            % number particle
T=500;              % max of iteration\
run = 100;

W=1;
C1=2.2;
C2=2.2;

alpha=0.01;

%%% initialization
tic
empty.pos=[];
empty.cost=[];
empty.velocity=[];

% load('result.mat');
particle=repmat(empty,NP,1);
% load('result_main2','gparticle')
% results;

best=zeros(T,run);
AVR=zeros(T,run);
```

```
for runs =1:run
for i=1:NP
%   particle(i).pos= lb+rand(24,nvar).*(ub-lb);
  particle(i).pos=(((ub)/NP)*i )+ rand(24,nvar).*((ub)/NP);
% particle(i).pos=gparticle.pos;
[particle(i).cost,particle(i).pos]=fitness_24_4(particle(i).pos,lb,ub,data1);
particle(i).velocity=0;
end

bparticle=particle;

[value,index]=min([particle.cost]);

gparticle=particle(index);

% main loop
for t=1:T
     for i=1:NP
            particle(i).velocity=W*particle(i).velocity...
                  +C1*rand(24,nvar).*(bparticle(i).pos-particle(i).pos)...
                  +C2*rand(24,nvar).*(gparticle.pos-particle(i).pos);

        particle(i).pos=particle(i).pos+particle(i).velocity;

        particle(i).pos=min(particle(i).pos,ub);
        particle(i).pos=max(particle(i).pos,lb);


        [particle(i).cost,particle(i).pos]=fitness_24_4(particle(i).pos,lb,ub,data1);

        if particle(i).cost<bparticle(i).cost
           bparticle(i)=particle(i);

           if bparticle(i).cost<gparticle.cost
              gparticle=bparticle(i);
           end
        end

     end


 W=W*(1-alpha);

 best(t, runs)=gparticle.cost;
 AVR(t, runs)=mean([particle.cost]);

  disp([ ' t = ' num2str(t)   ' BEST = '  num2str(best(t))]);
%   disp([ ' t = ' num2str(t)   ' AVR = '  num2str(best(t))]);



end
Answer_Full_system=gparticle.pos;
Answer_cost_Full_system(1, runs)=gparticle.cost;
```

```
for i = 1:24
      a(i)= sum(15.30 + 0.00024.*Answer_Full_system(i,1).^2+0.21.*Answer_Full_system(i,1)+ 14.88
+0.000435.*Answer_Full_system(i,2).^2+0.3.*Answer_Full_system(i,2)+ 9
+0.000315.*Answer_Full_system(i,3).^2+0.306.*Answer_Full_system(i,3));

      c(i)=  (545.016.*(Answer_Full_system(i,4)));
      d(i)= (155.616.* Answer_Full_system(i,5));

   if i~=0&& i < 8
      if Answer_Full_system(i,6)> 0
        F(i,1) = 133.5*(Answer_Full_system(i,6));
      elseif Answer_Full_system(i,6)< 0
        F(i,1) = 66.6*(Answer_Full_system(i,6));
      end
   end

   if i~=7 && i < 12
   if Answer_Full_system(i,6)> 0
      F(i) = 180*(Answer_Full_system(i,6));
   elseif Answer_Full_system(i,6)< 0
      F(i) = 90*(Answer_Full_system(i,6));
   end
   end

  if i~=11 && i < 18
   if Answer_Full_system(i,6)> 0
      F(i) = 132*(Answer_Full_system(i,6));
   elseif Answer_Full_system(i,6)< 0
      F(i) = 66*(Answer_Full_system(i,6));
   end
  end

  if i~=17 && i < 20
   if Answer_Full_system(i,6)> 0
      F(i) = 180*(Answer_Full_system(i,6));
   elseif Answer_Full_system(i,6)< 0
      F(i) = 90*(Answer_Full_system(i,6));
   end
  end

  if i~=19 && i <= 24
   if Answer_Full_system(i,6)> 0
      F(i) = 87*(Answer_Full_system(i,6));
   elseif Answer_Full_system(i,6)< 0
      F(i) = 43.5*(Answer_Full_system(i,6));
   end
  end

      total_new_Full_system(i,runs)= a(i) + c(i)+ d(i)+F(i,1);
end
end
% results
disp('==================================================')
% disp([' BEST    =  '  num2str(gparticle.pos)])
```

```
disp([' BEST fitness    = '   num2str(gparticle.cost)])
disp(['  Time           =  '  num2str(toc)])


figure(1)
plot(best,'r','LineWidth',2)
hold on
% plot(AVR(1:t),'b','LineWidth',2)

xlabel('Runs')
ylabel(' fitness ')

legend('BEST')

title (' PSO ')

for i = 1:24
A_PSO_FULL(i,1) = sum(total_new_Full_system(i,:))/run;
end

figure(2)
plot(A_PSO_FULL)
hold on
xlabel('Time (h)')
ylabel(' Cost ($) ')

legend('COST')

title (' PSO ')

for j = 1:T
BEST_PSO_FULL(j,1) = sum(best(j,:))/run;
end
 figure(3)
plot(BEST_PSO_FULL)
hold on

xlabel('Runs')
ylabel(' fitness ')

legend('AVR')
 title (' PSO ')

figure(4)
plot(Answer_Full_system,'LineWidth',2);

xlabel('Time (h)')
ylabel(' Power (MW) ')
title (' PSO ')
```

Appendix (b)

DE based EMS (Matlab Code)

```
%% parameters setting

Answer=zeros(24,6);

nvar=6; % number of variable

% load and lambda
data1=[3.3
3.3
3.2
3.15
3.625
4.2
4.35
4.1991
4.1
3.65
3.3
2.799
2.824
2.949
3.3
3.5
3.8
4.3
4.4
4.3
4.14
2.5
3.325
2.95];

lb=[0.2 0.1 0.1 0 0 -1
   0.2 0.1 0.1 0 0 -1
   0.2 0.1 0.1 0 0.004 -1
   0.2 0.1 0.1 0 0.009 -1
   0.2 0.1 0.1 0 0.011 -1
   0.2 0.1 0.1 0 0.056 -1
   0.2 0.1 0.1 0.013 0.094 -1
   0.2 0.1 0.1 0.033 0.0151 -1
   0.2 0.1 0.1 0.053 0.219 -1
   0.2 0.1 0.1 0.07 0.286 -1
   0.2 0.1 0.1 0.077 0.339 -1
   0.2 0.1 0.1 0.083 0.362 -1
   0.2 0.1 0.1 0.082 0.375 -1
   0.2 0.1 0.1 0.08 0.4 -1
   0.2 0.1 0.1 0.073 00.35 -1
   0.2 0.1 0.1 0.059 0.267 -1
   0.2 0.1 0.1 0.04 0.099 -1
   0.2 0.1 0.1 0.016 0.03 -1
   0.2 0.1 0.1 0.02 0 -1
```

```
    0.2 0.1 0.1  0 0 -1
    0.2 0.1 0.1 0 0 -1
    0.2 0.1 0.1 0 0 -1
    0.2 0.1 0.1 0 0 -1
    0.2 0.1 0.1 0 0 -1]; % lower bound

ub=[1.5 1 1 0 0 1
     1.5 1 1 0 0 1
     1.5 1 1 0 0.004 1
     1.5 1 1 0 0.009 1
     1.5 1 1 0 0.011 1
     1.5 1 1 0 0.056 1
     1.5 1 1 0.013 0.094 1
     1.5 1 1 0.033 0.0151 1
     1.5 1 1 0.053 0.219 1
     1.5 1 1 0.07 0.286 1
     1.5 1 1 0.077 0.339 1
     1.5 1 1 0.083 0.362 1
     1.5 1 1 0.082 0.375 1
     1.5 1 1 0.08 0.4 1
     1.5 1 1 0.073 0.35 1
     1.5 1 1 0.059 0.267 1
     1.5 1 1 0.04 0.099 1
     1.5 1 1 0.016 0.03 1
     1.5 1 1 0.02 0 1
     1.5 1 1 0 0 1
     1.5 1 1 0 0 1
     1.5 1 1 0 0 1
     1.5 1 1 0 0 1
     1.5 1 1 0 0 1];%upper bound


NP=500;              % number particle
T=500;                % max of iteration
run=100;

F=0.8;
CR = 0.5;


%%% initialization
tic
empty.pos=[];
empty.cost=[];
empty.pcost=[];
empty.ccost=[];
empty.NEWcost=[];
empty.mutationcost=[];
empty.mutation=[];
empty.m=[];
empty.crossover=[];

% load('result.mat');
particle=repmat(empty,NP,1);
% load('result_main2','gparticle')
% results;
```

```
best=zeros(T,run);
AVR=zeros(T,run);


for runs = 1:run

for i=1:NP
%  particle(i).pos= lb + rand(24,nvar).*(ub+lb);
 particle(i).pos=(((ub)/NP)*i)+ rand(24,nvar).*((ub)/NP);
% particle(i).pos=gparticle.pos;
[particle(i).cost,particle(i).pos]=fitness_24_4(particle(i).pos,lb,ub,data1);
% particle(i).velocity=0;
end

% bparticle=particle;
%
% [value,index]=min([particle.cost]);
%
% gparticle=particle(index);

% main loop


for t=1:T

%     for i=1:NP
%     [particle(i).cost,particle(i).pos]=fitness_24_4(particle(i).pos,lb,ub,data1);
%     end

    for i=1:NP

      Parent = particle(i).pos;

        xr= [1:NP];

          [A B]= find(xr==i);   %% locate when xr = i

          xr(B)= [];           %% delete it

          z= randperm((NP-1),(NP-1));
          a= particle(xr(z(1))).pos;
          b= particle(xr(z(2))).pos;
          c= particle(xr(z(3))).pos;

          % Mutation
%
%             particle(i).mutation =
          AC= a + F*(c - b);% apply mutation eq

          particle(i).mutation = AC;

         particle(i).mutation=min(particle(i).mutation,ub);
         particle(i).mutation=max(particle(i).mutation,lb);

        [particle(i).mutationcost,particle(i).mutation]=fitness_24_4(particle(i).mutation,lb,ub,data1);
```

```
%           A = [];
%           B = [];


          %% Apply Crossover
        LOL = rand;
              if (LOL < CR)

                    particle(i).crossover = particle(i).mutation;

              else
                  particle(i).crossover =  Parent;
              end

%
        [particle(i).ccost,particle(i).pos]=fitness_24_4(particle(i).pos,lb,ub,data1);
        [particle(i).pcost,particle(i).crossover]=fitness_24_4(particle(i).crossover,lb,ub,data1);

%         particle(i).mutation = [];

         if (particle(i).pcost < particle(i).ccost)
              particle(i).m = particle(i).crossover;
              particle(i).NEWcost=particle(i).pcost;
           else
              particle(i).m =  Parent;
              particle(i).NEWcost=particle(i).ccost;
         end


     end

 for i=1:NP
particle(i).pos = particle(i).m ;
 end

bparticle=particle;

[value,index]=min([particle.NEWcost]);

gparticle=particle(index);


best(t,runs)=gparticle.NEWcost;
AVR(t,runs)=mean([particle.NEWcost]);

  disp([ ' t = ' num2str(t)   ' BEST = '  num2str(best(t,runs))]);
%   disp([ ' t = ' num2str(t)   ' AVR = '  num2str(best(t))]);
%


end

Answer_Full_system=gparticle.pos;
Answer_cost_Full_system(i,runs)=gparticle.cost;
%
```

```
%
for i = 1:24
      a(i)= sum(15.30 + 0.00024.*Answer_Full_system(i,1).^2+0.21.*Answer_Full_system(i,1)+ 14.88
+0.000435.*Answer_Full_system(i,2).^2+0.3.*Answer_Full_system(i,2)+ 9
+0.000315.*Answer_Full_system(i,3).^2+0.306.*Answer_Full_system(i,3));
%       b(i)= (119.*abs(Answer_Full_system(i,4)));
      c(i)=  (545.016.*(Answer_Full_system(i,4)));
      d(i)= (155.616.* Answer_Full_system(i,5));

    if i~=0&& i < 8
      if Answer_Full_system(i,6)> 0
        Fa(i,1) = 133.5*(Answer_Full_system(i,6));
      elseif Answer_Full_system(i,6)< 0
        Fa(i,1) = 66.6*(Answer_Full_system(i,6));
      end
    end

    if i~=7 && i < 12
    if Answer_Full_system(i,6)> 0
       Fa(i) = 180*(Answer_Full_system(i,6));
    elseif Answer_Full_system(i,6)< 0
       Fa(i) = 90*(Answer_Full_system(i,6));
    end
    end

  if i~=11 && i < 18
    if Answer_Full_system(i,6)> 0
       Fa(i) = 132*(Answer_Full_system(i,6));
    elseif Answer_Full_system(i,6)< 0
       Fa(i) = 66*(Answer_Full_system(i,6));
    end
  end

   if i~=17 && i < 20
    if Answer_Full_system(i,6)> 0
       Fa(i) = 180*(Answer_Full_system(i,6));
    elseif Answer_Full_system(i,6)< 0
       Fa(i) = 90*(Answer_Full_system(i,6));
    end
   end

   if i~=19 && i <= 24
    if Answer_Full_system(i,6)> 0
       Fa(i) = 87*(Answer_Full_system(i,6));
    elseif Answer_Full_system(i,6)< 0
       Fa(i) = 43.5*(Answer_Full_system(i,6));
    end
   end

%       total_Full_system(i,1)= a(i) + b(i)+ c(i)+ d(i)+Fa(i,1);
      total_new_Full_system(i,runs)= a(i) + c(i)+ d(i)+Fa(i,1);
end
end
% results
disp('==================================================')
```

```
% disp([' BEST solution   =  '  num2str(gparticle.pos)])
disp([' BEST fitness    = '   num2str(gparticle.cost)])
disp(['  Time           =  '  num2str(toc)])


figure(1)
plot(best,'r','LineWidth',2)
hold on
% plot(AVR(1:t),'b','LineWidth',2)

xlabel('t')
ylabel(' fitness ')

legend('BEST','MEAN')

title (' DE ')

for i = 1:24
A_DE_FULL(i,1) = sum(total_new_Full_system(i,:))/run;
end

figure(2)
plot(A_DE_FULL)
hold on

for j = 1:T
BEST_DE_FULL(j,1) = sum(best(j,:))/run;
end

figure(3)
plot(BEST_DE_FULL)
hold on

figure(4)
plot(Answer_Full_system,'LineWidth',2);

xlabel('Time (h)')
ylabel(' Power (MW) ')
title (' DE ')
```