Energy Management of Micro-grid using Cooperative Game Theory

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Declaration

I, Ismaheel Oyeyemi Oladejo hereby declare that the thesis titled "Energy Management of Micro-grid" is my original work. No part or whole had earlier been submitted to any other University.

Signature: Signed by candidate…………………………………………

Date…2510/2019…………………………………………………….

Dedication

To my lovely wife, Omolara Nurat

To my Father, Late Mr. Sanni Oladejo

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I would like to first and foremost give thanks to Almighty Allah for giving me the patience, inspiration, time, and strength to finish the programme. I also extend my appreciation to my able supervisor, Professor Komla A. Folly for his continuous guidance and support during my Ph. D. study. His contagious enthusiasm, brilliant ideas, and helpfulness played an important role in renovating my interest and motivation in research work.

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Abstract

Micro-grid (MG) has been introduced as a low voltage and a very small power system connected to a distribution grid through the point of common coupling. It consists of distributed energy resources (DERs) such as solar Photovoltaic (PV), wind turbine, fuel cell, etc.), interconnected load and energy storage sources. It can operate in grid-connected (i.e. when connected to the main grid) or islanded (i.e. when not connected to the main grid) mode. It has an advantage of utilizing low carbon sources and the possibility of its use in the remote local environment, which means that the transmission infrastructures and their associated costs may be deferred. Although there has been a proliferation of optimization methods of energy management in the MG, most of these methods consider self-interest of the players in profit distribution. Moreover, only a few of them consider a fair profit distribution using Nash bargaining solution (NBS) (i.e. when utility function is linear) leading to even profit distribution and high degree of dissatisfaction. For the MG to achieve better economic outcomes, a novel method based on weighted fair energy management among the participants (i.e. building of different types, such as residential buildings, schools, and shops) is proposed. The novelty of the proposed method lies in the new profit sharing method to favour certain participant by assigning a weight to each participant with cooperative game theory (CGT) approach using generalized Nash bargaining solution (GNBS). The proposed approach achieves a fair (reasonable or just) profit allocation with negotiating power indicator.

In this work, a case study of six different participant sites is proposed using the CGT method of energy management. The proposed method is able to cope with the drawbacks of the existing independent method, which negotiate directly with other participants for selfish profit distribution. It is demonstrated that the independent method results in (1) a reduction in the profit of each participant of MG when compared with CGT approach and (2) the variation of

transfer prices in some participants having profit below the specified lower bound profit since the method does not take into consideration the lower profit bounds.

The use of CGT method (i.e. when participants form a coalition) to finding multi-partner profit level subject to specified lower bounds is demonstrated. This results in (1) increase in the profit of the MG participants (2) maintaining the profit level of all the participants above status-quo profit (lower specified profit bounds) with variation in transfer prices and (3) allowing certain participant to be favoured by assigning higher negotiating power to such participant.

To achieve the optimal solution in the proposed method, a teaching-learning-based optimization (TLBO) algorithm is presented to efficiently solve the problem. For TLBO algorithm, no specific control parameters are needed except the number of generations and population size. This is in contrast with other heuristic algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) that require other control parameters (i.e. GA requires selection and crossover operation, while PSO makes use of social parameters and cognitive weight). To demonstrate the effectiveness of the proposed TLBO method, the profit allocations are tested in the grid-connected and the islanded mode using both the CGT and the independent method. In this work, the proposed TLBO method is compared with one traditional method, i.e. Lambda iteration method and two heuristic methods, i.e. PSO and GA. Thus, by using TLBO a considerable amount of computation time is saved. Using the same parameter setting for all the heuristic algorithms used, 20 trials are performed to be able to compare the quality of solution and convergence characteristics. The investigation reveals that TLBO gives the highest quality solutions and better convergence characteristics compared to PSO and GA.

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Nomenclature

Abbreviations	**Definitions**
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AMGO	Archive-based Micro-genetic Algorithm
ANN	Artificial Neural Network
DE	Differential Evolution
DERs	Distributed Energy Resources
DG	Distributed Generator
DMOEADD	Dynamic Multi-Objective Evolution Algorithm
EMS	Energy Management system
ES	Evolution Strategy
EV	Electric Vehicle
GA	Genetic Algorithm
HMI	Human Machine Interface
LC	Local Controller
MG	Micro-grid
MGCC	Micro-grid Central Controller
MILP	Mixed Integer Linear Programming

MINLP	Mixed Integer Nonlinear Programming
MPC	Maximum Power Point
MPPT	Maximum Power Point Tracking
NBS	Nash Bargaining Solution
NTU	Non-Transferable Utility
PCC	Point of Common Coupling
PSO	Particle Swarm Optimization
PV	Photovoltaic
SCADA	Supervisory Control and Data Acquisition
SFC	Shuffled Frog Leaping
SOC	State of Charge
TCSC	Thyristor Controlled Series Capacitor
TLBO	Teaching-Learning-Based Optimization
TU	Transferable Utility

t time interval

K available electricity transfer price level

p sample day

s site

C^e Electricity export price when selling energy to the main grid.

C^e Electricity import price when buying energy from the main grid.

y Project lifetime

λ Reliability

CRF Capital recovery factor

SFF Sinking fund factor

C_{cap} Capital cost in US$

T_t Time duration for each time t

W_p Weight of day p

L_{tps} Total electricity demand of day p and at time t

SC Sell coefficient of grid electricity selling cost

$E_{ss'k}$ Binary k electricity transfer price from one site to another

I_{tps} Amount of electricity that is imported from the main grid

E_{tps} Amount of electricity exported to the main grid at certain time t, day p and site s.

$ACCs$ Annual capital cost of site s US ($)

$AOMs$ Annual operation and maintenance cost of site s US ($)

$ARCs$ Annual replacement cost of site s US ($)

$TBCs$ Transfer buying cost of sites s US ($)

$GBCs$ Grid electricity buying cost of site s US ($)

$TSCs$ Transfer micro-grid selling cost of sit s US ($)

$SOCs$ State of charge of site s

PBs Battery power at time t of site s

Ppv Solar PV power at site s

ACs Total annual cost of site s

$y_{tpss'}$ Amount of electricity transferred at time t, day p from site s

$Y^u_{ss'}$ Upper bound of electricity transferred from site s to site s'

Y^u_s Upper bound of electricity sent to site s

P^L_r Lower bound of the participant profit in site s

$$X_{ssik} = \begin{cases} 1 & If\ selected\ transfer\ price\ level\ k\ is\ between\ site\ s\ and\ s' \\ 0 & Otherwise \end{cases}$$

X^s_{tps} is equal to 1 if electricity is imported from the main grid or purchased from other sites and Zero otherwise.

Chapter 1

Introduction

Throughout the world, electricity is one of the most powerful forces influencing the economy and industrialization of any nation, which can give rise to technological change. It is worth mentioning that a country needs to first, build a reliable and adequate electricity infrastructure that can cope with her electrical power needs before moving towards industrialization and stable economic growth from subsistence economy [1].

The micro-grid (MG) is introduced as an ideal platform with distributed network sources in the distribution network system. The alternative sources of energy such as photovoltaic (PV), wind energy (WE), and fuel cell in electrical power system has been a major focus in recent years due to the environmental and economic concerns over the conventional sources [2]. The micro-grid emerges for the following reasons:

(a) the capability of utilizing energy resources with low carbon sources such as solar, wind energy, fuel cell, etc.,

(b) the possibility of its use in the remote local environment, which shows that transmission infrastructure and their associated costs, may be deferred.

(c) finally, the MG has an advantage of a local network interconnection so that the participants can form a coalition with each other and providing more benefit [3].

There are two distinct modes of operation of the MG, the grid-connected and islanded modes. In a grid-connected mode, there is a power exchange between the main grid and the MG. In islanded mode, the MG acts as an independent entity and therefore, manages its production independently. It also provides reactive power balance and control of frequency and voltage [4]. For example, if the power consumption is less than the net power generated the MGCC would reduce the total power generated. On the other hand, if the net power generated cannot cope with the load demand, the MGCC results in load shedding or immediate activation of the energy storage units to maintain power balance.

The major concern of the electrical supply authorities worldwide is the increase in demand for electrical power system [5]. The present grid systems, which have been in existence since last century are rapidly ageing [5]. The infrastructures of these grid systems are becoming congested and unable to meet the future demand of the energy requirements of economies of the nations.

1.1 Need for the Research

The demand for reliable and clean power supply is greater than ever. By 2030, it is expected that global energy production would increase by 77% [6]. It is, therefore, important to have reliable, efficient, and cost-effective of delivering new energy to meet new demand. The need for cost-effective, reliable and efficient means to deliver that new energy to meet new demand is very important. Moreover, interests on the renewable supply have been increased due to the issues related to the global environmental pollution and the uncertainty gas prices so that clean and reliable energy be provided by the electricity sector to its customers. In smart grid, the high penetration of renewable energy supply can ensure environmental and economic benefits, efficiency and reduction in fossil fuel dependency with higher reliability and reduction in the cost of electricity [7].

To provide economic benefit to the participant of the MG, several approaches are used in cost minimization of the MG [3], [8]. Some of these approaches selfishly minimize cost for each participant, but the mutual cost minimization is not considered [3]. This raises the challenges that the management and control of the MG need to be based on mutual interests of participants, rather than the self-interest of each participant. One of the ways of approaching these drawbacks is to use game theory so that Pareto-optimal can easily be obtained. The game theory technique can be regarded as a branch of applied mathematics, economics and applied sciences [9], [10], that is used in many disciplines. There have been several research works, which make use of game theory in designing and analysing a variety of issues for energy management in the smart grid [11], [12]. Even though the approach is a relatively young discipline, history has it that it has appeared in various forms and many sources, such as the Talmud, the works of Descartes and Sun Tzu and the writings of Charles Darwin [13], [14],

Game theory is a conceptual and logical framework having some mathematical tools, which enable the complex interactions among the independent intelligent players that are rational [15]. Since there are many components in micro-grid, it is, therefore, challenging to operate a micro-grid in a conventional, fully centralized way [16]. It is important to know that each component needs to be autonomous and cooperative to work together as a micro-grid. The participants (such as hospitals, fire stations, restaurants, residential building, etc. with their respective DGs) of MG can be better by forming cooperation. By allowing the MG participants to cooperate with each other will provide a better economic outcome than being in isolation with pure self-interest.

To obtain the full benefits of the micro-grid structure, several challenges were encountered by the micro-grid energy management, such as a fair multi-partner profit distribution with the difference in negotiation power. To tackle these challenges, a game theory of the multi-partner system using the generalized Nash Bargaining solution is proposed in this thesis. This has the advantages of providing better insights into the performance of the entire team when compared to the individual performance indices. Thus, the team profit function can be maximized with weighted fairness. A TLBO is also used to obtain the optimal solution.

1.2 Objective of the thesis

An energy management system can be composed of software, hardware or both, in which operators of power system control, monitor, and carry out the optimal energy management. The hypothesis that the research is based states that the framework based on generalized Nash bargaining solution can be used in MG to enhance fair profit distribution among MG participants with negotiation power. The research question is how do we maximize the profit of the participants in community MG to enhance mutual benefit with negotiation power? The problem can be solved by introducing a new approach to the existing MG operational method using novel cooperative game theory based on generalized Nash bargaining solution. In this proposed approach, a fair weighted method of settlement among MG participants is essential. The aim of this thesis is to provide a fair profit distribution to all the participants with least environmental effects.

In this research work, the optimal model of energy management system (EMS) is formulated as game theory approach, using the generalised Nash Bargaining solution approach with the objective to:

(1) Find an optimal profit level subject to the status-quo on the equivalent lifetime profit.

(2) Ensure a fair profit distribution with negotiation power

(3) Use of a robust and efficient algorithm, Teaching-Learning-Based Optimization (TLBO) to solve the resulting problem.

1.3 Research Methodology

In this work, an extensive review of relevant kinds of literature is initially carried out. This review includes the various methods of energy management systems. A comprehensive energy management system of a case study of six selected sites in a remote community is carried out to determine the profit allocation to the participants and to align the interest of the individual participant in the MG. These participants provide different energy consumption patterns which make it possible for them to cooperate with each other and benefit within the micro-grid. Each participant will have its own power source in which excess can be transferred to another location (participant) or sell to the grid. Each participant is expected to have a diesel generator, solar PV, and battery storage source to ensure adequate supply during island mode and a grid connection (allowing energy exchange).

1.4 Contribution of the Research

The thesis presents cooperative energy management where participants can form a coalition to exchange energy within the micro-grid and the main grid to utilize resources efficiently and allocate the resultant utility to the participants. The main goal of this research is to develop a new framework for energy management of MG. The propose framework will have three key features: a) ability to capture many participants, b) ability to integrate participant's needs in the MG, and c) ability to optimize participant profits based on different negotiation power. To this end, generalized Nash bargaining solution is used for fair profit distribution amongst MG participants.

In this EMS, a novel generalized Nash bargaining solution is proposed to allow the participants have different negotiation power indicators, compared to related work on [3], [17]- [18], the proposed model combines the advantages of both Nash bargaining solution with generalized Nash bargaining solution by allowing the participants to decide whether or not to favour certain participant. The approach is evaluated empirically and it is shown that:

1. There is an increase in overall profits of the participants in a grid-connected mode when using cooperative game theory with the aims of buying and selling electricity to

the main grid by 5.2% compared to when the participants independently manage their resources.

2. Application of cooperative game theory (CGT), using the generalized Nash bargaining solution (GNBS) gives a fair profit distribution with the difference in the participant negotiation power and thereby allocates higher bargaining power to a participant based on mutual agreement by all the participants.

1.5 Outline of the Thesis

The thesis is organized as follows:

Chapter 2

This chapter deals with the overview of the technologies that are important for energy management in the MG. It also discussed the rationale behind the introduction of MG, MG architecture, and management of MG. Introduction to cooperative game theory is discussed and particular emphasis is placed on axiomatic bargaining with analysis of Nash bargaining solution.

Chapter 3

This chapter introduces the modelling of components of MG. These components include a solar PV system, energy storage system, diesel generator, and the load.

Chapter 4

This chapter discusses the formulation of the EMS with regards to the objective function and its constraints. The use of game theory for fair allocation of the utility with special emphasis on proposed fairness scheme is discussed. This chapter also emphasizes the use of different optimization techniques employed in the energy management system.

Chapter 5

In this chapter, simulation results and discussions of the proposed approach are discussed.

Chapter 6

In this chapter, the conclusion and recommendations for future work are presented.

1.6 Summary

In this chapter, the concept of micro-grid and the rationale behind the introduction of micro-grid are presented. The need for the research and objective of the thesis are discussed. It is explained that the participants can be better by forming cooperation. The methodology use in this research is presented, which has to do with extensive review of relevant literatures in energy management system when consider six selected sites in remote communities. Also, research contribution is discussed, which employs the use of cooperative game theory using generalized Nash bargaining solution to allocate the profit to all the participants based in consensus. Finally, the structure of the thesis is presented.

Chapter 2

Literature Review

This chapter provides a framework on the subject matter related to this work. Before the modelling EMS is developed, there is a need to review general components necessary and sufficient for EMS. Section 2.1 focusses on technologies for energy management of micro-grid, which includes integration of DERs and energy storage system. Section 2.2 discusses the concept of MG, which relates to the MG architecture, centralized and decentralized energy management. In addition, section 2.3 provides some works in the context of game theory, in which cooperative and non-cooperative game theories are explained. Finally, section 3.4 provides bargaining theory, in which axiomatic and strategic bargaining are reviewed.

2.1 Technologies for Energy Management of Micro-grid

This section introduces some technologies that are important for the establishment of energy management in Micro-grid. The advancement and current trend are discussed so that the reader is equipped with the knowledge of the technology that is necessary and sufficient for energy management of micro-grid.

There is a need to determine the micro-sources that are adequate for electricity generation in sites/locations in remote communities. The distributed storage source also needs to be in the sites for each participant to store excess energy during off peak demand.

2.1.1 Micro-generation

Micro-generation is a technical term used for the production of electricity from low carbon technology, such as solar PV, wind turbine, small combined heat and power (small CHP), diesel generator, etc. This is a small-scale production of electricity that can be used in homes. Historical accounts have it that this type of micro-generation has many advantages over large-scale generations. For example, in a large-scale generation, electricity is transmitted over a long distance, which results in losses along the line. This can be avoided in a micro-generation. There are many ways of generating energy in homes. However, due to the comparatively low cost of installation and little maintenance required, the micro-sources used in this work are diesel generators and solar PV.

A. Diesel Generator

One of the modern energy generations, that proves to be versatile and robust in providing energy to the rural community is the diesel generator. The diesel generator proves to be reliable. It is very efficient in providing the critical backup generator at schools, residential, commercials, the high reliability of the diesel generators and its high power-to-weight ratio has made them very popular [19], [20]. The fuel for the diesel generator is relatively common and has a high weight and volumetric [21], which means it can be found in relatively large quantity. However, it has some drawbacks when using it for a rural, off-grid electrification as it may be inaccessible or extremely expensive. The energy cost could be high due to difficulty in transporting it to the rural areas. In case of the scarcity in the spare parts of the diesel generator, maintenance may be non-trivial.

In this research work, the diesel generator is used to cover the load deficit when solar PV and battery production are insufficient to provide sufficient and reliable power supply. The diesel generator is provided to cover the load demand and shut off when solar PV and battery are sufficient for energy production. The operation of diesel generator should be within the minimum and maximum power range recommended by the manufacturer. The generator operation bound is given as follows:

$$P_{Dmin} \leq P_g(t) \leq P_{Dmax} \tag{2.1}$$

where

$P_g(t)$ is the power generateD by diesel generator, P_{Dmax} is peak power, and P_{Dmin} is the minimum power.

B. Solar Photovoltaic (PV)

The fundamental source of all kinds of energy resources is the solar energy. There are two ways of production of this energy, i.e. the photovoltaic and the solar thermal systems. Our attention is focussed on the solar PV as it forms a major non-dispatchable source in this work.

Solar PV tends to be a renewable source that has a high rapid development. Although, throughout the world, the capacity of installed solar PV is much less than that of wind power (about 50%), the growth is faster than the wind power [22].. Figure 2.1 shows the global annual installed capacity of solar PV (2002-2018) [22].

Except for 2012, newly installed solar PV capacity for each year has been a year of record-breaking [22]. As opposed to early predictions, 2017 forecasts were estimated as 85 GW and therefore raised the estimate to 95GW at the near end of the year [22]. The cost of PV generation has continued to drop. In fact, it was said to have dropped from 0.9 $/kWh in 1980 to about 0.2 $/kWh in 2017 [23]. The main goal of the department of energy (DoE) in the United States (U.S) is to ensure a reduction in solar PV generation to 0.06 $/kWh by 2020 [23]. In remote, inaccessible areas, the solar PV system tends to be the most economical long-term solution [24]. However, in general, energy from the local utility cost less than the energy from the solar PV [23]. Currently, the capital cost of a diesel generator is on the lower side compared to a solar PV [23].

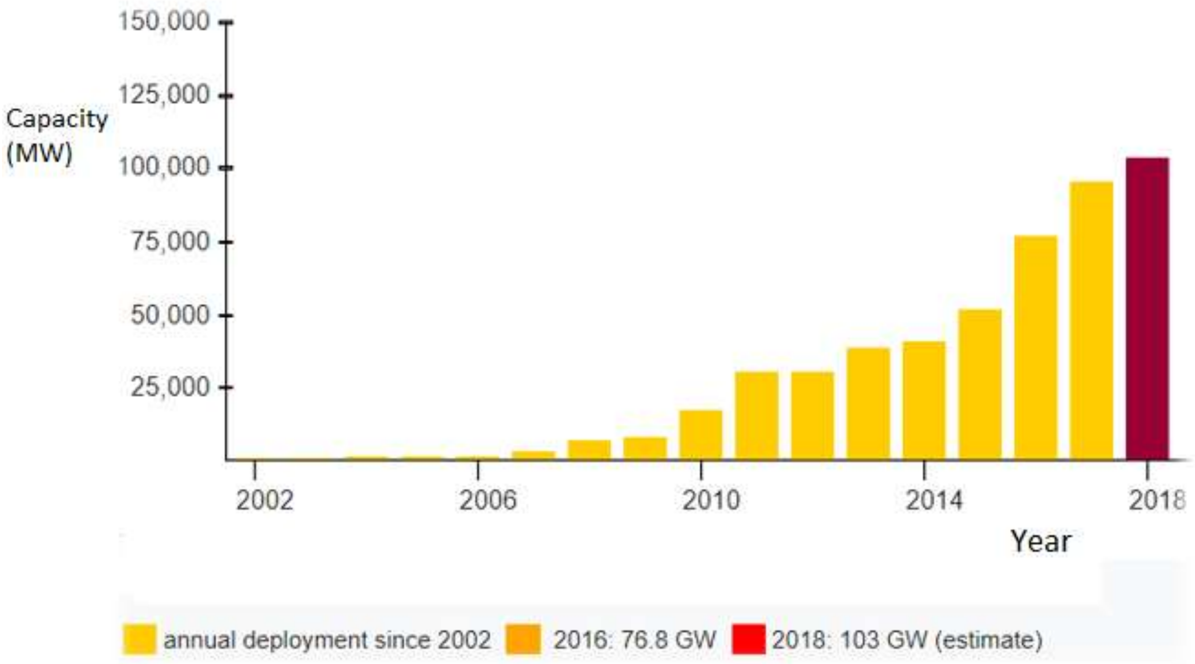


Figure 2.1: Global Annual Installed Capacity of Solar PV since 2002 in Megawatts [22].

The operation of the main distribution utility grid can be affected by the stochastic nature of renewable energy sources. The production of the electricity from solar PV depends on the light intensity. In this case, the connections of the solar PV to the main grid have a positive impact on the network. It may also as well have a negative impact. This is because the proliferation of PV systems in low voltage distribution network may cause problems such as voltage rise, overcurrent, network loss increase, unbalanced voltage, increase in potential harmonics, and distribution network reverse power flow [25]. The penetration of a solar PV depends on the intensity of sunlight that fluctuates daily, hourly, or even shorter periods. The PV output power due to the fluctuation in the light intensity is shown in Figure 2.2.

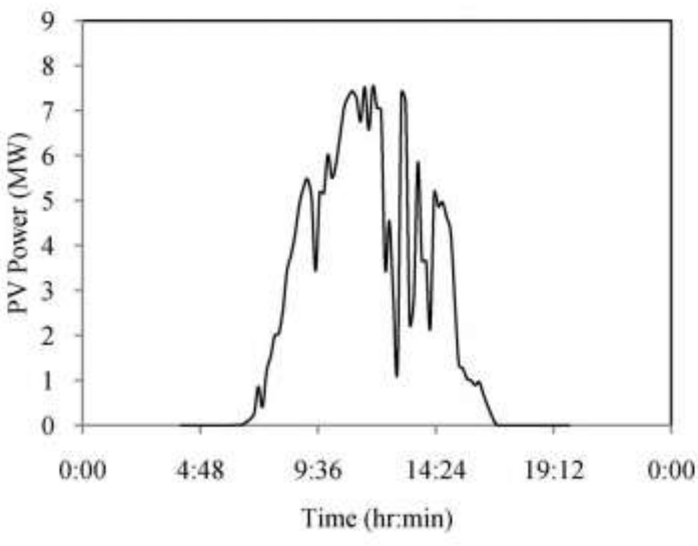


Figure 2.2: A Typical Solar PV Output Power [23]

It is essential to estimate the solar radiation so that the output power of the solar PV can be determined. The radiation prediction of solar PV using the mathematical model, e.g., artificial neural network (ANN) tends to be accurately determined when compared to the use of regression model, empirical coefficient model, empirical regression model, and model based on fuzzy logic [23], [26]. In [27], the PV system power output connected with battery is predicted using a neural model. The weather information is used to design the model to accurately predict the capacity of the battery necessary to compensate the fluctuation of power output of solar PV. The power output of the solar PV is mostly affected by the weather conditions such as rainfall and cloud movement.

2.1.2 Distributed Energy Storage Devices

Distributed energy resources (DERs) such as solar PV and wind turbine are stochastic in nature and therefore, are non-dispatchable sources. For example, power generated by solar panels can be available only during the day while the power generated in a wind turbine depends on the wind speed. Due to the stochastic nature of these sources, storage devices are often used with these DERs (renewable sources) to ensure that the energy supply is uninterrupted. A distributed storage source is used to provide power to the device to ensure continuity of supply when power is intermittent.

Energy storage can be in many forms, but our interest is focussed on a distributed storage source on a domestic scale. The electric batteries and thermal storage are the distributed storage devices in homes [28], [29]. In remote communities, electric batteries are used to store energy generated by wind turbine or solar panels. The storage capacity and power are the two terms used in assessing energy storage devices. Storage capacity is the total energy stored in the system, while power referred to the rate of energy charging or discharging to/from the device. Watt-hour (Wh) is the unit in measuring storage capacity while watt (W) is used in measuring charging and discharging of the electric battery.

Many factors determine the storage capacity and discharging rate. For example, a storage device may depend on the certain chemical reactions or on the battery size. Therefore, different devices may have different storage capacity and discharging rate.

The introduction of electric vehicle (EV) device as a storage device is another related topic that is used for the transition to a low carbon economy [30]. The capacity of the device could be 50kWh with 20-50kW power when used at home for electricity storage [29]. Modern vehicles with a battery pack of 50kW represent vehicles such as the Tesla Roadster from Tesla, Zhong Tai from Zotyg, etc. [28]. Electric vehicles of this nature have a high storage capacity as compared to the average energy consumption of 40kWh in a day per person for transportation [28], [31]. The next section will focus on concept of micro-grid and its configuration to form a distributed network for the participants.

2.2 Micro-grid

Micro-grid possesses much practicability in a smart grid and hence, represents an important and necessary part of the development of smart grid [32]. The principle of operation of a micro-grid has a relation to the production of the local power generation, load consumptions and electricity price in the main grid.

In a conventional power system, the power flow is unidirectional from generation to load distribution system via transmission and distribution systems. With the advent of micro-grid, microgeneration such as solar power and wind power generation become popular for residential, commercial, and industrial use, hence, bidirectional power flow came to an existence. This, in essence, makes a micro-generation energy distribution system into a micro-grid, which can either sell the excess energy to the main grid or purchase energy from the main grid. Different sizes of micro-grid are being used depending on the applications. For example, it may be used for smart homes, residential building, school, etc.

2.2.1 Micro-grid Architecture

A micro-grid consists of the distribution energy resources (DERs) such as renewable energy resources and conventional sources, smart homes and energy storage systems as shown in Figure 2.3. The connection of MG to the main grid is through a point of common coupling (PCC). The main grid determines the voltage at the point of the common coupling of the micro-grid [33]. To achieve the proper control, protection, and metering with plug and play features, each DER must be with the power electronic interface (PEI) in both grid-connected and islanded mode. In grid-connected mode, there is an energy trading with the utility grid. However, when upstream faults occur in the main grid, micro-grid can be islanded, and can act independently to manage its own resources to enhance system stability. In this case, the critical loads can be protected by integration of the distribution energy resources, demand response, and load shedding [33], [34]. The micro-grid central controller (MGCC) and the local controllers (LCs) act as a mediator to control and coordinate the entire operation of micro-grid. Proper coordination and the effective management of DERs enhance system performance and sustainable development of the micro-grid [33].

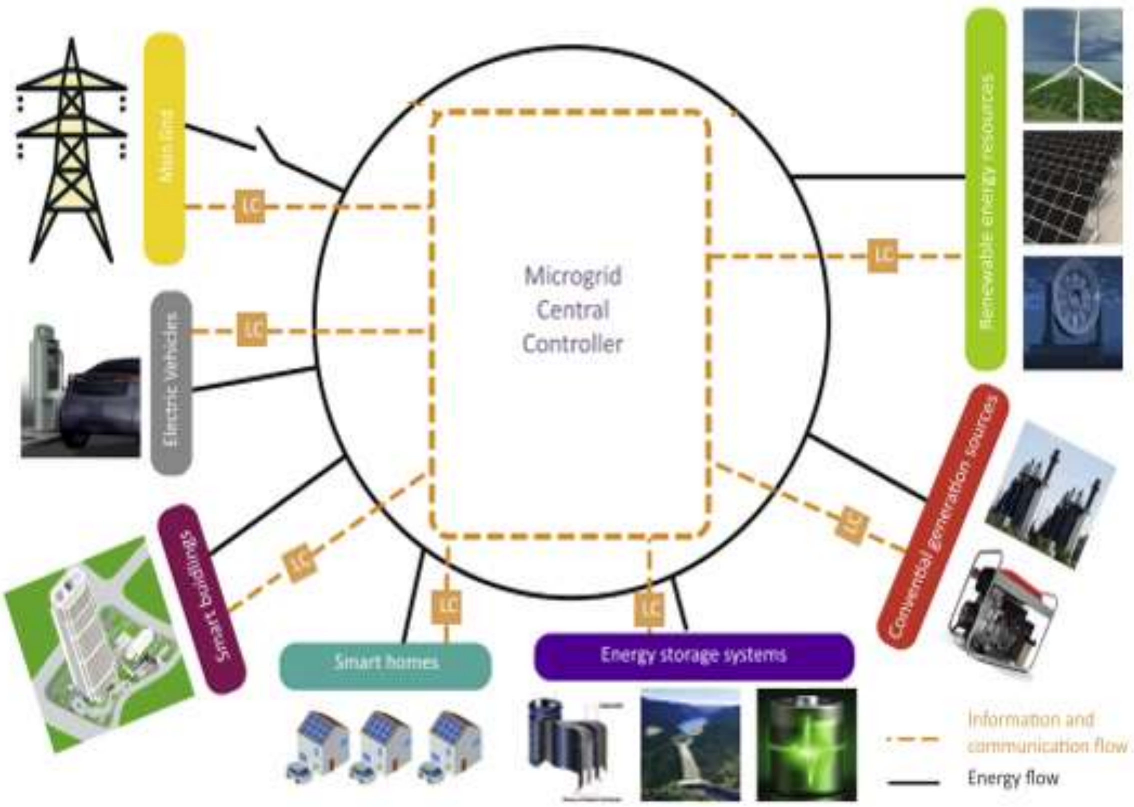


Figure 2.3: Micro-grid Architecture [33]

Due to the greenhouse gas emission in the conventional energy resources, the awareness created on the climate change and the need to sustain the environment, micro-grid mainly consists of the DERs such as the solar PV, wind turbine, diesel generator, etc., and energy system that uses local heat waste such as biomass, cogeneration plant, etc., [35]. In this case, the decision-making strategies are solved by the MG energy management system (MG EMS) which is achieved by the optimization of this energy system. For the sustainable development, the strategies consider would help to reduce the power consumption, enhance system reliability, reduce losses, mitigating greenhouse gas emission, and increase the energy system

2.2.2 Micro-grid Energy Management

Energy management is defined in [36] as the application of the computer system to ensure that the cost is minimized or profit is maximized with adequate security of energy supply. It makes use of the software platform that provide basic support services and some functional applications to ensure that the electrical generation and transmission facilities are operated effectively. The decision-making strategies are also implemented with the use of energy management system having these same features and required modules. The EMS decision-making is efficiently implemented with the use of modules of load forecasting, DERs, human-machine interface (HMI), supervisory control and data acquisition (SCADA), etc., by ensuring that the generation, load, and storage units receive an optimal decision [37]. There are many functions performed by EMS in a micro-grid such as analysing, monitoring, and forecasting generated power of DERs, energy market prices, etc., which help in optimization and satisfying necessary constraints.

Micro-grid EMS control architectures are in two folds viz: the centralized energy management and decentralized energy management. The information such as the generated power of DERs, demand profile of the consumers, cost functions, and meteorological data are collected and sent to the micro-grid central controller (MGCC) in centralized EMS. The optimal scheduling of energy in micro-grid is then determined and the decision is sent to all local controllers (LCs). However, in the decentralized energy management, all the information is sent/received in real-time by MGCC to/from all the local controllers. The generation schedule, future and the current demand are processed by each LC and sent to the MGCC, the optimal scheduling of energy is then determined by the MGCC and sent back to the LC. There may be a disagreement on the current operation between the duo and therefore, bargaining ensues until an equilibrium is reached and the global objectives are achieved. With the introduction of DERs such as solar PV, wind turbine and the storage sources, the advent of micro-grid EMS replaces unit-commitment and the conventional economic dispatch.

Other strategies performed by the micro-grid EMS are the control of the stochastic nature of the renewable energy sources, load and DERs scheduling, loss minimization and outages, the economic and reliable operation of micro-grid.

There are many approaches used in the past in the MG to solve these energy management strategies to obtain the efficient and optimal solution. In [17], a mix-mode EMS for the MG operation at a minimum cost and optimal battery sizing is presented. The linear programming methods are used to optimize the proposed power sharing and continuous run, while the mixed integer linear programming optimizes on/off mode. In [38], the optimal energy management system for the fuel consumption minimization of the diesel generator for remote military MG is presented. The effectiveness of mixed integer non-linear programming (MINLP) formulation was solved by special order sets 1 and 2, which, was validated experimentally. Vergara, et al. [39], present a mixed integer linear programming (MILP) model for the EMS of the electrical distribution system and three-phase residential MG. The proposed formulation penalizes the load shedding and minimizes the operational cost of MG. In [40], a real-time online EMS for cost minimization of the MG is proposed. Helal, et al. [41] presented an EMS for remote communities for the optimal scheduling of the generation technologies in hybrid AC/DC micro-grid. The problem is formulated using MINLP and solved by the micro-grid controller (MGC), which minimizes costs of DG units in the islanded mode. In [42], [43], a comprehensive framework for model predictive control (MPC) is proposed for cost minimization.

In the above models [17] - [43], the cost of the whole micro-grid was successfully minimized, but a fair cost minimization is not considered. To enable all the participants to benefit from the micro-grid, with fair profit/cost distribution, many existing works using the Nash bargaining model have been presented. In [3], a game theory, Nash bargaining solution (NBS) was applied for cost minimization of the grid-connected micro-grid to obtain a cost fair distribution among the participants. Hao Wang et al. [18] presented the Nash bargaining theory to achieve fair profit sharing and energy trading among micro-grids. However, the above approaches [3] and [18] to fairness is useful when the utility functions are linear (when the participants of MG are equal structurally and distribute profit equally). In reality, utility functions may be non-linear (i.e. the participants may not structurally equal). In this case, the surplus is unequal amongst the participants i.e. the result obtained when participants unanimously agreed upon a feasible outcome could be symmetric with the same profit or asymmetric with unequal profit distribution. As a variant of Nash bargaining power, the fairness can be improved by using asymmetric, which is the generalized Nash bargaining solution with the difference in negotiation power. This bargaining solution is proposed to achieve a trade-off between fairness and weighted fairness.

2.3 Game Theory

Game theory is used to design and model decision-making that involved interaction with conflicting mutual interest [44]. The complex economic behaviours are solved by using game theory. It is used in many fields such as philosophy, politics, sociology, military telecommunication, communication, etc. as a result of studying complex dynamic among the participants [45], [46]. Recently, the issues in power system particularly in MG with respect to profit distribution have been addressed with the use of game theory [3], [47].

Profit distribution among players is becoming an important issue in smart grid particularly in MG. In this context, cooperative game theory using NBS provides fair profit distribution and optimum allocation of profits among the players. Recently, game theory has been used to address power system issues including distribution energy management, dynamic pricing, demand smoothing, and matching the surplus [48]. Power systems are dynamic in terms of energy conservation, participant profit sharing, etc. All the participants ensure that their payoffs are maximized. The utility functions may be used in projecting the payoffs based on several decision criteria from all the participants where game theory can be well suited.

There are three components of game theory i.e. the player set, the action set, and the payoff set. By adopting certain strategy, the players can raise their payoffs to the maximum at a certain time. Payoff may be allocated among players by using NBS, which make use of set axioms. The approach was originated with Nash. The correlation between game theory and MG has been tabulated in Table 2.1.

Table 2.1: Correlation between Game Theory and the MG

Components of the game	Game Theory Concept	Micro-grid Concept
Strategies	Action involved while playing game.	Action involved while playing game such as available players, dynamic pricing, offered prices, etc.
Players	Involvement of players in the game.	Players involved in the game such as dwelling places, shops, factories, etc.
Payoffs	The profit allocated to each player	The profit allocated to each player based on the utility functions
Resources	Money, fame.	Profit needed by which the players are competing with each other, such as energy, power, etc.

The concepts of game theory have just been discussed, in this section, the review of non-cooperative game theory and cooperative game theory would be investigated.

2.3.1 Non-Cooperative Game Theory

Non-cooperative game theory studies game plan between interactions among contesting participants. In the game, an agent is a participant, which aimed at maximizing the payoff by selecting an appropriate strategy. In this case, each participant selfishly maximizes his own profits. With the non-cooperative game, the Nash equilibrium is obtained [49]. Nash equilibrium is one of the fundamental concepts of GT, which determines solution in a no-cooperative game by ensuring that no player has incentive in changing his/her own strategy.

In smart grids, where small-scale power system like micro-grid is used, there must be a generic framework, that can capture the problem arising between the load and the source because of competition over the energy resources. With this aim, Weaver et al. [11], proposed a non-cooperative game approach for controlling loads and power sources in electric energy system. In the paper, the authors described the static, non-cooperative game theory as a player having set $N = L\ U\ S$ to represent the set of loads depicted by L and energy source S and each player has its own strategy.

2.3.2 Cooperative Game Theory

The cooperative game theory is concerned with games where the mechanism is available to ensure binding agreement among a group of players. The idea is focussed on mutual (collective) benefit rather than the individual achievement of the players [28], [50]. For the implementation of the binding agreement, the mechanisms available are the formal legal contracts. The game theory considers a situation where the players act collectively and binding agreements are made by studying the strategies of individual players [28].

An example of the use of cooperative game theory can be demonstrated by considering a cluster of some factories, where the factory owners paid individually for their electricity consumption. To give them the ability to negotiate for a better deal (e.g. discount tariff) they can come together to form a coalition, this will save them some money, which can be shared among the participants. Cooperative game theory is a powerful tool that can be useful to determine how the coalition can be formed and the sharing formula of the realised savings among the players can be achieved [15].

The formation of a coalition depends on its stability. For a stable coalition, no solution in the coalition can improve any of the objectives without degrading at least one of the other objectives [28]. The surplus, thus obtained can be shared using the Nash bargaining solution, as one of the bargaining solution concepts, which will be introduced later in the section.

Two branches of the cooperative game theory are identified, they are, Transferable Utility (TU) game [51] and Non-Transferable Utility (NTU) game [28], [52]. In TU game, there is a transferable payoff of the measurement allocation game. For instance, in the above example, the profits obtained can be shared among the factories. In contrast, let us consider a situation where a supervisor collaborates with his student to publish a journal article. They will both benefit from the publication, but the benefits accruable to the student will be greater than that of the supervisor. This is because the student will derive higher value than the supervisor and the derived benefit of the student (scientific credibility, enhanced reputation) cannot be transferable to the supervisor. TU game attracts more popularity in a cooperative game theory to model game in this class [53]. Because of the relationship of TU game to the proposed work, we focus our attention on the formulation and discussion of TU game. There are two elements of TU game: the set of players and the characteristic function. The worth of a coalition is represented by the characteristic function. In TU game, a number represents the value. Let N= {1, 2, 3…, N} be the finite set of players and V the characteristic function that associate every subset of $S \subseteq N$ with a number i.e.$2^N \longrightarrow R$, the $V(S)$ may indicate the *worth* of coalitions S.

We assume that the characteristic functions are *supper additive* [54]. This means that the values of disjoint coalition unions should not be less than the individual value of coalitions i.e. $S \subseteq N \; and \; T \subseteq N$ such that $S \cap T = 0$, we have $v(SUT) \geq v(S) + v(T)$. With a given value of a coalition, sharing of the value among the players is challenging. Cooperative game theory gives a *solution concept* that will be used to share this coalition. A vector $x \in R^N$ is a solution concept, which represents a player N allocation. Many solution concepts were proposed by cooperative game theory on what resulting to a fair solution, e.g. two symmetric (identical coalition contribution to the coalition) players that are based on solution concepts, different profit sharing is not considered a fair solution. Some notions that are commonly found in cooperative solution concept is described below [28], [55].

(1) Individual Rationality

An individual player does not receive less than he will obtain independently.

(2) Efficiency

The total values of the coalition must be equal to the participant's distributed payoff.

(3) Symmetry

The player's payoff is identical

(4) Zero allocation to dummy player

A dummy player i.e., a player that has no contribution to the coalition receives zero value.

A great attention has been placed on coalition and has been applied in this thesis, which will be discussed in the next section.

2.3.2.1 Coalition Formation

A coalition game can be formulated by considering a distribution system that has a substation, which is connected to the utility grid and to micro-grids in the set N [15]. A number of cooperation micro-grids can be defined as a coalition S $\subseteq N$, which could be divided into two different groups i.e., the seller which is expressed as $S_s \subset$ S and the purchaser expressed by $S_p \subset$ S in such a way that $S_s \cup S_p = S$. In each coalition, there may be an exchange of power between sellers in S_s and the purchaser in $S_{p.}$

The formulation of coalition can be expressed as a function of S and equilibrium point of both the sellers and the purchasers (i.e., the types of sellers that give power to the purchasers). The issue of reaching equilibrium between the sellers and purchasers is a challenging task to be addressed by the use of game theory techniques. Consider a coalition S and let τ_s be the set of ordering on the buyer in S. With the order $\Pi \epsilon \tau_s$, the losses incurred because of energy transfer between the members of S can be expressed by

$$(\mathrm{S}, \Pi) = -\left(\sum_{i \epsilon Ss\ j \epsilon Sb} P_{ij}^{loss} + \sum_{i\ \epsilon\ Ss} P_{i0}^{loss} + \sum_{j\ \epsilon\ Sp} P_{j\ 0}^{loss}\right) \tag{2.3}$$

where P_{i0}^{loss} and P_{j0}^{loss}, respectively depict the power losses between the sellers and the purchaser and the utility grid during the energy distribution. P_{ij}^{loss} represents the losses in the distribution line when there is energy transfer between sellers and purchasers, with certain considerations. First, the energy transfer between the seller $i \epsilon S_s$ and the buyer $j \epsilon S_b$ inside S will cause no transfer loss because of their closeness. In addition, inside S, energy transfer between the seller $i \epsilon S_s$ and the purchaser $j \epsilon S_b$ is done at low-to-medium voltage.

Nguyen et al. [56], proposed deregulated power market where game theory approach was used to provide interaction among the interest groups. The coalition is formed by maximizing the profits of the participants, which will enhance cooperation and mutual benefits. In [57], multilateral trades are proposed by the use of cooperative game theory to solve the coalition formation. Many solution concepts are used in cooperative game theory [58], but a great attention has been put on Shapley value and has been applied in many works, which will be discussed in the next section.

2.3.2.2 The Shapley Value

Payments are allocated to the players in coalition using a solution concept called *Shapley value* [51], [59]. In Shapley value, there is consideration of a player's contribution to a coalition, which is called marginal contribution. The word marginal contribution refers to the amount that will shrink if a participant opts out of the game.

By considering the notation used in section (2.2), we consider $N \setminus i$ represent the set of players without the player i and v: $2^N \longrightarrow R$ represents the characteristic function. We can now consider the player's marginal contribution i defined as $v(N) - v(N \setminus i)$. With the given marginal contribution, the Shapley value $\phi_i$is defined for a player $x \in N$ as

$$\phi_i(N, v) = \sum(|S|!\ |N| - |S| - 1)N!\,[\,v(SUi) - v(S)] \qquad (2.2)$$

The characteristics of Shapley value include rationality, efficiency, symmetrical and zero allocation to dummy player [60]. In spite of this numerous advantages, Shapley value is said to be computationally complex, $(2^n \times 2 \times 0_v)$ where 0_v is considered as a complex function and thus, becomes difficult to use as the number of participant increases [28]. Many solution concepts are used in cooperative

2.4 Bargaining Theory

Bargaining theory can be described as a process of bargaining and its outcomes. This can also be referred to as bargaining problem [28]. According to Rubinstein [61], bargaining problem refers to the following situation and questions:

Two individuals have before them several possible contractual agreements. Both have interests in reaching an agreement but their interests are not entirely identical. What will be agreed contract, assuming both parties behave rationally?

For decades, economists had no answers to this bargaining problem. In order to tackle this challenge, Nash [62], and Rubinstein [61] presented axiomatic approach and strategic approach respectively to predict the outcomes of the bargaining problem. In this work, a review of both axiomatic and strategic bargaining solutions is provided.

2.4.1 Axiomatic Bargaining

Axiomatic bargaining theory uses a set of axioms to allocate payoff among the players. The approach was originated with Nash [62], and the players must satisfy certain axioms before the unanimous agreement. He initiated and formulated a bargaining process between two players and ensure that a set of axioms are satisfied, which results in multiple solutions or unique solution. Some of the axioms are given as follows:

(1) Invariance to equivalent utility representations

This axiom is otherwise referred to as scale-freeness or affine transformation. In this case, the bargaining solution must be invariant in respective of the rescaling of player's utility function.

(2) Pareto Efficiency

This is also referred to as the Pareto optimal solution. This solution cannot be improved in any of the objectives without making at least one of the other objectives worse-off.

(3) Symmetry

Symmetric solution should depend on utility function of the players and this utility function results in symmetric pay-offs i.e., the player's payoff should be identical.

(4) Independent of relevant alternatives

This is bargaining process. The axiom stipulates that in a choice set S, if a certain choice A is preferred over B, then the inclusion of another choice C should not make B preferable to A. Some Axiomatic bargaining solution and the axioms they satisfy will be considered in the following sections.

2.4.1.1 Nash Bargaining Solution

In cooperative game theory, Nash bargaining solution (NBS) can be used for fair cost/profit allocation. This bargaining solution must satisfy a set of axioms to ensure fair allocation. The interest of this approach is proportional fairness because the axioms consider user's utilities. The NBS is applicable to general network topology so that the resources are allocated in a fair manner [63], [64]. The result obtained in this condition is linear with the equal payoff. On the other hand, there is a disagreement value, which is status-quo representation when the players fail to cooperate to reach mutual agreement.

Let us consider two players A and B, which bargain over a set of utility functions, if they failed to reach the set agreement, then utility d_L, will be obtained by each of them, which is the disagreement point, denoted by $d = (d_A,\ d_L)$. This disagreement point is the cooperation break down and otherwise called 'threat' [65], [66]. The agreement that is mutually beneficial is represented as $x \epsilon X$ such that $U_{A\,(x)} > d_A$ and $U_{L\,(x)} > d_L$. The above bargaining problem represents a unique solution that has utilities represented by $(U_A^N,\ U_L^N)$ which solves the problems as follows:

$$Max_{U_A,U_L}(U_A - d_A)\ (U_L - d_L) \tag{2.4}$$

where $(U_A - d_A)\ (U_L - d_L)$ represents Nash product

The maximization in (2.4) under the axiomatic bargaining theory gives a Pareto efficient allocation of a permit [67]. The previous section describes the axioms imposed by the axiomatic bargaining theory. The implications of these axioms are discussed in [50], [59], [66]. The most unrealistic axiom is symmetry; this is because it assumes the same negotiation power for all the players. The axiom can be relaxed with the use of asymmetric NBS, given its formulation as follows:

$$Max_{U_A,U_L}(U_A - d_A)^{\alpha}\ (U_L - d_L)^{\beta} \tag{2.5}$$

where α and β are the bargaining powers of the players

An increase in α leads to an increase in utility of player A, and vice-versa. The resulting optimization problem in (2.5) is called asymmetric NBS [67], [66] or generalized NBS or non-symmetric NBS [59], [66]. A generalized Nash bargaining solution depends on the bargaining power and therefore, no unique solution is obtained. However, all other axioms are satisfied.

It is important to note that Nash solution does not depend on utility preferences but rather on the player's preferences (i.e., Invariance to equivalent utility representation axiom).

2.4.1.2 Kalai-Smorodinsky Bargaining Solution

Roth [68] describes that one of his axioms of independence of irrelevant alternatives has been a restrictive axiom for a solution and come under criticism. In the axiom, if some particular player prefer a solution in a set S, they must prefer a solution in a subset of S, as long as there is a solution in subset S [65]. However, a player could derive less satisfaction with its utility when there is enlargement in a solution set, this is shown in [69], [70]. Therefore, the extension of the NBS which negates this axiom is called Kalai-Smorodinsky solution.

Kalai-Smorodinsky solution can be computed by forming a rectangular solution space R. The four rectangular points are obtained as follows: the status-quo point or disagreement point (d^a, d^b) is the first point. The $(u^{a*}, 0)$ is the second point, where from u^{a*} represents the maximum utility for the first player. The second player's maximum utility forms the third point$(u^{b*}, 0)$. Finally, a point that lies at (u^{a*}, u^{b*}) forms the last point. A line is drawn from point (d^a, d^b) which is the origin to (u^{a*}, u^{b*}), which represent maximum utility for players A and B as shown in Figure 2.4. The point of intersection of Pareto frontier with the straight line obtained is Kalai-Smorodinsky solution.

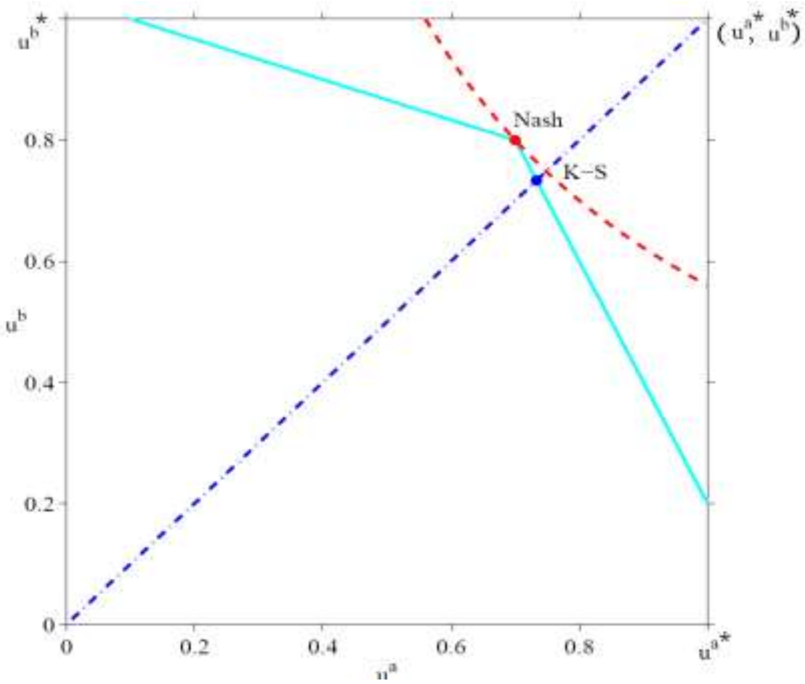


Figure 2.4: Nash and Kalai-Smorodinsky Solution [28]

This approach is useful when the axiom of independent of relevant alternatives is not important. Discussion and examples of Kalai-Smorodinsky solutions are given in [71]. In the diagram, Pareto-frontial is the solid line. The origin (i.e. $(d^a, d^b) = (0,0)$ is the disagreement point. In this case, all the points lie above this point represent the acceptable agreement. The dashed-dotted line in the diagram is the Kalai-Smorodinsky bargaining solution (K-S). The point $(u^{a*}, 0)$ is the point at which a player A gets maximum utility while player B gets maximum utility at point $(u^{b*}, 0)$. The maximum utility for the players A and B is at the point (u^{a*}, u^{b*}). The line K-S is drawn from the disagreement point to (u^{a*}, u^{b*}). At the point where the line intersects Pareto-frontial is the point of K-S solution

2.4.1.3 Other Relevant Bargaining Solutions: Egalitarian and Utilitarian Solutions

There are two different ways by which these bargaining solutions can be compared:

(1) The principle of equal gains: The argument is such that 'this thing should be done for me because I am doing more for you'. This is referred to as egalitarian solution.

(2) The principle of greatest good: The debate on this case is that 'this thing should be done for me because of the benefits to be derived more than it hurts you'. This is the concept of the utilitarian solution.

Consider a two-person bargaining problem, the point $(x_1,\ x_2) \epsilon F$ is the unique point of egalitarian solution, which must satisfy the condition of identical gain and must be weakly efficient in F given as:

$$x_1 - v_1 = x_2 - v_2 \quad (2.6)$$

The idea is that the expression $(x_1,\ x_2) \epsilon F$ is weakly efficient, if and only if there is no value $(y_1,\ y_2)\ \epsilon F$ such that $y_1 > x_1$ and $y_2 > x_2$. A utilitarian solution works on the principle of the greatest good because it gives goods to the players that needed it most.

Hence, the egalitarian solution deals with the equal gain principle, while the utilitarian solutions are guided by the principle of good. Both violate the axiom of invariance to equivalent utility representation [72]. Utilitarian solutions are useful when the players are not self-interested because group utility is maximized by conceding goods to the player, which has the highest utility for them. The strategy bargaining will be described in the next section, as it predicts the outcome by taking bargaining process into consideration.

2.4.2 The Strategy Bargaining

This is a process of bargaining whereby players reached unanimous agreement. This type of bargaining tends to predict outcomes by considering the strategies of the players. The goal is to consider the game outcome (i.e. Nash equilibrium) of bargaining that results from the self-enforcing interaction of the players. This is a non-cooperative game theory bargaining solution and has the solution concepts; the Nash equilibrium, dominant strategies and subgame perfect equilibrium, which will be defined as follows:

(a) Nash Equilibrium

Nash equilibrium comes to play where neither player can unilaterally change her strategy.

(b) Dominant Strategy

This states that no matter the strategy of other players, the dominant strategy is always at optimum. This implies that the highest payoff is achieved in dominant strategy.

By comparison, Nash equilibrium (NE) deviates in a way to benefit the players (i.e., weaker notion of equilibrium) than the dominant strategy. Although, NE is relatively weaker at least one equilibrium point is achieved at every finite game. Selten's subgame perfect NE happens to be a refinement of an NE for extension form game [28]. In extension form game, player makes a decision at every stage of the game.

(c) Subgame Perfect Nash Equilibrium

A strategy profile in an extensive form game is a subgame perfect Nash equilibrium if it represents an NE at every decision point. In strategy bargaining, there is also another related concept that specifies that the bargaining rules is the notion of a bargaining protocol [28]. The *alternating offers* protocol is the bargaining protocol that has received wide attention, where the players make an offer in turn. Rubinstein's pie dividing problem [61] tends to be the work that is most influential on the alternating offers protocol. The problem of the pie is the bargaining situation where mutual agreement by the two players is reached on the portion of shared resource. The players can suggest how the resource could be shared. When a player makes an offer, the bargaining continues whether or not the other players accept or reject it. The assumption of Rubinstein is that a complete information that is available for the players can make an alternative offer and no delay is tolerated. The dynamic game is modelled using Rubinstein's bargaining process and the solution is obtained using backward induction method [67]. The player who makes the last move of the game is determined optimally by using the idea of backward induction method. By considering the last player action, the optimal strategy of last but one player is determined. This procedure continues until Nash equilibrium is determined for each subgame of the original game, thus obtained the subgame perfect NE of this game.

2.4.3 Fair Settlement using Game Theory

Game theory has been used to obtain a fair solution but fairness can be measured in many ways. In [73] , a fairness is defined as a process of arriving at an acceptable and reasonable outcome. The solution of fairness proposes that all players of game can receive a fair or acceptable portion of benefits. Salles, et al. in [74] proposed the use of lexicographic maximum criterion to guarantee fairness. The approach considered the fairness maximization of the benefit of the worse-off individual. The solution of fairness suggests all the participants of game can receive a fair or justifiable portion of benefits. In [75], a classical production-planning problem in supply chain coordination is presented. The authors described a fairness as facilities burden sharing. The objective is for the absolute deviation maximization cost from the status-quo cost, which is considered a benchmark. In [76], a cooperative game to address a model for determining fair transfer prices in the supply chain is presented. In [77], a new profit-based security-constraint, unit commitment for industrial micro-grid is presented. The game theory using Shapley value method is proposed to minimize the final production cost by maximizing the profit of the factories when selling electricity to the main grid to obtain fair profit distribution.

The cooperative game theory using Nash bargaining solution has been applied in different areas to obtain a 'fair' solution. Yaiche et al. in [63] present a game theoretic framework to allocate bandwidth in high-speed network for the elastic services. The cooperative game theory, using Nash bargaining solution was proposed to provide the rate settings of the user that are Pareto optimal and consistent with the fairness axiom of game theory. In [78], a mathematical programming formulation for fair profit allocation between echelons in two-enterprise supply chain was presented. The authors considered the minimum profits of each participant and later obtained the objective function as the product of deviations from calculated and minimum benefit values. Gjerdrum, et al. in [79] also proposed a separable programming approach that uses game theoretic approach for fair profit settlement between supply chain partners. The paper uses Nash objective function to maximize the profit level of the enterprises. In [3], a game theory, Nash bargaining solution (NBS) was applied to minimize the cost of micro-grid for mutual cost distribution among the MG participants. Hao Wang et al. [18] presented the Nash bargaining theory to achieve fair profit sharing and energy trading among micro-grids. In [47], a multi-objective power management is modelled as a bargaining game. The proposed work uses game theory, Nash bargaining solution to find a unique and fair solution among different agents on the Pareto front of the optimization problem.

Cooperative game theory using generalized Nash bargaining solution has been applied in few areas to obtain a fair weighted solution. In [80], fair profit allocation supply chain optimization is proposed using revenue sharing policy to ensure total profit allocation and interest of individual participants in the supply chain is aligned so that overall supply chain performance is maximized. The approach uses generalized Nash type objective function, which takes into account the negotiation power of each participant in biofuel supply chain. In [81], a bargaining game based on one-pass RC scheme used for spatial H.264/SVC is presented. The optimal bit allocation solution is achieved using the generalized Nash bargaining solution obtained based on bargaining powers. Touati, C. et al. in [64] proposed a simple parametrization of the utility function using quadratic functions. A fairness approach is considered using generalized Nash bargaining solution for bandwidth allocation. It takes into account each connection of the assigned throughput and the utility that throughput represents.

In this thesis, a cooperative game theory using Nash bargaining solution with negotiation power is proposed to ensure fair profits distribution amongst the participants of micro-grid. The problem is nonlinear objective function, which is solved by using TLBO to optimize the product of the difference between the participant profits and the lower profits (i.e. status-quo profit).

2.5 Summary

In the chapter, the review of microsources related to energy management problem that is adequate for electricity in sites in remote communities has been presented. These microsources include diesel generator, renewable generation and energy storage system. A micro-grid is presented, in relation to the production of the local power generation, load consumptions and electricity price in the main grid. Both the axiomatic bargaining and strategic bargaining approaches to predict the outcomes of the bargaining problems are reviewed and discussed. Finally, fair settlement using game is reviewed. Based on the overview of existing works, a conclusion is drawn on the concept of cooperative game theory to address EMS and insight from the bargaining theory is utilized to address the problem of EMS in MG.

Chapter 3

Modelling of Micro-grid Components

Although modelling is not part of the contribution of the thesis but because the solar PV, battery and diesel generator are the main DERs used in the system and therefore need to be seriously considered.

This chapter introduces the modelling of components of micro-grid. In this research, the components to be modelled include solar PV system, energy storage system, diesel generator and the load.

3.1 Modelling of Solar PV Module

The optimum value of load is attained at a point where the power generated by PV cell is the maximum [82]. In a PV module, there are several number of series connected PV cells to ensure more energy is received than that which is converted by a single PV cell. The highest possible electrical efficiency is strived to be achieved by manufacturer of PV module by ensuring that the fabrication parameters of the PV cells are optimized. The current voltage (I/V) characteristic is one of the most characterization methods applied for PV cells, which is the main important parameters required of the PV module [82], [83].

3.1.1 Solar PV Module

A combination of solar cells forms a photovoltaic PV module, which may be in series or in parallel connection. Figure 3.1 shows the solar cell connections in a PV module. Both the solar cell module and PV module have a similar behavioural model.

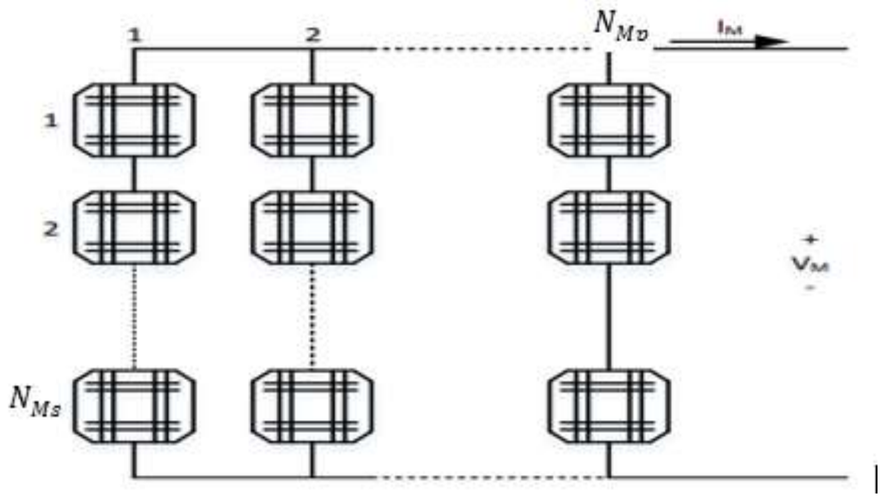


Figure 3.1: Solar cell connection in a PV module [84]

The behaviour of photovoltaic module is similar to the model of a solar cell. In a solar PV module, a series connection of appropriate number of solar cells increase the voltage while a parallel connection increases the current. When the solar cell is short circuited, the voltage across such solar cell is zero, thus, the current through the solar cell at that time is called short circuit current. The generation and collection of light generated carriers are due to the short circuit current. Therefore, the largest current to be drawn from solar cell is short circuit current. On the other hand, open voltage occurs at zero current, that is, when the solar cell voltage is at maximum. The amount of solar cell forward bias due to the bias of the solar cell junction with current due to the light generator corresponds to open circuit voltage.

The following equations are the derived solar cell equations

$$I_{Msc} = N_{Mp} I_{sc} \tag{3.1}$$

$$V_{Moc} = N_{Ms} V_{oc} \tag{3.2}$$

$$I_{Mmp} = N_{Mp} I_m \tag{3.3}$$

$$V_{Mmp} = N_{Ms} V_m \tag{3.4}$$

$$R_{Ms} = N_{Ms}R_s/N_{mP} \tag{3.5}$$

where M means module, I_{Msc} is the PV module short circuit current of a solar PV module, N_{Mp} is the number of parallel cells in PV module, V_{Moc} is the PV open circuit voltage of PV module, I_{Mmp} is the PV module maximum power point (MPP) current, V_{Mmp} is the PV module MPP voltage and R_{Ms} is the PV module series resistance (Ω).

3.1.2 Solar PV Array

A photovoltaic array has the characteristics similar to the one obtained in the photovoltaic module and solar cells. In this case, a combination of a PV module forms a PV array, which can be in series and in parallel connections. Figure 3.2 shows the connection of solar PV modules in a PV array. Both the PV array model and model of PV modules bear the same resemblance in behavioural model. The equations for the derived solar PV array is the same as those of the PV module, except for the use of an index A to replace index M, which stands for the array. The equations below are the PV array current and voltage equations [84].

$$I_{Asc} = N_{Ap}I_{sc} = N_{Mp}N_{Ap}I_{sc} \tag{3.6}$$

$$V_{Aoc} = N_{As}V_{Moc} = N_{Ms}N_{As}V_{oc} \tag{3.7}$$

$$I_{Amp} = N_{Ap}I_m = N_{Mp}N_{Ap}I_m \tag{3.8}$$

$$V_{Amp} = N_{As}V_m = N_{Ms}N_{As}V_m \tag{3.9}$$

$$R_{As} = \frac{N_{As}R_s}{N_{Ap}} = \frac{N_{Ms}N_{As}R_s}{N_{Mp}N_{Ap}} \tag{3.10}$$

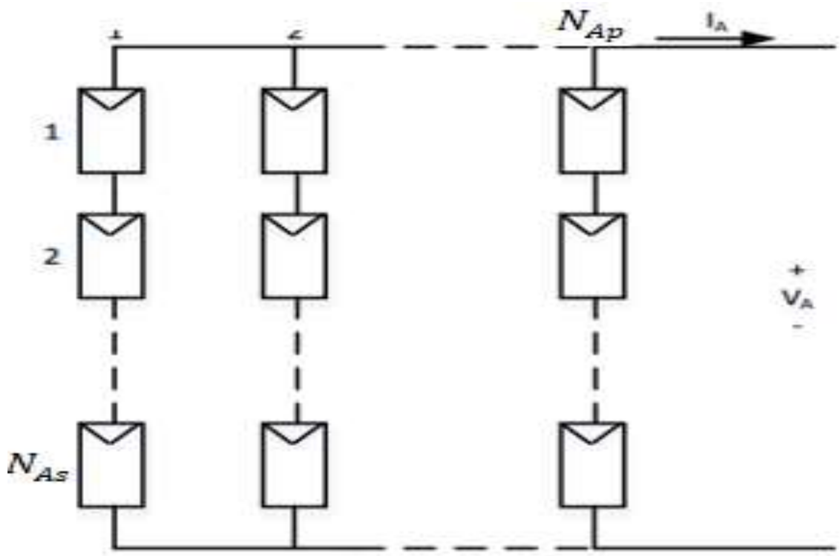
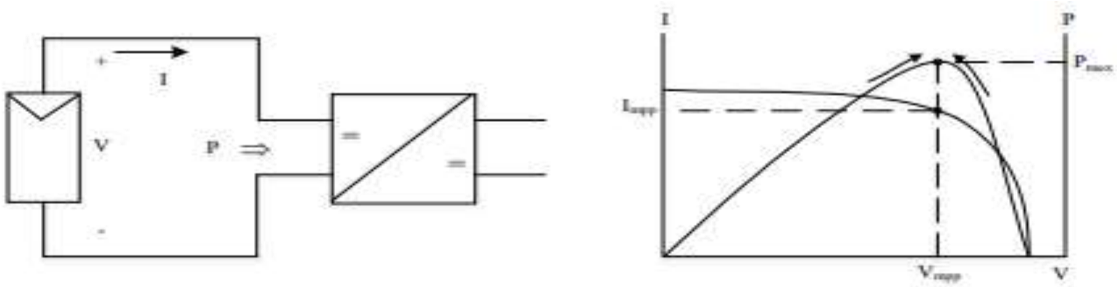


Figure 3.2: The Connection of Solar PV Modules in a PV Array [84].

3.1.3 Maximum Power Point Tracking

The power generated by PV module depends on the light intensity radiated by the sun. The maximum power point (MPP) of the PV array is the power at which the solar radiates maximum possible power, which is indicated in I-V and P-V characteristics curves. The maximum power is stochastic in nature and has to do with irradiance and temperature of the solar PV. Therefore, to utilize PV power efficiently, the use of the maximum power tracking (MPPT) comes to play [84], [85]. Figure 3.3 shows the basic principle of MPPT



(a) The Solar PV Power System (b) I-V and P-V Characteristics curve of the solar PV cell

Figure 3.3: The Basic Principle of MPPT [84].

The maximum power is delivered to the load by incorporating a DC-DC converter with an MPPT algorithm. As shown in Figure 3.3b, the two arrows indicate that the actual point can be tracked on either side so that maximum power can be obtained.

The main function of MPPT algorithm is to monitor the performance of MPP as the operating system condition changes. This can be achieved by ensuring that solar PV array terminal voltage is manipulated. Many algorithms can be applied to an MPPT; prominent among them are the constant voltage method, incremental conductance method, and non-linear function solution method. The type of algorithm that is applied to the application of MPPT in the thesis is incremental conductance algorithm, this is because of its high efficiency as it does not lead to excessive computational burdens.

3.2 Modelling of Battery

The solar PV is intermittent in nature and depends on solar irradiation during the day, but the load demand variation does not depend on availability of sunlight. The role of distributed storage sources is to ensure continuity of power supply to the load. Different forms of energy storage exists, such as flywheel, capacitor, and battery. The battery storage device is considered the most common type of storage widely in use, thus, it is used in this work.

In renewable energy system, lead acid battery is commonly used [84], [86]. Although, there are other types of batteries, some of them are off-shelf items and are more expensive. Prominent among them are lithium-ion ($Li - ion$), nickel-cadmium ($NiCd$) and nickel-metal-hydride ($NiMH$). For the energy storage element, the selection of lead-acid battery depends on its characteristics and the costs.

3.2.1 Characteristics of Battery

The lead-acid battery is made of two plates, anode (positive) and cathode (negative). The negative is composed of lead (Pb), while the positive is made of lead dioxide ($Pb02$).

At the charging mode, the flow of current into the battery is at the positive terminal, thus, there is a gradual increase in battery voltage and store charge. While decreasing, when in discharging mode and the flow of current out of the battery is at the positive terminal. For a battery to be in a better position, there are undercharge mode and overcharge mode [84], [86].

For the undercharge mode, the battery charge has gone below the minimum recommended value and the circuit conditions enabling the discharge of the battery. The action of battery in this mode results in a fast reduction of the electrolyte internal density, which result in forming sediments at the bottom of the battery element. In this case, there is a reduction in capacity of battery and this may lead to irreversible damage [84], [86]. For the overcharge mode, the battery has gone beyond the recommended maximum value and stores no more charges at this time. This will reduce the capacity of the battery and will reach saturation by further charging. The characteristics of batteries with different mode of operations are shown in Figure 3.4.

The following three main parameters are specifically used to rate and define a battery [84]:

1. the nominal capacity of the battery C_b
2. the rate of charge and discharge
3. the state of charge

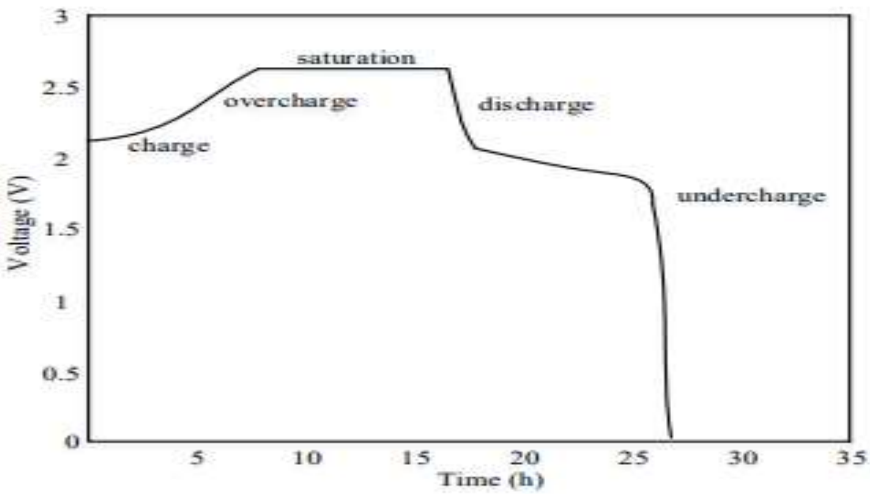


Figure 3.4: The characteristics of Battery with Different mode of Operation [84].

The nominal charge, which a battery can store, is referred to as the nominal capacity. This is normally specified by the manufacturers. At a given period and a given discharge rate, and temperature, the charge delivered by a battery is called measured parameter. The time of charge is related to the battery nominal capacity. The following hours represent the discharge duration provided by the manufacturers, 5hours, 10hours, and 100hours.

The charge and discharge rates of a battery are the relationship between the nominal capacity and the charge or discharge current. At constant current, the time the battery takes to discharge is called the discharge rate of the battery, while the charge rate is the duration it takes to charge up at a constant current. The state of charge SOC is discussed in [87], [88]. The variation of the charge is taken into consideration and is expressed in terms of temperature and current [88]. The battery SOC is expressed as follows [88]:

$$SOC = \frac{C(t)}{C_{ref}(t)} \tag{3.11}$$

where $C_{ref}(t)$ is the reference capacity of battery, $C(t)$ is the battery capacity.

- State of Health (SOH)

  The battery state of health is expressed as follows [88]:

$$SOH(t) = \frac{C_{ref}(t)}{C_{refnom}} \tag{3.12}$$

where C_{refnom} is the normal reference capacity of battery as provided by manufacturer data. At each step size, if the battery's capacity is a discharge, the reference capacity can now be expressed as

$$C_{ref}(t) = C_{ref}(t + \Delta t) - \Delta C_{ref}(t) \tag{3.13}$$

where $\Delta C_{ref}(t)$ is the losses of reference capacity which according to depth of discharge are considered linear [87].

The losses are calculated as follows:

$$\Delta C_{ref}(t) = C_{refnom}.Z(SOC(t - \Delta t) - SOC(t)) \tag{3.14}$$

The SOH can be deduced from (3.12), (3.13), and (3.14) as follows:

$$SOH(t) = \frac{C_{ref}(t-\Delta t)}{C_{refnom}} - Z(SOC(t - \Delta t) - SOC(t)) \tag{3.15}$$

where Z is the linear ageing coefficient.

3.3 Modelling of Diesel Generator

Many methods were proposed for the modelling of diesel generator [89], [90], [91], [92]. The fuel supplied to the diesel generator to maintain a specific range of speed can be regulated through an engine governor working as a sensor by comparing the difference between the actual speed and the desired speed. If a different exists, a speed command is given to adjust the governor setting and the speed will be maintained within the specific range.

A model of the fuel actuator system is represented using a first order phase-lag in which the network is characterized by time constant τ_2 actuator torque constant K_2. The fuel flow given by $\emptyset_{(s)}$ in (3.16) is shown in Figure 3.5. This represents the output of the actuator, having the input current I_s

$$\emptyset_{(s)} = \frac{K_3 K_2}{1+\tau_2 S} I_s \tag{3.16}$$

where K_3 is the current driver's torque constant.

After a time delay, τ_1 and torque engine constant, there is a conversion of fuel flow into mechanical torque $T_{(s)}$, which is represented by transfer function model of (3.17) as shown in Figure 3.6. Typical values for K_1, K_2 and K_3 are given as 1.15pu, 1pu and 1pu respectively [90].

$$T_{(s)} = \emptyset_{(s)} K_1 e^{\tau_1 S} \tag{3.17}$$

where K_1 is the engine torque constant.

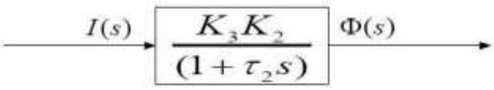


Figure 3.5: The Model of Actuator and the current driver constant

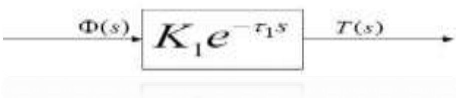


Figure 3.6: The Engine Model [92]

The speed of the engine is automatically controlled by mechanical or electromechanical device, known as 'governor'. Many types of governors exist, such as direct mechanical, microprocessor based, mechanical-hydraulic, and electro-hydraulic electronics [92], [93]. The complex dynamic effects of parameters, which are represented by 'flywheel', are angular speed of flywheel w_m, the inertial, the loaded alternator, and the viscous friction coefficient ρ. The model of the system is able to filter out noise effect and large proportion of the disturbance by the use of an integrator with flywheel accelerator constant J. In [90], an integrator is proposed to be inserted in between reference signal and engine actuator. Figure 3.7 represents diesel engine system block diagram, which indicate the way of eliminating the speed drop. In this case, the speed drop in the steady state operation needs to be eliminated by ensuring that the order of the whole system is raised.

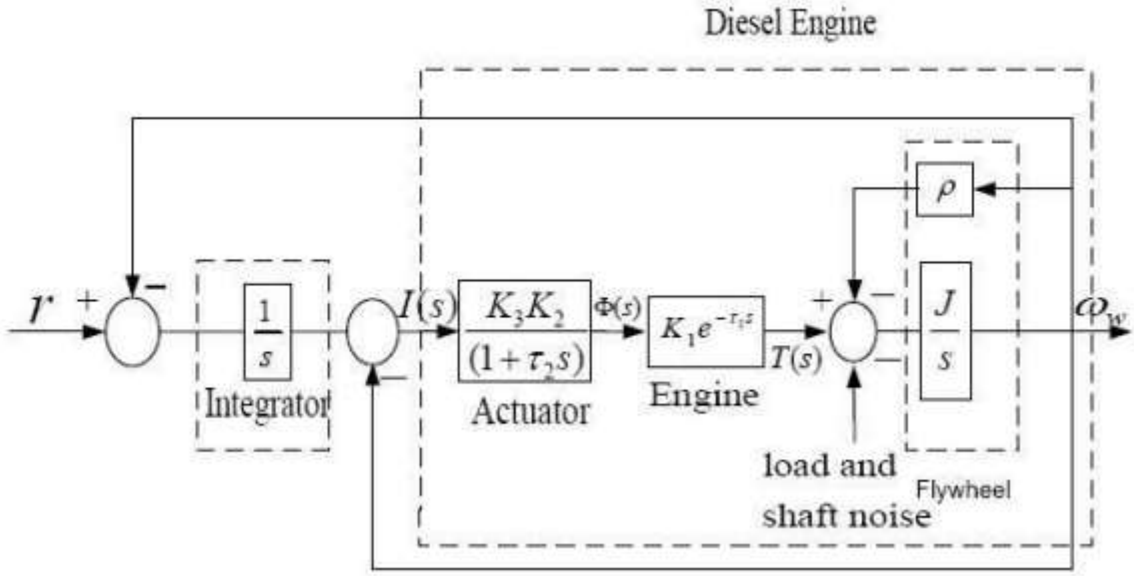


Figure 3.7: The Block Diagram of Diesel Engine System [92]

For a set up of a particular engine, the values of K_2 and K_3 are kept constant. The parameter K_3 represents the gain that determines the amount of mechanical torque obtained per unit of fuel flow. The temperature of the oil that is flowing to the actuator depends on time constant τ_2. The variation of variables K_2 and τ_2 is negligible at certain interval [90]. The torque of engine multiplied by a time delay is commonly represented by a combustion system [90], [92], [94]. There are three components of the dead time:

- The 'power stroke delay' is the time from which there is a change in actuator signal until any cylinder has fuel injected to it.

- The analogous of characteristics ‘combustion delay’ which is the time taken to burn the fuel in a cylinder in order to produce a torque output.
- The effect of multi-cylinder nature of the prime-mover, which represents the time taken to produce the required number of cylinder for a new torque level to allocate to the prime-mover.

3.4 Load Modelling

There is complexity in modelling a load because of the large number of connected appliances such as heater, refrigerator, and air conditioner. Therefore, modelling of exact load tends to be difficult. Moreover, many factors such as the weather condition, time of the day and economy contribute to the load changes [95], [88]. Two types of load model are identified: the static model and dynamic model [95]. When modelling load in a static condition, it is always modelled in terms of magnitude and frequency of bus at that instant.

The load modelling is used in areas of the voltage stability, long-term stability and inter-area oscillations [95], [88]. Statistics of basic electricity demand profile as adapted from [3] is shown in Table 3.1. This table presents statistics data of annual electricity demand. The residential building has the highest annual electricity demand and the same time highest peak power demand, which occurs between the periods of 6.00pm to 10.00pm, when workers return home from work. In addition, the lowest annual electricity demand is fire station and at the same time having the lowest peak power demand, which occurs between the periods of 9.00am to 6pm as shown in appendix A.

Table 3.1: Statistics Data of Annual Electricity Demand.

	School	Hotel	Restaurant	Fire Station	Residential Building	Hospital	Total
Annual Electricity Demand (kW)	49859	66028.5	90082	37631.5	68036	45004.5	456641.5
Electricity Peak Demand (kW)	10.7	11.6	17.7	6.8	18.6	7.2	0

CHAPTER 4

Optimization Model for Energy Management

The problems associated with the classical optimization methods have led to the development of non-conventional methods. The traditional methods can be divided into two distinct methods: direct search methods and gradient-based methods. These optimization methods are used to solve a large number of problems in engineering and are popular because they are efficiently used in solving problems with many design variables [96]. Some of these methods are very slow and requires many evaluation functions for the system to converge. Classical methods usually have a solution either exists or does not exist. These methods cannot cope with the uncertainty because the main feature of the application of these approaches is unpredictable and uncertain [96].

Generally, the disadvantages of the nonlinear and non-convex programming are the complexity of the design and convergence problems. For example, in Newton based technique, the system may fail if the initial conditions are not properly selected and therefore no convergence is achieved. In interior point method, the solution may not be feasible in its non-linear domain; this also has the problem of initial conditions, the termination problems and may not be able to solve nonlinear problems [97]. While solving complex problems, the classical methods are often trapped in a local optimum.

Lambda-iteration method is considered as one of the most popular traditional techniques to solve minimization and maximization problems in economic load dispatch [98]. It gives a decentralized solution to economic load dispatch method [99]. The method relies on local optimum solution convergence or divergence altogether. The procedure first assumes the starting value of Lambda and a small change in Lambda. Penalty factor and total profit is evaluated. Then, iteration is performed several times to obtain the solution. However, the Lambda iteration method has a slow convergence (as it converges slowly) [100]. To worsen the situation, the algorithm exhibits pathological behaviour, which implies that the correct solution is reached a long time after the solution has been stabilized [99].

The heuristic methods can be divided into different distinct groups based on different considerations such as iteration based, population based, deterministic, etc. The methods developed are in two groups: swarm algorithms and evolutionary algorithms. There are different variants of evolutionary algorithms such as genetic algorithm (GA), differential evolution (DE), evolutionary strategy (ES), and evolutionary programming (EP). For the swarm algorithms, there are particle swarm optimization (PSO), Artificial bee colony (ABC), shuffled frog leaping (SFL), ant colony optimization (ACO), algorithm, etc., are typical examples [101], [102].

The population size, elite size, and number of generations/iterations are the parameters used in GA and PSO algorithms, which constitute the common controlling parameters. In addition, they also required specific control parameters for their individual algorithms. In GA, for instance, the use mutation rate and crossover probability are employed, whereas PSO uses inertia weight as well as cognitive social and parameters [103]. It is important that the algorithm specific-parameters be properly tuned as lack of proper tuning may result in solution being trapped at local optimal. The latest approach of PSO and GA are not chosen because we want to compare the “standard” TLBO to the standard GA and PSO for consistency.

Genetic algorithm is a heuristic evolutionary algorithm that obtains optimal solution through a search space. GA has a unique feature of a procedure for searching a solution. The GA is a powerful tool that obtains the best solution by creating a population of possible solutions to a particular problem through a number of generations [104], [105]. GA works through three processes: selection, crossover, and mutation. The selection operator determines the likely times the chromosome will be chosen to reproduce [100].

The GA works; coding space (genotype) and solution space (phenotype) through two alternative spaces [106]. In GA, mapping of the object variables to a string code is represented by encoding function and decoding function is used to represent mapping of string code to its object variable. Encoding can be classified into 1-dimensional and 2-dimesional depending on the structure of encoding. The 1-dimensinal types are binary, octal, hexadecimal, permutation and value encoding, while 2-dimensional type is Tree encoding [106], [107].

Binary encoding is most common form of encoding, which is used in this research work. A binary structure is used to represent each chromosome.

The procedures in solving problems in GA are as follows

1. Determine a population.
2. Perform the following operations until the system converges.
    a. Determine a new-pop, which is referred to as empty pop
    b. Perform the following operation when new-pop is still having space.
        i. One at a time, randomly select two individuals from pop one at a time,
        ii. To produce new individuals by using crossover operator.
    c. Randomize the process of individual in new-pop which will change one part of generation i.e. mutation
    d. Get a new-pop to dislodge the old pop.

3. With highest fitness value, the individual from pop should be selected as the solution to the problem.

The population is always taken as a candidate solution in the algorithm. A single solution is otherwise called individual in a population. The measure of fitness of an individual is based on good performance of the solution represented by the individuals. The process of selection is comparable favourably to the survival of the fittest. Selection of fitness for crossover depends on the selection process. The fitness of the individual depends on the survival of the individual from one generation to another. The production of two new individuals is because of crossover, which occurs due to the mixing of the solution together. There is tendency for each individual to mutate during each generation, which may cause the individual to change.

In this work, the GA uses the real value coding. The main operations of GA are as follows:

1. Population:

   The possible solutions of population are created in the algorithm to obtain the best solution by evolving over multiple generations.

2. Fitness

   In this thesis, we tried to maximize the participant's profits. When the profit is higher the fitness of the participants will be correspondingly higher. To achieve the fitness, we ranked the solution in order of 'best' to 'worst'.

3. Selection

   In this operator, the solutions are selected from the current population, which in turn form the next population of solutions. This work uses as much as possible, a convergence and a small building simulation. From the population, n-solutions and the winner solution are selected randomly by the tournament operators, thus, exhibiting a better ranking, out of the tournament for necessary recombination.

4. Crossover

   The mixing of genetic information' is being controlled by recombination operators which are obtained from the paired individuals through a process known as 'crossover'. This occurs when the bits value between the two individuals are swapped. In this work, efforts are made to use uniform crossover operator and each pair of bits (i.e. the number of bits swapped will be an average of 50%) swaps a probability of 50%

5. Mutation

   In mutation operation, the genetic diversity is maintained from one generation of a population of genetic algorithm chromosomes to the next. From the previous solution, in mutation, there may be a change in solution. In this case, better solution is achieved by using mutation. One or more gene values in chromosomes are altered by mutation from its initial state. GA uses the operator to produce a better solution. In this work, the values of the gene were replaced with a uniform random value by using the non-uniform mutation type.

6. Elitism

   Elitism is used to automatically re-initialize the search whenever there is a collapse of the population to form a single solution. This, in essence, is used to guarantee the continuity of the search until simulation reaches a specific value.

In this thesis, a population size of 60, the number of generation is 300 were used and the rationale behind choosing these parameters is justified in the simulation results describe in section 5.7. The flowchart for general GA is shown in Figure 4.1

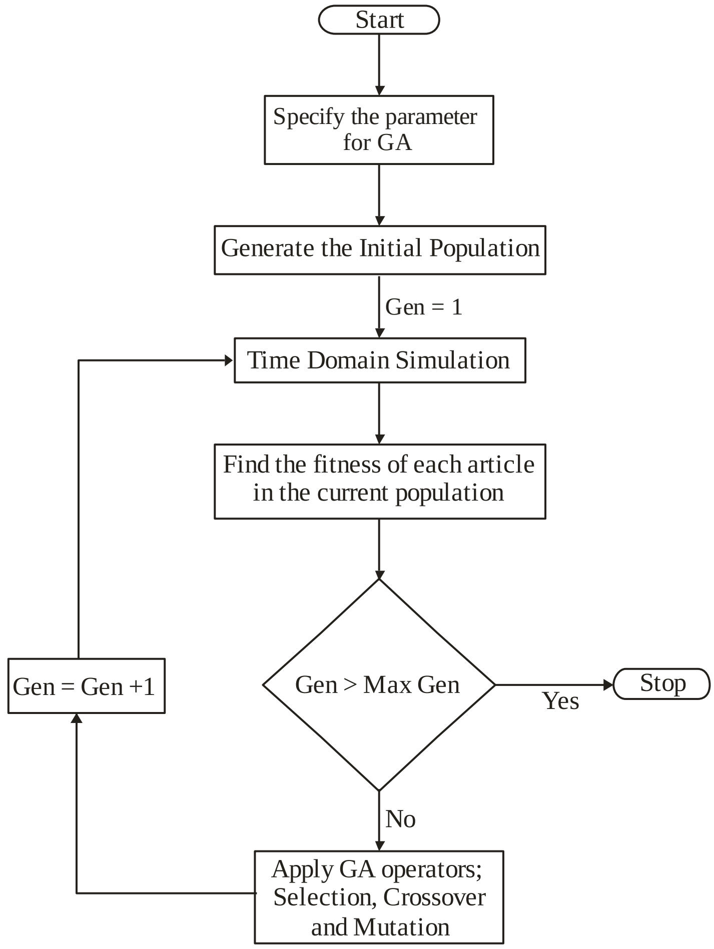


Figure 4.1: Flowchart for Genetic Algorithm

Particle swarm optimization technique is a population-based optimization technique and is inspired by a social behaviour of bird flocking or school fishing [23], [108], [109]. The particles are initialized in PSO, in the search space. For each particle in the swarm, the first thing is to ensure that the initial position of the particle is updated and later evaluate the objective function. The movement of particle in the search space is determined using the best solution ($pbest$) of the individual particle, swarm particle's best solution ($gbest$). After moving all the particles, the next generation/iteration commences. Optimal solution will be moved like a flock of bird searching for food. The flowchart for general PSO is given in Figure 4.2

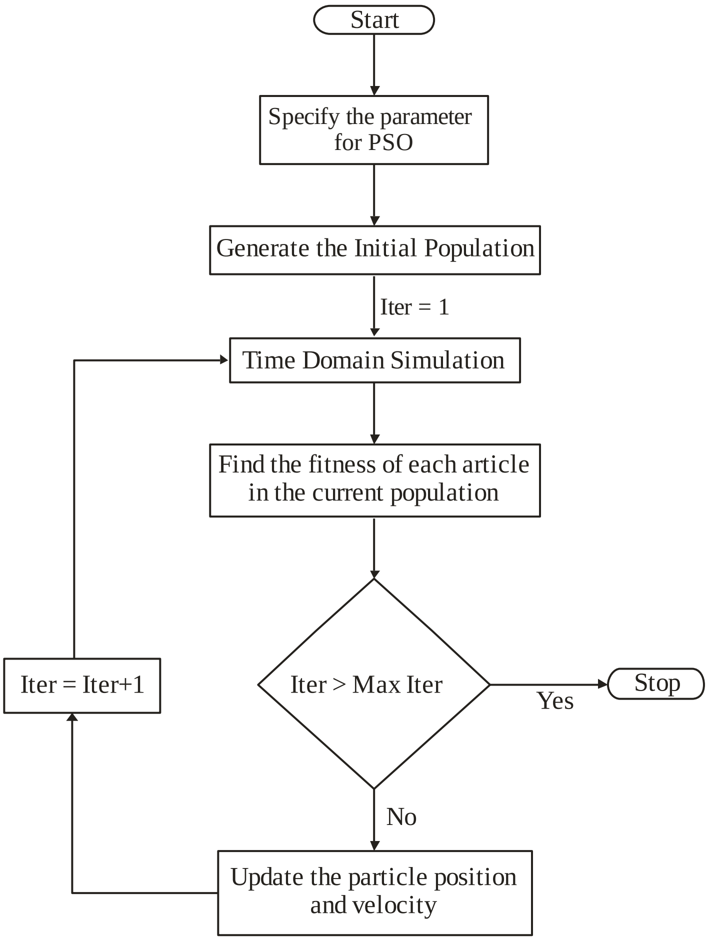


Figure 4.2: Flowchart for Particle Swarm Optimization

The general equations (4.1) and (4.2) given below are used to update the velocity and new position.

$$v_i(t+1) = v_i(t) + c_1 r_1 (pbest - x_i\,(t) + c_2 r_2 (gbest - x_i\,(t)) \tag{4.1}$$

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

where $r_1$and r_2 represent random selected number between 0 and 1, c_1, and c_2 are the inertia parameters, x_i is the particle position during iteration. The use of $pbest$ and $gbest$ make the velocity of each particle to update by using equation (4.2).

The main goal of this energy management is to develop the MG with many participants (which could be residential and commercial loads) to utilize the resources efficiently by cooperating with each other for mutual benefits. Figure 4.3 shows different participant's sites of micro-grid

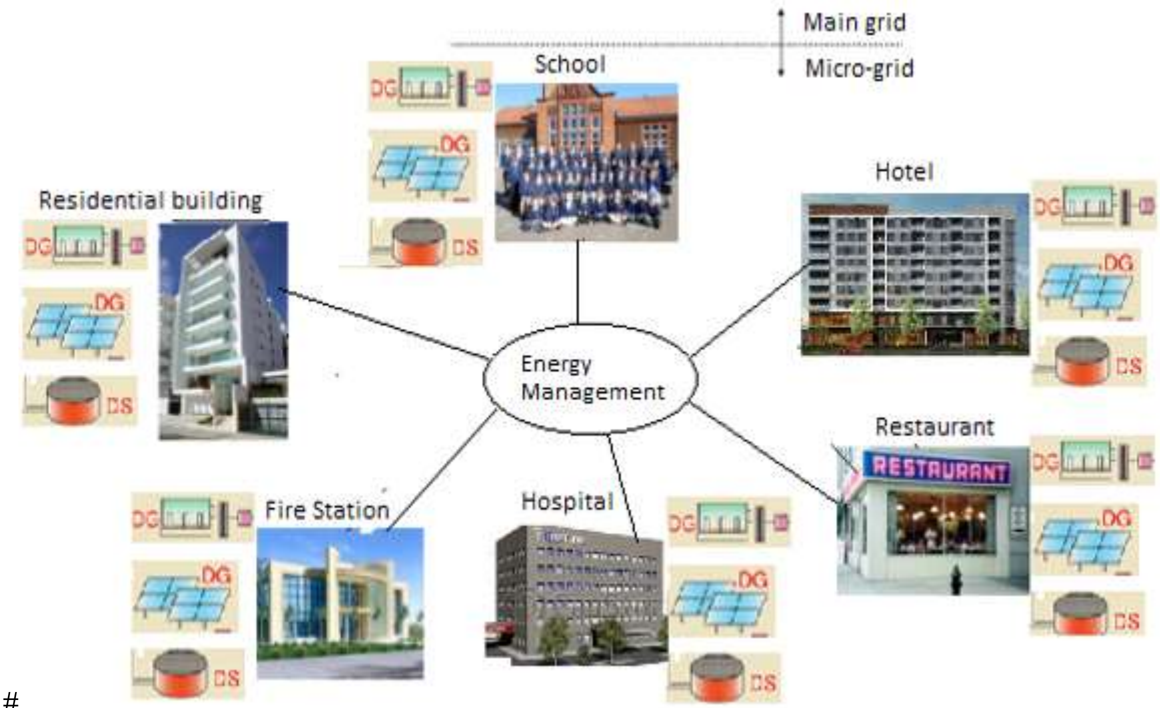


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Figure 4.3: Participants of a Micro-grid [3]

. In this chapter, an optimization formulation and model that could be used in energy management based on different market policies are described. Game theory based on the generalized NBS is used to obtain fair allocation of utility. Lastly, the application TLBO algorithm for solving energy management problem is presented.

4.1 Optimization formulation

In this research, an optimization problem has been developed. A micro-grid, which involved 6 participant's sites, is considered. The sites are school, hotel, restaurant, fire station, residential building and hospital. For each of the participant's sites, the following information is used:

- an hourly load forecasting
- equivalent lifetime lower profit EP^Lor status-quo profit
- solar PV generation hourly forecasting
- energy resources, e.g. diesel generator, solar PV, and battery storage source.

- a grid-connected mode, which enables energy import and export
- an islanded mode, which enables MG to manage its own local generation

Energy production is modelled by using the following information:

- the period of the day is partitioned into a number of reasonable intervals
- electricity demand profile on an hourly basis for each participant
- the battery charge and discharge rate
- weighting factors for day type (this will enable the model to accommodate a certain number of days in winter and summer periods)
- different transfer prices and negotiation power indicator

The optimization problem is formulated based on the assumed market scenarios as adapted from [88]. In the first scenario, the assumption is that there is a connection from MG to the main grid and therefore, controls the power, thus, there is power exchange between the main grid and the MG. In the second scenario, the MG is islanded and has no connection with the main grid but has diesel generator as back up.

Market Scenario 1

In this scenario, there is energy exchange between the main grid and the MG, i.e., purchase and sales of power from/to the main grid. The expectation of MG is to maximize the profit from the power trade with the main grid. The micro-grid central controller has the following information [88], [110].

- the price of electricity purchased from the main grid is fixed at $0.17 and the price sold to the main grid is fixed at $0.0131 as adopted from [3].
- demand of power by each participant's site
- the bids for each participant's site

The micro-grid central controller provides

- micro-sources set points for each site in the MG
- energy exchange between the participants of MG
- power bought from the main grid
- power sold to the main grid

The objective function is to maximize the total profits of all the participants of MG

$$max\ (f_{(x)} = (Income - Expense)) \tag{4.3}$$

The Micro-grid central controller (MGCC) transferred energy within the MG at an agreed transfer price. The MGCC also sells excess energy to the main grid. If the local generation in the MG cannot cope with the load demand, the main grid will sell energy to the MG and in turn will sell to the MG participants. The income is calculated as follows:

$$\text{Income} = A_1 \sum_{s=1}^{N} X_s \ + A_1 \ \sum_{s=1}^{N} X_y \tag{4.4}$$

where A_1 is the price of the active power selling to the grid (in \$/kW), X_s is the active power of DERs (in kW) that is sold to the grid, X_y is the active power of DERs that is sold to other players.

The expenses referred to the amount of power sold to the MG from the main grid, the costs of active production power consumed, cost of the power transfer from other players. This is expressed as

$$\text{Expenses} = A_2 \sum_{s=1}^{N} tabX_d + A_2X_g + \ A_2 \sum_{s=1}^{N} tab\ X_p \tag{4.5}$$

where tab is the total active bid, X_d is the production power (active power) of the DERs consumed (kW), X_g is the active power purchased from main grid (kW), X_p is the active power purchase from other players (kW)

In this case, we can express the objective function as follows

$$maximize\ (A_1 \sum_{s=1}^{N} X_s + \sum_{s=1}^{N} A_1 . X_y\ - A_2\ (\sum_{s=1}^{N}\ ab\ X_d + X_g + \sum_{s=1}^{N} tab\ X_p)) \tag{4.6}$$

Where *ab* is the active bid

The constraints for the optimization are

- limits of micro-generations
- the active power balance of the system in MG

$$\sum_{s=1}^{N} X_d\ \ + X_g + \sum_{s=1}^{N} X_p\ \ = P_{demand} \tag{4.7}$$

Market Scenario 2

In this scenario, the MGCC is islanded and uses its local generation only to meet the active power demand. MGCC is provided with the following:

- the demand for active power
- the price for both active power supply and demand
- the demand bids

where

$$\text{Income} = \ A_1 \sum_{s=1}^{N} X_y \tag{4.8}$$

The expense in this case is the total costs of active power generated, cost of the power transferred from other players and the other relevant costs.

$$Expense = \sum_{s=1}^{N} tab\ (A_2 X_d + A_2 X_p\ ) \tag{4.9}$$

The optimization problem constraints are given as follows:

- technical micro-sources limits, which contain maximum and minimum bounds of operation.

- active power balance of the system in islanded MG

$$\sum_{s=1}^{N} X_d + \sum_{s=1}^{N} X_p = P_{demand} \tag{4.10}$$

where P_{demand} is the active power load demand

4.2 Optimization of Energy management of MG

Maximization of the profit of all the participants is the main objective function. It consists of costs of necessary payment and initial investment of the project throughout the lifetime of the installation. In this case, we considered the lifetime of components to be the same apart from battery storage unit (since it needs replacement during the project lifetime). In this thesis, we proposed the annual cost of the systems with the following elements [88].

- The cost of installation of solar PV system, diesel generator and battery unit
- The cost of replacement of battery during the project lifetime.
- The battery and solar PV maintenance costs.
- The cost of fuel consumption for diesel generator during the project lifetime.
- The operation and maintenance cost of diesel generator.

In islanded mode, the diesel generators, solar PVs and battery storage units meant for the participants of micro-grid in the sites have been employed, whereas in the grid-connected mode diesel generator is absent. In the grid-connected mode, the possibility of transferring excess energy produced from one site to another or sold to the main grid at a certain agreed price is considered. In the next subsection, the objective function, constraints, and TLBO approach for energy management will be considered in both grid-connected and islanded mode.

4.2.1 Objective Function

A Economic Model in grid-connected mode

Before considering the objective function, we need to first obtain the system annual income and annual cost.

In grid-connected mode, the distributed energy resources used are the solar PV, battery storage unit and the main grid.

(a) Annual income of the system in grid-connected mode

Energy is transferred within the MG participants and the excess is sold to the utility grid with the agreed price. The term 'income' is estimated as follows:

$$I_{gs} = TSC_{gs} + SC.GES \tag{4.11}$$

where I_{gs} is the total income of the participants, TSC_{gs} is the transfer micro-grid selling cost in grid-connected mode for site s, SC is the sell coefficient, and GES is the grid electricity selling price to the main grid.

$$GES = \sum_{t,p} C^e \, W_p T_t E_{tps} \tag{4.12}$$

where C^e is the price of exported electricity to the grid, W_p is the weight of day t, T_t is the time duration of each time period p, and E_{tps} is the electricity exported to the grid.

$$TSC_{gs} = \sum_{t,p,s'} W_p \, T_t E_{ss'} y_{tpss'} \tag{4.13}$$

where $E_{ss'}$ is the electricity transfer price from site s to site s' and $y_{tpss'}$ is the electricity transferred on day t at time p from site s to site s' *(b) Annual cost of the system in grid-connected mode*

The system annual micro-grid cost (AC_{gs}) in the grid-connected mode for site, s includes the annual capital cost (ACC_{gs}), annual operation and maintenance cost (AOM_{gs}), annual replacement cost (ARC_{gs}), the MG buying cost (TBS_{gs}), and the cost of purchasing energy from the main grid (GBC_S). AC_{gs} is estimated as follows:

$$AC_{gs} = ACC_{gs} + AOM_{gs} + ARC_{gs} + TBS_{gs} + GBC_S \tag{4.14}$$

where

- the annual capital cost is calculated as follows [88]:

$$ACC_{gs} = \ (C_{cap,})CRF(i, y) \tag{4.15}$$

in which

C_{cap} represents the capital cost (US \$), CRF denotes the capital recovery factor, i is annual real interest rate (12% interest rate is applied in this work), and y is the project lifetime in a year. The CRF is calculated as follows [111]

$$CRF = i\,\frac{(1+i)^y}{(1+i)^y - 1} \tag{4.16}$$

- The annual operation and maintenance cost (AOM_{gs}) of the MG is a function of the capital cost C_{cap} component reliability(λ), and project lifetime. This is calculated as follows [88].

$$AOM_{gs} = C_{cap}\,\frac{1-\lambda}{y} \tag{4.17}$$

- The annual replacement cost (ARC_{gs}) is the cost of the replacement of a certain equipment during the project lifetime. In grid-connected mode the equipment that needs replacement is battery unit. This is calculated as follows [112].

$$ARC_{gs} = (C_{rep})SFF(i, y_{rep}) \quad (4.18)$$

where

C_{rep} represents the replacement cost of battery units in US \$, y_{rep} is the battery lifetime. In this work, the replacement cost is the same as battery capital cost. SFF represents the sinking fund factor, a ratio that is used to determine the future value of a series of equal cash flows. This is given as follows [112].

$$SFF = \frac{i}{(1+i)^{y_{rep}}-1} \quad (4.19)$$

It is common to confuse when first determining the battery storage system costs. Some of the major contributions to the battery costs are the chemical materials that make up the battery, the life cycle of battery, the storage capacity, and the usable capacity. These factors can determine the costs of battery. With the regards to this research work, the annual cost of battery replacement is determined from (4.18).

- The transfer micro-grid buying cost (TBS_{gs}) represents the cost of buying electricity among the participants of MG. This is determined in [3] as follows:

$$TBS_{gs} = \sum W_p\, T_t E_{s's} y_{tps's} \quad (4.20)$$

where

$E_{s's}$ is the price of electricity transferred from site s' to site s and $y_{tps's}$is the quantity of electricity transferred on a day p at time t from site s' to site s.

- The main grid buying cost (GBC) is calculated in [3]as follows:

$$GBC_S = \sum_{t,p} C^i\, W_p T_t I_{tps} \quad (4.21)$$

where C^i is the price of electricity exported to the main grid, I_{tps} and is the quantity of electricity imported from the main grid. W_p and $T_t$are defined as before.

The profit (P_{rgs}) of the grid-connected MG is expressed as

$$P_{rg} = I_{gs} - AC_{gs} \tag{4.22}$$

The function (F_{xg}) is the surplus which is also referred to as profit can be calculate as follows:

$$F_{xg} = \prod_{s=1}^{6}(P_{rgs} - P_{rgs}^{L})^{\alpha_s} \tag{4.23}$$

where

P_{rgs}^{L} is the lower bound profit (otherwise called status-quo profit) of the participants for site s in grid-connected mode and α_s is the participant negotiation powers. Since there are 6 sites, then *S= 1,...6*

The objective function of the system in grid-connected mode is to maximize the profit i.e.

$$\text{Max}\{F_{xg}\} \tag{4.24}$$

B Economic Model in Islanded mode

(a) Annual income of the system in islanded mode

The annual income (I_{ds})of the participants in islanded mode of operation of MG is as follows:

$$I_{ds} = TSC_{ds} \tag{4.25}$$

where

TSC_{ds} is the transfer micro-grid selling cost in islanded mode.

In this case, the same calculation holds as in (4.13) i.e. $TSC_{ds} = TSC_{gs}$

(b) Annual cost of the system in islanded mode. The term annual cost (AC_{ds}) of the MG includes the annual capital cost (ACC_{ds}), annual operation and maintenance cost (AOM_{ds}), annual replacement cost (ARC_{ds}), annual fuel cost of DG (AFC_{ds}), the MG buying cost (TBC_{ds}).

AC_{dS} is estimated as follows:

$$AC_{ds} = ACC_{ds} + AOM_{ds} + ARC_{ds} + AFC_{ds} + TBC_{ds} \tag{4.26}$$

- The annual capital cost, annual operation and maintenance cost of solar PV and diesel generator are calculated as in (4.15) and (4.17).
- In addition, annual replacement cost of battery and transfer micro-grid buying cost are calculation as in (4.18), (4.19), and (4.20) respectively.
- The annual fuel cost ($\mathrm{AFC_{ds}}$) is related with the generated power and the rated power. In this case, diesel should be operated at a rated power. Annual diesel generator cost is the same as annual fuel cost and is calculated as follows:

$$AFC_{ds} = C_f \sum_{i=1}^{8760} F(t) \tag{4.27}$$

where C_f is the fuel cost per litre.

$F_{(t)}$ is the hourly consumption of diesel generator. This is expressed as follows [113]:

$$F_{(t)} = 0.246P_{DG}(t)+0.08415P_R \tag{4.28}$$

where P_{DG} is the diesel generator actual power output in kW and P_R is the rated (nominal) power of the generator.

The profit (P_{rds}) of MG in islanded mode is expressed as

$$P_{rds} = I_{ds} - AC_{ds} \tag{4.29}$$

where I_{ds} and AC_{ds} are defined as in (4.25) and (4.26)

Table 4.1: Economic Data for energy management in both grid-connected and islanded modes, [3], [19]. [88].

S/N	Item Description	Value
1	Project lifetime (years)	20
2	Interest rate (%)	3
3	Inflation rate (%)	1.6
4	Inverter lifetime (years)	20
5	PV panel lifetime (years)	20
6	Reliability of Inverter (%)	98
7	Reliability of PV panel (%)	98
8	Reliability of diesel generator (%)	90
9	Cost of diesel generator (US $/kW)	500
10	Cost of PV panel (US $/W)	1830
11	Cost of Inverter (US $/kW)	138
12	Fuel cost (C_f) (US $/l)	0.55
13	Cost of the battery (US $/l)	200
14	Reliability of battery (%)	98

The function (F_{xd}) is the surplus which is also referred to as profit and can be calculated as follows:

$$F_{xd} = \prod_{s=1}^{6}(P_{rds} - P_{rds}^{L})^{\alpha_s} \tag{4.30}$$

where P_{rds}^{L} is the lower bound profit (otherwise called status-quo profit) of the participants for site s in islanded mode.

The objective function of the system in islanded mode of MG is given as:

$$\text{Max}\{F_{xd}\} \tag{4.31}$$

4.2.2 Constraints

A Constraints in grid connected mode

a. Electricity demand constraints:

At a certain time interval, electricity demand is equal to the output of solar PV, battery, quantity of electricity transferred from other locations/sites and imported electricity from the main grid minus quantity of electricity transferred to other sites and electricity exported to the main grid.

$$\sum_{s\prime} y_{tps\prime s} - \sum_{s'} y_{tpss'} + I_{tjs} - E_{tps} + P_{B_S}(t) + P_{pv_s}(t) = L_{tpgs} \qquad (4.32)$$

where $y_{tps's}$ is the electricity transferred from other sites, $y_{tpss'}$ is the electricity transferred to other sites, I_{tps} is the electricity imported from the grid, E_{tps} is the electricity exported to the grid, $P_{B_S}(t)$is the battery energy at time t and $P_{pv_s}(t)$ is the solar PV power at time t.

b. Transfer price level

Generally, in MG, electricity transfer price cost is non-linear. In this work, we applied the following formulation to convert it to a linear equivalent. The assumption is that the electricity transferred between locations have transfer price levels that are discrete in nature i.e. k discrete. Therefore, price $E_{ss\prime}$ between two locations is expressed by the product of the decision variable $X_{ss\prime k}$ and the parameter $E_{ss\prime k}$ and summed it over all the transfer price levels.

$$E_{ss\prime} = \sum_k E_{ss\prime k} X_{ss\prime k} \qquad \forall s, s' \qquad (4.33)$$

One transfer price level at most must be chosen at a time i.e. at certain particular time, only one transfer price can be used for all the participant sites.

$$\sum_k X_{ss\prime k} \leq 1 \qquad \forall s, s' \qquad (4.34)$$

For each pair of site and between two transfer directions, electricity transfer prices are the same.

$$X_{ss\prime k} = X_{s\prime sk} \qquad \forall s, s' \qquad (4.35)$$

c. Electricity transfer amount

The total amount of the electricity transferred $y_{tpss\prime}$ is equal to the sum of the amounts that is transferred at each transfer price level k i.e. transfer price levels such as (0.039, 0.049…0.109) \$/kWh as shown in Tables 5.13 to 5.18

$$y_{tpss'} = \sum_k Y_{tpss'k} \qquad \forall t, p, s, s' \tag{4.36}$$

$$Y_{tpss'k} = y_{tpss'}\, X_{ss'k} \qquad \forall t, p, s, s', k \tag{4.37}$$

The upper bound of the electricity to be transferred from one site to another has been introduced, so that the linear transfer amount at k transfer price level given by $Y_{tpss'k}$ cannot exceed Y_{ss}^u which is the upper bound of electricity transferred from site s to site s'. The electricity cannot be transferred if the transfer price level k is not selected, so that $Y_{tpss'k} = 0$

$$Y_{tpss'k} \leq Y_{ss'}^u \,.\, X_{ss'k} \qquad \forall t, p, s, s', k \tag{4.38}$$

The demand of the participants must first be met before selling electricity to other sites. In the same vein, it is forbidden to purchase electricity from one site and at the same time while selling to the main grid. To overcome this problem, we introduced the binary variable X_{tps}^m to satisfy the above two conditions by using the constraints as indicated below, where Y_s^u represents the upper bound of electricity transferred to the site s.

$$X_{tps}^m = \begin{cases} 1 \; if \; imported \; electricity \; from \; the \; grid \; or \; purchase \; from \; other \; sites \\ 0 \quad otherwise \end{cases}$$

$$\sum_{s'} y_{tps's} + I_{tps} \leq Y_s^u X_{tps}^m \qquad \forall t, p, s \tag{4.39}$$

$$\sum_{s'} y_{tpss'} + E_{tps} \leq Y_s^u (1 - X_{tps}^m) \qquad \forall t, p, s \tag{4.40}$$

The expression $E_{ss'} y_{tpss'}$ in transferred electricity selling cost TSC is formulated as $\sum_k E_{ss'k}\, Y_{tpss'k}$ which is considered as linear.

d. Power balance constraint

The power balance indicates the amount of power to be supplied/ absorbed in the system so that balance of power is achieved in grid-connected mode. The power balance equation gives the relationship between the power generated and power demanded at a certain time.

$$P_{Lg_s}(t) = P_{pv_s}(t) + P_{B_s}(t) + P_{grid_s}(\mathrm{t}) \tag{4.41}$$

where $P_{Lg_s}(t)$ is the load power in grid connected mode at time t, $P_{pv_s}(t)$ is the PV system power at time t, $P_{B_s}(t)$ is the battery power and P_{grid_s}(t) denotes the grid power at time t for site s.

e. Grid power limits constraint

The main grid power exchange is limited as follows:

$$P_{grid}^{min} \leq P_{grid_s}(\mathrm{t}) \leq P_{grid}^{max} \tag{4.42}$$

where P_{grid}^{min} is the minimum grid power, P_{grid}^{max} is the maximum grid power

f. Battery power output.

The battery power is limited as follows:

$$P_{Bmin}(t) \leq P_{B_s}(t) \leq P_{Bmax}(t) \tag{4.43}$$

$P_{B_s}(t) < 0$: Battery is charging

$P_{B_s}(t) > 0$: Battery is discharging to serve the load

$P_{B_s}(t) = 0$: Battery is at rest

e. Battery energy state of charge constraint.

$$SOC_{min} \leq SOS_S \leq SOC_{max} \tag{4.44}$$

B Constraints in Islanded mode

a. Electricity demand constraints:

At each time interval, electricity demand is equal to the output of diesel generator, solar PV, battery, and the amount of electricity transferred from other locations/sites.

$$\sum_{s'} y_{tps's} - \sum_{s'} y_{tpss'} + P_{B_s}(t) + P_{pv_s}(t) + P_{DG_s} = L_{tps} \tag{4.45}$$

where $y_{tps's}$ is the electricity transferred from other locations, $y_{tpss'}$ is the electricity transferred to other locations, $P_{DG_s}(t)$is the energy from diesel generator, $P_{B_s}(t)$ is the Battery energy at time t and $P_{pv_s}(t)$ is the solar PV power at time t.

b. Transfer price level and electricity transfer amount:

This is the same as transfer price and amount of electricity in grid-connected mode, given in (4.34) – (4.36) and (4.37) – (4.41).

c. Power balance constraint

The power balance indicates the amount of power to be supplied/ absorbed in the system so that balance of power is achieved in islanded mode. In this work, the solar PV, battery, and the diesel generator are used. The power balance equation gives the relationship between the power generated and power demanded at a certain time.

$$P_{Ld_s}(t) = P_{pv_s}(t) + P_{B_s}(t) + P_{DG_s}(\mathrm{t}) \tag{4.46}$$

where $P_{Ld_s}(t)$ is the load power in grid connected mode at time t, $P_{pv_s}(t)$ is the PV system power at time t, $P_{B_s}(t)$ is the battery power and P_{DG_s}(t) denotes the generator power at time t for site s. .

d. Battery power and the battery state of charge:

This is the same as the battery power and battery state of charge in grid connected mode given in (4.44) and (4.45).

4.3 Fair Allocation of Utility

Game theory has been used to find a solution that is 'fairness'. The word 'fairness' can be measured in different ways. In [73], fairness is defined as the process of judgement used to arrive at an acceptable, reasonable or just of an outcome. Maxwell [114] and Huppert, et al. [115] reported that the perceived unfairness can decrease the utility, which may discourage willingness of customers to purchase a certain commodity. There are many ways by which fairness can be influenced to eliminate offers that are unfair from purchase options. With fairness, utility of an offer can be reduced through necessary adjustments that result in fairness. In addition, a decision rule, which is applied to the purchase, can be changed with the use of fairness. Lastly, increase in choice variability can be manifested by the use of fairness.

In this section, the common criteria used for fair sharing utility are discussed. The criterion can be obtained in both the weighted form and a simple form. The weighted form has been introduced because of the need to provide for more utility for the player with higher bargaining power. The simple form has to do with a situation when utility is linear, which is Nash bargaining solution that is discussed in the next section.

4.3.1 Nash Criterion

Cooperative game theory uses the Nash bargaining solution (NBS) to obtain a fair resource allocation [62]. The approach must be able to satisfy certain axioms to obtain a fair utility distribution. These axioms deal with the resources associated with the players of the game, which is the main goal of this method when compared with the fairness previously described. In utility distribution, the NBS has been used for fair cost distribution [3]. In this case, the utility function is linear. In reality, the utility function could be non-linear i.e. concave function.

Let us consider N players and profit function J. The allocation of profit using NBS proceeds in these steps as adapted in [116]:

(1) There is cooperation amongst the players to maximize their profits

(2) The status-quo profit (which is regarded as disagreement point) is calculated as $D = (D_1, D_2, \dots, D_n)$ where the status-quo profit D_i is the minimum profit, which is ready to be received by i^{th} players

Note that the bargaining is successful when the normal profit exceeds the status-quo profit.

On the other hand, the profit of each player must be greater than the status-quo profit

$$\epsilon = J_i - D_i \geq 0 \tag{4.47}$$

where ϵ represents the cooperation discount and the players in this case, have identical discount of cooperation. Lastly, by adapting [116] and [117], the profit J is the maximum profit that is allocated to player i when given J and D in step 2, which results in a fair profit allocation to the players. In the next section, we present fairness scheme, which is the main contribution of the thesis.

4.3.2 Proposed Fairness Scheme

We have presented a linear utility function in which the NBS is suitable for solving profit allocation bargaining game. In reality, the utility function may be non-linear i.e. concave function.

Cooperative game theory may be defined in terms of fairness criteria [64] . This work concentrates on the generalised Nash bargaining solution and this is formulated from the generalised function of proportional fairness. Because utility function is concave, the NBS, which is expressed in the following theorem, is used to solve profit allocation to the participants of MG.

Theorem 1: (NBS) [81] Let consider a function G_s defined as $G_s\colon (J_S, d_s) \longrightarrow \mathcal{R}^N$, the concept of the NBS can be considered as a bargaining solution that is unique having $J_s^* = G_s(J_s,\ d_s)$ to the resource allocation bargaining game provided necessary axioms are satisfied and can be described as

$$J_s^* = \prod_{i=1}^{N}(J_{i,s} - d_{i,s}) \tag{4.48}$$

The necessary axioms for the NBS are given below.

(1) Individual rationality: $J_{i,s}^* \geq d_{i,s})$ for all players i, s.

(2) Feasibility: $J_{i,s}^* \epsilon J_s$.

(3) Pareto optimality: J_s^* is Pareto optimal.

(4) Independence of irrelevant alternatives.

(5) Independence of Linear Transformations.

(6) Symmetry

From these axioms, the efficiency and existence of the NBS is guaranteed by axioms 1-3. Solution fairness satisfied axioms 4-6. The axiom of symmetry guarantees equal utility of the players [81], [118]. In this case, the same bargaining power is assigned to each player if the symmetric axiom is satisfied. If the players are different structurally it may not be reasonable to use equal utility distribution for them.

In [118], [81], the generalized NBS is used as a variant to relax the axiom of symmetry by assigning different bargaining power to the players. In this case, (4.48) is modified as

$$J_s^* = \arg\ max \prod_{i=1}^{N} (J_{i,s} - d_{i,s})^{\alpha,\beta,\gamma} \tag{4.49}$$

where

$\alpha,\ \beta, \gamma$ are the corresponding bargaining power of the three players

If $\alpha = \beta = \gamma = 1$ then the criterion proposed coincides with the NBS. The approach is more of the utility functions by quadratic parameterized functions.

4.4 Proposed Algorithm for Solving Energy Management in Micro-grid

4.4.1 Teaching-Learning-based Optimization (TLBO)

Through the constrained and unconstrained benchmark functions, the TLBO algorithm had been tested and proved to be better than other advanced optimization techniques like PSO, differential evolution (DE), GA, artificial bee colony (ABC), etc. [119] . It also proved better in other fields of engineering such as those reported by Krishanand et al. [120], Togan [121] in civil engineering, Satapathy et al [122] in the field of electrical engineering etc. Rao and Patel [119] had justified that the TLBO algorithm is an algorithm specific parameter-less algorithm, which requires only common control parameter, such as population size, number of iteration and elite size.

In [123], the linear programming model has been applied for high-level system design, and unit commitment of DERs to minimize the cost of the micro-grid. In [124], the economic benefit of MG is estimated and high efficiency as well as cost saving are achieved. Agrawal, et al. in [125], proposed a new algorithm, TLBO for the management of congestion in a pool based electricity market. The algorithm is validated on the IEEE 30- and IEEE 5- bus systems and the results obtained are compared with the PSO and random search method. The results showed that the rescheduling cost and losses are much lower than other approaches. The results achieved have proven the efficiency of this method. In [126], the TLBO is proposed to optimize mechanical design problems. The robustness and good performance of the algorithm is validated on five different constraint benchmark test functions. The algorithm is compared with other heuristic algorithms (i.e. PSO, ABC, PSO-DE, etc.), which showed that TLBO algorithm is more robust, effective and efficient when compared to other optimization methods under investigation. In [127], TLBO is proposed to solve a combined heat and power dispatch with bounded feasible operating region. The results of TLBO are compared with other heuristics algorithms like PSO, real coded GA, DE, and bee colony optimization (BCO). It was demonstrated that the TLBO is able to reach optimal solution with faster convergence.

The heuristic approaches discussed above have specific-parameters that must be tuned properly as lack of proper tuning results in the local optimal solution. To deal with the drawbacks [126], [128], [129] proposed the teaching-learning-based-optimization (TLBO) algorithm in which no algorithm-specific parameters are used. It only needs the common controlling parameters (e.g. population size and the number of generations) for its operation. TLBO algorithms is robust, effective and good potential with reduced optimization parameters for solving complex and multi-objective functions. The TLBO algorithm is an inspired method based on the process of teaching and learning, i.e., the effect a teacher has on the learner's output in a classroom. The method considers two learning processes; the teacher phase and the learner phase. The method considers the population as a learner's group and the different types of subject taught to the learners correspond to the design parameters of the problem. In addition, the learner's result is the fitness value of the TLBO problem. The teacher is taken to be the best solution in the algorithm and the parameters involved in the given problem actually represent the design variables in the objective function. The best value in the objective function depicts the best solution of the algorithm. The TLBO algorithm requires not only the population size but also the number of iteration and no specific control parameters are involved.

TLBO algorithms have been involved in optimization problems. In [103], TLBO performance was validated when compared with some popular optimization methods such as generalized differential evolution (GDA), the dynamic multi-objective evolutionary algorithm (DMOEADD) and the archive-based micro-genetic algorithm (AMGO). With the benchmark of the multi-objective functions, the results reveal that TLBO has performed better than other optimization methods. In [97], the authors considered the TLBO to solve optimization problems involving non-linear system. The algorithm is tested using different benchmark models. When the results are compare with other inspired optimization methods, the TLBO showed the best performance. It also requires less computational effort with better performance.

In [130], the authors present TLBO to obtain the optimal sizing and the best position for the thyristor controlled series capacitor (TCSC) in a certain power system. The results obtained when compared with other heuristic methods such as ABC and PSO showed that the line losses due to the bus voltages, active and reactive power are improved. This shows that TLBO gives better results than PSO and ABC. Agrawal, et al. in [131], propose the use of TLBO algorithms for congestion management. The algorithm having tested on the bus systems (i.e. IEEE bus systems) the results obtained are compared with the PSO and random search method. The results showed that the rescheduling cost and losses are much lower with TLBO than other algorithms.

TLBO algorithm is robust, effective and good potential with reduced optimization parameters for solving complex and multi-objective functions.

4.4.2 Application of TLBO in Energy Management of Micro-grid

A. Teaching-Learning-based Optimization Algorithm

In this thesis, teaching-learning-based optimization (TLBO) algorithm is presented to efficiently optimize Nash objective function. The algorithm is population-based and thus, the optimal solution is obtained using the population of a solution. The TLBO algorithm is an inspired method that depends on the teaching-learning process, i.e. the effect a teacher has on the learner's output in a classroom. There are two learning processes: the teacher and the learner phases. The teacher is selected to be the start of the algorithm, which is considered the most intelligent student in the class. The entire population needs to be updated in order to obtain a better teacher. After obtaining the teacher, a new teacher is used to update the population and the iteration continues. In addition, the number of the iteration can be reduced by using a larger population size to obtain the optimal solution.

(a) Teacher Phase: A teacher is first selected in the algorithm and this is done to achieve the maximum value of the objective function by taking into consideration the member of the population. After teacher selection, the mean, teacher value, and a random variable are the parameters used to update the population value of each subject. To apply this to our problem of maximization of profit, the population is set to 60.

(b) Learner Phase: In learner phase, there is interaction amongst the learners to increase their knowledge. The procedure is that one learner is selected randomly and will be used to compare with other learners in order to update the learner. If the learner selected has a higher objective function, the result will be added to a random number multiplied by selecting minus random member. If the objective function of the learner selected does have a higher objective function, there will be addition to a random number multiplied by the random minus selected member. The first iteration using TLBO is completed.

B. Application of TLBO Algorithm for the Energy Management

In this work, a TLBO algorithm is proposed for profit maximization of the MG participants. The algorithm has a population size of 60, the number of generation is 300 as applied in the previous algorithms (i.e. GA and PSO) and the rationale behind choosing these parameters is justified in the simulation results. The problem at hand to be solved contains six variables to be optimized.

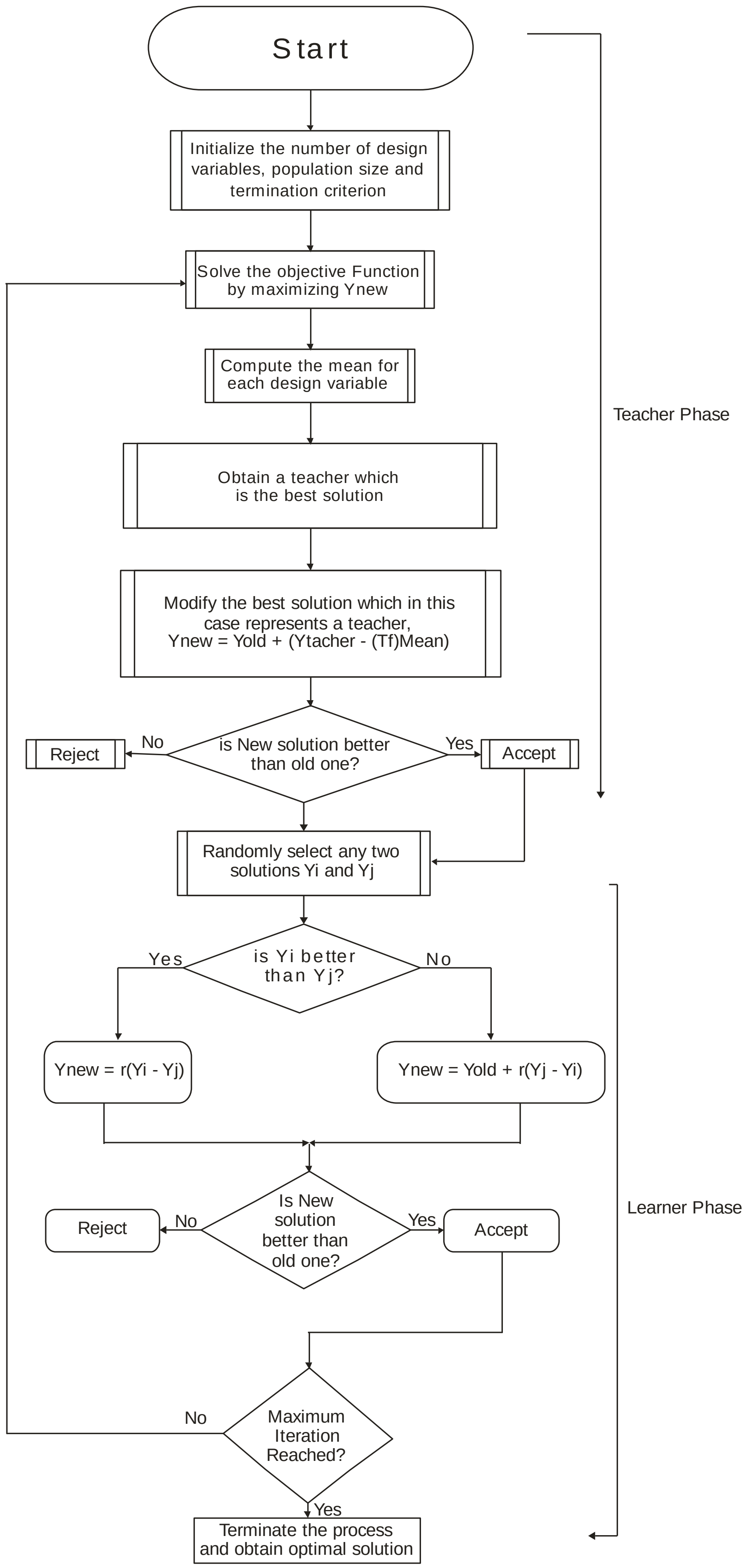

Figure 4.4: Flowchart for Teacher and Learner Phases

When using TLBO algorithm in optimizing the solution, the procedure is to execute the program by first run it and obtain the results. The next step is to select a teacher, which results in the highest outcome. This is followed by updating each variable using concept of teaching phase, the best solution $Ynew$ is calculated with the teacher $Yteacher$ for each of the 300 iterations as indicated in Figure 4.4

Let the teacher Ti with mean Mi and at any iteration i, teacher Ti will then try to move towards its own level thereby making new mean to be Ti represented by $Mnew.$ The solution is updated in accordance with the difference between the old and the new mean given by

$$Diff.m = r_i(M_{new} - T_f M_i) \tag{4.50}$$

where r_i is a random number between 0 and 1, T_f is a teaching factor which can be either I or 2. The existing solution is modified according to the following expression

$$Y_{new,i} = Y_{old,i} + Diff.m \tag{4.51}$$

The learner phase begins with the values obtained in teacher phase, and the learner is then compared to another learner that is randomly selected. The next step is to update the learner depends on which learner optimized better. Something new is learnt by a learner if the other learner is more knowledgeable than the other. The expression below gives learner modification

$For\ i = 1$

Select two learners Yi and Yj at random, where $i \neq j$

$Y_{new,i} = Y_{old,i} + r_i(Y_i - Y_j)$

Else

$Y_{new,i} = Y_{old,i} + r_i(Y_j - Y_i)$

End if

End for

Accept $Y_{new,i}$, if it gives a better function

Chapter 5

Simulation, Results and Discussions

The emergence of the micro-grids tends to reduce the emission and utility demand burden because MGs use renewable energy as DERs to serve local communities. The selection of various types of DERs, modelling and operation plan are the key factors that determine the deployment of a successful micro-grid. Micro-grids are regarded as a collaborative network and formation of a coalition can be beneficial to all the participants as a group rather than being independent from one another with pure self-interest. Therefore, a cooperation will allow the participants of micro-grid to benefit for the improve design and operation. Many researchers in power system have developed a number of models in the energy management for the cost optimization but the model in which the participants cooperate with the bargaining powers, is usually not considered. In this chapter, the results of the simulation are presented.

5.1 Case Study

The simulation studies are carried out on a case study of a micro-grid with six sites: a school, a hotel, a restaurant, a fire station, a residential building, and a hospital. The case study is developed to test the propose approach. Figure 5.1 shows the output power of solar PV. The data of solar PV, generators and batteries are extracted from [88], [132]. The installed distributed generations are shown in Table 5.1. The installed distributed generation for each participant site is assumed the same despite variations in the load demand and solar PV power.

This is because other participants will efficiently use the excess power generated from the participants' DERs with low power consumption due to cooperation and coordination that exist amongst them.

The simulations are carried out on an HP with Intel(R) Pentium (R) CPU 2020M @ 2.40GHZ with a RAM size of 4GB. In the MG, global profit distribution using cooperative game theory in both the grid-connected and islanded mode is compared with a situation when the game theory is not applied.

A transfer price of 0.039$/kWh, the price of electricity import from the utility grid is $0.17, and the cost of electricity export to the utility grid $0.0131 are considered [3]. Rated power of diesel generator is given as 10kVA for each participant. Under a given fixed electricity selling and buying prices the status-quo profits (lower bounds profits) are determined by the main grid scenario costs (when it is connected to the main grid) and micro-grid scenario costs (when operates in islanded mode).

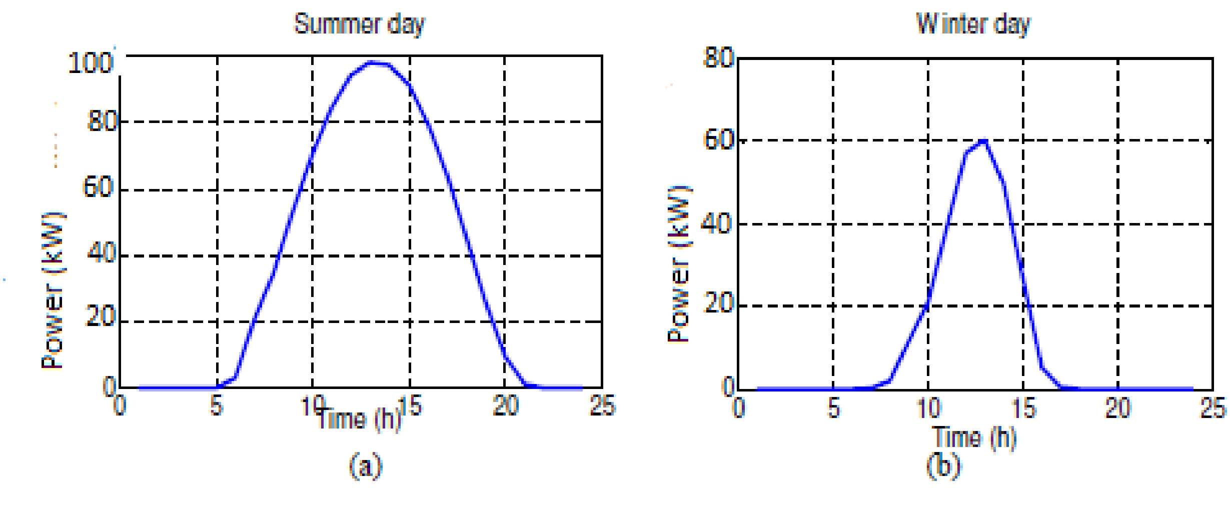

Figure 5.1: Solar Power for each site (a) Summer (b) Winter [88]

In the fair profit, each participant obtained maximum profit. The unfair profit distribution is obtained in which some participants obtained the profit lower than the status-quo profit.

Finally, a fair weighted profit distribution is obtained by assigning negotiation power indicators to all the participants using game theory based on generalized Nash bargaining solution.

Table 5.1: Installed Distributed Generation in each Site

Unit Type	Min Power (kW)	Max. Power (kW)
Solar PV	0	20
Diesel Generator	3	10
Battery	-10	10

5.2 Energy Demand and Generation Scheduling for the Participants of Micro-grid.

5.2.1 Energy Demand Profiles

In this study, we consider the energy demand profiles having a total number of 14 different periods per day for two representative days per year (197 winter days, and 168 summer days) as shown in Table 5.2 [3]. The weighting factor W_P depicts the weight of the day for each of the seasons.

Table 5.2: Duration for energy demand profile [3]

Period	Duration (hr)	Hours in the day
T_1	6	1.00am-7.am
T_2	2	7.00am-9.00am
T_3	3	9.00am-12.00pm
T_4	1	1200pm-1.00pm
T_5	5	1.00pm-6.00pm
T_6	4	6.00pm-10.00pm
T_7	3	10.00pm-1.00am

The participants of the MG are as follows: school, fire station, hotel, hospital, restaurant and residential building. All the buildings are built to passive-Haus standard according to the information provided by the developer of [3]. The electricity demand profiles for each participant for both the winter and summer days are shown in Table 5.3.

Table 5.3: Electricity demand for both winter and summer seasons (Day 1 for winter and Day 2 for summer) [3].

Day	Time (hr)	School (kW)	Hotel (kW)	Restaurant (kW)	Fire Station (kW)	Residential Building (kW)	Hospital (kW)
Day 1	T_1	2.1	2.3	8.9	2.1	3.7	3.0
Day 1	T_2	2.1	9.3	3.5	3.3	5.6	4.5
Day 1	T_3	10.7	11.6	8.9	6.8	7.5	7.3
Day 1	T_4	10.7	11.6	17.7	6.8	7.5	7.3
Day 1	T_5	10.7	11.6	8.9	6.8	7.5	7.3
Day 1	T_6	4.3	9.3	17.7	4.1	18.6	5.4
Day 1	T_7	2.1	2.3	8.9	2.1	3.7	3.0
Day 2	T_1	2.1	2.3	8.9	2.1	3.7	3.0
Day 2	T_2	2.1	9.3	3.5	3.3	5.6	4.5
Day 2	T_3	10.7	11.6	8.9	6.8	7.5	7.3
Day 2	T_4	10.7	11.6	17.7	6.8	7.5	7.3
Day 2	T_5	10.7	11.6	8.9	6.8	7.5	7.3
Day 2	T_6	4.3	9.3	17.7	4.1	18.6	5.4
Day 2	T_7	2.1	2.3	8.9	2.1	3.7	3.0

For each period, the energy profiles provide the constant energy demand [3], [133]. The school, fire station and hospital have energy consumption hours majorly during the daytime; the restaurant has its peak demand of electricity during lunchtime and dinnertime. Moreover, the peak electricity demand for residential building is in the morning when people are preparing to go to work and in the evening time when workers return home from work and the hotel has peak energy demand during the working hours. These different energy demand patterns bring about the possibility of the sites/locations to come together and benefit from MG.

5.2.2 Energy Generation Scheduling for Micro-grid Participants

Simulations are performed in both grid-connected and islanded modes to show the generation schedule of MG.

A Grid-Connected Mode

In this mode, simulations are carried out in the following cases: generation scheduling, import and export electricity and electricity transferred between the participants of MG.

(a) Generation schedule and import and export electricity

Table 5.4a presents the demand schedule on an hourly basis. Table 5.4b presents own generation and excess/deficit for each participant on an hourly basis. The restaurant has a high electricity demand in the morning and in the night than other participants. This site (restaurant) is even considered the highest energy demand among the sites. Generally, the profile of energy demand for all the participants indicates that the electricity demand occurs virtually every hour of the day because of their differences in energy demand patterns.

The optimal generation schedule for the micro-grid (MG) in this mode of operation is shown in column 1 of Table 5.4b for each participant. From the table, it can be observed that during the periods 7a.m. to 5p.m. when there is solar radiation the battery operates in a high level state of charge (SOC) and when fully charged it hibernates so that longer life of battery will be preserved. However, there is insufficient power to cope with the demand in certain periods. For example, during the periods 1a.m. to 6a.m and 6p.m. to 12midnight solar generation is unavailable and battery discharges power to supply the loads to each participant in the sites. The performance of battery during charging and discharging modes are shown in Figure 5.2.

The optimal electricity exported and imported to/from the main grid is shown in the second to the last column and the last column respectively of Table 5.4b. The rule is that during the day when there is high solar radiation the participants must first satisfy their own demand and if surplus exists, satisfy another participant in other sites that may need power before selling energy to the grid. Hence, solar power radiation is present during the day and energy demands are met by solar PV of each site and/or by exchanging energy with other participants to meet the load demand and the surplus energy is sold to the main grid. The last column of Table 5.4b depicts the total hourly energy exported to the main grid. By plotting the values of export electricity in the last column of Table 5.4b with time, the curve obtained is shown in Figure 5.3.

During the night and early in the morning, there is no solar generation, the capacity of each battery in each site cannot cope with the load demand, and in this case, the energy is imported from the grid to meet the load demand. It can be seen from the load demand profile that the restaurant, residential building, and the hospital have relatively higher electricity demand in the night than other participants. The optimal energy imported from the main grid is shown in the second to the last column of Table 5.4b. It can be seen from the results obtained that between the periods of 1a.m. to 6a.m. and 7p.m. to 12 mid-night, the local generation is grossly inadequate to meet the load demand, thus, electricity is imported from the main grid. By plotting the values of import electricity in the second to the last column of Table 5.4b with time, the curve obtained is shown in Figure 5.4. It is observed that electricity is imported in the morning and in the night when solar PV is not charging..

Table 5.4a: Hourly Electricity Demand Schedule.

Hour	School (kW)	Hotel (kW)	Restaurant (kW)	Fire Station (kW)	Residential Building (kW)	Hospital (kW)
1	2.1	2.3	8.9	2.1	3.7	3
2	2.1	2.3	8.9	2.1	3.7	3
3	2.1	2.3	8.9	2.1	3.7	3
4	2.1	2.3	8.9	2.1	3.7	3
5	2.1	2.3	8.9	2.1	3.7	3
6	2.1	2.3	8.9	2.1	3.7	3
7	2.1	9.3	3.5	3.3	5.6	4.5
8	2.1	9.3	3.5	3.3	5.6	4.5
9	10.7	11.6	8.9	6.8	7.5	7.3
10	10.7	11.6	8.9	6.8	7.5	7.3
11	10.7	11.6	8.9	6.8	7.5	7.3
12	10.7	11.6	17.7	6.8	7.5	7.3
13	10.7	11.6	8.9	6.8	7.5	7.3
14	10.7	11.6	8.9	6.8	7.5	7.3
15	10.7	11.6	8.9	6.8	7.5	7.3
16	10.7	11.6	8.9	6.8	7.5	7.3
17	10.7	11.6	8.9	6.8	7.5	7.3
18	4.3	9.3	17.7	4.1	18.6	5.4
19	4.3	9.3	17.7	4.1	18.6	5.4
20	4.3	9.3	17.7	4.1	18.6	5.4
21	4.3	9.3	17.7	4.1	18.6	5.4
22	2.1	2.3	8.9	2.1	3.7	3
23	2.1	2.3	8.9	2.1	3.7	3
24	2.1	2.3	8.9	2.1	3.7	3

Table 5.4b: Generation Schedule of the participants in grid-connected mode.

Time (Hrs)	School (kW)		Hotel (kW)		Restaurant (kW)		Fire Station (kW)		Residential Building (kW)		Hospital (kW)		Import (kW)	Export (kW)
	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D		
1	2.1	0	2.1	-0.2	2.1	-6.8	2	-0.1	2.1	-1.6	2	-1	9.7	0
2	2.1	0	2.1	-0.2	2.1	-6.8	2	-0.1	2.1	-1.6	2	-1	9.7	0
3	2.1	0	2.1	-0.2	2.1	-6.8	2	-0.1	2.1	-1.6	2	-1	9.7	0
4	2.1	0	2.1	-0.2	2.1	-6.8	2	-0.1	2.1	-1.6	2	-1	9.7	0
5	2.4	0.3	2.3	0	2.4	-6.5	2.3	0.2	2.2	-1.5	2.3	-0.7	8.2	0
6	2.7	0.6	2.5	0.2	2.8	-6.1	2.6	0.5	2.8	-0.9	3.1	0.1	5.6	0
7	5.5	3.4	5.3	-4	5.6	2.1	5.3	2	5.5	-0.1	5.4	0.9	0	4.3
8	7.7	5.6	7.2	-2.1	7.8	4.3	6.5	3.2	7.3	1.7	6.3	1.8	0	14.5
9	10.2	-0.5	9	-2.6	9.5	0.6	7.9	1.1	10.5	3	7.8	0.5	0	2.1
10	11.7	1	10.9	-0.7	11.4	2.5	8.4	1.6	11.5	4	8.5	1.2	0	10.5
11	12.8	2.1	12.1	0.5	12.6	3.7	9.5	2.7	12.6	5.1	9.6	2.3	0	16.4
12	13	2.3	12.8	1.2	13.1	-4.6	10	3.2	13	5.5	10	2.7	0	10.3
13	15	4.3	14.8	3.2	15	6.1	10	3.2	15	7.5	10	2.7	0	27
14	14.8	4.1	14.8	3.2	15	6.1	9.8	3	14.6	7.1	9.7	2.4	0	25.9
15	14.3	3.6	13.9	2.3	14.5	5.6	9.3	2.5	14.2	6.7	9.1	1.8	0	22.5

Time (Hrs)	School (kW)		Hotel (kW)		Restaurant (kW)		Fire Station (kW)		Residential Building (kW)		Hospital (kW)		Import (kW)	Export (kW)
	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D		
16	12.9	2.2	12.4	0.8	13.1	4.2	8.5	1.7	12.8	5.3	8.7	1.4	0	15.6
17	10.7	0	10.2	-1.4	10.8	1.9	7.1	0.3	10.6	3.1	7.2	-0.1	0	3.8
18	7.7	3.4	7.7	-1.6	7.8	-9.9	5.6	1.5	7.5	0	5.7	-1.6	8.2	0
19	5	0.7	4.8	-4.5	5.2	-12.5	3.6	-0.5	4.9	-13.7	3.4	- 2	32.5	0
20	3.5	-0.8	3.2	-6.1	3.7	-14	2.9	-1.2	3.6	-15	3	- 2.4	39.5	0
21	2.8	-1.5	2.5	-6.8	2.9	-14.8	2.2	-1.9	2.7	-15.9	2.3	- 3.1	44	0
22	2.1	0	2.1	-0.2	2.1	-6.8	2	-0.1	2.1	-1.6	2	-1	9.7	0
23	2.1	0	2.1	-0.2	2.1	-6.8	2	-0.1	2.1	-1.6	2	-1	9.7	0
24	2.1	0	2.1	-0.2	2.1	-6.8	2	-0.1	2.1	-1.6	2	-1	9.7	0

where: Dem=demand, own gen. = own generation, E/D= excess/deficit. Negative sign under E/D column means deficit.

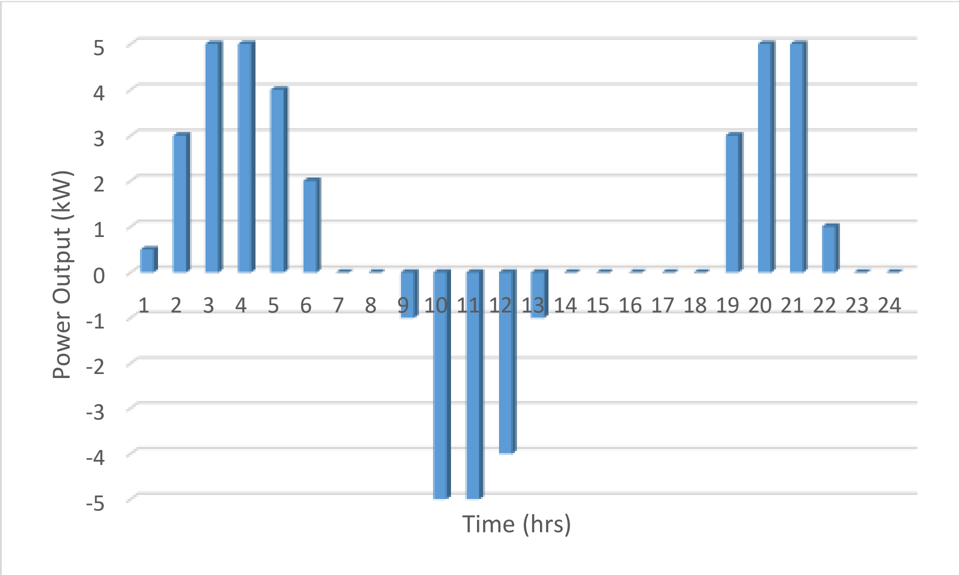

Figure 5.2: Power output of battery for each hour of the day.

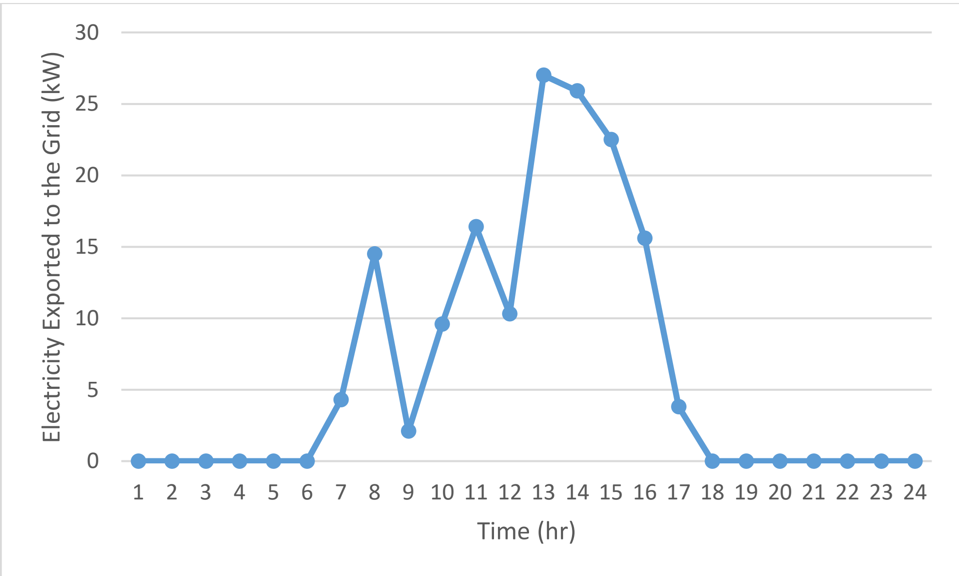

Figure 5.3: Total Electricity Exported to the main grid

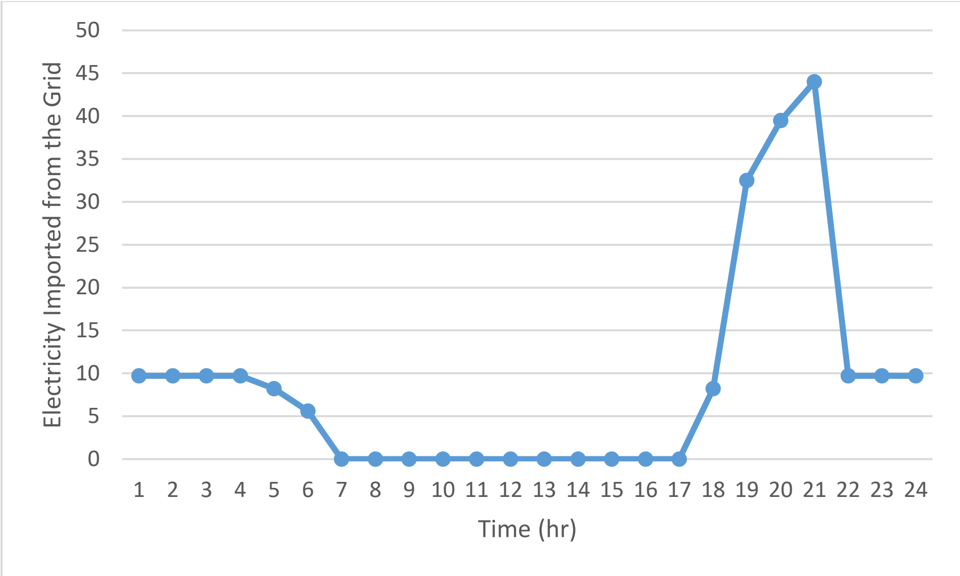

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Figure 5.4: Total Electricity Imported from the main grid

(b) Electricity Transfer between Participants of MG in a Grid-connected mode

Electricity can be transferred between the MG participants at an agreed price. In this case, electricity can be transferred at a fixed transfer price of 0.039kWh as adopted in [3]. Table 5.5 gives the optimal energy transfer from one site to another site on an hourly basis. From 1am to 4am and 8pm to 12mid-night, no electricity transfer is possible because there is no solar power at that time and battery is not sufficient to provide the surplus energy. However, there is a high electricity transfer between 7am to 10am, 12noon and 5pm to 6pm.The optimal amount of electricity transfer for a period of one year between the participants is shown in Table 5.6.

The electricity transfer amongst the participants is made possible based on the differences in peak electricity demand profile for each participant. The participant with surplus energy during a particular time will transfer the excess to other participants in need of energy. For example, school transfer a total amount of 328.5 kW of electricity to the residential building in a year, whereas, in a year, the fire station transfer 720 kW of electricity to the residential building, and so on.

Table 5.5: Hourly Electricity Transfer between Sites in Grid-Connected Mode.

Time (hr)	Site		Amount of Electricity Transferred (kW)
	From	To	
1	Nil	Nil	0
2	Nil	Nil	0
3	Nil	Nil	0
4	Nil	Nil	0
5	School	Residential Building	0.3
	Fire Station	Residential Building	0.2
6	School	Residential Building	0.6
	Hospital	Residential Building	0.1
	Fire Station	Restaurant	0.5
	Hotel	Residential Building	0.2
7	School	Hotel	3.4
	Restaurant	Hotel	0.6
8	School	Hotel	2.1
9	Residential Building	Hotel	2.6
	Fire Station	School	0.5
10	Fire Station	Hotel	0.7
11	Nil	Nil	0
12	Residential Building	Restaurant	4.6
13	Nil	Nil	0
14	Nil	Nil	0
15	Nil	Nil	0
16	Nil	Nil	0
17	Restaurant	Hotel	1.4
18	School	Restaurant	3.4
	Fire Station	Restaurant	1.5
19	School	Hospital	0.7
20	Nil	Nil	0
21	Nil	Nil	0
22	Nil	Nil	0
23	Nil	Nil	0
24	Nil	Nil	0

To ensure that MG electricity demand is satisfied, the participants purchased 75,153.5 kW electricity from the main grid, which is 16.48% of annual electricity demand. The local micro sources such as solar PV and battery storage unit provide 381,488kW of electricity to the MG annually, of which the amount of electricity sells to the utility grid is 55,808.5kW. Within the participants of MG, the amount of electricity transfer in a year is 8,541kW, which is 1.9% of annual electricity demand. Figure 5.5 shows the contribution to MG energy demand.

Table 5.6: The annual amount of Electricity transfer between sites in Grid-Connected Mode.

Site		Amount of Electricity Transferred (kW)
From	To	
School	Residential Building	328.5
Fire Station	Residential Building	73
Hospital	Residential Building	36.5
Fire Station	Restaurant	730
Hotel	Residential Building	73
School	Hotel	2007.5
Restaurant	Hotel	730
Fire Station	Hotel	255.5
Residential Building	Restaurant	1679
School	Restaurant	1241
School	Hospital	255.5
Residential Building	Hotel	949
Fire Station	School	182.5
Total		8541

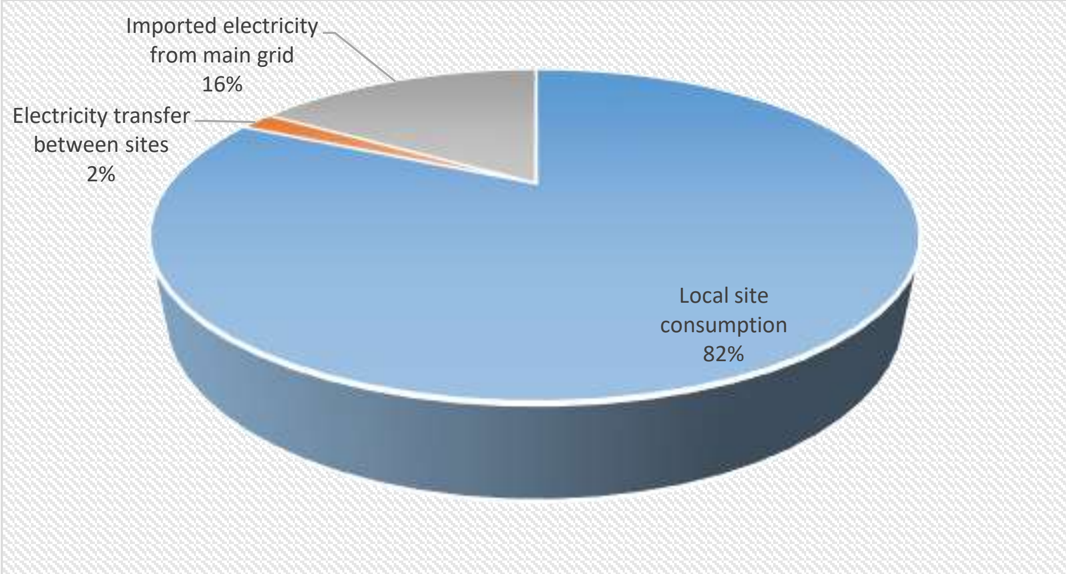


Figure 5.5: Contribution of MG Energy Demand in Grid-Connected mode.

B Energy Scheduling in Islanded Mode

In islanded mode of operation, the variation in demand must be met by local generated electricity supply, if there is any imbalance between demand and supply, there would be poor power stability and even poor quality of power supply. Table 5.7 shows the energy scheduling in Islanded mode. In this case, the main grid is absent and thus, MG utilizes only the local micro-sources (local generation) to meet the load demand. At this time, a diesel generator is only the dispatchable source to back up the non-dispatchable source (solar PV) during this mode of operation.

From the load demand profile in Figure 5.4a and generation schedule in columns 1 for each participant in Table 5.7, we observe that the operation of diesel generator for each participant changes according to the load demand. As usual, the battery is charged when there is high solar radiation and discharged when solar radiation is low, which acts as a storage device for solar PV in the MG. As seen in this table, the combinations of the solar PV, diesel generator, and the battery as a storage unit are adapted to answer the power load variations. However, in the grid-connected mode, 16.48% of energy is imported from the main grid, which implies that the diesel generator should not be operated every time to reduce the fuel cost. For example, between the hours of 1a.m. to 6a.m the solar generation is operating, thus, a diesel generator and a battery are used to meet the load demand. During these periods, load demands are low in some participants, but high in other participants. In this case, some diesel generators have to be interrupted while others are uninterrupted. For some diesel generators that tripping off at certain times of the day, their power deficits in that site would be covered by the power of other participants. For example, at 1am to 6am restaurant, residential building, and hospital have their diesel generators turned ON to cope with the power deficits and sell power to other participants in need of power. At this time, diesel generators of other participants are in off state.

At 7 a.m. to 5p.m, the solar PV system production supply is used to meet the load demand. At this time, diesel generators for all the participants are off and the battery charged up similar to the case of grid-connected generation scheduling and energy transfer amongst the participant of MG is possible. In the case, when solar PV suddenly reduces, all the diesel generators and battery are turned on to keep balance between production and consumption. For example, at 6p.m to 9pm, we observe that nearly all the participants of MG have a high electricity demand, thus, the diesel generators and battery are used to meet the load demand to cover the power deficit. At 10pm to 12pm, demand is less in some participants and high in other participants (as indicated in the load profile). In this case, the battery storage unit of each participant is discharged with the same power value to meet the load demand. For example, hotel, restaurant and residential building have high electricity demand. Therefore, the diesel generators for school, hotel and residential building are on to cover the load demand, whereas, the diesel generators for other participants are de-energized to reduce the use of fuel and lengthen the life span of the generators. The battery scheduling for this mode of operation is the same as that of grid-connected mode as shown in Figure 5.2.

Table 5.7: Generation Schedule of the Participants in Islanded mode

Time (Hrs)	School (kW)		Hotel (kW)		Restaurant (kW)		Fire Station (kW)		Residential Building (kW)		Hospital (kW)		Total Excess Elect. (kW)	Total Electricity Transf. (kW)
	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D		
1	2.1	0	2.1	-0.2	5.4	-3.5	2	-0.1	5.5	1.8	5	2	3.8	3.8
2	2.1	0	2.1	-0.2	5.4	-3.5	2	-0.1	5.5	1.8	5	2	3.8	3.8
3	2.1	0	2.1	-0.2	5.4	-3.5	2	-0.1	5.5	1.8	5	2	3.8	3.8
4	2.1	0	2.1	-0.2	5.4	-3.5	2	-0.1	5.5	1.8	5	2	3.8	3.8
5	2.1	0	2.3	0	5.6	-3.3	2.3	0.2	5.6	1.9	5.3	2.3	4.4	3.3
6	2.7	0.6	2.5	0.2	5.8	-3.1	2.4	0.3	5.8	2.1	5.9	2.9	5.5	3.1
7	5.3	3.2	5.3	-4	5.6	2.1	5.3	2	5.5	-0.1	5.4	0.9	8.2	4.1
8	7.7	5.6	7.2	-2.1	7.8	4.3	6.5	3.2	7.3	1.7	6.3	1.8	16.6	2.1
9	10.2	-0.5	9	-2.6	9.5	0.6	7.9	1.1	10.5	3	7.8	0.5	5.2	3.1
10	11.7	1	10.9	-0.7	11.4	2.5	8.4	1.6	11.5	4	8.5	1.2	10.3	0.7
11	12.8	2.1	12.1	0.5	12.6	3.7	9.5	2.7	12.6	5.1	9.6	2.3	16.4	0
12	13	2.3	12.8	1.2	13.1	-4.6	10	3.2	13	5.5	10	2.7	14.9	4.6
13	15	4.3	14.8	3.2	15	6.1	10	3.2	15	7.5	10	2.7	26.8	0
14	14.8	4.1	14.8	3.2	15	6.1	9.8	3	14.6	7.1	9.7	2.4	25.9	0

Time (Hrs)	School (kW)		Hotel (kW)		Restaurant (kW)		Fire Station (kW)		Residential Building (kW)		Hospital (kW)		Total Excess Elect. (kW)	Total Electricity Transf. (kW)
	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D	Own Gen	E/D		
15	14.3	3.6	13.9	2.3	14.5	5.6	9.3	2.5	14.2	6.7	9.1	1.8	22.5	0
16	12.9	2.2	12.4	0.8	13.1	4.2	8.5	1.7	12.8	5.3	8.7	1.4	15.6	0
17	10.7	0	10.2	-1.4	10.8	1.9	7.1	0.3	10.6	3.1	7.2	-0.1	5.3	1.5
18	11.7	7.4	11.7	2.4	11.8	-5.9	9.9	5.8	11.5	17.1	10	4.6	20.2	13
19	11.1	6.8	11.2	1.9	11.2	-6.5	9.6	5.5	10.6	-8	9.8	4.4	18.6	14.5
20	10.9	6.6	10.8	1.5	10.9	-6.8	9.5	5.4	10.4	-8.2	9.5	4.1	17.6	15
21	10.5	6.7	10.6	1.3	10.7	-7	9.2	5.1	10.1	-8.5	9.3	3.9	16.5	15.5
22	2.1	0	2.1	-0.2	5.4	-3.5	2	-0.1	5.5	1.8	5	2	3.8	3.8
23	2.1	0	2.1	-0.2	5.4	-3.5	2	-0.1	5.5	1.8	5	2	3.8	3.8
24	2.1	2.1	2.3	2.1	8.9	5.4	2.1	2	3.7	5.5	3	2	3.8	3.8

where Own gen. =Own generation schedule, E/D= Excess/deficit. Negative sign under E/D column means deficit.

Table 5.8 shows the amount of energy transfer between the sites on an hourly basis. It can be observed that the amount of energy transfer in the morning was very low due to low power consumption at that time. For example, at 1a.m. to 6am, only the restaurant has a high electricity demand of 8.9kWh, whereas other participants have relatively low power demand and hence, low power transfer. In the afternoon, nearly all participants have sufficient solar production to cope with their electricity demand hence, no electricity transfer occurs in some hours of the day. For example, at 1pm to 4pm, no electricity transfer occurs between the participants of MG.

At 6pm to 9pm, the amount of electricity transfer is very high, this is largely due to the high electricity demand in some sites in which their generation cannot cope with such demand at that time. To utilized energy efficiently, there is a need to exchange energy with other participants with surplus energy. Between the hours of 10pm to 12 midnight, apart from the restaurant, there is relatively low power demand thus, facilitation of low electricity transfer occurs among the participants.

Table 5.9 shows the annual electricity transfer among sites. The total amount of electricity transfer in a year is 37,590.5kW, which is 8.2% of annual energy demand and the local site consumption is 419,052kW, which is 91.8% of annual electricity demand. Figure 5.6 shows the MG energy demand contribution in islanded mode.

Table 5.8: Hourly Electricity Transfer between Sites in islanded mode

Time (hr)	Site		Amount of Electricity transferred (kW)
	From	To	
1	Hospital	Restaurant	2
	Residential Building	Restaurant	1.5
	Residential Building	Fire Station	0.1
	Residential Building	Hotel	0.2
2	Hospital	Restaurant	2
	Residential Building	Restaurant	1.5
	Residential Building	Fire Station	0.1
	Residential Building	Hotel	0.2
3	Hospital	Restaurant	2
	Residential Building	Restaurant	1.5
	Residential Building	Fire Station	0.1
	Residential Building	Hotel	0.2
4	Hospital	Restaurant	2
	Residential Building	Restaurant	1.5
	Residential Building	Fire Station	0.1
	Residential Building	Hotel	0.2
5	Hospital	Restaurant	2.3
	Residential Building	Restaurant	1
6	Hospital	Restaurant	2.9
	Residential Building	Restaurant	0.2
7	Nil	Nil	0
8	School	Hotel	2.1
9	Residential Building	Hotel	3.1
10	School	Hotel	0.7
11	Nil	Nil	0
12	Residential Building	Restaurant	4.6
13	Nil	Nil	0
14	Nil	Nil	0

Time (hr)	Site		Amount of Electricity transferred (kW)
	From	To	
15	Nil	Nil	0
16	Nil	Nil	0
17	Restaurant	Hotel	1.4
	Restaurant	Hospital	0.1
18	School	Residential Building	7.1
	Fire Station	Restaurant	5.5
	Hotel	Restaurant	0.4
19	School	Residential Building	6.8
	Fire Station	Restaurant	5.5
	Hotel	Residential Building	1.2
	Hospital	Restaurant	1
20	School	Restaurant	6.5
	Hotel	Restaurant	0.3
	Fire Station	Residential Building	5.4
	Hospital	Residential Building	2.8
21	School	Restaurant	6.2
	Hotel	Restaurant	0.8
	Fire Station	Residential Building	5.1
	Hospital	Residential Building	3.4
22	Hospital	Restaurant	2
	Residential Building	Restaurant	1.5
	Residential Building	Fire Station	0.1
	Residential Building	Hotel	0.2
23	Hospital	Restaurant	2
	Residential Building	Restaurant	1.5
	Residential Building	Fire Station	0.1
	Residential Building	Hotel	0.2
24	Hospital	Restaurant	2
	Residential Building	Restaurant	1.5
	Residential Building	Fire Station	0.1
	Residential Building	Hotel	0.2

Table 5.9: The annual amount of Electricity transfer between sites in islanded mode

Site		Amount of Electricity Transferred in a Year (kW)
Hospital	Restaurant	77044.5
Residential Building	Restaurant	5945.5
Residential Building	Fire Station	255.5
Residential Building	Hotel	1642.5
School	Hotel	1022
Restaurant	Hotel	511
School	Residential Building	5000.5
Fire Station	Restaurant	4015
Hotel	Restaurant	547.5
Hotel	Residential Building	438
School	Restaurant	4635.5
Fire Station	Residential Building	3832.5
Hospital	Residential Building	2263

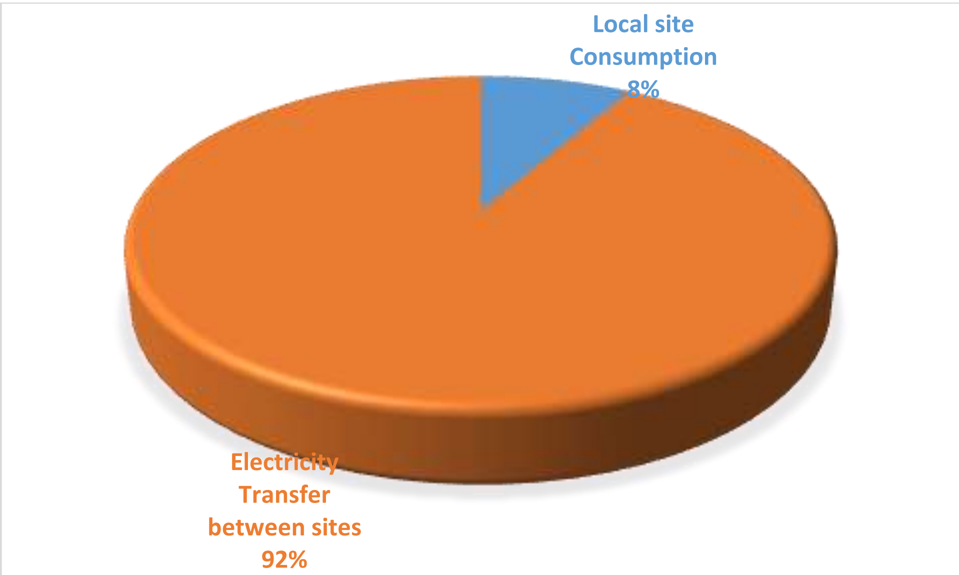


Figure 5.6: Contribution of MG Electricity Demand in islanded mode.

5.3 Equivalent Lifetime Profit (ELP_s^L) lower bounds

For the case study, the price of the electricity imported from the main grid is 0.17$/kWh and the price of the electricity exported to the grid is 0.0131$/kWh. The equivalent lower profit bounds (status-quo profit) in grid-connected and islanded mode are determined according to main grid scenario profit and micro-grid scenario profit respectively (i.e. optimized lifetime profits). By maximizing the profit of each participant (i.e. maximize (4.22) subject to (4.32), (4.41) – (4.44) in grid-connected mode and maximize (4.29) subject to (4.43) – (4.466) in islanded mode, the optimal results are shown in optimized lifetime profit in Table 5.10.

Table 5.10: Determination of equivalent lower profit bound (ELP_s^L) of the participants

	Operation Strategy	School	Hotel	Restaurant	Fire Station	Residential Building	Hospital
Optimized Lifetime profit (US $)	Islanded mode	24411	24722	25437	23452	24851	24158
	Grid-connected	24311	24499	24925	23402	24735	24046
ELP_s^L or Status-quo Profit (US $)	Islanded mode	24411	24722	25437	23452	24851	24158
	Grid-connected	25527	25725	26171	24572	25972	25248

In promoting the implementation of the micro-grid, the minimum equivalent lower bound profit (i.e. ELP_s^L or Status-quo Profit) is assigned based on the main grid scenario profit in grid-connected mode and based on MG scenario profit in islanded mode. It is expected that the participants of micro-grid in each location will not have the profit lower than the assigned equivalent lower profit bound (ELP^L or status-quo profit) In this research work, 105% of the optimized annual cost is assigned for grid-connected and 100% is used in islanded mode as shown in the second column in Table 5.10.

5.4 Application of cooperative game theory using the Nash Bargaining Solution

In order to show the performance of the cooperative game theory using the Nash bargaining solution, the case study of Table 5.11 is simulated in both grid-connected and islanded modes. Six case studies are investigated as shown in Table 5.12.

Table 5.11: Simulated Case Studies

Case Study	Types of Micro-grid Operation	Participant Strategy
1	Islanded Mode	Independent
2	Islanded Mode	Cooperative
3	Grid-connected Mode (Buying and selling electricity)	Independent
4	Grid-connected Mode (Buying and selling electricity)	Cooperative
5	Grid-connected Mode (Buying electricity only)	Independent
6	Grid-connected Mode (Buying electricity only)	Cooperative

A Micro-grid in islanded mode (case studies 1-2 Table 5.11)

In islanded mode, the main grid is disconnected, thus, MG acts as an independent entity and manages its production and sales of energy. Table 5.12 compares the overall expenses and profits of test study. Case study 1 takes cognizance of the participant that manages its sales independently. Obviously, this case is the most expensive strategy. In case study 2, the MG manages its production and sales through the cooperation of its participants. The overall expense in case study 1 is $175,935, which reduces by 2.5% in case study 2 to $171,472 due to cooperation of the participants. The overall profit of the participants in case studies 1 and 2 is zero, because within the micro-grid, revenue obtain from selling electricity to one participant is the cost of purchase electricity for other participant.

B Micro-grid in grid-connected mode (case studies 3-6 Table 5.10)

We consider four case studies (Table 5.12 case studies 3-6) to investigate the performance of the cooperative game theory, the Nash bargaining solution in a grid-connected mode with the possibility of power exchange with the utility grid. In all the case studies (3-4) of Table 5.12, the micro-grid can buy/sell electricity from/to the utility grid, while in the case studies (5-6) of Table 5.12, it can only buy electricity from the utility grid.

Table 5.12: Comparison of overall expense and total income of the Participants in the case studies

Case Study (Table 5.11)	Overall Expenses $	Income $	Overall Profit $
1	175,935	175,935	0
2	171,472	171,472	0
3	167,806	176,510	8,704
4	145,918	155,257	9,339
5	173,171	173,171	0
6	171,602	171,602	0

The overall expenses compare with the total income that is obtained in the grid-connected mode is shown in case studies (3-4) of Table 5.12. It can be seen that for the case study 3, the overall expense is $167,806 and the total revenue generated is $176,510 when the participants independently manage their production and sales, thus, resulting in a saving of 5.2%. When the participants cooperate with each other for mutual benefit as in case study 4, the expense incurred is $145,918, and income is $155,257, which yield an increase of 6.4%. By comparing the two profits in case studies 3 and 4 of Table 5.12, it can be seen that there is a sharp increase of 7.3% in favour of the cooperative game theory approach.

In case studies 5 and 6 of Table 5.12, the micro-grid only purchases electricity from the utility grid. Therefore, the overall profit will be zero, which agrees with the results obtained in [134]. In this case, the overall expenses are $173171 and $171,602 in case studies 5 and 6 respectively. It is, therefore, evident that the use of cooperative game theory usually reduces the expenses incurred by the participants. In cooperative game theory approach, the participants can jointly purchase/sell electricity from/to the main grid through the micro-grid central controller. In this case, the MGCC acts as a mediator to coordinate the energy transfer amongst the micro-grid participants. We can then say that the cooperative game approach is not only beneficial to the participants but to the energy providers as well.

C Individual Profit Allocation in Micro-grid

Figure 5.7 shows the profit of individual participants when they cooperate with each other and when they selfishly maximize their individual benefits in grid-connected mode. In this case, the fire station has the lowest profits and restaurant record the highest profits. Comparing the profit level of the participants, the following changes are observed. In the first case, the fire station has a profit of $25441 when it is independent, but when the participants cooperate using the Nash bargaining solution, the profit increases by 2.42% to $26056. The restaurant, on the other hand, has a profit of $28558 under independent scenario, and the profit of $29005 when cooperating with each other, which represents an increase of 1.6%. This shows that the use of cooperative game based on Nash bargaining solution ensures an increase in profit of the participants compare to the situation when they independently maximize their profits.

In islanded mode, similar deduction is obtained with the exception that the fire station has an increase of 2.8% and restaurant's profits is increased by 2.1% due to the cooperation of the participants as indicated in Figure 5.8.

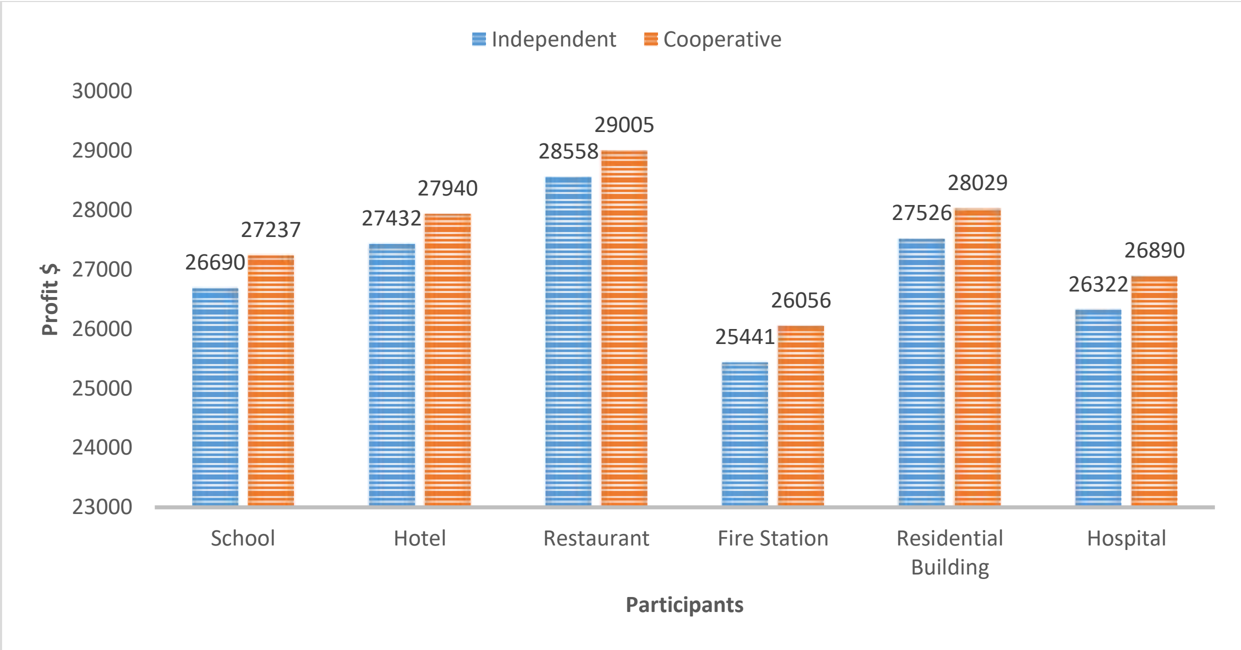


Figure 5.7: Profit of the participants in grid-connected mode

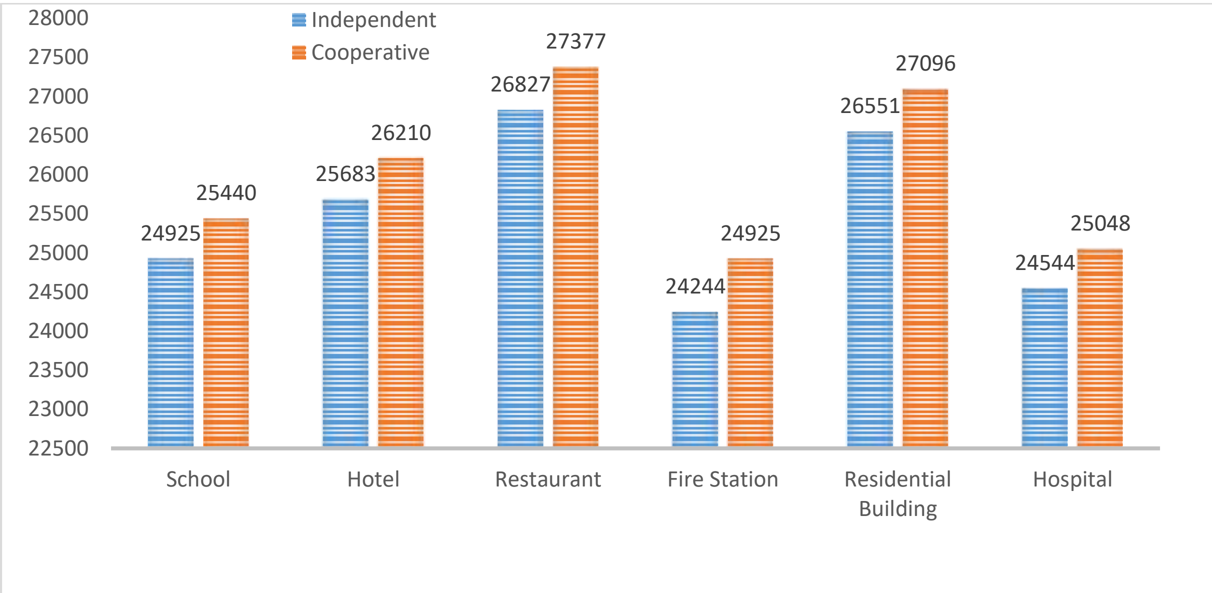


Figure 5.8: Profit of the Participants in islanded mode

5.5 Application of Cooperative Game Theory using Generalized Nash Bargaining Solution.

To find the generalized Nash bargaining solution we shall consider the Nash bargaining solution with negotiation power indicator. We then, maximize Nash type objective function given in (4.24) and (4.31) in both grid-connected and islanded mode respectively subject to their listed constraints.

A Effect of applying negotiation power indicator

For the optimal solution obtain in Figure 5.9 in grid-connected, the transfer price level for all the participants needs to be specified before solving the problem. We also need to specify the negotiation power indicator for each participant. We consider eight transfer price levels one at a time for all the participants. In the first case, we assume that all the six participants have the same negotiation power thus $\alpha 1, \alpha 2, \alpha 3, \alpha 4, \alpha 5$ and $\alpha 6$ are all set to 1 and the transfer price is fixed at \$0.039. For this problem, TLBO algorithm was used to obtain the optimal solution. When the generalized Nash bargaining solution is used with given lower profit, the objective functions in (4.24) is maximized subject to (4.32) - (4.44) in grid-connected mode and in islanded mode, the objective function (4.31) is maximized subject to (4.33) – (4.38), (4.43)–(4.46). Considering the profit allocation mechanism, i.e., the Individual participant obtains the same profit under this scenario. The optimal solution is shown in Figure 5.9.

We consider the possibility of having different negotiation power in which the negotiation power n, for example, determines the utility preference of the participants. A large value of n indicates that the participants will obtain a higher profit than that of other participants. Therefore, the necessary tools are provided by game theory to carry out the weighted fair profit among the participants, although the savings in the distributed case could be smaller for the other participants.

In order to investigate the possible scenario with the propose model, there is a need to consider the differences in participant negotiation power. In this case, only the negotiation power indicator for a participant needs to change while the other information remains the same as in case 1. To favour certain participant, we assume the negotiation power of the School to be higher than that of all other participants. Therefore, we set $\alpha 1 = 1.06$ and $\alpha 2 = \alpha 3 = \alpha 4, = \alpha 5 = \alpha 6 = 1$ Again, the problem is solved directly using TLBO algorithm. Figure 5.9 shows the optimum profit allocation of each participant in grid-connected mode. As can be seen, due to its higher negotiation power, the school obtained a higher profit when compared to case 1. For example, for transfer prices of 0.039$/kWh the school surplus increases from the $27,237 to $35,044, which is 28.7% increase as indicated in Figure 5.9. This is possible because of the need to favour this participant, and thus reduce the profit of other participants. In islanded mode, the main grid is disconnected and the diesel generator is substituted to deliver the power. The same condition as in the grid-connected is applied and the optimal solution is obtained as shown in Figure 5.10, which shows that the school surplus increases from $25440 to $33085 by 30% due to school having a higher bargaining /negotiation power.

The generalized Nash bargaining solution has the negotiating power indicator, which determines whether to favour certain participant. If by consensus the participants of MG deem it fit to favour certain participant (i.e. because such participant is structurally different) the negotiation power for such participant will be higher than other participants. On the other hand, if by consensus no participant is to be favoured, then all the participants will be assigned the same bargaining power. This means that the symmetrical axiom is satisfied. When using the proposed fairness approach the participant may have higher profit than the other participants. These participants could sacrifice their benefits to achieve mutual benefits.

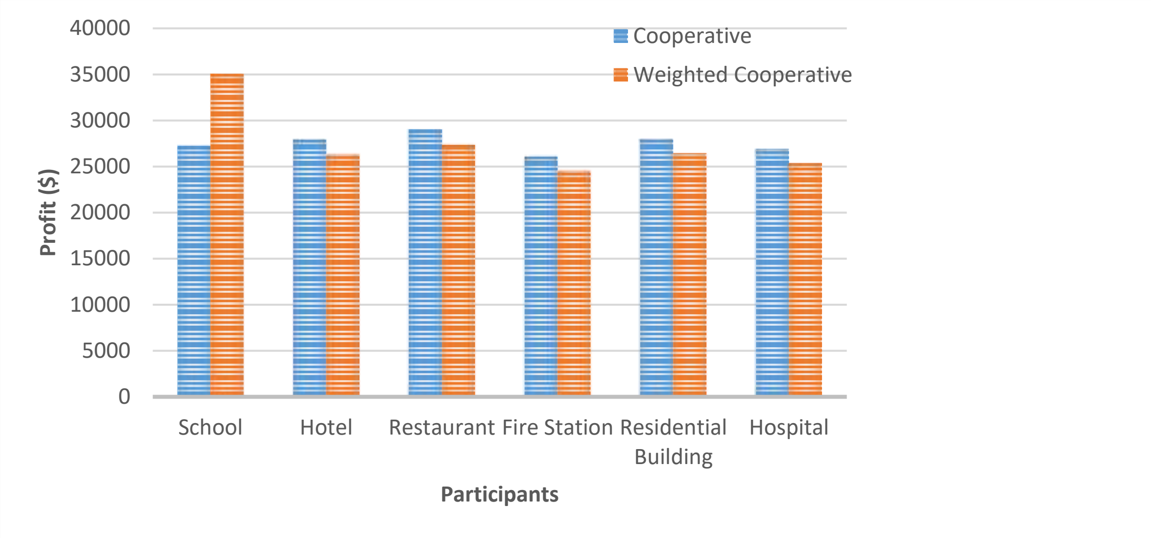


Figure 5.9: Optimized profit allocation profile for all participants in grid-connected mode with the school having a higher negotiation power.

Figure 5.10: Optimized profit allocation profile for islanded mode with the school having a higher negotiation power.

B Effect of Transfer Prices

<u>Case 1</u>

When the Nash bargaining solution is used to maximize the total profit of the six locations as given in (4.24) in grid-connected mode, it is expected that all the participants will benefit. The transfer prices of the electricity within the micro-grid are taken as 0.039-0.109 $/kWh and the optimal results are shown in Tables 5.13 and 5.14. These results are obtained using the cooperative game theory with the same negotiation power indicators.

In the MG system, the intra-electricity transfer price does not affect the total profit; this is because the profit obtained when electricity is sold to the participant means the cost of purchasing electricity for other participants. The total profit obtain by the participants when in grid-connected mode for the cooperative game theory for any transfer price is approximately $165,157 and is about 7.8% of the status-quo profit as shown in Tables 5.13 and 5.14. With the school having higher negotiation power, which cost a drop in the profit of other participants as in Table 5.14, the variation of transfer price still maintains the profit level of other participants above the status-quo profit level. The savings for each participant is fairly distributed. Although the profit varies differently in the fixed electricity transfer price and the total profit of the whole micro-grid is approximately the same. It is, therefore, obvious that none of the participants have profits lower than the status-quo profit (lower profit as indicated in Table 5.10).

Similarly, in the islanded mode of operation, the cooperative game theory is used to maintain the profit of each participant in the site above the status-quo profit with variation in transfer prices. Table 5.17 shows the variation of transfer price when different negotiation power is applied, just as in the case of grid-connected mode. In this case, the total profits obtain by the participants in cooperative game theory for any transfer price is $161,969 and is about 10.2% above the status-quo profit.

<u>Case 2:</u>

In this case 2, the participants independently manage their resources and therefore not using game theory in both grid-connected and islanded mode. By maximizing (4.222) subject to (4.32) – (4.44) in grid-connected and maximizing (4.29) subject to (4.33) to (4.38) and (4.43) to (4.45) in islanded mode, the optimal results obtained are shown in Tables 5.16 to 5.18. The optimal results obtained in the simulation also vary differently depending on the transfer prices. The total profit obtained with the participants without game theory in grid-connected for any transfer price is approximately $161,969 and is about 5.7% of the status-quo profit as shown in Table 5.15.

By comparing the results obtained in Table 5.15 with status-quo profit as shown in Table 5.10, we observe that some participants have obtained profit less than the assigned status-quo profit at a certain transfer prices, and even less than the optimized annual cost. For example, in a fire station, in Table 5.15, for the transfer prices of 0.089, 0.099, and 0.109$/kWh, the profit obtain is less than status-quo profit level and at the same time less than the optimized annual costs. Again, for hospital, in Table 5.15 at transfer prices 0,099$/kWh and 0.109$/kWh, the profits are $25095 and $24001 and the status-quo profit is $25248. This implies that both the hospital and fire station have negative profits at certain transfer prices. The negative profit is because of having a profit lower than specified lower profit (status-quo profit) as in cooperative game theory NBS.

In addition, for islanded mode of operation, the total profit obtained with the participants without game theory for any transfer price is approximately $15609 and is about 6.2% of the status-quo profit as shown in Table 5.18. In this islanded mode, some participants do not benefit, the results indicate that some participants have their profits lower than the status-quo profits. This is because lower profit level is not considered in this case and may lead to high profit in some participants and negative profit in other participants, whereas, in a cooperative approach some participants could sacrifice their benefits to achieve mutual benefits [3]. For example, for fire station, in Table 5.18, the transfer prices are 0.099 and 0.109$/kWh and the optimal simulation results obtained are $23365 and $23224 respectively, which is lower than the status-quo profits (i.e. $23452). Ditto for hospital, when the transfer price is 0.109$/kWh.

These solutions imply that some participants may not benefit when transfer prices are varied as the higher transfer prices may become unbearable for some participants to make profit without been helped.

Table 5.13: Optimal results for cooperative game theory with the same negotiation power in grid-connected mode

Transfer Price $/kWh	School $	Hotel $	Restaurant $	Fire Station $	Residential Building $	Hospital $	Total $
0.039	27237	27940	29005	26056	28029	26890	165157
0.049	27001	27711	29562	25672	28563	26648	165157
0.059	26910	27501	29687	25672	28537	26850	165157
0.069	26891	27700	29500	25776	28480	26810	165157
0.079	26751	27315	29828	25772	28540	26951	165157
0.089	26714	26910	29468	26931	28468	26666	165157
0.099	25990	27452	29754	26141	28755	27065	165157
0.109	26421	27231	29665	26222	28664	26954	165157

Table 5.14: Optimal results for cooperative game theory with the different negotiation power in grid-connected mode (i.e. when $\alpha 1 = 1.06$ (School) and $\alpha 2 = \alpha 3 = \alpha 4, = \alpha 5 = \alpha 6 = 1$)

Transfer Price $/kWh	School $	Hotel $	Restaurant $	Fire Station $	Residential Building $	Hospital $	Total $
0.039	35044	26358	27363	24581	26443	25368	165157
0.049	34784	26112	27725	24926	26211	25399	165157
0.059	34652	25944	27870	24670	26521	25500	165157
0.069	34515	26411	27185	25114	26322	25610	165157
0.079	34261	26351	27921	24981	26222	25421	165157
0.089	34731	25950	27531	25623	25991	25331	165157
0.099	34992	25883	26899	25723	25983	25677	165157
0.109	34589	25931	27367	25332	26264	25674	165157

Table 5.15 Optimal results without cooperative game theory in grid-connected mode

Transfer Price $/kWh	School $	Hotel $	Restaurant $	Fire Station $	Residential Building $	Hospital $	Total $
0.039	26690	27432	28558	25441	27526	26322	161969
0.049	26721	27582	28983	24671	27579	26433	161969
0.059	26822	27389	29542	24622	27590	26004	161969
0.069	26804	27970	28739	24798	27980	25678	161969
0.079	26873	28446	28323	24671	28245	25411	161969
0.089	26927	28570	29842	23304	28002	25324	161969
0.099	26962	28674	29794	23341	28103	25095	161969
0.109	27838	28746	29655	23384	28345	24001	161969

Table 5.16: Optimal results with cooperative game theory in the Islanded mode

Transfer Price $/kWh	School $	Hotel $	Restauran t $	Fire Station $	Residential Building $	Hospita l $	Total $
0.039	25440	26210	27377	24925	27096	25048	156096
0.049	25422	26661	27249	24269	27521	24974	156096
0.059	25405	26463	27401	24605	27432	24790	156096
0.069	24901	26278	27600	25085	27611	24621	156096
0.079	24816	26104	27800	25254	27701	24421	156096
0.089	24803	26349	27920	25186	26981	24857	156096
0.099	24923	26299	28000	25111	26851	24912	156096
0.109	24865	26811	27826	24806	26791	24997	156096

Table 5.17: Optimal results with cooperative game theory in the Islanded mode with different negotiation power (i.e., when $\alpha 1 = 1.06$ (School) and $\alpha 2 = \alpha 3 = \alpha 4, = \alpha 5 = \alpha 6 = 1$)

Transfer Price $/kWh	School $	Hotel $	Restauran t $	Fire Station $	Residential Building $	Hospita l $	Total $
0.039	32085	24726	25828	23521	25467	24469	156096
0.049	31829	25121	25563	23562	25763	24258	156096
0.059	31732	25321	26000	23611	25221	24211	156096
0.069	31654	25422	25658	23617	25101	24644	156096
0.079	31239	25477	26115	23660	25076	24529	156096
0.089	31286	24877	26410	24006	25095	24422	156096
0.099	31521	24811	26110	23799	25644	24211	156096
0.109	31414	24738	26000	24046	25539	24359	156096

Table 5.18: Optimal results without cooperative game theory in the islanded mode

Transfer Price $/kWh	School $	Hotel $	Restaurant $	Fire Station $	Residential Building $	Hospital $	Total $
0.039	25440	26210	27377	24925	27096	25048	156096
0.049	25321	26100	27096	25002	27602	24975	156096
0.059	25205	25900	27235	25473	27451	24832	156096
0.069	25009	26470	27474	24932	27432	24779	156096
0.079	25103	26500	27009	24875	27987	24622	156096
0.089	25339	26007	27150	24862	28199	24539	156096
0.099	25921	26566	27633	23365	28322	24289	156096
0.109	25893	26678	27877	23224	28415	24009	156096

5.6 Comparison of Algorithms for Different Optimization Techniques

In this section, three heuristic optimization methods are presented.

A Genetic Algorithm (GA)

The working principle of a genetic algorithm (GA) has to do with the population of strings, which consists of generations. A string can be divided into many substrings and each of them denotes a problem variable. In the energy management system, the problem variables represent the profits of each participant. The participant of a micro-grid corresponds to a substring. The decision on the length of each substring is based on the maximum/minimum on the profit of the participant it represents and accuracy of the solution desired. The choice of string length is based on a trade-off between the accuracy of the solution and the time to take in solving the problem. Although, the longer the string, the better the accuracy, the solution time will be higher.

The procedures for solving GA are as follows:

1. Select the possible population size, number of generations, length of substring and the number of runs

2. In the first generation, the initial coded string is generated as population members.

3. Decode the population in the string to obtain the profit of each participant

4. Evaluate the surplus of all the participants.

5. Determine the fitness value of the population members.

6. Carry out selection based on reproduction. Repeat the procedures 2 – 6 for the first trial for all the numbers of generations and the maximum profit is noted. This is done repeatedly for the selected number of trials and the maximum for the augmented profit is taken as the solution.

Table 5.19: Parameter values for the GA-based energy management of micro-grid

Control Parameter	Value
Number of generations	300
Number of design variable	6
Population size	60
Selection mode	Tournament
Crossover method	Directional based crossover
Crossover rate	0.9
Mutation method	Non-uniform
Mutation rate	0.1

B Particle Swarm Optimization (PSO)

The steps used in the algorithm are presented as follows

Step 1: Input the relevant data needed such as load demand, power generation profiles and all other data necessary for the computation process.

Step 2: Initialize the profits and the status-quo profits of each participant as an operation parameter of PSO.

Step 3: Compute the objective function for each population vector.

Step 4: Generate the position and velocity of the particle in a certain dimension and at a certain iteration.

Step 7: Compute the objective function for each participant location.

Step 8: Determine $pbest$ and $gbest$ of the swarm.

Step 9: Update the velocity of the particle and the position of the particle.

Table 5.20: Parameter values of the PSO-based energy management of micro-grid.

Control Parameter	Value
Number of iterations	300
Number of design variables	6
Population size	60
Initial weight	1
Inertial weight damping ratio	0.99
C1 (learning factor)	2
C 2(learning factor)	1.5

C. Teaching-Learning-Based Optimization (TLBO)

In a search space, a group of learners, which consists of a population in TLBO is randomly generated and is bounded by the number of subjects (or design variable). The number of optimization parameters used represents the number of subjects offered to the students. The objective function of the optimization problem is the output of the learners. It is through learning of the learners that the teacher searches in TLBO for the optimal value. There are two phases of the working principle of TLBO, the teacher's phase and the learner's phase. In the teacher's phase, the learning is done through a teacher, whereas, in the learner's phase, the learning is accomplished through interactions with other learners.

The step by step procedures of TLBO is as follows:

1. Randomly initialize the population in bounded search space.

2. Teacher's phase – The objective function is computed for each design variable.

3. The mean value of each design variable offered to the learners is arranged column-wise.

4. Set the generation count.

5. The highest value of the learners is chosen as maximum fitness function, which is considered as a teacher of the subject. The best teacher aims at changing the average from ‘mean’ to ‘new mean’.

6. Evaluate the difference between the new average mean and the new current mean by using teaching factor.

7. Update the learner’s knowledge by adding the difference mean and the existing learner’s population.

8. Learner’s phase – In this phase, the operation of TLBO enables the learners to interact with each other, thereby increasing their knowledge. Randomly select another learner to update the learner’s knowledge.

9. Generation count updated. Check the criterion for termination, otherwise, proceed to step 2.

Table 5.21: Parameter values for TLBO-based energy management of micro-grid

Control Parameter	Value
Number of generations	300
Number of design variable	6
Population size	60
Rand	0 – 1
Selection method	Elitism

5.7 Comparison of the Algorithms

A Justification of parameters used in the algorithms

In order to justify the adequacy of some common parameters use in the heuristic technique, the variation number of generations/iterations is investigated for both grid-connected and islanded mode. In this case, the population size is fixed at 60, then the number of generations/iterations varies. Figures 5.11 and 5.12 show the comparison of number of generations/iteratios for system to converge as a function of exact value when population size is fixed at 60 for the three hueristics optimization techniques i.e. TLBO, PSO, and GA for both grid-connected and islanded mode.

Through 20 trials, for grid-connected mode in TLBO method, there is rapid increase in average exact value as the number of generation increases in the range of generation between 50 and 190. However, between 190 to 198, there is a slight increase in the exact value. At 200, there is no more increase in exact value and therefore, the recommended number of generations is 200, which corresponds to a exact value of $2389. In the case of PSO, the graph shows a similar increase in the number of iterations just like TLBO but the increase is extended to 240. Hence, for PSO, the recommended number of iterations is 250, which corresponds to exact values of $2295. For GA, the increase goes until it reaches 290 and the recommended number of iterations is 300, which corresponds to exact value of $2180. Therefore, for the fixed population size of 60, then the number of generations of 300 can be selected

Similar deduction holds for islanded mode of operation of MG as shown in Figure 5.12. In this case, the recommended number of generations/iterations of 240 with exact values of $2260, 280 with exact values of $2140, and 300 for a exact values of $1911 for TLBO, PSO and GA respectively.

Therefore, population size and number of generations/iterations 60 and 300 respectively to accommodate all the algorithms under investigation are selected.

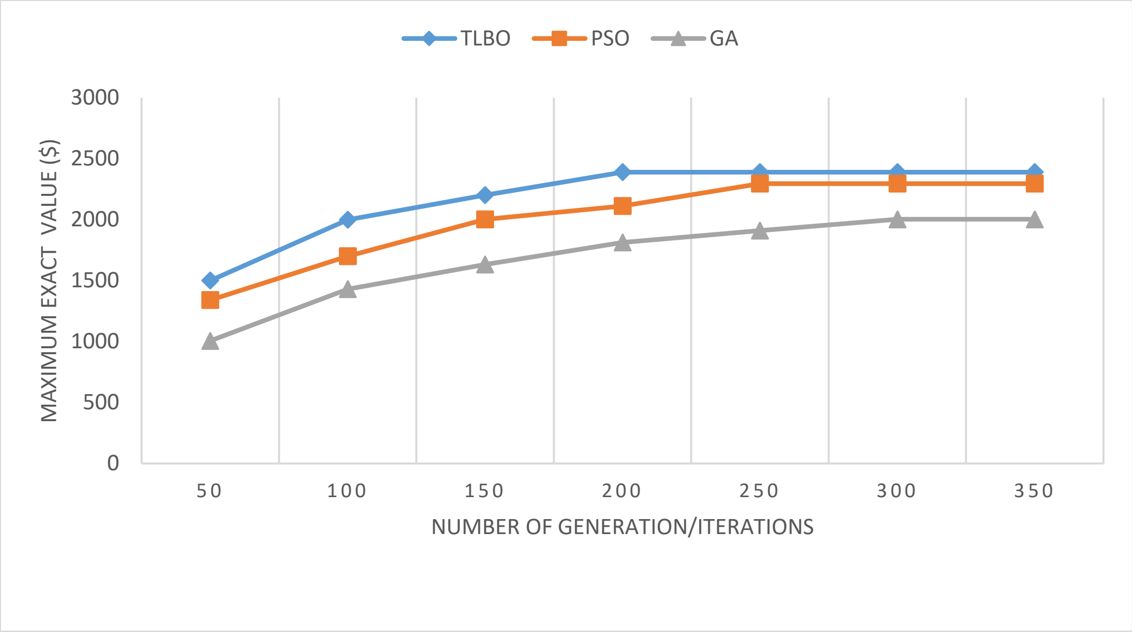


Figure 5.11: Comparison of necessary number of generations/iterations for convergence for fixed population size of 60 in grid-connected mode.

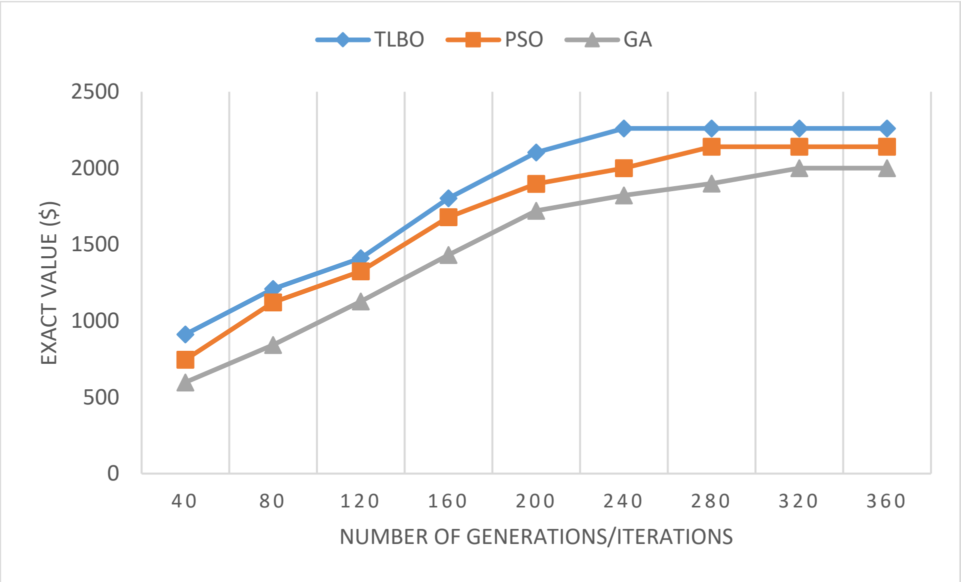


Figure 5.12: Comparison of necessary number of generations for convergence for fixed population size of 60 in islanded mode.

B. Comparison of algorithms in terms of participant's profits

This system consists of six participant sites: Tables 5.22 and 5.23 listed all the statistic results that evolve the profit distribution, average profit each strategy and execution time in both grid-connected and islanded mode.

To demonstrate the effectiveness of the proposed TLBO method, the profits allocation to the six participants are tested in both the grid-connected and the islanded mode using both the game theory (cooperative) and without the game theory (independent) approach. In this work, the propose TLBO method is compared with one traditional method, i.e. Lambda iteration method and heuristic methods, i.e. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). At the same parameter setting (i.e. the number of generations and population size) we perform 20 trials using the four algorithms to indicate the variation during the processes and be able to compare the quality of the solutions and convergence characteristics. Through 20 trials, the algorithms have different average profit distribution, different profit of each strategy and the different rate of convergence. Tables 5.22 and 5.23 showed the average profit distribution outlines of the optimal solution.

In these two tables, it is observed that the TLBO obtained the highest profit distribution for each participant in both the grid-connected and islanded mode amongst the algorithms and therefore, having the highest solution quality, followed by PSO, GA and Lambda in that order. The closeness of the value of PSO to TLBO is due to ability of PSO to achieve better solution and convergence characteristics than GA. Some of the parameters such as crossover rate and mutation rates for GA, c1 and c2 for PSO have been selected based on guidelines in the literature.

Table 5.22: Comparison of the algorithms in grid-connected mode.

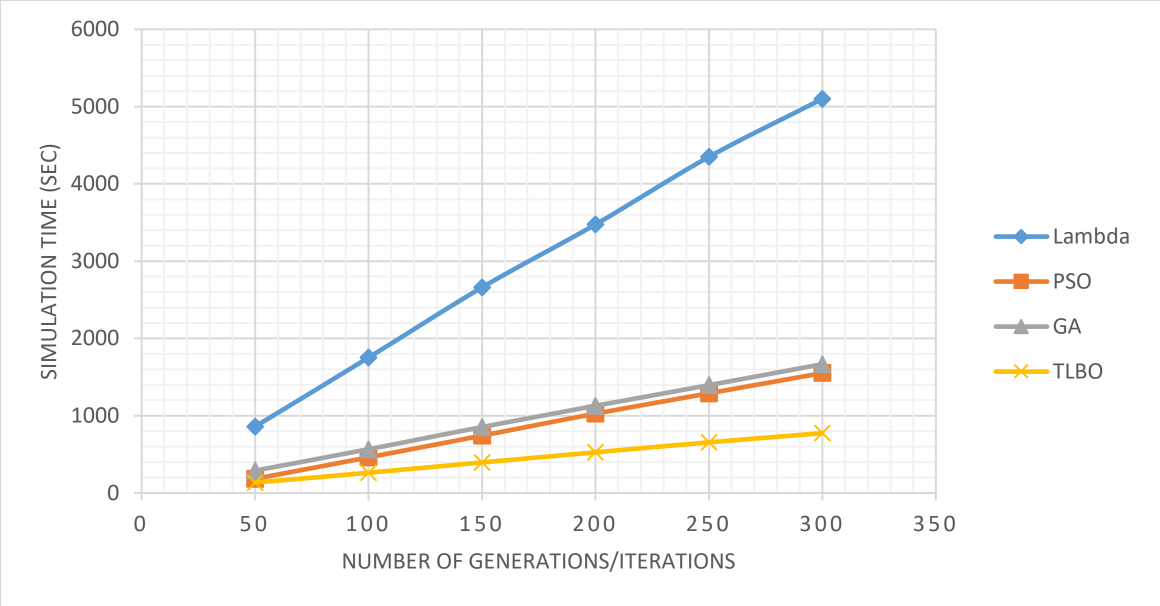
Algorithm	Participant Strategy	Profit of Each Participant ($)						Av. Profit of each strategy ($)	Simulation time (sec.)
		School	Hotel	Restaurant	Fire Station	Residential. Building	Hospital		
Lambda	Independent	25355	26061	27130	24169	26150	25006	25645	5260
	Cooperative	25844	26571	27663	24636	26665	25483	26144	
PSO	Independent	26156	26884	27987	24932	26976	25796	26622	1639
	Cooperative	27000	27599	28410	25990	27766	26820	27261	
GA	Independent	25889	26609	27701	24678	26700	25533	26185	1658
	Cooperative	26788	26571	28399	25986	27666	26811	26870	
TLBO	Independent	26710	27510	28560	25461	27499	26322	27010	759
	Cooperative	27300	27951	28915	25994	28011	26887	27510	

Table 5.23: Comparison of the algorithms in Islanded mode.

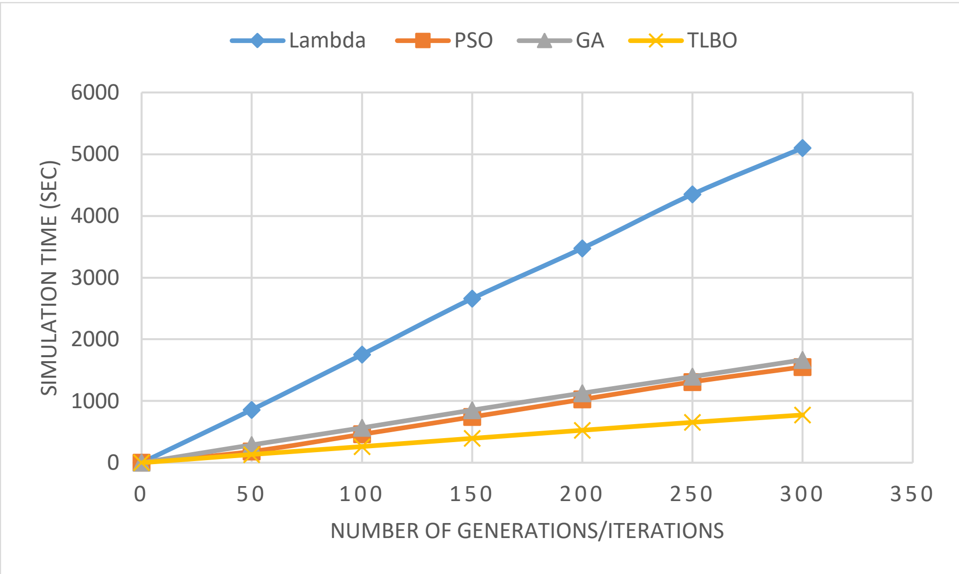
Algorithm	Participant Strategy	Profit of Each Participant ($)						Av. Profit of each strategy ($)	Simulation time (sec.)
		School	Hotel	Restaurant	Fire Station	Residential Building	Hospital		
Lambda	Independent	22147	22299	22530	21890	22318	22071	22209	5100
	Cooperative	23432	23570	23821	23155	23601	23335	23486	
PSO	Independent	23888	24053	24302	23612	24074	23807	23956	1652
	Cooperative	24967	25085	25286	24919	25168	25148	25096	
GA	Independent	23391	23552	23796	23120	23572	23311	23457	1667
	Cooperative	24210	24294	24564	24304	24540	24583	24416	
TLBO	Independent	24137	24304	24556	23858	24325	24055	24206	774
	Cooperative	25367	25528	25772	25096	25549	25287	25433	

Figure 5.13 show the graphs of average simulation time in both grid-connected and islanded modes with different number of generations for the profit obtained in Tables 5.22 and 5.23. It is observed that the average simulation time obtained by the TLBO is smaller compared to other algorithms. This implies that the TLBO method saves computation time than all other algorithms under investigation. This is because TLBO method does not need any specific control parameter as we have in PSO and GA, thus, reducing the optimization parameters for solving any complex problem [97]. The results indicate the superior properties of the TLBO over other algorithms. The results obtained show the better computational efficiency of TLBO compared to other existing methods. The PSO is next to TLBO in terms of good performance. It also saves time compared with GA and Lambda methods. As compared with GA, PSO saves more time because it does not perform selection and crossover operation as GA does. The Lambda is the slowest of all the entire algorithms, as it takes a very long time to converge. With the Lambda, it converges slowly and therefore, takes more computation time than all other algorithms to converge as stated in [100].

A single run of any heuristic algorithm cannot show the performance of that method. The performance should be judged when the program is run for a certain number of trials, typically 20 runs. A conclusion about the performance of any heuristic method depends largely on the number of trials use to obtain the results



(a) Grid-Connected Mode

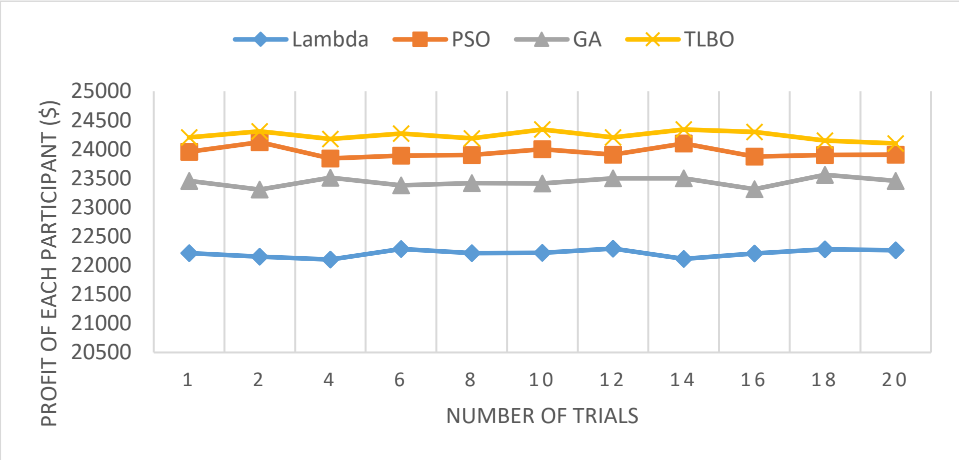


(b) Islanded mode

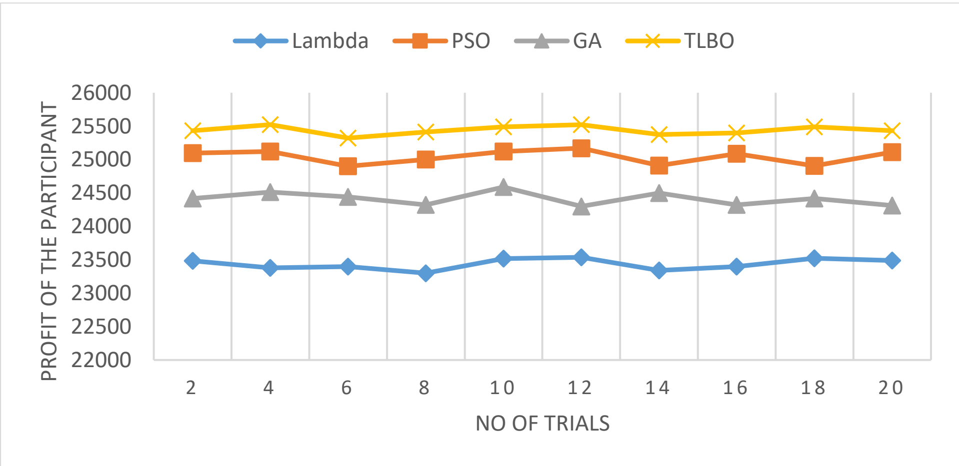
Figure 5.13: Average Simulation Time Versus Number of Generations/iteration (a) Grid-Connected mode (b) Islanded mode.

Figures 5.14 and 5.15 show the graphs of average profit of both independent and cooperative in both islanded and grid-connected modes against the number of trials. These Figures show the distribution patterns of the best solution of each trial. It can be seen that almost all values of the TLBO method are higher than other algorithms in both grid connected and island mode, which shows it consistency. The consistency of TLBO approach is due to the TLBO efficiency and the fewer parameters that involved during the renewal process. It also possesses simple concept, no specific algorithm parameters, rapid convergence and ease of implementation. TLBO has the best solution and convergence characteristics. The PSO also performs better than GA and Lambda. The Lambda performance is the least of them.

mode (b) Islanded mode.

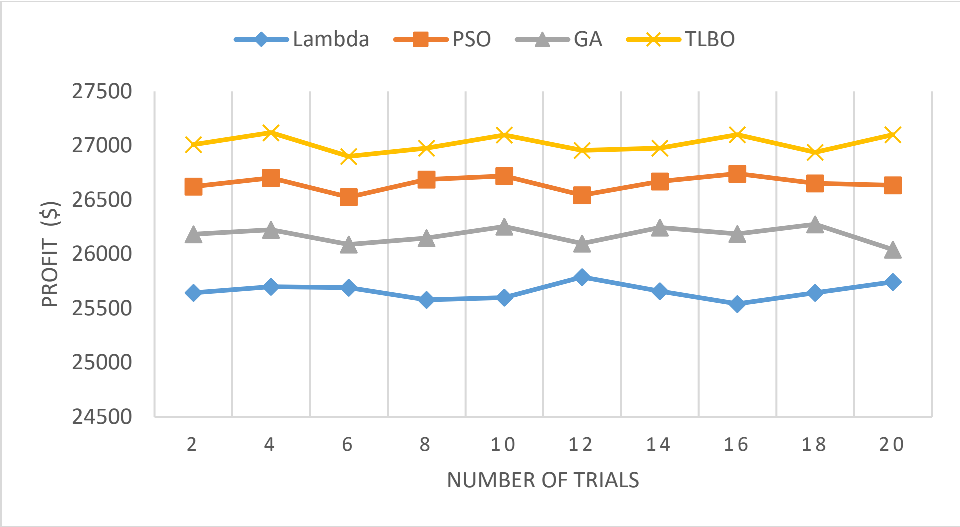


(a) Independent

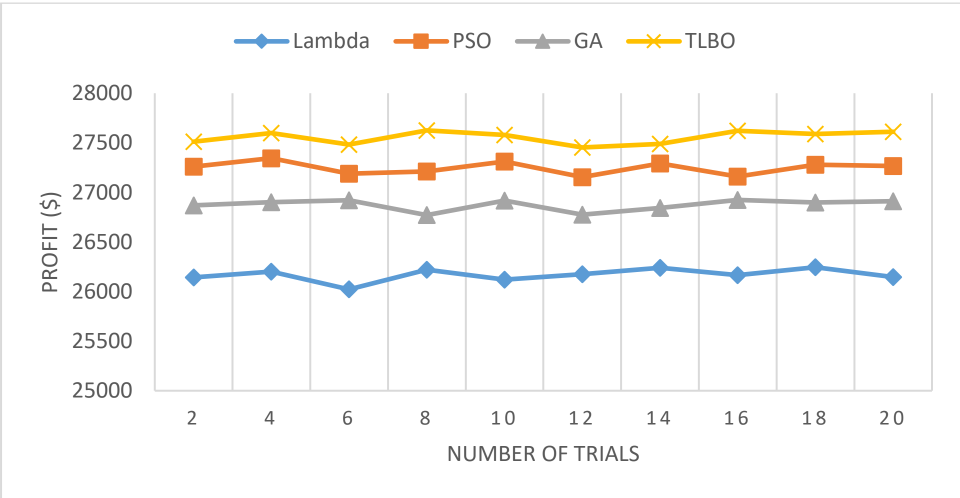


(a) Cooperative Strategy

Figure 5.14: Average Profit of both independent and cooperative strategies on the number of Trials in Islanded mode.



(a) Independent



(b) Cooperative

Figure 5.15: Average Profit of both independent and cooperative strategies on the number of Trials in Grid-connected mode

5.7 Summary

In this chapter, the use of cooperative game theory using generalized Nash bargaining solution is applied to tackle problem of EMS in remote communities. More specifically, six local sites are used as a case study. It reveals that the use of cooperative game theory usually reduces the expenses incurred by the participants than to independently manage their sales or production.

It is also demonstrated that the fair weighted profit distribution amongst the participants can be achieved by using cooperative game theory based on the generalized Nash bargaining solution

Furthermore, it is guaranteed that by participating in EMS using cooperative game theory based on generalized Nash bargaining solution a participant will obtain fair weighted profit distribution. Thus, it is rational for the participants to form coalition for mutual benefits, the weighted fairness in profit distribution is inherited from the use of cooperative game theory.

Robustness of TLBO is also demonstrated in this chapter. It shows that TLBO possess superior qualities with high quality solution and convergence characteristics that are stable. The results obtained therefore, show that the propose method is indeed robust and capable of providing quality and efficient solution to energy management problems.

Chapter 6

Conclusion and Future Works

In this chapter, conclusion of the thesis and the future work directions are presented.

6.1 Conclusions

From the thesis, it can be deduced that the generalized Nash bargaining solution is used to achieve weighted fair profit distribution amongst the MG participants. The proposed model combines the advantages of both Nash bargaining solution and generalized Nash bargaining solution to favour certain participants. Moreover, the TLBO algorithm is proposed to achieve optimal solution. The investigation reveals that the TLBO gives the highest quality solution and better convergence characteristics that are stable.

The simulation results in this thesis can be summarized as follows:

(a) The energy management with overall profit allocation to the participants using cooperative game theory and without cooperative game theory.

In grid-connected mode, a cooperative energy management is presented where the participants of the micro-grid can cooperate for mutual benefit and to utilize resources efficiently. A case study of six sites is considered and the solutions are empirically evaluated to show that cooperative game theory increases profit compare to when there is no game theory. In this case, overall expenses and total revenue generated are investigated and savings obtained are higher in cooperative game theory than when participants independently manage their resources and sales. In islanded mode, micro-grid is disconnected from the main grid thus, acting as an independent entity. Obviously, the mode of operation is very expensive. In this case, the overall profit for both with game theory and without game theory is zero, mainly because the MG is islanded and overall revenue to be obtained from selling electricity to a participant means the cost of purchase electricity for another participant.

(b) Individual Profit allocation in micro-grid.

The individual profit allocated to each participant of MG in both grid-connected and islanded mode was investigated. In the simulations, it was observed that higher profit is obtained when participants cooperate with each other compared with when the participants independently manage their own resources. The investigation is extended to a novel approach of a game theory using generalized Nash bargaining solution, when a particular participant needs to be favoured, therefore, such participant receives higher profit than other participants. The higher negotiation power is due to a participant that is different structurally from other participants and need to be favoured (i.e. the participant site to be favoured may be non-profit making establishment such as a school). However, any other participant site may be considered due to some other reasons to favour such participant. Under this condition, the participant with the different negotiation power indicators is assigned, so that the participant with higher bargaining power receives higher profit than other participants. Under this condition, cooperative game theory still maintain higher profit compared with when the participants independently manage their resources.

By increasing the number of participant in the MG, both the total and individual profit would be increased, which depends largely on the pattern of the load demand (energy consumption) of the participants of MG. If peak power demand and energy consumption patterns of each participants are different from each other there would be more benefits. Higher income is derived by selling electricity to other participants than selling to the grid in grid-connected mode.

(c) Effect of different transfer prices on the profit of the participants.

The effect of different transfer prices on the profit of each participant is investigated with game theory and without game theory in both grid-connected and islanded mode. In islanded mode, intra-electricity transfer price does not affect the total profit; this is because the profit obtained when electricity is sold to the participant means the cost of purchasing electricity from another participant, which actually agrees with reference [3]. However, the transfer prices actually have an effect on individual profit of the participants. This is because variation of transfer prices on individual profit of the participant in an independent mode may lead to negative profits. This is because no cooperation is involved to allow participants to make sacrifices for other participants using lower profit bound.

From the simulation carried out, it is observed that for different transfer prices in cooperative game theory approach, all the participants benefited from MG, as their profit is above the status-quo profit, even when the profits accruable to participant decreases because of introduction of higher bargaining power assigned to a particular participant.

When the participants without game theory are investigated, the variation of transfer prices causes many participants to incur negative profits in some transfer prices. This actually shows the great advantage of cooperative game theory approach over when game theory does not apply to EMS.

(d) The use of Teacher-Learning-Based Optimization method to solve energy management problem.

An algorithm known as TLBO is used to solve energy management problem considering the constraints. TLBO is a heuristic algorithm use to optimize the solution to the EMS problem, while a cooperative game theory on the other hand, is a powerful tool is used to obtain a solution that is fairness with well-defined status-quo point.

To show the effectiveness of TLBO method, the results obtained are compared with other heuristic method such as GA and PSO and one classical approach i.e. Lambda-iteration method. The results obtained demonstrate that the TLBO method possess superior qualities with a high quality solution and convergence characteristics.

The thesis also investigates the contribution of intra-electricity transfer amongst the participants of MG. The research work shows that intra-transfer of electricity contributes 11% of energy demand to generation scheduling, whereas, in grid-connected mode, it only contributes 2% of energy demand because of the possible energy exchange with the main grid.

6.2 Future Works

The thesis investigates the problem of energy management system of micro-grid as regards profit distribution to the players. A lot of limitations and future works are identified. For the MG to be optimally design, the distances between sites are relatively small, so the energy management model considers no electricity loss. Also, the privacy of the participants operating in a big system, upgrade the system in a regular manner and EMS reliability issues have not been addressed. Such challenges and limitations may affect EMS operations.

Based on the results obtained in the thesis, the proposed future works are described as follows:

(a) Validating the developed models

In the proposed EMS, simulation results are not validated. In the future work, validating the simulation results need to be added to the existing EMS.

(b) Real time simulation

The issue such as real time simulation are not considered in the proposed EMS. This work can be extended to a real time simulation, so that evolution of simulated time will match actual time simulation.

(c) Adaptive bargaining power

The proposed EMS is concerned with choosing the bargaining power arbitrarily. In the future work, the bargaining powers will be updated adaptively during the EMS coding process.

(d) Reliability, scalability and data communication privacy

In this work, the issues of reliability, scalability, and communication data privacy issues have not been addressed. In the future work, these issues could be addressed.

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APPENDIX

Appendix A

Input Parameters used in the simulation

Table A1: Electricity demand for both winter and summer seasons (Day 1 for winter and Day 2 for summer) [3].

Day	Time (hr)	School (kW)	Hotel (kW)	Restaurant (kW)	Fire Station (kW)	Residential Building (kW)	Hospital (kW)
Day 1	T_1	2.1	2.3	8.9	2.1	3.7	3.0
Day 1	T_2	2.1	9.3	3.5	3.3	5.6	4.5
Day 1	T_3	10.7	11.6	8.9	6.8	7.5	7.3
Day 1	T_4	10.7	11.6	17.7	6.8	7.5	7.3
Day 1	T_5	10.7	11.6	8.9	6.8	7.5	7.3
Day 1	T_6	4.3	9.3	17.7	4.1	18.6	5.4
Day 1	T_7	2.1	2.3	8.9	2.1	3.7	3.0
Day 2	T_1	2.1	2.3	8.9	2.1	3.7	3.0
Day 2	T_2	2.1	9.3	3.5	3.3	5.6	4.5
Day 2	T_3	10.7	11.6	8.9	6.8	7.5	7.3
Day 2	T_4	10.7	11.6	17.7	6.8	7.5	7.3
Day 2	T_5	10.7	11.6	8.9	6.8	7.5	7.3
Day 2	T_6	4.3	9.3	17.7	4.1	18.6	5.4
Day 2	T_7	2.1	2.3	8.9	2.1	3.7	3.0

Table A2: Time duration Tp in a day [3]

Period	Time Interval (hr)
T_1	6
T_2	2
T_3	3
T_4	1
T_5	5
T_6	4
T_7	3

Table A3: Weighting factor Wp

Season	Weighting Factor
Winter	197
Summer	178
Total	365

Table A4: All other Parameter values

Parameter	Description	Unit	Location/Value	Reference
y	Project Lifetime	Year	20	[88]
y	Lifetime of Solar Panel	Year	20	[88]
$yrep$	Lifetime of Battery	Year	10	[88]
C^i	Price of electricity imported from main grid	$/kWh	0.17	[3]
C^e	Price of electricity exported from main grid	$/kWh	0.0131	[3]
P_{Bmax}	Battery upper limit	kW	10	Self-defined
P_{Bmin}	Battery lower limit	kW	-10	Self-defined
PV_{max}	Solar PV upper limit	kW	20	Self-defined
PV_{min}	Battery lower limit	kW	0	Self-defined
P_{Dmax}	Diesel gen. upper limit	kW	10	Self-defined
P_{Dmin}	Diesel gen. lower limit	kW	3	Self-defined
i	Interest rate	%	12	[3]
ELP_s^L	Lower bound Value for site s	$	Table	From Calculation
λ	Reliability of Solar PV panel	%	0.98	[88]
$E_{ss'}$	k- electricity transfer price level from site s to site s'	$/kWh	0.039-0.109	[3]
λ	Reliability of diesel generator	%	0.98	[88]
λ	Reliability of Battery	%	0.98	[88]
	Cost of diesel generator	US/$kW	500	[88]
	Cost of solar PV panel	US $/W	0.92	[88]
C_f	Fuel Cost	US $/l	0.7	[88]

Appendix B

B1 Conference Paper

1 Ismaheel Oyeyemi Oladejo, Komla Folly “Energy Management of Grid-connected Micro grid using Game Theory” Conference Proceedings SAUPEC/ROB MUCH PLASA, Central University of Technology Free State, Bloemfontein. South Africa, January 28-30, 2019.

2 Ismaheel Oyeyemi Oladejo, Komla Folly: “A Game Theory Based Energy Management System for a Smart Grid: A Review” IEEE AFRICON 2019 Conference (Accepted)

B2 Journal Paper

1 Ismaheel Oyeyemi Oladejo, Komla Folly “Energy Management of Micro grid using Generalized Nash Bargaining Solution” (A paper to be submitted for publication)

2 Ismaheel Oyeyemi Oladejo, Komla Folly “Energy Trading of Islanded Micro grid using Game Theory” (A Paper to be submitted for publication)

Appendix C

Table C1: Breakdown of electricity transferred between sites in grid-connected mode

Site		Amount of electricity transferred between sites (kW)	Annual amount of electricity transferred (kW)
From	To		
School	Residential Building	0.9	328.5
Fire Station	Residential Building	0.2	73
Hospital	Residential Building	0.1	36.5
Fire Station	Restaurant	2	730
Hotel	Residential Building	0.2	73
School	Hotel	5.5	2007.5
Restaurant	Hotel	2	730
Fire Station	Hotel	0.7	255.5
Residential Building	Restaurant	4.6	1679
School	Restaurant	3.4	1241
School	Hospital	0.7	255.5
Residential Building	Hotel	2.6	949
Fire Station	School	0.5	182.5

Table C2: Breakdown of electricity transferred between sites in islanded mode

Site		Amount of electricity transferred in a day (kW)	Annual amount of electricity transferred (kW)
From	To		
Hospital	Restaurant	20.2	7373
Residential Building	Restaurant	16.3	5945
Residential Building	Fire Station	0.7	255.5
Residential Building	Hotel	4.5	1642.5
School	Hotel	2.8	1022
Restaurant	Hotel	1.4	511
School	Residential Building	13.9	5073.5
Fire Station	Restaurant	11	4015
Hotel	Restaurant	1.5	547.5
Hotel	Residential Building	1.2	438
School	Restaurant	12.7	4635.5
Fire station	Residential Building	10.5	3832.5
Hospital	Residential Building	6.2	2263
Restaurant	Hospital	0.1	36.5