Integration of distributed diesel generators in power system, Iraq case study

by

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DECLARATION

This work has not been submitted in substance for any other degree or award at this or any other university or place of learning, nor is being submitted concurrently in candidature for any degree or other award.

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ABSTRACT

In this work, existing off-grid diesel generators of the Zyounah region in Baghdad are investigated to provide an understanding of the real challenges of these generators for the consumers in terms of environmental and economic perspectives. The result reveals that if the load in which a generator operates is less than the generator's size, the generator's efficiency will drop, and the generator will consume a large amount of fuel and ultimately emit more CO2 emissions. Hence, the selection of a diesel generator should be close to the required load demand.

Due to the mismatch between generation and supply in Iraq, the integration of existing off-grid diesel generators into the Iraq power system is important in providing flexibility in localized areas and help avoid or reduce the number of blackouts. The optimal location and sizing of these generation units is a suitable option for improving the operation of electrical networks. This study presents a methodology to find the best placement and the right size of the diesel generators in the distribution network of Ziyounah in the Baghdad area.

In this study, demand forecasting using Linear Regression (LR) and Artificial Neural Networks (ANN) is presented to provides the power operator for Ziyounah in Baghdad with valuable information that is used for minimising the operational cost for integrated unit generations and accurately match electricity production to consumption in summer and winter seasons of 2020. Based on the forecasted demand, economic dispatch analysis was carried out using Lagrange multiplier (LM) and linear programming methods (LP) and assisted by the MATLAB application. The overall objective is to determine the optimal dispatch power for various types of generator sources including PV and grid import subject to several constraints to reduce the total operating cost for the integrated generation units while meeting the peak during 24hour in the summer and winter season.

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LIST OF PUBLICATIONS

Journal Papers (under review):

- **S. K. Khalaf**, Mazin M Mohsin and L. M. Cipcigan. The paper entitled ‘‘Optimal placement of distributed diesel generators for enhancing the performance of the Iraq distribution network” (Under review) - Electric Power Systems Research - Elsevier Journal. (Submission date: 22/ January/2022)
- **S. K. Khalaf** and L. M. Cipcigan. The paper entitled ‘‘Economic Dispatch for diesel generators on Iraq Power System” (Under review) - Journal of Modern Power Systems and Clean Energy. (Submission date: 23/ December/2021).
- **S. K. Khalaf** and L. M. Cipcigan. The paper entitled ‘‘Short-term load forecasting for resedential demand, Iraq case study” (Prepared for submittion) - IET Renewable Power Generation.

Conference Papers (published):

- **S. K. Khalaf** and L. M. Cipcigan, "Optimal integration of distributed generators in the Iraq power system," Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MEDPOWER 2018), 2018, Dubrovnik, Croatia,12-15 November 2018, pp. 1-7.
- Y. -O. Udoakah, **S. Khalaf** and L. Cipcigan, "Blackout and Black Start Analysis for Improved Power System Resilience: The African Experience," IEEE PES/IAS PowerAfrica, 2020, pp. 1-5

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Nomenclature

ANN	Artificial neural networks
C.I	Carbon Intensity
DG	Distributed generators
ED	Distributed Generation
EF	Emission Factor
GA	Genetic Algorithm
IMOS	Iraqi Meteorological Organization and Seismology
LF	Load Forecast
LM	Lagrange multiplier
LP	Linear programming
LR	Linear regression
MAPE	Mean Absolute Percentage Error
MLP	Multi-Layer Perceptron
MLR	Multiple linear regression
MOE	Ministry of Electricity for Iraq
NI	Noise Index
NPI	Network Performance Index
PD	Power Demand
PSO	Particle Swarm Optimisation
PV	Photovoltaic
RPM	Revelations Per Minute
SCADA	Supervisory Control And Data Acquisition
SLR	Single linear regression
STLF	Short Term Load Forecast
VPII	Voltage Profile Improvement Index
VSI	Voltage Stability Index

Chapter 1

Introduction

1.1 Background

The Iraq power system is facing a severe shortage of generation. This is due to the security situation[1] and lack of natural gas for use in power plants[1],[2]and[3]. In fact, Iraq does not have the required infrastructure for treating and using natural gas. Consequently, natural gas is flared before it can be used as a fuel for power generation[4]. In 2011, for example, almost 60% of the natural gas production in Iraq was flared, which led to a significant economic loss [1]and [4]. As a result of this malpractice concerning the usage of natural gas, many of the gas power plants have been modified to use heavy oil or diesel fuel rather than natural gas for producing electricity but at lower efficiencies.

Increasing demand is widening the gap between the electricity demand and the generation supply, see Figure1-1. The population is growing at a rate of approximately 1 million per year and it was estimated that 4.5GW of generating capacity suffered damage, and about one-fifth of the transmission lines were rendered inoperable during the war [5]. Hence, consumers hardly have four to six hours of power during the hot summer days, particularly when the temperature hits its maximum of more than 48°C.

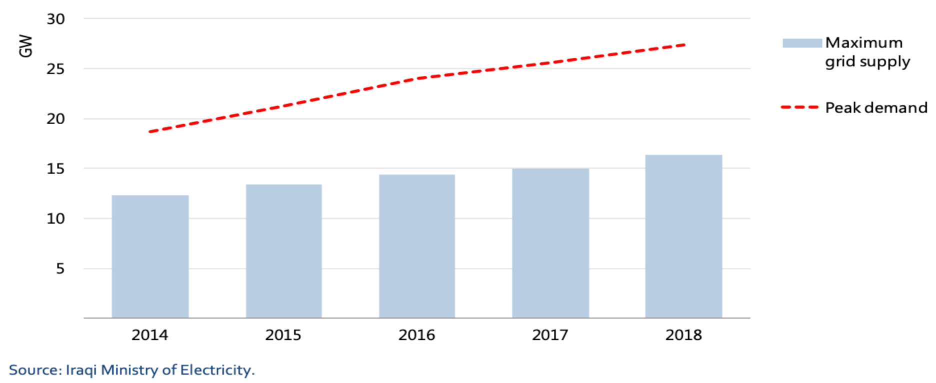

Figure 1-1 Peak demand and maximum power supply from the grid, 2014-18 [6]

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[1] Security problems affect Ministry personnel movements, and discourage international contractors from working in Iraq

1.2 The high temperature issue

Iraq is generally a hot, dry, arid region, with a semi-arid/ Mediterranean climate in the north and north-eastern areas. Temperatures can vary significantly, for example, the summer season in Iraq is hot and dry, with temperatures frequently exceeding 48°C. Meanwhile, the temperature in the winter season drops to 5°C and is even below 0°C during a few days in December and January.

1.2.1 The effect of temperature on power plants

In Iraq, the maximum demand occurs on hot summer days when the temperature is typically around 45°C. Because of this, the available capacity of the power plants has to be reduced at these times of peak load to reflect their output at this temperature. The maximum achievable output from thermal power plants declines at high ambient temperatures compared to their production under normal conditions. Figure 1-2 shows the gap between gross installed generation and available peak capacity on hot summer days in 2011[7]. The achievable peak output from steam turbine plants reduces at high ambient temperatures.

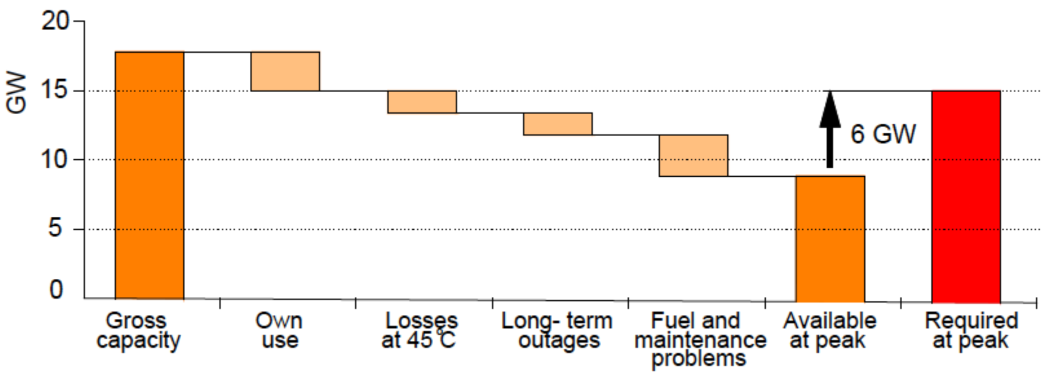

Figure 1-2 Iraq difference between gross installed generation capacity and available peak capacity in Summer days, 2011 [7]

1.2.2 The effect of temperature on energy consumption

In Iraq, electrical demand is growing far more quickly than supply, contributing to electricity shortages and forcing the country to import electricity from Iran, about 2GW, despite its rich energy resources [2]. Population and economic growth as well as rapid urbanization, are the main reasons underpinning the rise in consumption[8].

In 2017 the demand increased to about 22,000MW during the summer season, because of the increased use of air conditioning units on hot summer days [7], see Figure 1-3, but the maximum supply did not met this demand, particularly in the summer.

The long-standing gap between supply and demand is estimated to have caused about $40 billion losses for the Iraqi economy[7].

The focus of this thesis is on the growth of residential load which is represents approximately 75% of the total demand in Baghdad[7].

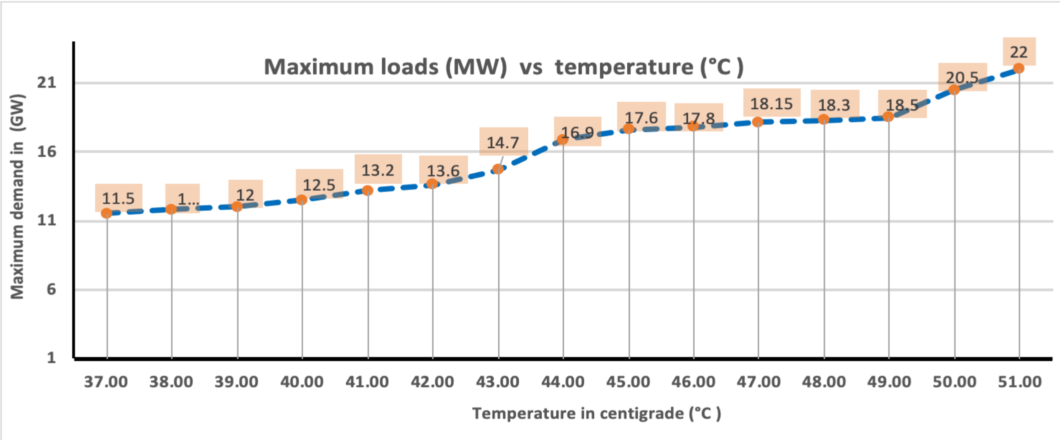

Figure 1-3 Relationship between the electrical load and the temperature, data recorded by SCADA of distribution network May- September 2016 for Iraq as a whole

1.3 The availability of generation

Electricity generation in Iraq is from various power-generating units, including steam turbines, gas turbines and hydroelectric power stations, as shown in Figure 1-4. It can be seen that the electrical energy supplied from the natural gas power plants is 48%. This is the most significant proportion of the total electrical energy supply, compared to other types of power plants for Iraq in 2013. In the same year, the energy supply from hydropower plants accounted for 8% and this is the smallest percentage of the total.

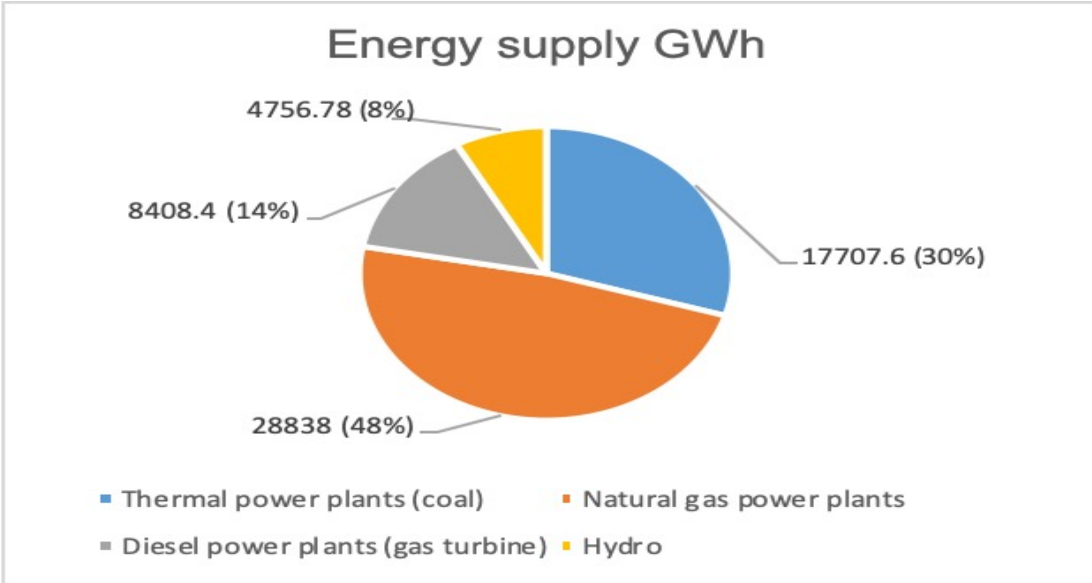

Figure 1-4 The energy supply in GWh for various power plants in Iraq and their weights in percentage for 2013 [9]

Figure 1-5 shows the installed, available and peak supply generation for the existing power plants in Iraq for the 2017 year [10]. The Ministry of Electricity had increased the peak supply capacity to 15,500MW by 2017. However, this was far from being adequate to match the peak demand.

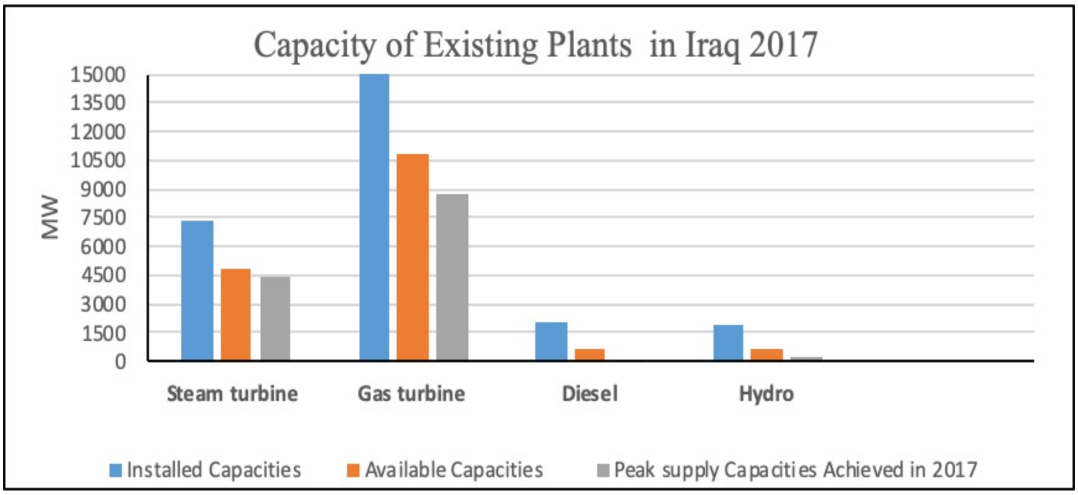

Figure 1-5 Comparison of Installed, Available and Peak Supply Capacities 2017 [7]

Figure 1-6 compares the nameplates capacity and the effective generation (peak supply capacity) of power plants between 2003-2017. It is noted that since 2003 the effective capacity of power plants has been smaller than the nameplate rating, due to plant de-rating, maintenance problems, very high temperatures of 45°C during the hot summer season and fuel switching[5]. However, significant increases in the generation installed were made since 2003, with available capacity expanding by 10 GW, see Figure 1-6.

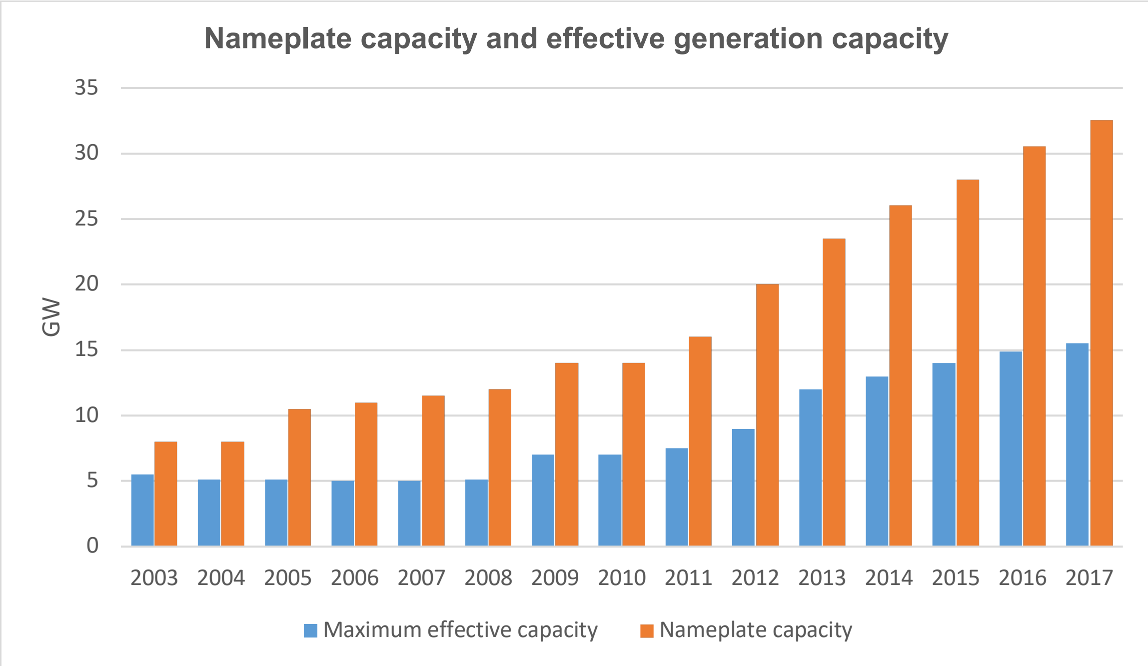

Figure 1-6 The difference between the installed and effective capacity of power plants in Iraq 2003-2017 [5]

1.4 Power Transmission and Distribution System in Iraq

The generation and use of electricity in Iraq was introduced in 1917 during the First World War. The generation sector at that time was made up of small mobile DC sets supplying specific local loads[11]. During 1960 and 1970, Iraq experienced fast economic progress because of the increased revenue from the oil industry. During that period, the Iraq power system was expanded with the introduction of 132 kV and 400 kV power transmission systems, and sufficient generation to meet the 6,000 MW demand.

By 1990, the peak demand in Iraq was approximately 5,100 MW with the total installed generating capacity of about 10,000 MW. The following year, as a result of the war in the region, several power plants and substations were significantly damaged resulting in a reduced generating capacity below 2,500 MW. Several transmission lines were put out of service. After the 2003 war, The distribution networks were seriously degraded and many substations and overhead lines were damaged or looted[11]. However, there was an international effort by the United

States in Iraq, which allocated US$4.5 billion, to restore electricity generation level and to rehabilitate the electrical power systems by replacing the looted and vandalized plants, and repairing partially damaged, poorly repaired and outdated power plants. The Ministry of Electricity in Iraq has also expanded the power transmission lines and distribution substation networks after the war of 2003. Nevertheless, the generation suppliers are still far from being adequate to satisfy the peak demand, see Figure 1-7.

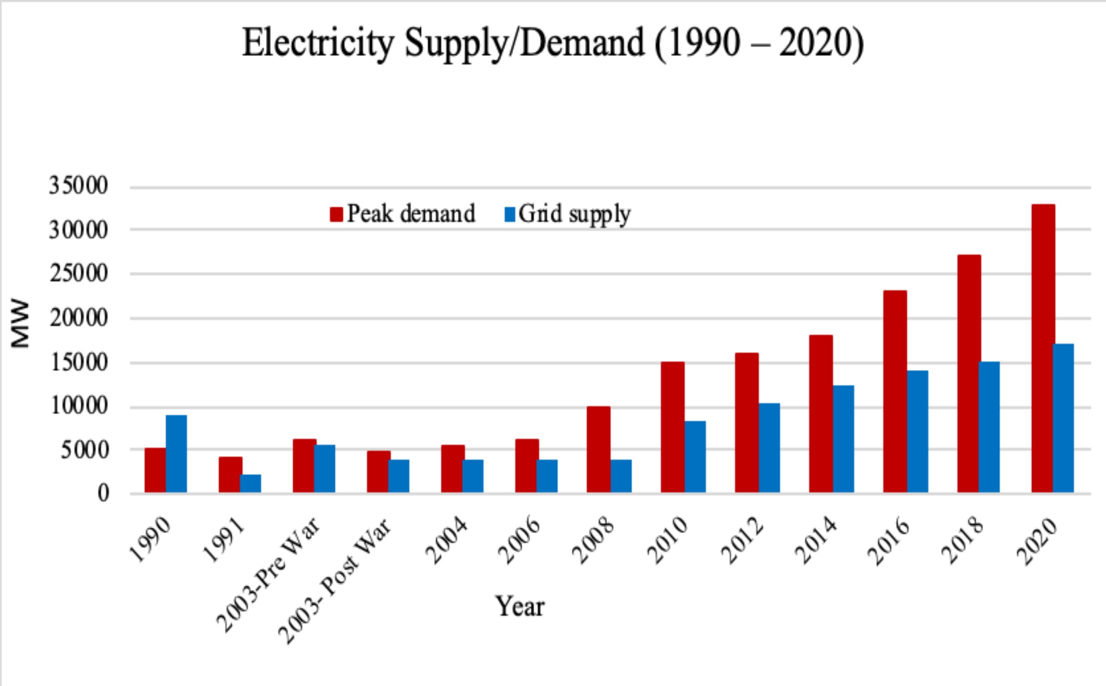

Figure 1-7 Available electricity supply and peak demand before and after the war 2003 (1990-2020) [2]

Despite continuing progress towards adding more generation to the power system, there will be a gap between generation supply and peak demand of electricity in Iraq for several years to come, see Figure 1-8.

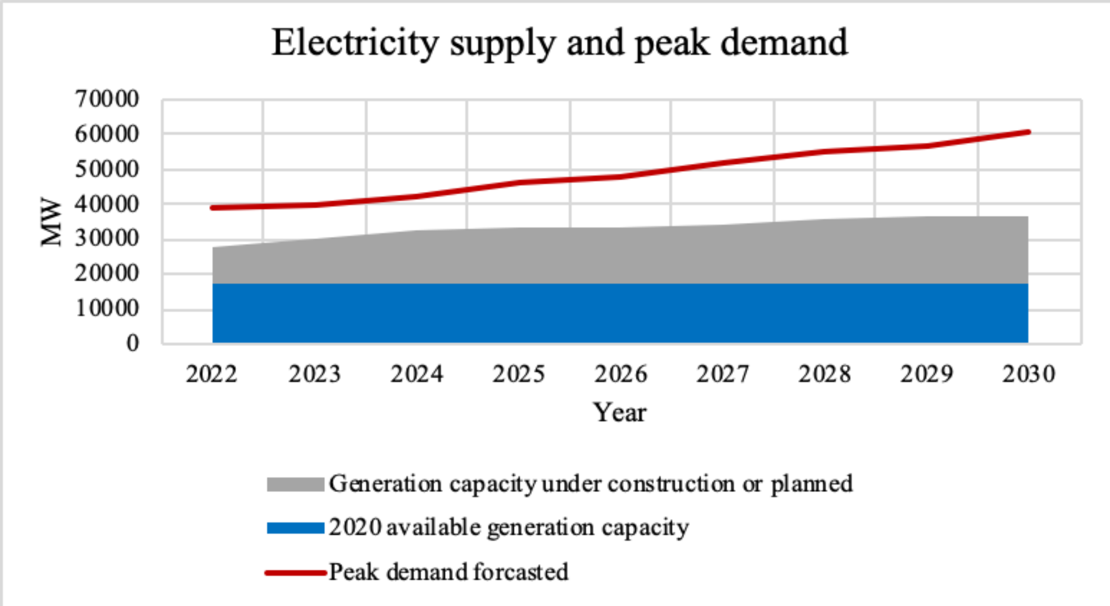

Figure 1-8 Predicted peak demand against available and planned generation supply for the future (2022-2030) [6]

Generally, Iraq's power transmission lines consist of 400 kV and 132 kV systems. Power generation plans are connected to either the 400 kV or the 132 kV system. In 2016, the entire power transmission system consisted of 21 substations at 400 kV with 2,400 MVA installed capacity and 403 substations (68 of which were mobile substations) at 132 kV with 37,796 MVA installed capacity. Whilst the power distribution system (33/11 kV) consisted of 412 substations with 29,702 MVA installed capacity.

1.5 Load shedding in developing countries

Load shedding is applied by operators of an electrical system that is short of generation to balance the power supply with the demand by temporarily switching off some loads in different geographical areas[12][13]. Load shedding is commonly used in countries whose electrical supplies are not able to meet their peak demand such as Nigeria, India, Bangladesh, Pakistan, and South Africa as well as Iraq [14][15][16].

In Iraq, the load shedding program plays an important role in managing the load by a deliberate shutdown of supply in some parts of the distribution network. The system operator in Iraq uses this program to prevent system blackouts particularly when the demand is high during the hot summer season.

1.6 Environmental impact

Due to climate change and greenhouse gas emission problems, environmental impact has become one of the most concerning factors in any electrical power system scheme because of the gaseous emission from the fossil fuel that is utilised in power generation plants [17],[18]and[19]. Cities are responsible for a large amount of the world's CO_2 environmental pollution. In developing countries, existing global sustainability guidelines for cities are often not appropriate due to climate differences between developed and developing countries. There are also problems specific to countries suffering from political instability, e.g. the degradation of public services and utilities, severe damage to the infrastructure and economic deterioration. The environment of cities is, therefore, one of the main areas where work can be undertaken to reduce undesirable impacts on the environment caused by conventional power generation, traffic congestion, greenhouse emissions, and rapid population growth [20]. In developing countries like Iraq, the demand for energy from fossil fuels is a particular problem which is exacerbated by a lack of investment in renewable resources. The developing countries such as Arab gulf countries and Iraq, rely on burning fossil fuels for as much as 90% of their power generation, this dramatically increases CO_2 emissions and environmental pollution [21].

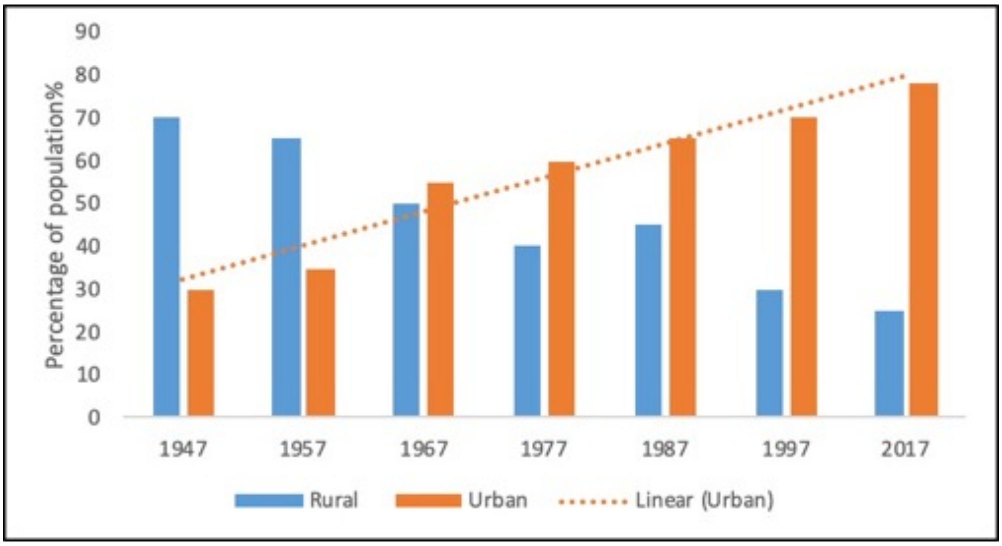

Figure 1-9 Percentage of population in Urban and Rural, Iraq [2]

In developing countries, there is extreme use of natural resources and environmental pollution as a result of their use of conventional power production, particularly in hot dry and arid regions. The main reason for increasing energy demands lies in the growth of the economy and population. In countries such as China, India and the Middle East regions [22] this has resulted in rapid urbanization. For example, in Iraq, there has been a rapid shift from the population living mainly in rural areas to urban regions as shown in Figure 1-9. In 1947, 70% of the population resided in rural areas; by contrast, today, more than 70% of the population lives in cities [23]. Such urbanization and increase in population density are identified as the key factors shaping future cities [24]. Therefore, there is a significant challenge to find an acceptable solution for new and existing cities developments taking the impacts of climate change, and managing a balance between various dimensions of sustainability[25].

Over 90% of energy is produced by burning fossil fuels in Arab Gulf countries. This is because these countries are rich in oil and other fossils fuels. There is limited uptake of renewable resources like solar generation, despite favourable climatic conditions [26]. However, a shift in global practices to reduce energy consumption and an increased reliance and investment in renewable resources could contribute to reducing CO_2 emissions. Many developed countries already emphasize the use of energy-saving systems, but these renewable technologies are mostly absent in the Middle East [27]. Therefore, energy consumption is causing significant challenges that need to be addressed by sustainable planning, focusing on the transition from the concept of energy-consumption to energy-producing homes, by exploiting the use of solar energy.

1.7 Off-Grid diesel generators in Iraq

Iraq's power system is facing significant challenges due to the mismatch between generation and supply. To overcome this problem a large number of households are using private diesel generators. The private diesel generators in Baghdad are classified as stand-alone diesel generators and community diesel generators. The community diesel generators have been introduced since1999 by third parties to overcome the electricity shortage and to accommodate uninterrupted 24-hour power to consumers throughout the year. The stand-alone diesel generators supply a single house while the community diesel generators supply a neighbourhood with private wires, see Figure 1-10. Most stand-alone units have capacities ranging between 10-50 kVA, while community diesel generators have capacities of more than 100 kVA.

Generally, there is one community diesel generator for 350-450 houses in domestic areas in Baghdad. For example, Zeyouna region of Baghdad has approximately 9,000 houses supplied by 19 community generators whose total capacity is 10MW. A survey in 2009 estimated that there were approximately 900MW of small diesel generation units in Baghdad. Most types of generators use engines from: Scania, Volvo, Perkins, Cummins, and they are connected at low voltage (LV) 0.4 kV. These units have drawbacks such as pollution, bad wiring and acoustic noise, as shown in Figure 1-10.

(a) (b)

Figure 1-10 Private diesel generators connected (a) to a single house (b) to the community with private wires

1.8 New Ziyouna area of Baghdad

The area under investigation in this research is an Iraqi district (Ziyouna) which is located in the heart of Baghdad City (see Figure 1-11) and has about 9,000 residential consumers (houses). Existing off-grid diesel generators are distributed around Ziyounah.

Figure 1-11 New Ziyouna area / Baghdad[2]

The numbers and capacities of diesel generators in the New Ziyouna area of Baghdad are shown in Table 1-1.

Table 1-1The numbers and capacities of diesel generators in New Ziyounah area of Baghdad

Generator Size (kW)	250	500	750	1000
Number of Generators	6	6	4	3

The location of the diesel generators between houses in the New Ziyouna area of Baghdad is shown in Figure 1-12.

[2] The map of Ziyounah district has been provided by Ministry of Electricity of Iraq/ Department of GIS; this area consists of 9000 residential consumers (houses).

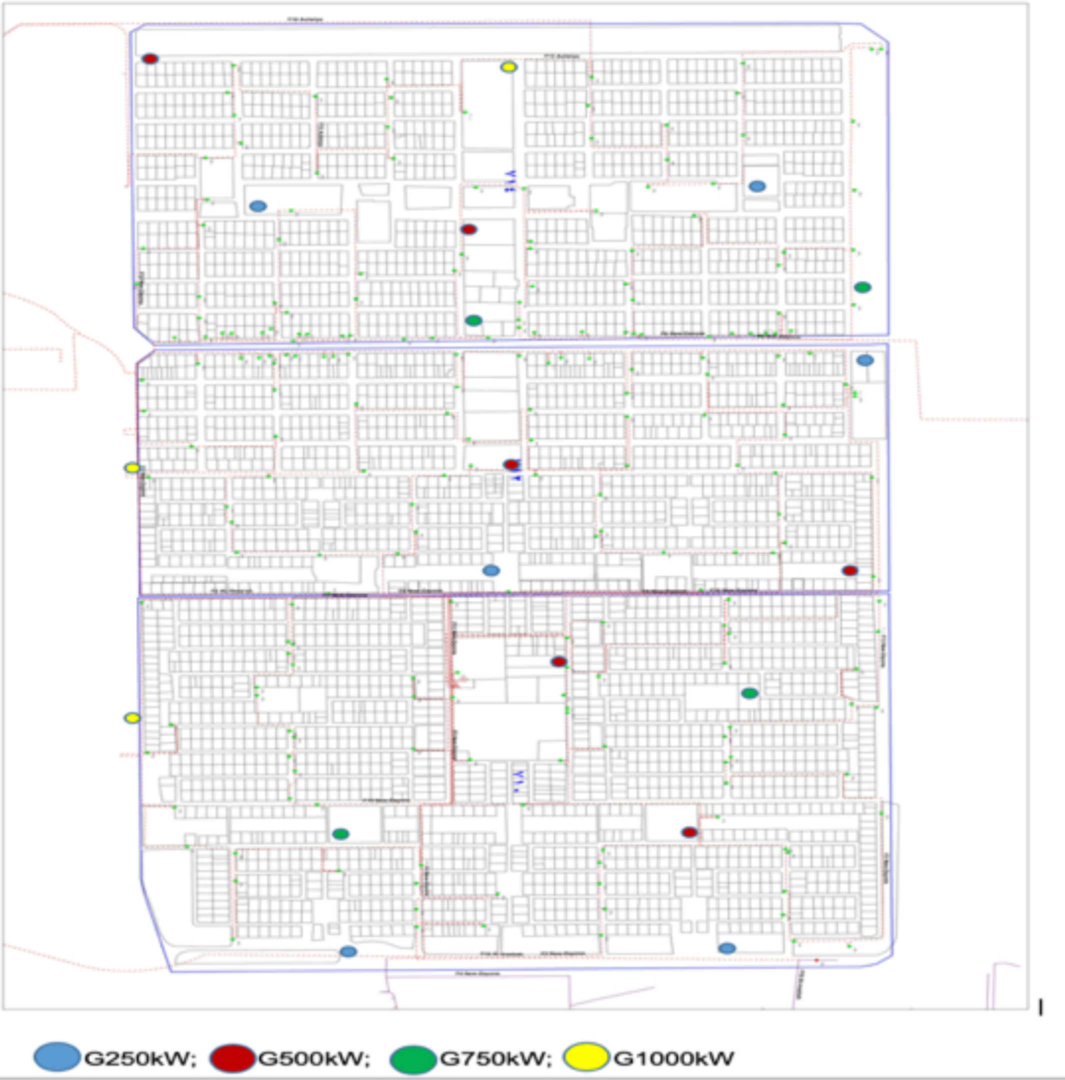

Figure 1-12 The locations of off-grid diesel generators in the New Ziyounah area of Baghdad

1.9 Challenges

The challenges of electricity supply in Iraq are illustrated clearly in the district of Ziyounah and include:

1. The electricity consumption in Iraq is very high due to economic development, population growth, and the usage of low efficiency domestic appliances.
2. Generation units including diesel generators and PVs are needed to supply the peak demand.
3. Inefficient operating of diesel generators (e.g. non-optimal dispatch of generation units) leads to an increase in fuel consumption, operation cost

and CO_2 emissions from the generators. This means, the size of the generators generators (DG) must be selected suitably.

4. There are blackouts in the power system due to the mismatch between the electricity supply and demand in Iraq.
5. The diesel generators in Ziyouna of Baghdad are presently operated off-grid, and managed independently of the distribution system. They need to be integrated into the distribution system and re-located to improve the performance of the network and to reduce the acoustic noise to the consumers.

1.10 Research questions

RQ1: How do the third parties sell electricity from the diesel generators to Iraqi consumers? (to understand and identify the difference in electricity tariff between the government supply and neighbourhood generators for lower-class households).

RQ2: How are carbon emissions and fuel consumption estimated for a diesel generator at any operating load?

RQ4: How would the integration of the stand-alone neighbourhood diesel generators into the Iraq power system provide technical and economic benefits with low environmental effect?

RQ5: Is there a strong relationship between the maximum power demand and the maximum temperature in Iraq during the days in the summer, winter and spring seasons?

RQ6: What are the techniques considered to predict the daily and hourly peak demand, which is required for planning and operating, for Ziyonah area of Baghdad based on the historical data collected in this research?

RQ7: Can the operator overcome the mismatch between demand and supply, i.e. what are the required numbers of diesel generators and PV to meet the peak daily demand for Ziyounah area of Baghdad in the summer and winter season of 2020? What is the method to calculate the number of diesel generators?

RQ8: In what ways can the operators for the Iraq power minimise the total operating cost for integrated generation sources during 24 hours while meeting the demand?

1.11 Objectives of the thesis

The objectives of the thesis are:

1. Investigate the real challenges of off-grid diesel generators for the decision makers in terms of environmental and economic perspectives.
2. Compare the electricity tariff provided by the government with the cost of supplying the demand using private off-grid diesel neighbourhood generators over the months of hot summer days.
3. Estimate the models of diesel fuel consumption and carbon emissions for the diesel generators.
4. Provide a feasible solution to the Iraqi power system by integrating off-grid private diesel generators into the distribution network.
5. Develop an algorithm to find the best location and size of diesel generators at the peak load in a 35- bus radial distribution network in Ziyounah district of Bagdad.
6. Evaluate and investigate the impacts of integrated private diesel generators in electricity savings and networks performance.
7. Test and compare the performance of forecasting the daily and hourly demand for Ziyounah district of Bagdad using linear regression and ANN techniques.
8. Provide the results of daily and hourly forecast, used in chapter 6, for minimising the operational cost of integrated diesel generators and accurately match electricity production with consumption in the summer and winter seasons of 2020.

9. Produce a cost model for different sizes of diesel generators used to estimate the fuel consumption and operating cost.
10. Estimate the additional required PV generation units to meet the peak demand based on maximum daily forecasted demand.
11. Generate the optimal diesel generators scheduling using Lagrange multipliers and Linear Programming techniques to reduce the total operational cost and carbon emissions whilst meeting the demand constraints.

1.12 Research plan

Figure 1-13 illustrates the research plan. Main objectives are provided, and the links between the tasks are shown.

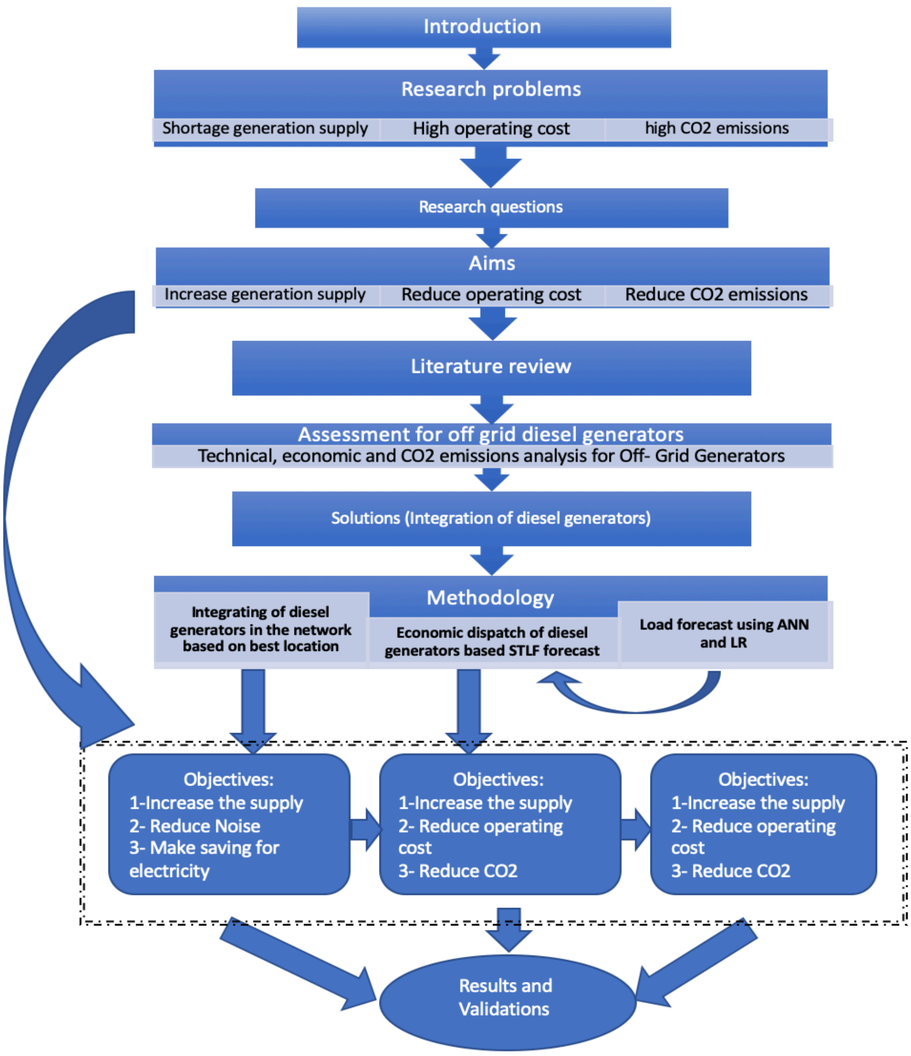

Figure 1-13 Research plan of the thesis

Chapter 2

Literature review

This literature review discusses the established knowledge of each of the subjects studied in this PhD: optimal location of distributed generators, load forecasting, and economic dispatch.

2.1 Optimal location of distributed generators

Distributed power generation, which in the past was known as embedded generation in Anglo-Saxon countries, decentralized generation in Europe and Asian countries and dispersed generation in North American countries [28], is a power source connected directly to the distribution network. It refers to small generating units installed near local loads or load centres to avoid the need for network expansion and to satisfy new load areas. This section is related to Chapter 4 which presents a methodology to find the best placement and the right size of the diesel generators in the distribution network of Ziyounah in the Baghdad area.

According to The Electric Power Research Institute (EPRI), distributed generation is generation from ‘a few kilowatts up to 50 MW’ [29]. Distributed power generation can be renewable energy sources or internal combustion reciprocating engines [28].
International Energy Agency (IEA) defines distributed power generation as on-grid generating plants supplying consumers or providing support to a distribution network, integrated to the grid at distributed level voltages. The contribution of the power distributed generation in power systems is relevant worldwide and their use in the future power systems is expected to increase further [29].

Due to considerable costs, the size of distributed generators (DG) must be selected suitably to improve the system performance such as to reduce system losses and improve the voltage profile while meeting the demand and the network constraints. The problem of distributed generators planning has recently received much attention by power system operators and researchers. Selecting the best places for distributed generators units and their preferred sizes in large power systems is a complex combinatorial optimization problem[28].

The integration of distributed generators units in non-optimal places may reduce the network performance such as an increase in system losses and have a negative effect on voltage profile which is problematic particularly in developing countries facing high-power loss and poor voltage profile [30]and[31].Therefore, distributed generators should be allocated in an optimal way to maximize the system efficiency [29].

Various literatures have focused on optimal sizing and placement of DGs to minimize real and reactive power loss using several techniques such as particle swarm optimization (PSO) and hybrid PSO [32]–[34] generic algorithm (GA) [35], artificial bee colony (ABC), and hybrid ant colony optimization (ACO) [36] have all been suggested for DGs sizing and siting. In a few recent studies, heuristic methods such as hybrid harmony search algorithm (HSA) and particle artificial bee colony (PABC) [37] and intersect mutation differential evolution (IMDE) [38] have all been applied for the optimal design of capacity and placement of both DGs and shunt capacitor. However, the mentioned studies are usually computationally demanding and share common criteria which is the minimization of real power loss as a single objective. In [39], a less computationally intensive method which uses analytical expression was proposed. The DGs are considered to be located in the primary distribution system and the objective of DG placement is to reduce the losses. Further studies have used different approaches to reduce the search space of the algorithm and the computational burden. For example, in references [37] and [40]the authors have approached location optimization based on the ratio of change in real power loss in the line connecting the bus to changes in active or reactive power of the same bus in a radial network. However, this method is not suitable for the allocation of multiple distributed generators.

Many approaches have been developed for placing distributed generators units optimally in the network. An evolutionary programming optimization method has been developed to determine the optimal size of the DGs[41]. Two new approaches based on the sensitivity of real and reactive power losses with respect to the size of DGs have been proposed to obtain the best size and location of these generators towards minimizing power losses in the distribution networks. The proposed methods have been developed based on the constant impedance and current load characteristics. The developed techniques have been tested on a practical long radial distribution network [42]. In [43] it is proposed a backtracking search optimization algorithm (BSA) to assign DGs along with radial distribution networks (RDNs). The objective function is adopted with a weighting factor to enhance the performance of the network and reduce the real losses of the network. The proposed methodology is applied to 33- and 94-bus RDNs to investigate its viability.

The loss sensitivity factor based on the current injection technique for sizing and location of DGs units in radial distribution system is given in [44]. Calculation of cost of DGs is provided in [45] based on triangular, conventional, and complex power limits. Reference [46] presented two new methodologies for optimal location of DGs utilising an optimal power flow (OPF) based model in real time. The optimisation problem is formulated for two different objectives, namely, social welfare maximization and profit maximization. The candidate locations for DGs placement are identified based on Locational Marginal Price (LMP). [47] proposed the hybridization of GA and artificial bee colony algorithm (ABC) for obtaining the optimal location and size of multiple generators and capacitors in radial distribution systems to reduce the cost of the system. This hybrid algorithm is tested on IEEE 33- and 69-bus radial distribution systems. Reference [48] describes a Novel methodology to calculate optimal DGs sizes based on real power loss. This method considers optimal DGs sizes at unity power factor.

Several authors have presented a methodology for optimal DGs allocation and sizing in the distribution network considering loss minimization, and to guarantee an acceptable level of voltage profile. A GA based optimization technique has been used to obtain the results. The results for voltage profile and losses have been determined based on the load flow[49]. The authors in [50] presented a method for optimal sitting and sizing of multiple DGs using particle swarm optimization (PSO) based approach. Research presented in [51]deals with the impact of voltage dependent load models on the predicted energy losses in DGs planning. A multi-objective optimization approach based on losses reduction and voltage profile improvement for distributed generators allocation using GA was proposed in [52].

A mixed-integer linear programming approach to find optimal size and allocation of DGs in radial distribution systems is presented in [53]. The proposed formulation accounts for the steady-state operation of the radial distribution system, considering different load levels, different types of DGs with their capability curves, and different topologies of the radial distribution system. [54] proposed a reconfiguration methodology based on a cuckoo search algorithm (CSA). The objective is to minimize active power losses and maximize voltage magnitude. The CSA method is a new metaheuristic algorithm inspired from the obligate brood parasitism of some cuckoo species for solving optimization problems. The effectiveness of the proposed CSA is investigated on three different distribution network systems: 33-, 69-, and 119-node systems. A simple method for optimal placement of distributed generators in a radial distribution system based on voltage sensitivity index (VSI) analysis is presented in [54]. The main objective is to minimize real power loss, voltage profile improvement. [55] presented an optimal proposed approach (OPA) to determine the optimal sitting and sizing of DGs subject to the system constraints to achieve multi-objectives using a genetic algorithm. This approach could bring benefits such as voltage profile improvement, spinning reserve increasing, power flow reduction and total line loss reduction.

The authors in [56] presented a simple method for investigating the optimisation problem for location and capacity of DGs in three-phase unbalanced radial distribution systems (URDS) to reduce power loss and to improve the voltage profile of the distribution network using voltage index (VSI) analysis. Loss sensitivity factors (LSFs) are utilised to select the candidate locations for the multiple generators placements and Simulated Annealing (SA) is used to estimate the optimal size and locations of generators [57]. [58] proposed a PSO method to study the optimal power flow (OPF) of a power system integrated with a renewable generator like wind and photovoltaic (PV) to minimize the transmission losses system on an IEEE 30-bus RDN. A new method for optimal sizing and location of distributed generation units in radial distribution systems was proposed in [59]. In this method, the optimal location for generators obtained by power loss sensitivity and optimal size is given by Harmony Search Algorithm (HSA). [60] proposed a novel combination of nondominated using GA and fuzzy method to minimize four objective functions, namely, cost, emission, power losses, and voltage deviation, on a typical 34-bus test microgrid. In [61]optimal location of DGs is given based on loss sensitivity and voltage stability index. A simple conventional iterative search technique along with Newton Raphson method of load flow study is carried out for the optimisation problem to reduce both cost and power loss very effectively. The paper also focuses on optimization of the weighting factor, which balances the cost and the loss factors. [62] proposed a population-based incremental learning (PBIL) algorithm to find the optimal location of DGs and PSO to define the size of those devices. The objective is to reduce the computation time and real power losses and improve the voltage profiles. The proposed algorithms are tested on IEEE 33- and 69-bus radial distribution systems. [63] proposed an efficient analytical method for optimally allocating distributed generators in electrical distribution systems to minimize power losses. [64] proposed a hybrid GA-PSO algorithm to reduce losses and maintain acceptable voltage profiles in a radial distribution system simultaneously. The objective function is to optimally size and place DGs in appropriate buses in the system to reduce operating cost and real power losses

(RPLs) and enhance voltage stability. The proposed algorithm is demonstrated on IEEE 33- and 69-bus distribution systems.

Ref [65] proposed a backtracking search algorithm (BSA) to study the effect of different load models on determining sizes and optimal locations of the DGs. The main aims were to improve the network voltage profile and reduce power loss in RDNs. The proposed algorithm is tested on 136-bus and 69-bus radial distribution networks with four load models, but it has a random mutation scheme that uses only one direction individual for each target individual [65].

Table 2-1 presents a taxonomy of the reviewed optimal placement of distributed generators models.

Table 2-1 Distributed generator placement methods

Ref	Proposed approach	Objectives	Gap identification
[43]	BSA	Reduce the real power losses and enhance the voltage profile	• It has not included stability and Noise Index • It has not provided economic assessment
[54]	CSA	Minimise active power losses and maximise voltage magnitude	• It has not included stability and Noise Index • Case study not real
[63]	Analytical	Minimise power losses	• Lack of knowledge in methodology • Case study not real • Target is limited to power losses only

[64]	GA-PSO	Minimise power losses and maintain acceptable voltage profiles	• Lack of clarity in methodology • Economic assessment was not provided
[47]	GA-ABC	Reduce the cost of the system and decrease RPLs	• Lack of clarity in methodology • Lack of data presented • No improvement for network
[60]	GA and Fuzzy	Minimise cost, emission, power losses and voltage deviation	• It has not included stability and Noise Index
[62]	PBIL and PSO	Reduce active power losses and improve voltage profile	• It has not provided economic assessment • Not real system
[58]	PSO	Minimise transmission losses	• It has not provided economic assessment • Lack of clarity in methodology • Target is limited to real power losses only
[65]	BSA	Reduce power losses and improve network voltage	• It has not provided economic assessment • Lack of clarity in methodology • It has not included stability and Noise Index
[41]	Evolutionary programming	Minimize the distribution losses while satisfying the voltage constraint in the system	• Target is limited to real power losses only • Not real system

[42]	Sensitivity analysis	Minimise power losses	• Target is limited to real power losses only • Lack of clarity in methodology
[44]	Loss sensitivity factor	Minimise total power losses of the network	• Target is limited to real power losses only • Proposed method is complicated • Lack of clarity in methodology • It has not included stability and Noise Index • Economic assessment was not provided
[48]	Sensitivity method	Minimising cost of power obtained from distributed generators	• Target is limited to real power losses only
[49]	GA	Evaluate generation units' impact in system reliability, losses and voltage profile	• Economic assessment was not provided • It has not included stability and Noise Index
[52]	GA	Reduce Losses and Improve Voltage Profile	• Economic assessment was not provided • Noise Index was not included
[53]	A mixed-integer linear	minimizes the annualized investment and operation costs	• Complicated technique • Test case study (not real) • Economic assessment was not provided
[54]	Cuckoo Search	Voltage profile improvement, spinning	• Test case study (not real)

	Algorithm (CSA)	reserve increasing, power flow reduction and total line loss reduction.	• Economic assessment was not provided • Lack of clarity in methodology • It has not presented DGs
[56]	Voltage index (VSI) analysis	Reduce Losses and Improve Voltage Profile	• Economic assessment was not provided • It has not presented DGs • Noise index was not included
[57]	Loss sensitivity factor method (LSFs)	Obtaining optimal sizes of capacitors.	• Lack of clarity in methodology • It has not presented DGs • Economic assessment was not provided • It has not included stability and Noise Index
[59]	Harmony Search Algorithm (HSA).	Reduce Losses and Improve Voltage Profile	• Economic assessment was not provided • Test case study (not real)
[61]	Newton Raphson method	Reduce both cost and power loss	• It has not included stability and Noise Index • Not improved voltage profile • Economic assessment was not provided

A review of distributed generator placement methods showed that the optimisation of generator location and size have many advantages such as meeting the incremental demand, reducing the total real power losses and enhancing the network performance. The comprehensive review revealed that the optimal location and sizing of generation units using GA proved to be a suitable option to be used in this study that describes a realistic problem for the power systems in the context of the case study in Iraq. Due to the lack of studies in Iraq and based on the collected real data, the proposed approach of finding the best placement for diesel generators will address multiple directions of practical solutions, including future planning vision for researchers and power operators.

2.2 Load forecasting

Due to the non-storable nature of electrical energy, it is necessary to balance at all times the electrical power network to ensure that the power supply is equal to the demand. However, an increase in the gap between the generation supply and the demand creates voltage/frequency deviations, which are harmful to electric networks devices and consumers and can even cause serious damage as in the case of blackout [66]. To keep the relationship between production and consumption in compliance with different standards and to secure the operations of the power system, electric load consumption must be predicted and controlled instantaneously. Prediction of electricity demand is a necessary task for power system operation because it can help the operators make decisions including unit commitment or load switching. Electrical distribution designers and operators use a wide range of electrical load forecasting techniques for resource planning and generation dispatch [67]. Predicting the load on a system helps operators minimize the costs of operation, as well as increase the reliability of meeting demand.

The accuracy of load forecasts can have a significant impact on power system operations, because the economy of operation and the control of the power system may be very sensitive to forecasting errors. Forecasting errors can lead to either overly conservative or overly risky scheduling, which can produce large economic penalties [68]. Extremely high forecasts may result in the start-up of too many generation units and unnecessarily high levels of reserves. On the other hand, forecasts that are too low may result in failure to have the necessary spinning and operating reserves required. In both cases, inaccurate forecast could result in increased operating costs. Consequently, efforts aimed at the development of forecasting techniques that reduce the magnitudes of forecast errors can often be justified based on the resulting high savings. For example, in the predominantly thermal British power system, it was estimated in 1985 that the increase in operating costs correlated with a 1% rise in the forecasting error was £10 million per year[69].

Load at a given hour depends not only on the load at the past hour but also on the load at the same hour on the past day, as well as weather variables, events, human behaviours and so on. Hence, there are several important exogenous variables that must be considered, particularly the weather-related variables [70]. Usually, historical load data are utilised for the forecast. These data show a short-term correlation between the demand and climatic information. This information may include temperature, the day of the week, and other factors[71].

The research methods of load forecasting are classified into two main groups: statistical methods and artificial intelligence methods. In statistical methods such as regression methods, an equation determines the relationship between load and its corresponding factors after training with historical data. Several statistical forecasting techniques have been applied to load forecasting such as time series[72], similar-day approach [73], regression methods[68], expert systems[74], and so on. These methods are linear models and the load pattern is usually a nonlinear function [70]. While in the artificial intelligence techniques, a human being's way of thinking and reasoning in forecasting would be copied.

In chapter 5, Linear Regression (LR) and Artificial Neural Networks (ANN) techniques are implemented to improve a decision of the daily and hourly peak demand during the summer and winter days 2020. Based on correlation factor and the type of historical data collected from the Ministry of Electricity in Iraq, it was found that these techniques are suitable for this study.

2.2.1 Statistical methods

Regression analysis is a well-known statistical technique which is mainly used for two conceptually distinct purposes. First, regression analysis is widely used for prediction and forecasting. Second, in some situations, regression analysis can be used to understand causal relationships between the independent and dependent variables[75]. In recent years many companies used regression analysis in their forecasting efforts [76]. According to Institute of Business Forecasting (IBF), about 16% of the companies use regression for their forecasting needs[76]. The advantage of regression analysis is that it can be used to capture important relationships between the forecast variable of interest and the predictor variables. The main challenge, however, is that in order to generate the forecasts, the model requires the future values of each predictor. In power systems, regression analysis is used to predict electric loads based on historical data such as past load and weather [77].

Regression methods can be classified into two categories as simple linear regression and multiple linear regression. In simple linear regression, a bivariate model is built to predict a response variable (y) from an explanatory variable (x). In multiple linear regression, the model is extended to include more than one explanatory variable producing a multivariate model[78].

2.2.1.1 Simple linear regression analysis

A simple linear regression estimates the relationship between a response variable y , and a single explanatory variable x [78] and finds a linear function that, as accurately as possible, predicts the value of y as a function of x [79]. This method has been presented in Section 5.2.1. Linear regression analysis is an important technique which is extensively used for predicting the unknown values of a variable from the known values of other related variables (factors). In linear regression, the variable whose values will be predicted is the dependent variable. On the other hand, known variables that are used for prediction, are independent.

In other words, forecasting is the process of creating predictions of the future based on historical data and future independent variables.

Among the statistical models, the linear regression analysis has revealed promising results due to the reasonable accuracy and relatively simple implementation when compared to other techniques [80]. It can be used, for example, to examine the relationship between variables such as weather and time of the day and the variable being forecast. The general form of the linear relationship between the dependent and independent variables can be expressed as follows [81]:

$$Y = a_1x_1 + a_2x_2 + \cdots + a_\mathrm{n}x_\mathrm{n} + \varepsilon \qquad (2.1)$$

where, y is the real output, $x_1$to x_n represent the influence parameters, $a_1$to a_n represent the coefficients for the corresponding influence parameters, and ε is the associated error term.

Usually, the objective of the regression model is to minimize the sum of squared errors by varying the coefficients $a_1$to a_n [82]. For electricity load forecasting in power systems, regression models correlate a relationship between the historical values of the load with the influence parameters such as weather and the day of the week to predict the future value of the load [82].

2.2.1.2 Multiple linear regression analysis

Multiple linear regression extends simple linear regression to include more than one explanatory variable. In both cases, we still use the term 'linear' because it is assumed that the response variable is directly related to a linear combination of the explanatory variables [78]. It is generally represented by the relationship between a single outcome variable (Y) and some explanatory variables (x_i)[71]. This method has been discussed in Section 5.2.3. The equation for multiple linear regression has the same form as that for simple linear regression but has more terms[78],[83] :

$$Y_i = B_0 + B_1 x_{1i} + B_2 x_{2i} + \cdots B_{\mathrm{n}} x_{\mathrm{n}i} + \varepsilon_i \tag{2.2}$$

Where: B_0 , $B_1, \ldots B_{\mathrm{n}}$ are the model parameters to be estimated, *i= {1,2, 3, .., n},* and *n* is the number of explanatory variables.

These equations shown can be represented in matrix form as follows:

$$\mathrm{y} = X\beta + \epsilon \tag{2.3}$$

Where:

$$\mathrm{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix}, \; X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1n} \\ 1 & x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{\mathrm{k}1} & x_{\mathrm{k}2} & \cdots & x_{\mathrm{k}n} \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_n \end{bmatrix}, \text{and } \epsilon = \begin{bmatrix} \epsilon_0 \\ \epsilon_1 \\ \vdots \\ \epsilon_k \end{bmatrix}$$

The matrix X and y contain information about the independent variables and dependent variables of all historical data, respectively. Using the least square method, β of (2.3) can be derived by the following equation:

$$\beta = (X'X)^{-1}X'y \tag{2.4}$$

From the above regression coefficient β, the future load can be forecasted from the multiple linear regression model as below:

$$\hat{y} = X\beta \tag{2.5}$$

Where: $\hat{y}$ is the prediction of y and the difference of those two is the error of forecasting. After collecting the future independent variable matrix X_f , the forecasted independent variable y_f is calculated as:

$$y_f = X_f\beta \tag{2.6}$$

For big data, the number of rows is high in X and y and matrix and the operation is very time intensive. Therefore, multi-core parallel processing is used for big matrix transpose, multiplication and inverse operations to solve Equations (2.4) -(2.6).

2.2.2 Artificial Neural Networks

ANN structure can be classified into two categories as single and multilayer network. Networks with only input and output layer connected by the synaptic weights are termed as single layer network as presented in Figure 2-1 [84] . Networks having neuron layers between input and output layers are known as the multi-layer neural network (MLN). Figure 2-2 shows a multi-layer ANN structure with three layers. The layer between the input and output layer is referred to as the hidden layer. Multi-layer neural networks have higher computational abilities as compared to single-layer networks. These MLP networks can learn the complex relationship between the input and output patterns which are not possible in the case of single layer networks [84].

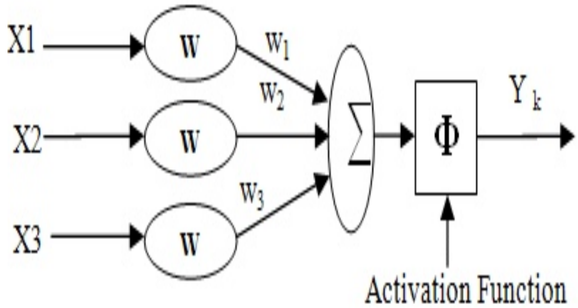

Figure 2-1 A Neuron Structure [84]

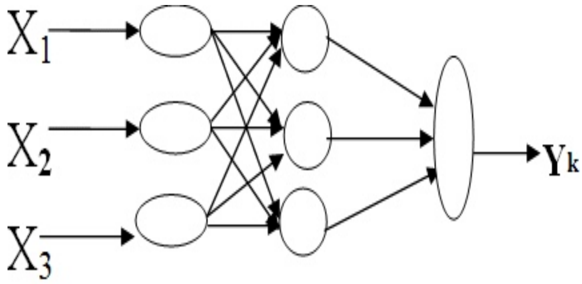

Figure 2-2 Multi-Layer Network[84]

2.2.3 Review of load forecasting based on regression analysis and ANN

In the last 25 years many papers have focused on the forecasting of electrical demand using different methods[85]. The authors in [86] studied a model for electricity forecasting in New Zealand using multiple linear regression analysis, taking into account demographic and economic variables. It was found that the electrical demand is correlated effectively with all variables. Ranjan and Jain [87] analysed the electrical consumption pattern in Delhi as a function of population and weather sensitive parameters for the period 1984–1993. They developed multiple linear regression models of electrical consumption for the winter, summer and post monsoon seasons. [83] presented short term load forecasting of system loads from hours to days ahead based on historical data and future independent variables using the multi-variable linear regression (MLR) method. It was found that weather has a significant role in short term load forecasting. [68] studied the application of the linear regression approach in short term load forecast and resolved that this method provided reliable results under different conditions.

Recent researches have been accomplished on the utilization and implementation of artificial intelligence approaches particularly Neural Networks (NNs) to the electrical load forecasting problem. The authors in [88] and [89] implemented load prediction using ANN for the first time. Various variants, homogenous and hybrid models by using artificial neural network combined to stochastic learning approaches have been successfully applied in forecasting short term load consumption [90]. The back-propagation training algorithm is mostly considered to train the neural network models. However, Artificial Immune System (AIS) learning algorithm [91] and backpropagation momentum training algorithm [92] were used to overcome accuracy speed and convergence problem. The number of neurons and the weights of the neural network forecasting model is generally optimized using heuristic approaches or combined with some other techniques to improve the prediction accuracy and performances[93]. The authors in [94],[66]and[95] presents approaches for load forecasting using ANN tools in MATLAB.

In Ref. [96], a Deep Belief Networks (DBN) made up of multiple layers of constrained Boltzmann machines is utilised for short-term electricity load forecasting based on the Macedonian hourly demand data. The layer-by-layer unsupervised training scheme succeeds in setting the parameters by using a supervised backpropagation training algorithm. A novel input variable selection is also introduced to enhance the quality of the electrical demand data. The mean absolute percentage error (MAPE) is reduced by up to 8.6% compared to the predicted data supplied by the Macedonian system operator (MEPSO) for the 24-h ahead forecasting, and the MAPE for daily peak forecasting is decreased by up to 21%. Certainly, results from this research show the suitability and the superior accuracy of DBN for both daily peak and daily load curve prediction compared to traditional methods. In the work presented by [97], various artificial neural network combined models based on multi-objective optimization and data pre-processing methods were presented simultaneously to find high accuracy and great stability of the forecasting model. The experimental outcomes from an application to the half-hourly electrical load data of three Australian states revealed that both the accuracy and stability of the combined model are excellent to those of other benchmark models. In Ref. [98] a probability density forecasting method based on quantile regression, neural network utilising triangle kernel function is presented to quantify the uncertainty associated with power load demand and finding more information of future load. The nonlinear structure of the neural network is applied to transform the quantile regression model for constructing a probabilistic forecasting technique. Furthermore, the triangle kernel function and direct plug-in bandwidth selection method are used to achieve kernel density estimation. The experimental study from the case of the study shows a suitable performance of the probability density forecasting technique compared to several existing forecasting methods.

[67] presents an artificial neural network (ANN) for forecasting the short-term electrical demand of a university campus using real historical data from Colorado State University. The typical structure of ANNs in this area of research has 24 output nodes representing the hourly loads of the day, 30 output nodes representing the day loads of the month. Each of these hours and days have multiple inputs, which often includes historical data as well as weather and time variables. Reference [99] presents an in-depth look at which variables most affected the load profile, based on case studies on a realistic system, i.e., the Egyptian Unified System, by determining linear correlation coefficients. It was revealed that the identification of the historical load is the most influencing factor, while the temperature is the most influential weather variable, especially in summer and fall. Based on the type and granularity of collected historical data and correlation factor, the most suitable methods for selected case study in Iraq are LR and ANN.

2.3 Economic dispatch

This Section is related to the work which describes an optimal dispatch for the power operator of Ziyounah distribution network. Economic dispatch is the process of allocating generation levels to the generating units in the mix, so that the load demand may be supplied entirely and most economically. Real power economic dispatch aims to make the generator's fuel consumption or the operating cost of the whole system minimal by obtaining the power output of each generating unit under the constraint condition of the system load demands. The idea behind the optimal dispatch problem is that at the central power monitor the load varying is continuously monitored (in real-time), and the power operator (dispatcher) regulates generation supply (typically only real power is considered) to match the total power generation supply with the total power demand. This

generation is controlled in such a way as to minimize the operating cost while satisfying all the operating constraints.
Generation dispatch has been extensively studied and investigated by many authors in books on power system analysis [100],[101],[102],[103]and[104]. The problem of the economic dispatch of generation over the power system generation portfolio has attracted the attention of engineers since the early 1920s [105]. Since then, many comprehensive surveys on the economic dispatch have been provided. One of the first surveys on ED practices appeared at the end of the 1970s [106]. Happ in [106] and the IEEE Working Group present the work of authors from the inception of economic loading to the present status. Happ evaluated the progress of optimal dispatch going as far back as the early 1920s when power operators were concerned with the problem of economic allocation of generation units, i.e., the proper division of the load among the generating units available. Before 1930, several approaches were considered such as (a) the base load method where the next most efficient generation unit is loaded to its maximum capability, then the second most efficient generation unit is loaded, etc., (b) ”best point loading,” where units are successively loaded to their lowest heat rate point, beginning with the most efficient generation unit and operating down to the least efficient unit, etc. It was identified as early as 1930, that the incremental method, later known as the equal incremental method, provided the most economic results. The theoretical work on optimal dispatch was later aided by the development of analogue computers for suitably executing the coordination equations in a dispatching environment. A transmission loss penalty factor computer was developed in 1954 and was used in conjunction with an incremental loading slide rule for scheduling daily generation in a load dispatching office. By 1955, an electronic differential analyzer was developed for economic scheduling for off-line or on-line use. The use of digital computers for obtaining power dispatch was investigated in 1954.

In the last two decades, there have been fundamental changes in the structure of power systems, as well as significant progress in the economic dispatch problem formulation and the solution methodologies. There is a need to keep track of the changes in the solution approaches to enable the power operators to choose the most relevant solutions for their systems, as well as for researchers to have a solid understanding of the problem and of the progress made to date[107].

Economic dispatch can be classified based on the type of generation units as economic dispatch with conventional generation sources and dispatch with non-conventional generation sources. The economic dispatch with conventional generation sources which is also called the classic economic dispatch, in which line security constraints are neglected [108]. The fundamental of the ED problem is the set of input–output characteristics of a power generating unit such as Thermal unit and Hydroelectric Units [108]. The dispatch with non-conventional generation sources, such as solar photovoltaic, solar thermal, diesel generators, wind, geothermal, storage batteries, etc. have an important feature compared to conventional generation [109]. These renewable energy sources have been implemented in the power dispatch as an alternatives way to reduce pollution and operation costs. A decades ago, researchers have included these sources in the power dispatch system instead of focusing mainly on thermal [110]. The availability of their installation is easy as compared to conventional power plants with the lowest transmission power losses. However, the use of PV faces many challenges. Firstly, the PV systems are not much reliable to dispatch the power as per regulated power generation demand. Secondly, PV still have a costly investment in many areas of the world [111].

Optimized power dispatch is the process of optimization to find the generating unit's schedule to meet system constraints and to supply the demand power [112]. The optimization methods of power dispatch are classified into three categories, which are hybrid, non-conventional, classical methods [112]. The conventional approach for solving economic dispatch problems is known as the classical method while non-conventional methods are used to handle the nonconvex and practical dispatch problems. The third category is hybrid methods which combine two or more classical and/or non-conventional methods to improve the performance of individual methods. Figure 2-3 illustrates the three types of optimization methods for economic power dispatch

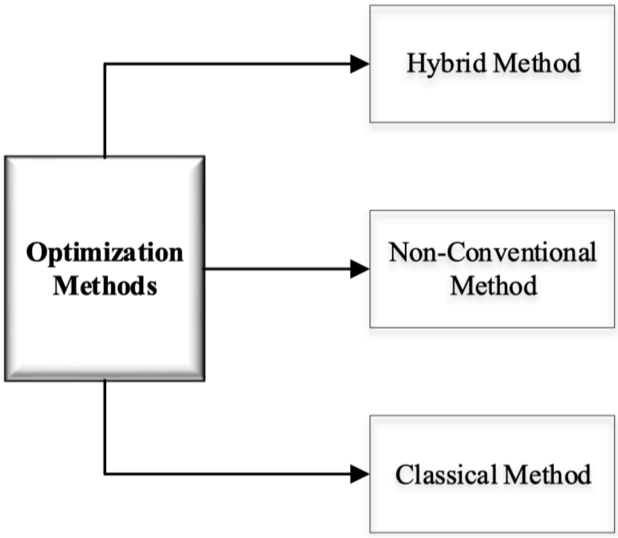

Figure 2-3 Types of optimization methods for optimal power dispatch

2.3.1 Classical methods

There are several classical methods that have been used in order to solve the economic dispatch problem such as the lambda iteration method which is extensively used. Other methods like Newton's method [113], gradient search method [114] and quadratic programming method [115]. have solved economic dispatch problems with different objective functions included cost, loss, and reductions. The proposed algorithms have been achieved the best optimal solution and less computational time. In addition, the system operation is satisfied simultaneously. The classical methods are adaptive, flexible when analysing the problem and easy to understand. The conventional methods include the lambda iteration method provide a feasible solution when the fuel cost function is convex[116].

2.3.1.1 Lagrange Multipliers method

Section 6.6 presents optimal dispatch using Lagrange Multipliers method. The Lagrange multipliers technique is widely used to solve extreme value problems in science, economics, and engineering[117]. The Lagrange multipliers method, named after Joseph Louis Lagrange, provides an alternative method for the constrained nonlinear optimization problems [118]. The Lagrange multipliers method is also called as lambda iteration method[119]. The authors in [117] used lambda iteration to solve the linear quadratic equation to minimize the operating cost for the power system, considering no losses and with losses. [120] proposes a fast and easy to use generic MATLAB syntax to help in solving dispatch problems using the modified L Iteration Method.

The Lagrange multipliers or lambda iteration method deals with both equality and inequality constraints. Without the inequality constraints, the standard form of the nonlinear optimization problems can be formulated as [118]:

$$min\ f(x_1, x_2, \dots x_n) \tag{2.7}$$

Subject to:

$$G\ (x_1, x_2, \dots x_n) = 0 \tag{2.8}$$

G is a function vector. The variables are restricted to the feasible region, which refers to the points satisfying the constraints.

G= $f\ [G_1\ (x_1, x_2, \dots x_n) = 0, \dots \dots, [G_k\ (x_1, x_2, \dots x_n) = 0]\ ^T$, the constraints function vector.

The Lagrange function *F* is constructed as [117]:

$$\mathrm{F(X, \lambda) = F(X)\ - \lambda\, G(X)} \tag{2.9}$$

Where X =$(x_1, \dots x_n)$, the variable vector, λ = $(\lambda_1, \dots \lambda_k)$ are called Lagrange multipliers.

The extreme points of the f and Lagrange multipliers λ satisfy:

$\nabla F = 0$ (2.10)

That is $\frac{\partial f}{\partial x_i} - \sum_{m=1}^{k} \lambda_m \frac{\partial G_m}{\partial x_i} = 0$ (2.11)

and

$G_1\,(x_1, x_2, \ldots x_n\,) = 0$ (2.12)

At the solution, multiple generators have the same marginal (or incremental) cost. This common marginal cost is equal to **λ**. If the power demand changes, changes in total costs can be estimated from λ, and the solved value of **λ** can be used to obtain *Pi*. Fuel cost of power generation of each generator can be expressed as a quadratic function of real power generation [121]:

$Ci = \alpha i + \beta iPi + \gamma i\, Pi^2$ *£/h hourly fuel consumption of DG* (2.13)

Where: αi, βi, and γi are the coefficients for the cost equations; *i= {1,2, 3, .., N}, N= the number of generation units.* This equation is used to determine the incremental cost (λ) using the differential equation shown in Equation (2.14):

$\frac{d(F_i(p_i))}{d(p_i)} = \lambda$ (2.14)

Total fuel cost is lowest when λ values are equal for each generator. The value of λ for the initial configuration of the system can be determined by using Equation (2.15), and the electric power output of each generator unit can be determined from Equation (2.16)

$\lambda = \frac{\boldsymbol{PD} + \sum_{i=1}^{n} \frac{\beta i}{2\,\gamma i}}{\sum_{i=1}^{n} \frac{1}{2\,\gamma i}}$ (2.15)

$Pi = \frac{\lambda - \beta i}{2\,\gamma i}$ (2.16)

2.3.1.2 Linear programming method

Section 6.7 presents optimal dispatch using Linear programming method. Linear programming can be applied to various studies. It is widely used in mathematics and engineering problems and practical planning applications. It has proven useful in power system optimization problems [122],[123]. Linear programming methods are attractive to power operators and researchers because they include the system operation constraints in their formulation and have no convergence problems as they resolve the problem in its primal form. There were three major linear programming-based methods introduced for the solution of the economic dispatch problem in the last 20 years: (i) the simplex method (ii) the interior-point method, and (iii) the mixed-integer linear programming [107]. In addition, Lagrangean approaches were introduced to deal with constraints that may be part of the solution strategy. Simplex linear optimization methods deal with seeking a set of feasible solutions placed on the vertex of the feasible convex polyhedron and then driving along edges of the polyhedron to vertices with successively better values of the objective function until the optimum is given. Contrary to the simplex method, the interior-point-based methods reach the best solution by traversing the interior of the feasible region and have proved to be more efficient in practice, particularly for large systems. Additional to the efficiency in terms of computational effort, interior-point methods do not need a feasible starting point [124].

The application of linear programming methods is based on either the transformation of the quadratic approximation of the generation cost into the piecewise linear format or the use of the Incremental Cost (IC), ignoring several constraints in the first stage and correcting the solution in additional stages if the constraints considered were violated [107].

In [125], a nonlinear primal–dual interior-point method was applied to solve the extended optimal power flow model of a pool-bilateral electricity market. The objective function of the dispatch power model in deregulated markets comprises a linear approximation of the power generation cost, a linear approximation of a penalty cost for the deviation of the vector of the contracted power from the proposed values and a linear approximation of the transmission losses.

In [126], contingency constraints (reserve constraints) were taken into consideration, in addition to the standard economic dispatch formulation, to include the impact of an outage or loss of a generation of any generating unit. The simplex method is applied to solve the linear formulation of the economic dispatch problem with implicit upper and lower generation constraints.

Linear programming techniques can also deal with a quadratic function using a linear function approach as a series of straight-line segments [127].

Linear programs are problems that can be expressed in a mathematical form as:
Find a vector x
That minimizes c^Tx

$$\min_{x} f^T x \text{ such that } \begin{cases} Ax \leq b \\ A_{eq}x = b_{eq} \\ lb \leq x \leq ub \end{cases} \tag{2.17}$$

Where *f*, x, b, *beq*, lb, and ub are vectors, and A and Aeq are matrices.

2.3.2 Hybrid and non- conventional methods

The hybrid method is to combine two or more algorithms to mitigate their weaknesses and provide better performance for solving optimization problems[128]. The proposed hybrid algorithms such as GA-PS-sequential quadratic programming [129], NM-FAPSO [129]and differential evolution algorithm-PSO [130] showed a highly efficient technique to solve the economic dispatch problem. The drawback of this type of algorithm sometimes is a long computational time because it uses two or more algorithms.

Non-conventional methods can deal with the complicated optimization problem and are developed to solve the Combined Economic-Emission Dispatch (CEED) problem. Numerous methods of this type like Ant colony optimization (ACO) [131], Genetic Algorithm (GA) [132], Bat algorithm (BA)[133] and Particle swarm optimization (PSO) [134] have been used to solve the dispatch problem.

2.4 Summary

This chapter presented a review of optimization methods of the latest research on optimal location and size of DGs on the distribution network. It presented various optimization methods applied to different test systems to improve the performance of the power system. According to previous researches, it is clear that if the DGs such as existing diesel generators are well-placed, they could provide benefits to the grid by providing flexibility in localized areas and help avoid or reduce the number of blackouts. Based on a comprehensive review it was selected GA method for the optimal location and sizing of these generation units for improving the operation of electrical networks. Based on the type and granularity of collected available data, it was shown that this approach is more suitable for the real case study in Iraq.

Load Forecasting is a very necessary task for power system operation because it can help the operators make significant decisions for generation dispatch including unit commitment. A comprehensive review of the latest techniques of simple regression and ANN has been applied to load forecast was provided. It was shown that linear regression analysis has revealed promising results due to the reasonable accuracy and relatively simple implementation when compared to other techniques, especially, when it deals with causal relationships between the independent and dependent variables such as power demand and temperature. A review of load forecasting methods based on ANN shown that this technique produces accurate results for short term load forecasts with a time lead ranging from an hour to a week due to its clear model, easy implementation, and good performance. In addition, the other important feature of this technique is its capability of generalization and non-linear learning relationships between variables such as the relationship between load at a given time and load at the same hour on the past day.

This chapter also presented a review of optimization techniques of the latest research for the economic dispatch of DG units on the distribution network. It is shown that economic dispatch is an important approach that can allocate the DGs output so as to minimise the total operational cost while meeting the constraints of total load demand. An extensive literature review of solution techniques for optimal power dispatch problems has shown that The Lagrange multipliers and linear programming methods are very efficient techniques for economic dispatch on power systems that are capable of dealing with both equalities constrained and inequality constrained nonlinear optimization problems. However, the Lagrange multipliers method deals with quadratic functions only while the linear program method can be applied only when the objective function and all the constraints can be expressed in terms of linear equations/inequations.

Chapter 3

Assessment of off-grid diesel generators in Iraq

3.1 Introduction

A diesel generator is a source of energy that can be used as a backup generation unit or an emergency power supply to generate power for commercial, residential and industrial loads during a short interruption of power [135],[136],[137]. They are generally used as off-grid small electrical generation units in remote locations across the world because of their low capital costs [25]. A diesel generator is a compound of a diesel engine with an electrical generator to generate electrical energy [25]. Typically, there are two types of diesel generators in the market, either two poles (3000 rpm) or four poles (1500 rpm) characteristics. The following expression can match the speeds of 50 Hz synchronous diesel generators with 3000 or 1500 rpm:

$$120 \times f = n \times P \tag{3.1}$$

Where:

$\boldsymbol{n}$ is the speed (rpm);

$\boldsymbol{f}$ is the frequency;

P is the number of poles of the diesel generator.

The 3000 rpm machines are structurally simpler with 2-poles and thus results in lower acquisition cost. These are most suitable for light-duty applications and appropriate for the operation of fewer than 400 hours per year. While the 1500-rpm units are 4-pole machines which are more common for heavy-duty applications and are rather more expensive. 4-poles diesel generators are desirable when more than 400 hours of operation per year is anticipated. Generally, the higher the rpm the generator has, the more wear and tear on the bearings, therefore more recurrent maintenance requirements. The diesel generator technically has a lifetime period that varies from 5000 to 50,000 hours, with an average of 20,000 hours, depending on the quality of the engine and its proper installation and execution with regular operation and maintenance [137].

This chapter aims to provide an analysis of the fuel consumption of diesel generators during operation, which contributes to carbon emissions in Ziyounah region of Baghdad. It also compares the operational cost for the generators with the price of electricity from the National Grid in Iraq.

3.2 Carbon dioxide emissions from diesel generators

Diesel engines have many undesirable effects such as greenhouse gases (GHG), including particulate matter (diesel soot and aerosols), oxides of nitrogen and carbon dioxide. The total amount of greenhouse gases (GHGs) released by any system to support people activities, directly and indirectly, is termed as carbon footprint [138]. It is not easy to get all the required data for every particular greenhouse gas emissions due to technical and monitoring problems. Therefore, for simplicity, it is usually stated in terms of the amount of CO_2 emissions [139]. The calculation of carbon dioxide emissions is based on the amount of fuel consumption from diesel generator[139]. The carbon content of fuels lightly varies, but typically the average carbon content values to estimate CO_2 emissions could be adapted [140]. The consumption of one-litre diesel produces about 2.7kg of CO_2 [25],[141]. However, the CO_2 emissions produced and consumed by the diesel generator depends upon the characteristics of the generator set and the characteristics of the fuel and is usually in the range of 2.4–2.8 kg of CO_2 /L [25].

3.3 Diesel fuel consumption and the efficiency of diesel generators

A diesel generator is characterised by its efficiency and rate of specific fuel consumption. The efficiency of the diesel generator depends on the ratio of rated power to output power. The overall efficiency of the diesel generator depends upon its thermal, generator and mechanical efficiency. The thermal efficiency relies on the quality of diesel oil. The specific fuel consumption (L/kWh) of a diesel generator is defined as the consumption of fuel required to produce 1kW of electrical power for supplying a given load during 1 hour time. The fuel consumption of a diesel generator depends on the generator size and the load at which the generator operates, as shown in Figure 3-1. For example, a diesel generator with a size of 20kW has a fuel consumption of about 0.55 L/kWh when the generator operates near 25% of its rated power [142]. In contrast, the same generator consumes approximately 0.363 L/kWh if it is operating between 75% and 100% of its rated power[143]. Generally, a typical diesel generator consumes between 0.32 and 0.53 L/kWh at its rated power[144].

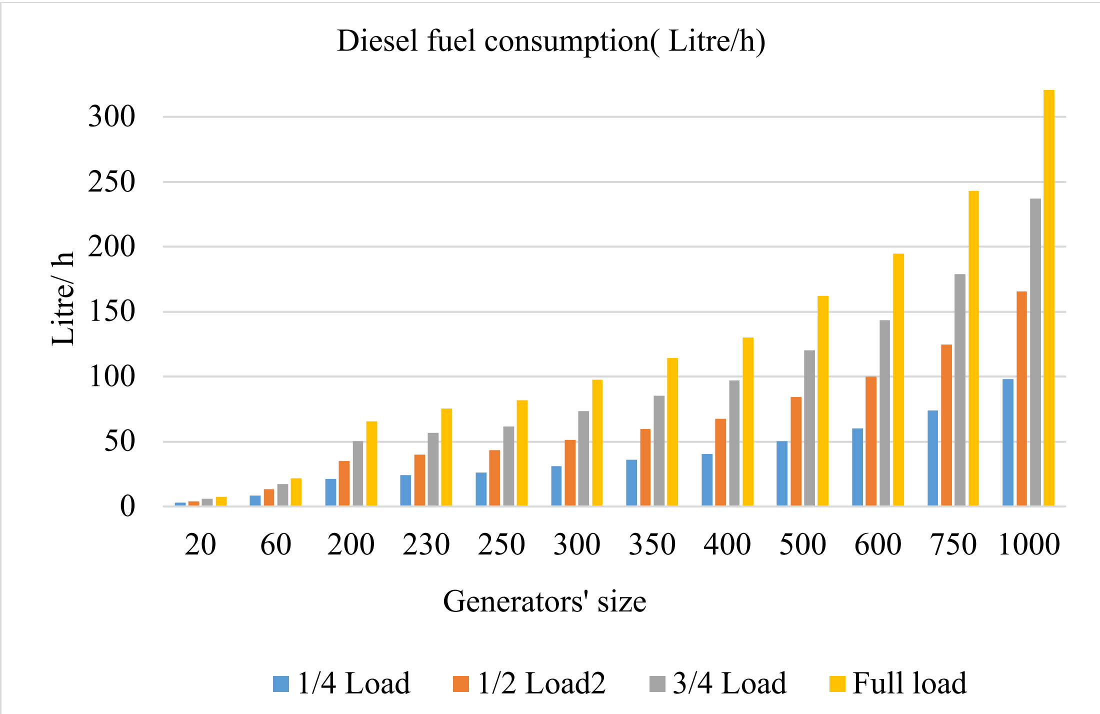

Figure 3-1 The fuel consumption of diesel generators based on the size of the generator and the load at which the generator operates at [145].

3.3.1 Model of Diesel fuel consumption

For estimating the model of diesel fuel consumption, linear regression analysis with two independent variables, which are nominal capacity and power output of the diesel generator, was conducted in this study based on the data from Figure 3-1. It was found that the coefficients (α_{dg} and β_{dg}) of the model of fuel consumption for the diesel generators are 0.0811 L/kWh and 0.2982 L/kWh respectively.

The hourly fuel consumption for a diesel generator is assessed by Equation (3.2) [146],[147],[148].

$$F_c = \alpha_{dg}\, Pn + \beta_{dg}\, Po \qquad \text{L/h} \tag{3.2}$$

Where:

α_{dg} and β_{dg} are the coefficients of the fuel consumption model.

Pn is the nominal capacity of the diesel generator.

*P*o is the power output of the diesel generator

3.3.2 Calculation of diesel generators' efficiency

The efficiency of the diesel generator is directly proportional to its rated power and the load at which the generator operates at. The efficiency of a diesel generator (η_{dg}) is defined as the power output divide by the thermal input energy of fuel consumption, and this efficiency is assessed by Equation (3.3) [146].

$$\eta_{dg} = \frac{Po}{F_c \times T} \tag{3.3}$$

F_c is the hourly fuel consumption of a diesel generator in L/h,

T is a conversion from diesel fuel to kWh thermal =10.723 kWh thermal / litre,

*P*o is power output of the diesel generator.

Equation (3.3) is used to calculate the efficiencies for diesel generators, taking into account the energy of 1MJ = 0.2778kWh thermal and 1 litre of diesel = 38.6MJ, or 1 litre of diesel = 38.6 x 0.2778 = 10.723kWh thermal. That means one litre of diesel fuel has an input energy content of approximately 38.6MJ, which approximates to 10.723kWh. The calculations of diesel generators' efficiencies for different capacities and operating are shown in Table 3-1.

Table 3-1 The efficiencies of diesel generators 20kW-1000kW during operating

Generator Size (kW)	¼ Load	½ Load	¾ Load	Full load
20	17.1%	22.8%	23%	25%
60	17.1%	21.2%	21%	25.7%
200	21.8%	26.6%	27.9%	28.4%
230	22.2%	26.8%	28.3%	28.4%
250	22.4%	26.9%	28.2%	28.4%
300	22.6%	27.2%	28.6%	28.6%
350	22.7%	27.4%	28.7%	28.6%
400	23.0%	27.5%	28.8%	28.6%
500	23.3%	27.7%	29.1%	28.7%
600	23.3%	27.9%	29.3%	28.7%
750	23.5%	28.0%	29.3%	28.8%
1000	23.7%	28.1%	29.5%	28.8%

3.4 Carbon intensity calculation at various efficiencies

The calculations of carbon intensity are presented in Figure 3-2. The Figure shows that 73.11kg of CO_2 are produced per 10^6BTU[3] when diesel is burnt. In other words, 73.11kg of CO_2 is produced when 292.7 kWh thermal of diesel is burnt. Therefore 0.249 kg of CO_2 is produced when 1 kWh thermal of diesel is burnt. The Carbon intensity (C.I) of a diesel generator is expressed as:

$$\mathrm{C.I} = \frac{0.249}{\eta_{dg}} \text{ kg of } \mathrm{CO_2/kWhe} \tag{3.4}$$

[3] Conversions BTU to kWh, multiply by 2.9275x10^{-4}, Lbs to kg multiply by 0.4535392.

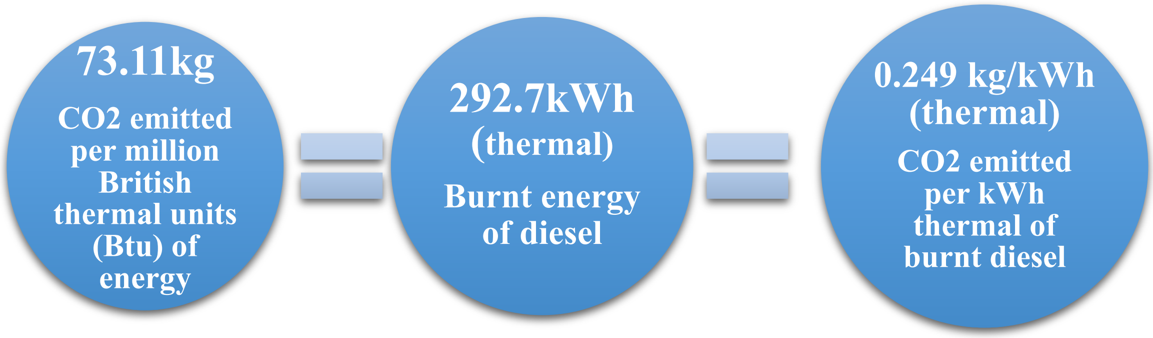

Figure 3-2 Carbon dioxide emissions calculations from diesel fuel

It is assumed an engine efficiency of 28.8%. This gives a carbon intensity of diesel generation of 865 $gCO_2/kWhe$.

For calculating the carbon intensities for diesel generators at various efficiencies, Table 3-1 is considered. The calculation is presented in Table 3-2 by using Equation (3.4)

Table 3-2 The carbon intensities of diesel generators based on their efficiencies

Generator Size (kW)	1/4 Load	1/2 Load	3/4 Load	Full load
	Carbon intensity gCO2/kWhe	Carbon intensity gCO2/kWhe	Carbon intensity gCO2/kWhe	Carbon intensity gCO2/kWhe
20	1456	1092	1083	996
60	1456	1175	1186	969
200	1142	936	892	877
230	1122	929	880	877
250	1112	926	883	877
300	1102	915	871	871
350	1097	909	868	871
400	1083	905	865	871
500	1069	899	856	868
600	1069	892	850	868
750	1060	889	850	865
1000	1051	886	844	865

The Emission Factor (EF) is calculated as:

$$\mathrm{EF} = \frac{0.249\mathrm{kg\ of\ CO_2}}{\mathrm{kWh\ thermal}} \times 10.723(\text{conversion from kWh thermal to litres})$$

$$\mathrm{EF} = 2.67\ \mathrm{kg/litre}\ \text{(absolute value)}$$

3.5 Model of carbon emissions for a diesel generator

The estimation of the total CO_2 emissions from a diesel generator is expressed in Equation (3.5) [136]

$$CO_2\ \text{emissions} = \textstyle\sum_1^t Fc \times EF \tag{3.5}$$

Where: t= Time period during operation of generator in hour(h)

$Fc = \frac{\mathrm{Po}}{\eta_{\mathrm{dg}} \times \mathrm{T}}$ is fuel consumption in litre/h, and *EF* is the emission factor in kg of CO_2 / litre for diesel generator, which depends on the type of fuel and diesel engine characteristics. Or anothery way to express CO_2 emission is:

$$CO_2\ \text{emissions} = \textstyle\sum_1^t \mathrm{CI} \times \mathrm{Po} \tag{3.6}$$

Where CI is carbon intensity in kg/kWh.

The results presented in Section3.4 and 3.5 for the carbon intensity or carbon dioxide emitted by diesel generators is relatively higher than the carbon intensity emitted by other generation units such as Combined Cycle Gas Turbine (CCGT), which has a carbon intensity of 490kg of CO_2 per kWh. This is because the carbon intensity depends strongly upon the generator's efficiency and fuel type. In addition, a diesel generator should operate close to its rated power to avoid high fuel consumption and CO_2 emissions.

3.6 Off-Grid diesel generators in Iraq

3.6.1 Background

Currently, diesel generators are becoming more important for supplying Iraq's consumers. According to the Ministry of Planning in Iraq, the number of diesel generators that supply communities in the country as a whole is about 90,000 units, supplying the consumers directly contributing to about 20% of demand. However, this is a costly stop-gap measure. At a tariff of GB£ 450-900/MWh by the third party charging around £15/Ampere.Month of capacity, this option is more expensive than the supply from the national grid. These generators captured annual revenues of around £3 billion in 2018, which is equal to the amount allocated to the electricity sector in the federal budget for capital expenditure in 2019 [6].

3.6.2 Financial considerations

Electricity supply, helping to mitigate some of the most acute shortages in the peak demand, with three-quarters of it providing cooling in the summer months. In 2018, the combined total of these generators was 5 GW[6]. The private generators are provided with a certain amount of diesel fuel by Baghdad Provincial Council at the official price of about GB£0.24/litre, which is cheaper than that from the market, which is about £0.45/litre. The fuel is provided to the diesel owners based on the size of generators (i.e. up to 5,000 litres/month).

The cost of electricity from diesel is higher than the electricity from the public supply because the government heavily subsidises the electricity supply to consumers. The grid provides the majority of electricity, but more than 90% of the consumers' electricity bill goes to an expensive neighbourhood generation[6] because of load shedding operation. It is expected that the household might pay as much as £3,000 per year to the neighbourhood generator as the generator charges are as much as £15/Ampere.Month of capacity during hot summer days despite regulations in place that asked for lower charges. It is well known in Iraq that consumers buy electricity from the generators' owner based on electrical current (Ampere) instead of energy (kWh). This is, however, not sufficient to supply all the demand from fundamental appliances such as lighting, refrigerators, ceiling fans, water coolers as well as air coolers (low current). These fixed charges translate to around £750/MWh for consumer, or an average price of £180/MWh for electricity delivered, which is eight-fold the average residential electricity price in the Middle East region today[6].

In 2018, the electricity tariff from the government had been categorised into four levels (see Figure 3-3) to provide a progressive tariff scheme to consumers, which aimed to make electricity more affordable for low-income households.

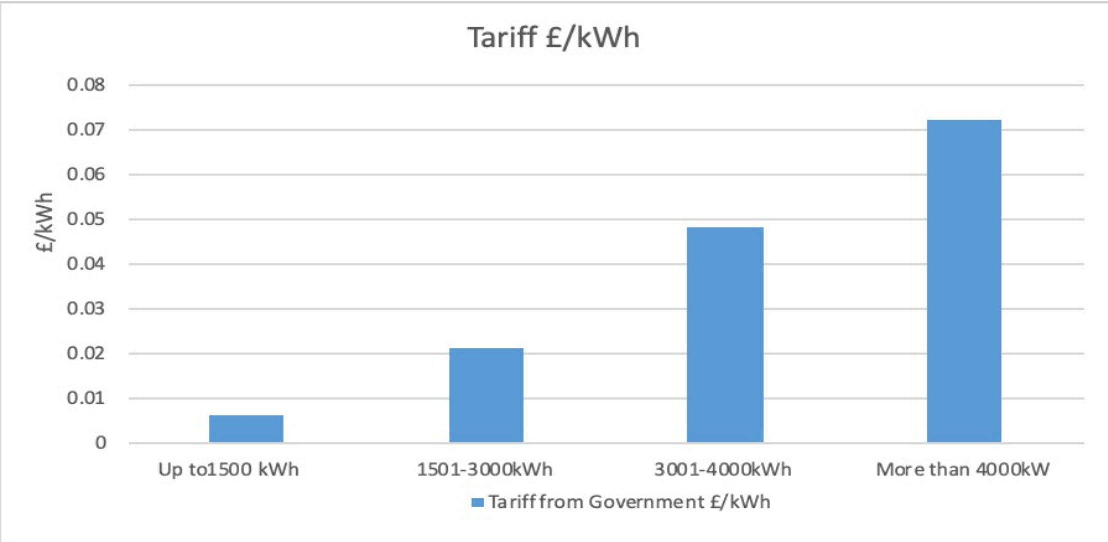

Figure 3-3 Electricity Tariff from Iraq government in (£), source: Ministry of Electricity, Currency converter: IQD= 0.0006 GBP

To calculate the maximum electrical current (Amper)[4], which is supplied to the consumers from the generator, providing the same amount of the consumption using electricity from national grid, the data from the government tariff (kWh) in Figure 3-3 is considered.

[4] The electricity supply from diesel generators is sold to consumers in electrical current (Amper) instead of energy(kWh) in Iraq, and it is controlled by circuit breakers to avoid exceeding the required maximum current.

It is known that consumers in whole Iraq buy electricity from diesel generators in electrical current (Amper) instead of energy(kWh), and it is controlled by the diesel generators owner to avoid exceeding the required current.

In the calculation, it is considered that the generator operates 10 hours per day at 0.85p.u. power factor. Therefore the consumption for 1kWh per month is calculated as

$$1\text{kWh} = 220V \text{ x current (Amper)x } 0.85 \text{ pf x } 10\text{hours x } 30\text{days}$$

It was found that the electricty tariff (kWh/ month) from diesel generator is equal to £0.267 ($0.01782\text{A} \text{ x £}15$). In contrast, tariff for electricity from the national grid using the lower tariff for 1,500kWh shown in Figure 3-4 is equal to £0.02, which is cheaper than the tariff from the diesel generators.

Figure 3-4 compares the electricity tariff for the government and neighbourhood generator in four categories of consumption over the month. It can be seen that the tariff from generators is almost the same at £0.288/ kWh. This is because the cost of 1A per month from the generators is constant regardless of whether consumers use it or not. The tariff from the government, by contrast, increases from 0.006£/kWh to 0.072£/kWh over the four categories of consumptions.

The government introduced the cheapest tariff for the first level of consumption to support the lower-class households. This means, or these customers 1500kWh of monthly consumption, using the tariff from diesel generators is 47 times more expensive than the electricity tariff provided by the government. Therefore, the efforts to reduce the contribution or costs of neighbourhood diesel generators could improve electricity affordability for most, if not all, families. Without urgent and concerted action, these pressures are likely to increase as rapid population growth and economic development increases electricity demand. Achieving a stable, affordable and reliable electricity supply is essential not just to serve the basic needs of the Iraqi people but to improve living conditions stimulating economic growth.

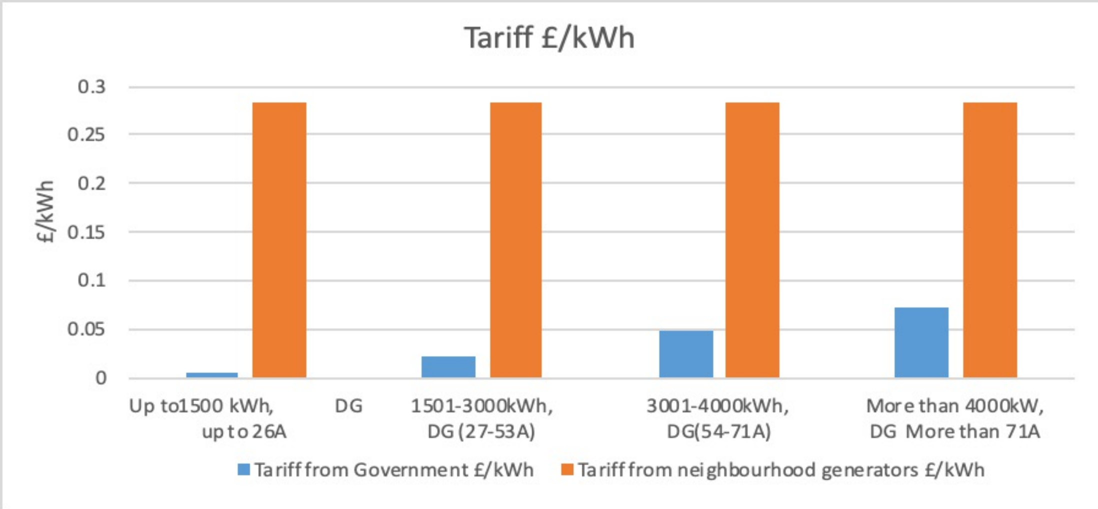

Figure 3-4 Comparison between tariff in £/kWh from Iraq's National Grid and neighbourhood generators

3.6.3 CO_2 emissions and fuel consumption for diesel generators in Ziyounah

3.6.3.1 Methodology

Off-Grid diesel generators, which are detailed in section 3.6.3, are assumed to be distributed in Ziyounah region. A constant load demand of 200 kW with 10 hours of operation of a diesel generator per day (2,000kWh/day) is assumed for this analysis. The amount of fuel consumption and CO_2 emissions of these diesel generators is determined using Equations(3.2), (3.5) and (3.6). There are four different sizes of existing off-grid diesel generators in this study. The capacities of these generators are: 250kVA, 500kVA, 750 kVA and 1,000kVA. Hence, the rated power capacity of diesel generators is changed from 250kW to 1,000kW for comparative results, see Figure 3-5.

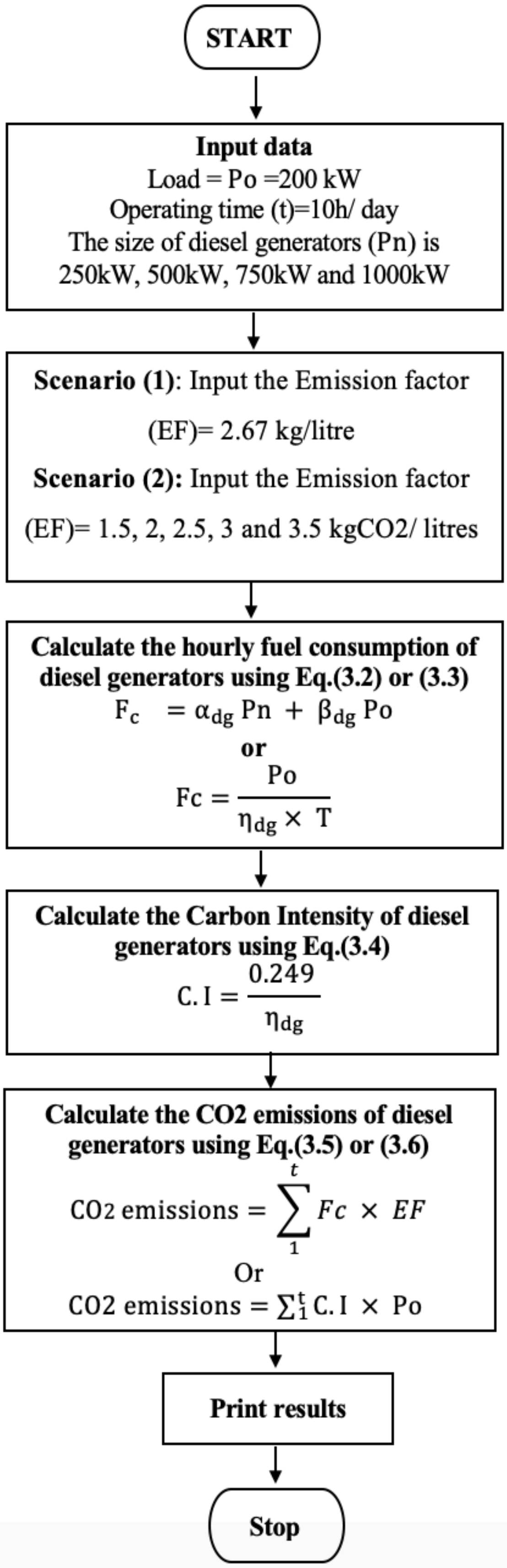

Figure 3-5 Flowchart for calculating fuel consumption, carbon intensity and CO2 emissions for diesel generators based on 100kW power load

3.6.3.2 Results and discussion

SCENARIO (1): Estimation of fuel consumption and CO2 emissions from diesel generators based on the absolute value of Emission Factor (EF)= 2.67 kg/litre

In this scenario, the fuel consumption and the CO_2 emissions for the diesel generators are determined based on the Emission factor (EF) =2.67 kg/ litre.

It is assumed that the Emission Factor is constant at 2.67 kg/ litre. To determine the fuel consumption and carbon emission emitted from different sizes of generators, Equation (3.2) or Equation (3.3) is applied at a constant load demand of 200 kW with 10 hours of operation of a diesel generator per day, see Figure 3-5.

It can be observed that the efficiency of a diesel generator decreases from 23.34% to 13.25%, with increasing of its rated power capacity from 250kW to 1,000kW with a load demand of 200kW. The fuel consumption for the generators was found to be 799.15 litres/day (0.4 litres/kWh) with a 250kW rated power and 1407.40 litres/day (0.7037liters/kWh) with a 1,000kW rated power diesel generator as shown in Table 3-5. Similarly, the CO_2 emissions were found to be 2,133kg/day (1.066kg/kWh) with a 250kW rated power and 3757.76kg/day (1.8789kg/kWh) with a 1,000kW rated power diesel generator.

It is estimated that the use of a 250kW rated power diesel generator will consume 799.15 litres of diesel oil and emit 2133 kgCO_2 per day. Similarly, a 1,000kW rated power diesel generator will utilize 1407.40 litres of diesel oil and produce 3,757 kgCO_2 per day with a load demand of 200 kW per hour or 2,000kWh/day, see Table 3-3.

If the load in which a generator operates is less than the generator's size, the generator's efficiency will drop, and the generator will consume a large amount of fuel and ultimately emit more CO_2 emissions.

Table 3-3 Estimation of fuel consumption and CO2 emissions from diesel generators

Rated power of Diesel Generator	Efficiency of Diesel Generator	Fuel consumptions		CO_2 emissions	
		(Litres/ kwh)	(Litres/ day)	(kg/day)	Intensity (kg/kWh)
250 kW	23.34%	0.3996	799.15	2133	1.06688
500 kW	18.62%	0.5010	1001.90	2675	1.33755
750 kW	15.48%	0.6023	1204.65	3216	1.60822
1000 kW	13.25%	0.7037	1407.40	3757	1.87890

SCENARIO (2): Estimation of CO2 emissions from diesel generators based on variable value of Emission Factor (EF), EF changed from 1 to 1.3

In this scenario, it is assumed that the Emission Factor is varying from 1 to 1.3. To determine the carbon emission emitted from different sizes of generators, Equation (3.5) or Equation (3.6) is applied at a constant load demand of 200 kW with 10 hours of operation of a diesel generator per day. In the case of calculation the carbon intensity Equation (3.4) is carried out, see Figure 3-5.

In Tables 3.4 and 3.5, the input value of the emission factor is changed from 1 to 3.5kgCO_2/litre, and the rated power of the diesel generator is varied from 250kW to 1,000kW. It was found that the amount of CO_2 emissions increased by 3.5 times as the emission factor is increased from 1 to 3.5kgCO_2/litre (see Table 3-5). For example, the carbon emissions from a 1,000kW rated power diesel generator increases from 1,407kg to 4,925kg when the emission factor is increased from 1 to 3.5kgCO_2/litre.

Table 3-4 Carbon emissions (kgCO2/day) at a various rated power of diesel generator and emission factors

Rated power capacity of Diesel Generator	Carbon emissions (kgCO2/day)					
	EF=1	EF= 1.5	EF= 2	EF= 2.5	EF=3	EF=3.5
250 kW	799.15	1198.73	1598.30	1997.88	2397.45	2797.03
500 kW	1001.90	1502.85	2003.80	2504.75	3005.70	3506.65
750 kW	1204.65	1806.98	2409.30	3011.63	3613.95	4216.28
1000 kW	1407.40	2111.10	2814.80	3518.50	4222.20	4925.90

Table 3-5 shows the carbon intensity for the diesel generators at various rated power and emission factors. It can be seen that the carbon intensity is directly proportional to the emission factor and the rated power of the diesel generator. Therefore, the rated power of the selected diesel generator should be closely matched to the load demand to reduce CO_2 emissions.

Table 3-5 Carbon Intensity (kgCO2/kWh) at various rated power of diesel generator and emission factors

Rated power capacity of Diesel Generator	Carbon Intensity (kgCO2/kWh)					
	EF=1	EF= 1.5	EF= 2	EF= 2.5	EF=3	EF=3.5
250 kW	0.40	0.60	0.80	1.00	1.20	1.40
500 kW	0.50	0.75	1.00	1.25	1.50	1.75
750 kW	0.60	0.90	1.20	1.51	1.81	2.11
1000 kW	0.70	1.06	1.41	1.76	2.11	2.46

3.6.4 Summary

In this chapter, existing off-grid diesel generators of the Zyounah region in Baghdad are investigated to provide an understanding of the real challenges of these generators for the consumers in terms of environmental and economic perspectives.

It is estimated that for households who consume less than 500kWh/month, the tariff from diesel generators is 47 times more expensive than the electricity tariff provided by the government because the government heavily subsidizes the electricity supply to consumers.

Models of both diesel fuel consumption and carbon emissions for these units are presented to determine the hourly fuel consumption, efficiencies and the total CO_2 emissions of the diesel generators during any period of time.

The fuel consumption and CO2 emissions for four diesel generators in the New Ziyouna region of Baghdad case study are determined during the day based on a constant Emission factor (EF) = 2.67 kg/litre. It is found that the efficiency of the diesel generator is inversely proportional to the fuel consumption rate, CO2 emissions and rated power of the diesel generator with a constant load demand of 200kW (2,000kWh/day) in the hot summer days.

In scenario 2, it is assumed that Emission Factor (EF) is changed from 1 to 3.5 because the value of this factor depends on fuel quality and the diesel engine characteristics. It is revealed from the analysis that both the carbon intensity and the emission of carbon dioxide increased by 3.5 times as the emission factor is increased from 1kg to 3.5kgCO_2/litre.

If the load in which a generator operates is less than the generator's size, the generator's efficiency drop, and the generator consume a large amount of fuel and ultimately emit more CO_2 emissions. Hence, the selection of a diesel generator should be close to the required load demand.

This outcome is especially relevant for the power operators and policy decision-makers in countries and governments that are in the process of shaping their own climate policies. The lesson learnt form this study is that operating of isolated diesel generators with limited load is expensive and environmentally damaging which can be a disadvantage especially if they are operating around a well-populated neighbourhood. The model of carbon emissions for the generators in section 3.5 is significant, and it is linked to the discussion in chapter 6 because the output of CO_2 emissions can be calculated depending on the dispatch power of diesel generators.

Chapter 4

Optimal integration of distributed generators in the Iraq power system

4.1 Introduction

Iraq's power system is facing significant challenges due to the mismatch between generation and supply. If these existing diesel generators were to well-placed, they could provide benefits to the grid by providing flexibility in localized areas and help avoid or reduce the number of blackouts [37]. The optimal location and sizing of these generation units is a suitable option for improving the operation of electrical networks [34], [29]and[149].

This chapter presents a methodology to find the best placement and the right size of the diesel generators in the distribution network of Ziyounah in the Baghdad area. The optimization of these two parameters reduces the real power losses, stabilizes the grid voltage, and improves the network performance [149], [150],[37],[40] and [151]. This optimization approach also contributes to minimizing the level of acoustic noise from existing diesel generators that are installed at the neighbourhood location. The objective function looks to minimize the real power losses of the network keeping the voltage within the permissible levels[5]. In addition, the economic impact was assessed by calculating the saving obtained when the diesel generators are best placed in the network.

4.2 Mathematical formulation

One advantage of deploying distributed generators in distribution networks is to minimize the total system real power loss and improves the network performance while satisfying certain operating constraints. In other words, the problem of DG application can be interpreted as obtaining the optimal size and

[5] The permissible voltage level for Iraq's power system (low and medium voltage) is (0.95- 1.05pu) [160].

location of that generator to meet the desired objective function subject to equality and inequality constraints. The power-flow analysis is the heart of the DG-unit solution algorithm [152]. Accordingly, the power-flow algorithm offered in [40],[152]and [153] is applied in this work. The mathematical formulations of the non-linear optimization problem for the DG-unit application is shown in Figure 4-1.

Consider a three-phase, balanced radial distribution feeder with n buses, *l* laterals and sub laterals. Also, DG units and shunt capacitors as shown in Figure 4-1.

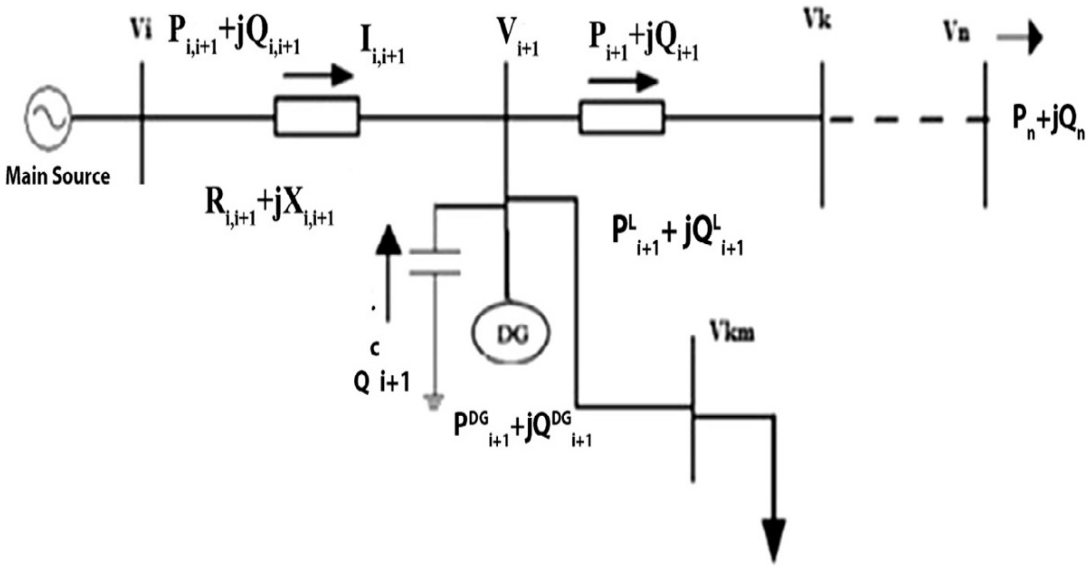

Figure 4-1 Radial distribution feeder model including DG and capacitor [37]

The power flow is carried by the following set of recursive equations derived from the single line diagram shown in Figure 4-1.

$$V_{i+1} = V_i - 2(r_{i+1} P_i + x_{i+1} Q_i) + (r_{i+1}^2 + x_{i+1}^2) \text{ x } \frac{(p_i^2 + Q_i^2)}{V_i^2} \quad (4.1)$$

$$P_{i+1} = P_i - \frac{r_{i+1}(p_i^2 + Q_i^2)}{V_i^2} - P_{Li+1} \quad (4.2)$$

$$Q_{i+1} = Q_i - \frac{x_{i+1}(p_i^2 + Q_i^2)}{V_i^2} - Q_{Li+1} \quad (4.3)$$

Where

i= {1,2, 3, .., n}, n= The total number of buses

P_i and Q_i = The real and reactive power flowing out of bus $_i$

P_{Li} and Q_{Li} = The real and reactive load power at bus $_i$

The resistance and reactance of the line section between *bus i* and *bus i + 1* are donated by r_{i+1} and x_{i+1} respectively.

To incorporate the method, Equations (4.2) and (4.3) are modified as [153].

$$\mathrm{P_{i+1}} = \mathrm{P_i} - \frac{\mathrm{r_{i+1}}(p_i^2 + Q_i^2)}{V_i^2} - \mathrm{P_{Li+1}} + \mu_\mathrm{p} + A\mathrm{P_{i+1}} \tag{4.4}$$

$$\mathrm{Q_{i+1}} = \mathrm{Q_i} - \frac{\mathrm{x_{i+1}}(p_i^2 + Q_i^2)}{V_i^2} - \mathrm{Q_{Li+1}} + \mu_q + R\mathrm{P_{i+1}} \tag{4.5}$$

Where

μ_p = Real power multiplier, set to zero when there is no active power source or set to 1 when there is active power source

μ_q = Reactive power multiplier, set to zero when there is no reactive power source or set to ±1 when there is a reactive power source

$A\ P_{i+1}$ = Active Power magnitude injected at bus i + 1

$R\mathrm{P_{i+1}}$ = Reactive Power magnitude injected at bus i + 1

The following terminal conditions should be satisfied:

i. At the end of the main feeder, laterals and sub laterals

$$\mathrm{P_n} = \mathrm{Q_n} = 0$$

$$\mathrm{P_{km}} = \mathrm{Q_{km}} = 0$$

ii. The voltage at bus k is the same voltage as its lateral

$$\mathrm{V_k} = \mathrm{V_{ko}}$$

The real and reactive power losses of each section connecting two buses are:

$$\mathrm{P_{Loss_{\mathit{i+1}}}} = (p_i^2 + Q_i^2 / V_i^2)\mathrm{r_{i+1}} \tag{4.6}$$

$$Q_{Loss_{i+1}} = (\,p_i^2 \; + Q_i^2 \,/\; V_i^2\,)x_{i+1} \tag{4.7}$$

4.3 Distribution power flow solution algorithm

The method is used to solve the radial distribution feeders with laterals and sub laterals taking into account any embedded distribution generation and shunt capacitors. The analysis was carried out by the MATLAB application. The feeders can be divided into single line feeders and laterals.

The solution steps for single line feeders including the proposed approximation formulas are summarized as:

Step 1: Read the feeder data.

Step 2: Find the sum of power loads (active and reactive) for all buses and the sum of all resistances and inductive reactance's of each section connecting two buses.

Step 3: Assume the sending end real power, reactive power and voltage to be:

$$P_o = \sum_{I=0}^{n} P_{L_{i+1}} + P_{Factor} \tag{4.8}$$

$$Q_o = \sum_{I=0}^{n} Q_{L_{i+1}} + Q_{Factor} \tag{4.9}$$

$$V_o = 1 + j\,0 \text{ p.u.} \tag{4.10}$$

Where

$$P_{Factor} = \frac{\frac{\left(\left(\sum_{I=0}^{n} P_{L_{i+1}}\right)^2 + \left(\sum_{I=0}^{n} Q_{L_{i+1}}\right)^2\right) \sum_{I=0}^{n} r_{i+1}}{V_0^2}}{n-1} \tag{4.11}$$

$$Q_{Factor} = \frac{\frac{\left(\left(\sum_{I=0}^{n} P_{L_{i+1}}\right)^2 + \left(\sum_{I=0}^{n} Q_{L_{i+1}}\right)^2\right) \sum_{I=0}^{n} x_{i+1}}{V_0^2}}{n-1} \tag{4.12}$$

The approximation factors in Equation (4.11) and (4.12) are used to reduce the iterations required for solution as in reality, there are no lossless systems and rarely feeder with only two buses. In other words, the result gets closer to the exact loss values. Then, we use these values P_o and Q_o in the initial iteration.

Step 4: Apply power flow Equations (4.1), (4.4) and (4.5) for the feeder.

Step5: If the absolute values of P_{n} and Q_{n} of the last bus are zero or within an acceptable tolerance ≤ 10^{-7} p.u., the power flow solution is acceptable, otherwise go to next step.

Step 6: For the first bus in the main feeder set:

$$\mathrm{P}_{\mathrm{o}_{new}} = \mathrm{P}_{\mathrm{o}_{old}} - \mathrm{P}_{\mathrm{n}} \tag{4.13}$$

$$\mathrm{Q}_{\mathrm{o}_{new}} = \mathrm{Q}_{\mathrm{o}_{old}} - \mathrm{Q}_{\mathrm{n}} \tag{4.14}$$

Then, use these new initial values and follow step 4

The solution steps for laterals is presented in Figure 4-2.

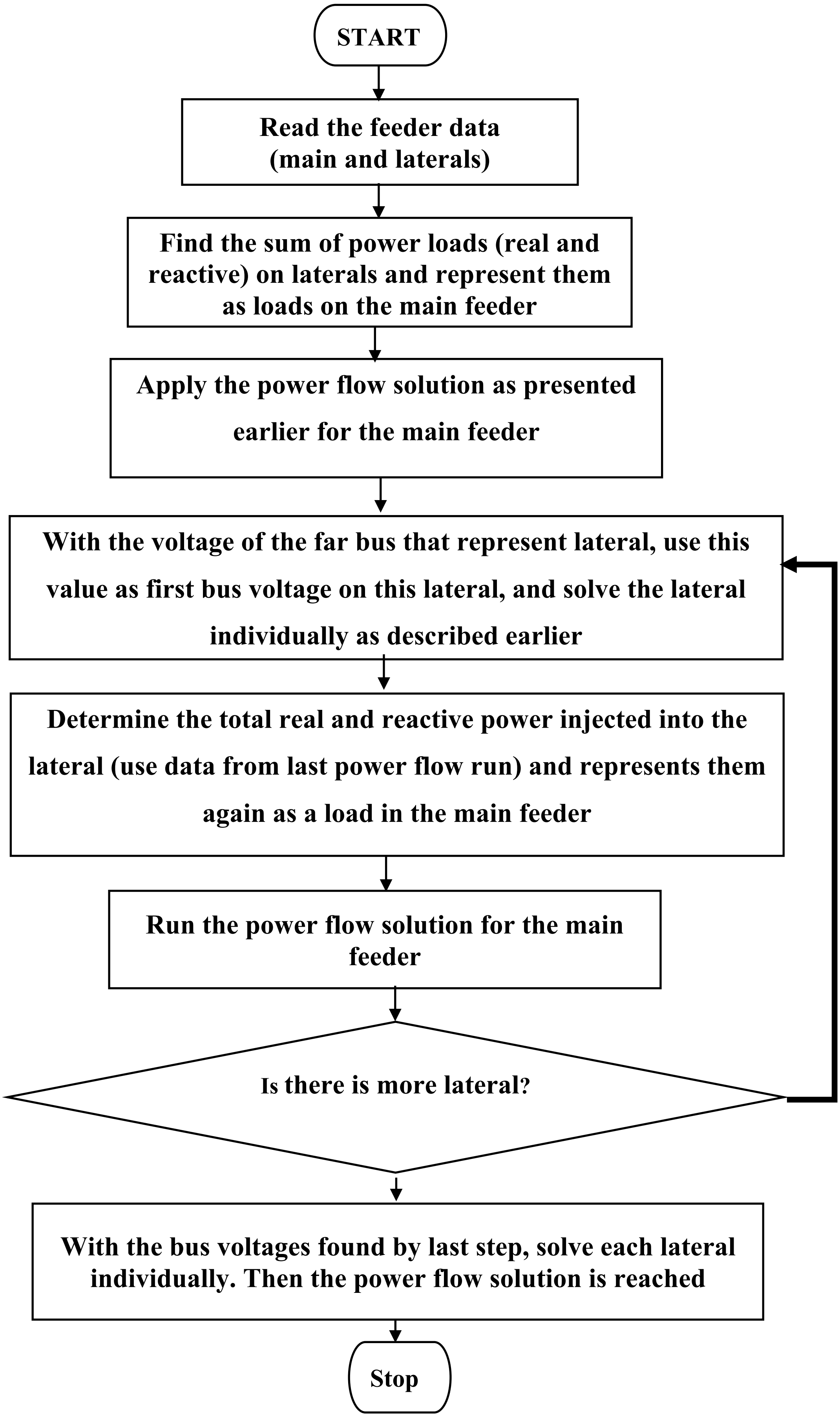

Figure 4-2 Flowchart for power flow Solution for Laterals

4.4 Optimal placements of the diesel generators using Genetic Algorithm (GA)

Optimal integration of the generators is achieved by improving the system performance such as to reduce the system loss, improve the voltage profile while maintaining the system stability[28]. In this thesis, the existing diesel generators are used as distributed mobile generators units and an optimisation algorithm was developed to re-locate these generators in an efficient way to minimise losses and reduce the local pollution in the urban areas. Re-locating the existing diesel generators reduces the acoustic noise significantly and overcomes the drawbacks of the load shedding program.

The selection of the best location and the optimal size of the distributed generators in distribution networks is a complex, stochastic and non-linear problem [154][155]. Therefore, the optimization framework is implemented using Genetic Algorithms (GA) with the goal to enhance the network performance by maximizing Network Performance Index (NPI) considering the Real Power Loss Index, Voltage stability Index and Voltage Profile Improvement Index.

The Network Performance Index (NPI) numerically describes the impact of diesel generators on the distribution networks considering the maximum load. NPI close to unity value means higher diesel generator benefits. Network Performance Index (NPI) gives an indication of best location and size for DG source. The technique incorporates genetic algorithms combined with heuristic rules to evaluate most feasible locations based on NPI so that all network performance parameters are improved. In some cases, the best combination of locations may not be feasible for connecting of DG units due to geographical, social constraints. Hence it is important to obtain the other alternatives. To cater this need a priority list of bus numbers is prepared with decreasing order of NPI. This aspect provides flexibility for the power designer to select the suitable locations satisfying technical and implementation constraints.

The genetic algorithm approach assists to identify bus locations for insertion of multiple DG units. The convergence of the GA search is conducted on the basis of a fitness function as defined by the designer. The selection of GA parameters such as type of crossover, size of population, mutation and termination criteria is to be decided depending on nature of application.

The power flow is obtained by recursive equations, taking into account the connection of embedded diesel generators. The power flow results are used to calculate parts of the objective function. The Genetic Algorithms (GA) is searching the diesel generator locations, by knowing the total number of the generators that the operator is interested to connect. The Network Performance Index is implemented as the fitness function for GA playing an important role in the capacity allocation of the diesel generators.

The developed algorithm is in the following steps:

Step 1: Read the network data: the loads connected to the different buses, the resistance and reactance for transformers and lines.

Step 2: Run the power flow algorithm to obtain the base case, without generators connected.

Step 3: Read the available generators capacity to be connected to the network.

Step 4: Generate the bus numbers where the generators need to be connected using Genetic Algorithm GA.

Step 5: Run the power flow for the network with generators connected to find the bus locations.

Step 6: Calculate the Network Performance Index (NPI).

Step 7: Maximise the value of NPI based on the optimisation function as shown in Figure 4-3.

Step 8: Choose the best three combinations with the highest values for NPI. genetic algorithm iterates to find an optimum.

Step 9: Find the best combination.

The best combination will have the highest value of NPI indicating that the value of real power loss is minimised. Also, the voltage profile is improved. The NPI values are computed for the first three best combinations and sorted out in a descending order.

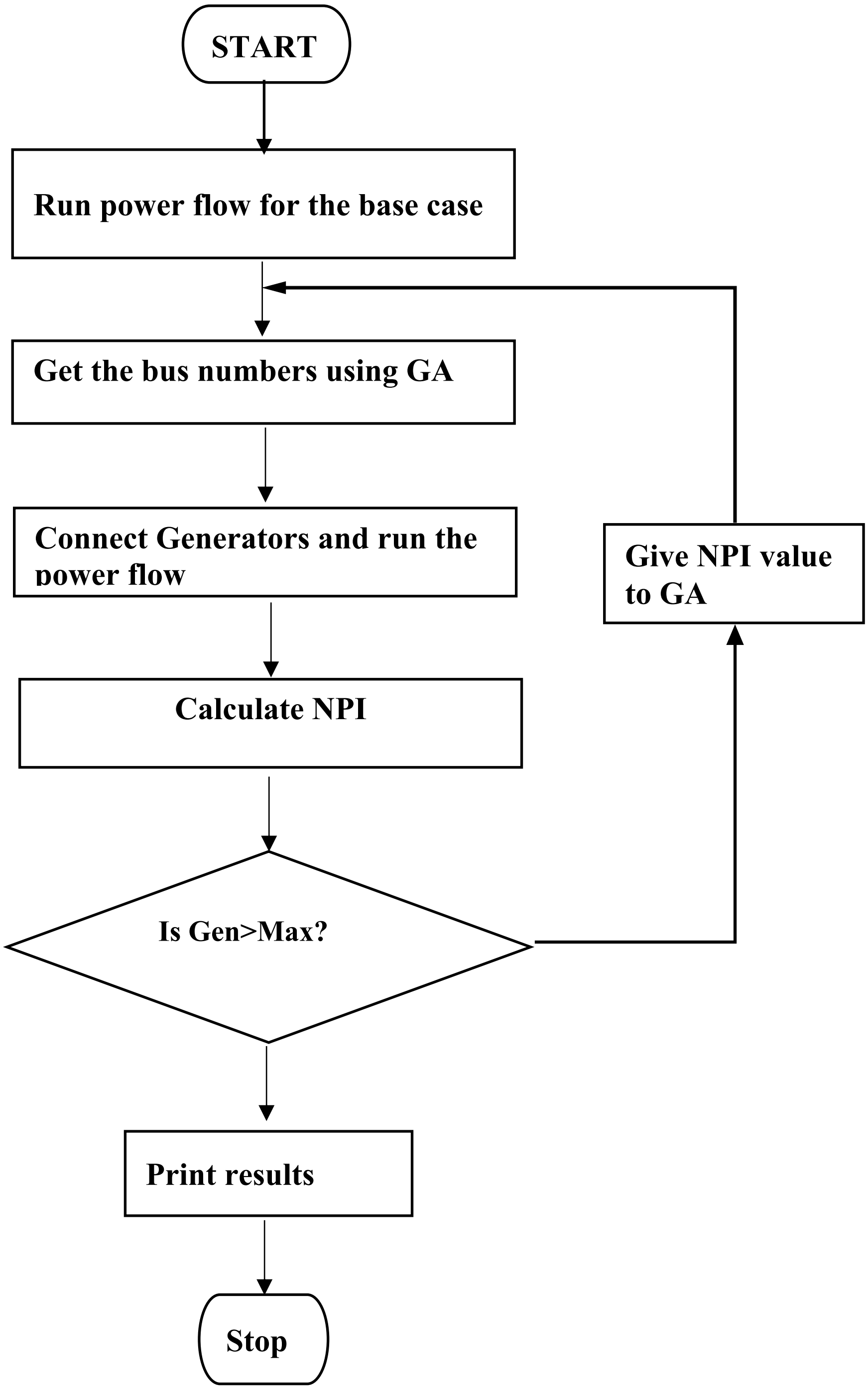

Figure 4-3 Flow Chart for NPI

4.5 Indices for network performance

To evaluate the performance of the network, there are various indices that can be used. These are incorporated in the Network Performance Index (NPI) [156].

Real Power Losses Index (PLoosIn):

One of the most important benefits offered by connecting diesel generators is the reduction of real power losses [156]. This index is expressed as follow:

$$\mathrm{PLossI_n} = 1 - \frac{(\mathrm{PLoss})_{\mathrm{dg}}}{(\mathrm{PLoss})_0} \tag{4.15}$$

Where *(PLoss)dg* is real power losses with diesel generators connected, and *(PLoss)o* is real power losses without the generators connected.

Voltage Stability Index (VSIn): the voltage stability problem is discussed in [156], [157] and [158]. VSIn is presented as a voltage stability index from a simple power system shown in Figure 4-4. The improvement in voltage stability is important because the power system with lesser voltage stability may move to uncontrollable state [159].

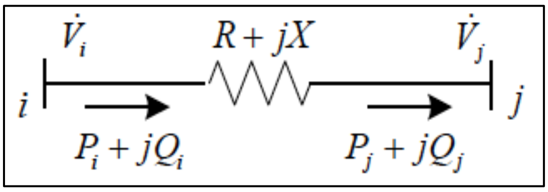

Figure 4-4 Simplified power system [14]

Voltage stability index of branch j ($VSIj$) is written as:

$$\mathrm{VSIj} = 4[(\mathrm{XPj} - \mathrm{RQj})^2 + (\mathrm{XQj} + \mathrm{RPj})\,^2\mathrm{V_I^2}] \tag{4.16}$$

Where *Pj*, *Qj* are real and reactive power received at *jth* bus and *R* and *X* are the resistance and reactance of the branch connecting the *jth* bus. If the system has lower *VSI* that means the system is considered to be more stable.

The voltage stability index *VSIn* of the total network is expressed as:

VSIn = max {VSI1, VSI2, ……VSIn……VSI(N) (4.17)

The branch in the distribution network that corresponds to the index of *VSIn* is called the weakest branch [156]. Voltage collapse is likely to start from the weakest branch. Hence, the margin of the static voltage stability can be found according to the deviation between the value of VSIn and the critical value 1.0.

Voltage Profile Improvement Index (VPIIn):

Diesel generators connection to the distribution networks at the best location will improve the voltage profile keeping the voltage level between the acceptable limits [158][160][150].

(*VPIIn*) is defined as [161] by:

$$VP_i = \frac{(\mathrm{V_i} - \mathrm{V}_{min}) \cdot (\mathrm{V_{max}} - \mathrm{V_i})}{(\mathrm{V_{nom}} - \mathrm{V}_{min}) \cdot (\mathrm{V_{max}} - \mathrm{V_{nom}})} \tag{4.18}$$

Where i= {1,2, 3, .., n}, n= The total number of buses

VPi is the voltage profile of the *ith* bus.

Vmin is the minimum permissible voltage and *Vmax* is the maximum permissible voltage of the network buses.

Vnom is the nominal voltage, which typically is 1p.u.

The voltage profile index of the network is expressed as:

$$VPI_n = \frac{1}{n}\sum_{i=1}^{n} VP_i \tag{4.19}$$

Voltage profile Improvement Index (*VPII*) is defined as the ratio between the voltage profile of the network with generators and the voltage profile without generators and is expressed as:

$$VPII = \frac{\mathrm{VPIn_{\,dgi}}}{\mathrm{VPIn}} \tag{4.20}$$

Where $VPIn_{\,dgi}$ is the voltage profile index of the network with generators for *ith* node and $VPIn$ is the voltage profile index of the network without generators.

Then $$VPII_n = \frac{\mathrm{VPII_i} - 1}{\mathrm{VPII_{max}} - 1} \tag{4.21}$$

Noise Improvement Index (NIn):

This index represents the improvement in the overall noise level from diesel generators connected to the community neighbourhoods. Since the location of some diesel generators is very close to the consumers, the location of the generators in the network should be chosen carefully in order to mitigate the noise level. According to Cummins Power Company [162] the permitted noise levels for diesel generators at property is between 52dB and 72dB depending on their locations. NIn is given as:

$$NI_n = 1 - \frac{(\mathrm{Noise})_\mathrm{a}}{(\mathrm{Noise})_\mathrm{b}} \tag{4.22}$$

Where $(Noise)_\mathrm{a}$ and $(Noise)_b$ are the noise levels at the consumer site after and before the diesel generators connection.

$$\mathrm{Noise} = 70\mathrm{dB} - \log(\mathrm{d}) \tag{4.23}$$

Where d is the average distance between a generator and consumers.

Network Performance Index (NPI):

The Network Performance Index is a composite index proposed to quantify the benefits of diesel generators. This index represents a comprehensive improvement in the network performance such as real loss reduction, and voltage profile improvement. The Weighting factors are decided by the power operator or designer of the distribution system. The parameter which was given the highest weightage factor will have the most significant improvement after the connection of the generation units. In addition, all other parameters which are included in NPI also have an improvement over the base case. Hence, choosing the best combination of buses for the location of generators is made by the highest value of NPI. Such a selection will result in an overall improvement in network performance, such as reduction in system power loss, improvement in voltage profile, improvement in voltage stability as well as a reduction in acoustic noise from the generators. A priority list with reducing the value of NPI is prepared so

that the generators can be connected at the most feasible locations. The top priority places give the highest value of NPI, enhances the system performance to the maximum extent. Hence this turns out to be the best solutions. If the priority with the highest NPI is not feasible, the designer can select the following best places in the network with decreasing order of priority. This manner gives flexibility and choices for efficient planning of the network.
The NPI is computed as:

$$\mathrm{NPI} = \mathrm{W_1\ PLossI_n} + \mathrm{W_2\ VSI}_n + \mathrm{W_3\ VPII}_n + \mathrm{W_4\ NI_n} \tag{4.24}$$

Where W_1 , W_2 , W_3 *and* W_4 are the weightage factors.

Weighting factors are expressed as:

$$\sum_{\mathrm{i=1}}^{4} W_i = 1.0 \ \wedge \mathrm{W_i} \in [0,1] \tag{4.25}$$

4.6 Economic analysis

To get the best combination along with the economic benefits, a separate cost analysis is done as shown in Figure 4-5. When generators are connected to the system the load is supplied partly by the generators, and the rest is met from the grid. Hence, the total cost will be the cost of the utility power drawn and the power from the generators. Then the savings obtained is calculated by comparing it with the base case, i.e. without generators. Thus, the savings are computed for the first three best combinations and sorted out in descending order.
Both the results are analysed and compared, and the best combination has a higher value for both the NPI and savings.

The economic analysis is considering the following steps:
Step 1: Calculate the operating cost for delivered electricity from the national grid before the connection of generators (Base cost). The operating cost for the electricity from the national grid *(£/hr.)* is equal to the power from the utility *(P utility) x Cost for Iraq power (£0.09/kWh*) [6].

Where

$P\ utility = P_L + P_{Loss}$

Step 2: Calculate the operating cost for delivered electricity from the national grid ($C_{Utility}$) after connection of generators, same as in step1.

Step 3: Obtain the operating cost of diesel generators (C_{Ge}) = Consumption (litre/hr) x £0.24 (Cost of diesel in Iraq £/litre). Based on the calculation presented in Section 3.3, the consumption for generators of 0.2MW, 0.25 MW and 0.3MW at full load is 65, 81 and 114 litres respectively. Therefore, Total operation cost of generators $C_{tGe} = C_{G200} + C_{G250} + C_{G300}$ = (65x0.24) + 81x0.24+114x0.24= 62.4£/hr.

Step 4: Calculate the total cost of electricity (total cost) = $C_{Utility} + C_{tGe}$

Step 5: Calculate the saving = Base cost - Total cost

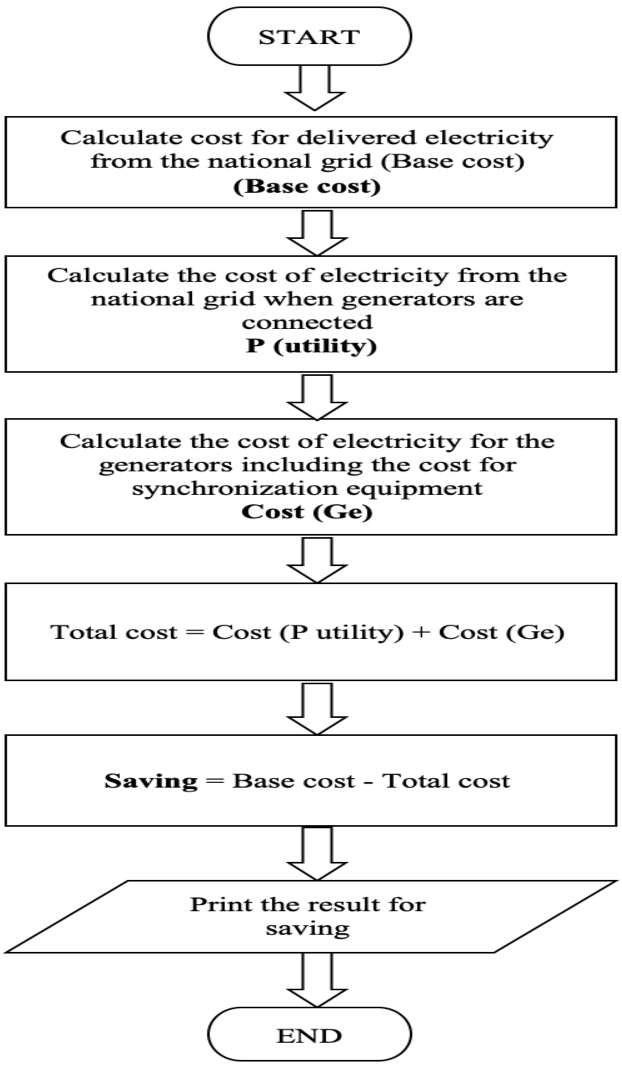

Figure 4-5 Flowchart for cost savings

4.7 Case study: new Ziyounah area of Baghdad

The network under study is an Iraqi radial 11/0.4kV distribution network with 35 buses and 22 lines with the total load of 2.07MW. This network uses underground cables and consists of 11 transformers whose capacities are 630kVA, supplying 377 residential load consumers. The single line diagram is shown in Figure 4-6.

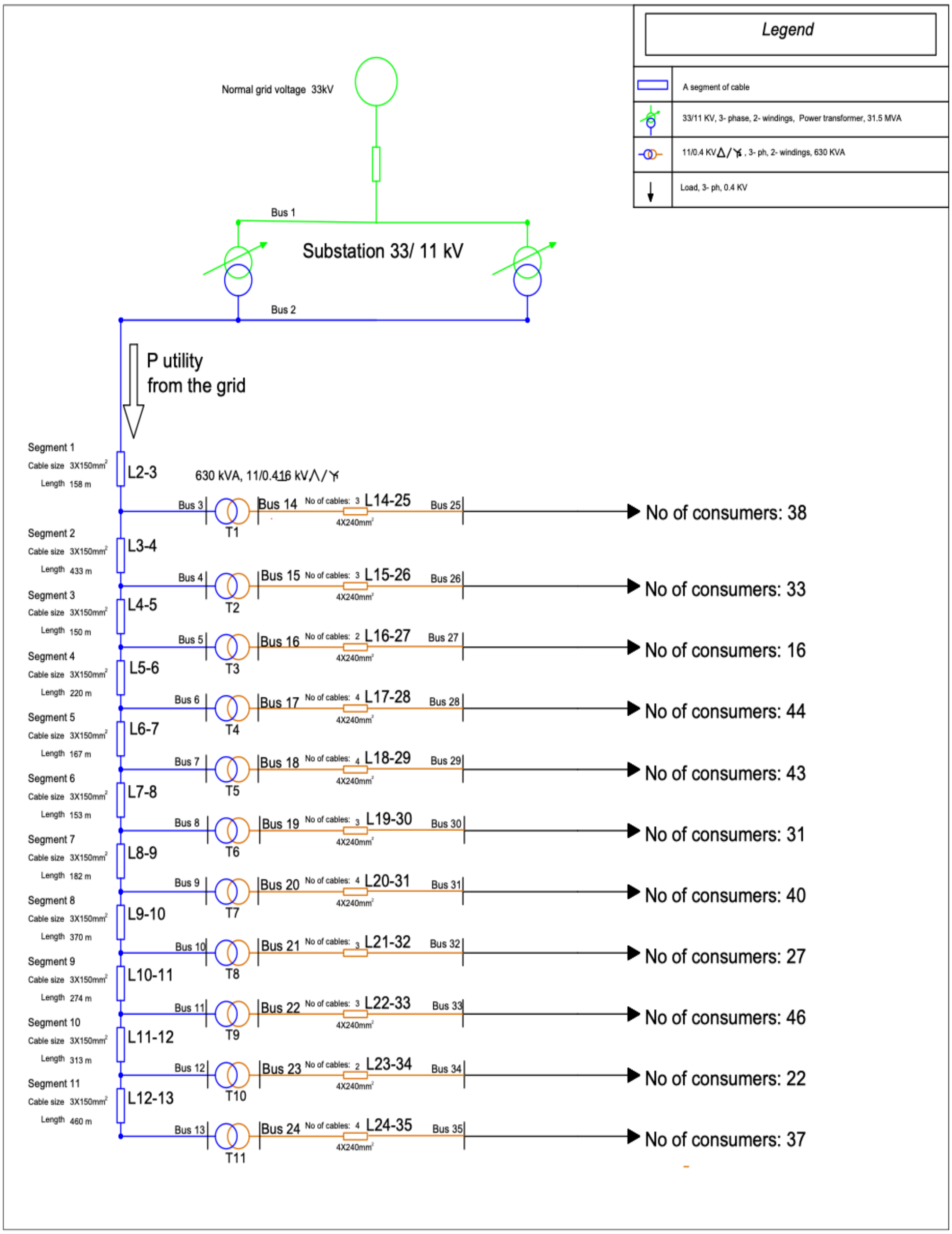

Figure 4-6 The 11/0.4 kV distribution network, 35 busbars and 22 lines

There were 0.75MW of diesel generation installed for every 377 houses. These generators supply the houses through the network. Weighing factors for calculating NPI are presented in Table 4-1:

Table 4-1 Weighing factors for NPI

W1(PLoosIn)	W2(QLoosIn)	W3(VSIn)	W4(VPIIn)
0.4	0.2	0.2	0.2

Table 4-2 Base data before insertion of the generators

P load MW	P utility MW	P losses MW	Cost=P utility x 90£/MW
2.0725	2.7325	0.66	245.92

To calculate the noise levels at the consumer site before and after the diesel generators are connected, it is important to collect real data of the average distance between the network's buses and the consumers as shown in Table 4-3. In this study, buses between 14 and 24 i.e. the low voltage side of the transformers in the distribution network were considered.

Table 4-3 Average distances from buses to the consumers

Bus No.	*Average distance to consumer (m)*	*Bus No*	*Average distance to consumer (m)*
14	35.5	20	18
15	22	21	20.5
16	28.5	22	31.5
17	22	23	18.5
18	34	24	37
19	17.5		

4.8 Results and discussion

This section presents the finding of NPI algorithm which describes in Figure 4-3 to determine the optimal size and locations of three diesel generators on the distribution networks. Cost saving showing in Figure 4-4 is also presented considering two scenarios.

4.8.1 Scenario (1): maximum load in the summer season of 2017

In this scenario, there are three generators with capacities of 200kW, 250kW and 300kW to be connected to the residential area. The total power generation from these units is less than the maximum load which occurs in the summer season, and is about 36% of the total load. As a result of this mismatch, the power is taken from the grid to supply the remaining load and the generators are operated at their rated capacity.

4.8.1.1 Performance evaluation:

The results for this scenario with three diesel generators are presented in Table 4-4. It was found that the optimum capacities for three diesel generators are 0.2MW, 0.25MW and 0.3MW and the optimum placement is at the bus bars 18, 22 and 24 respectively. The first three best combinations are chosen based on the highest NPI value leads to overall system improvement. For example, bus 22 has the largest demand with 47 consumers (see Figure 4-6), and it is relatively located far from the consumers 31m (see Table 4-3). Hence, it has been selected as the best place to be connected with the generator of 0.25MW to improve the network performance and reduce the acoustic noise from the generator to consumers.

Table 4-4 The best location for three generators based on Max NPI (in the decreasing order of NPI)

Gen sizes MW	Bus No	Ploss MW	VPIIn	VSIn	NPI	NIn
0.20 0.25 0.30	18 22 24	0.62	1.075	0.9763	0.507	0.362
0.20 0.25	14 18	0.625	1.069	0.9769	0.503	0.351

Gen sizes MW	Bus No	Ploss MW	VPIIn	VSIn	NPI	NIn
0.30	24					
0.20	14					
0.25	18	0.63	1.063	0.9769	0.494	0.339
0.30	22					

Figure 4-7 shows the voltage profile along with the radial network with and without diesel generators connection in the summer season of 2017. It can be observed from the result that the minimum voltage obtained after the connection of the generators was 0.951 p.u at busbar 32, wherein the case of without generators , the minimum voltage was 0.948 p.u. at the same busbar which is lower than the acceptable voltage limits (0.95 p.u.-.05p.u.). Hence, the result verifies the ability of the proposed method to improve the voltage profile at maximum load (see Figure 4-7).

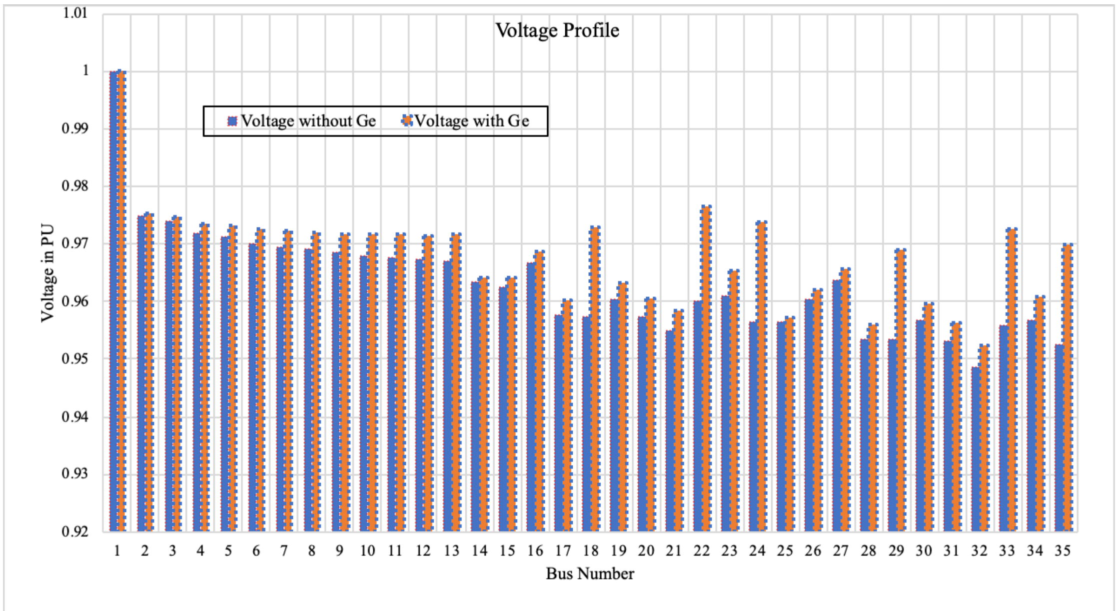

Figure 4-7 Voltage profile when the generators are connected at bus 18, 22 and 24

The results in terms of loss reduction are illustrated in Figure 4-8, which compares the loss of real power in each branch before and after the connection of the diesel generators to the network. It was found that the highest percentage of losses reduction on L3-4 was recorded at 62.7%; losses reduction

$$= \frac{5.1 - 1.9}{5.1} = 62.7\%$$

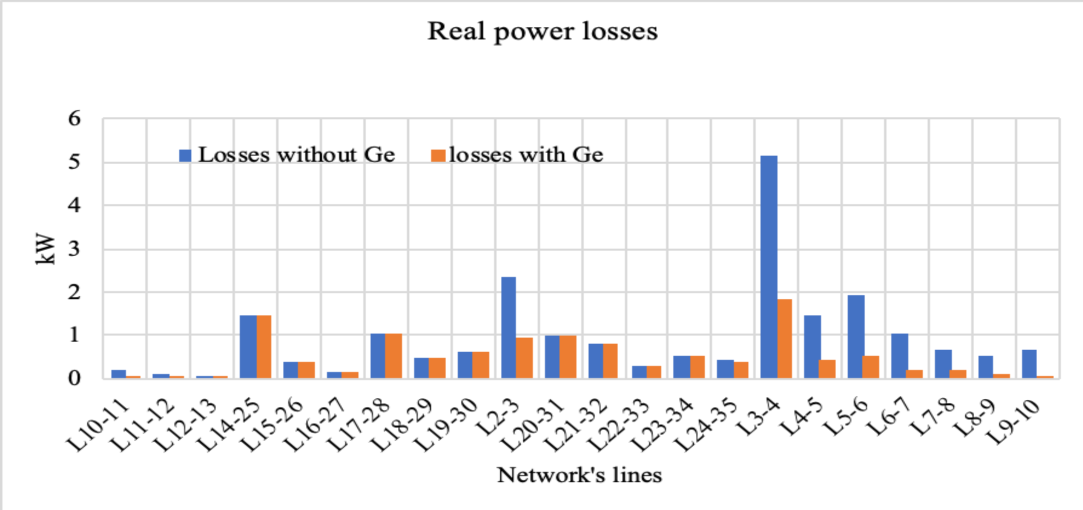

Figure 4-8 Real power losses of networks lines with and without generators connected at buses 18, 22 and 24

Figure 4-9 shows the impact of the diesel generators on the transformers and lines loading when the generators are connected to the buses 18, 22 and 24. It can be observed that the loading of most of the transformers and lines on the network have reduced after connecting the generators.

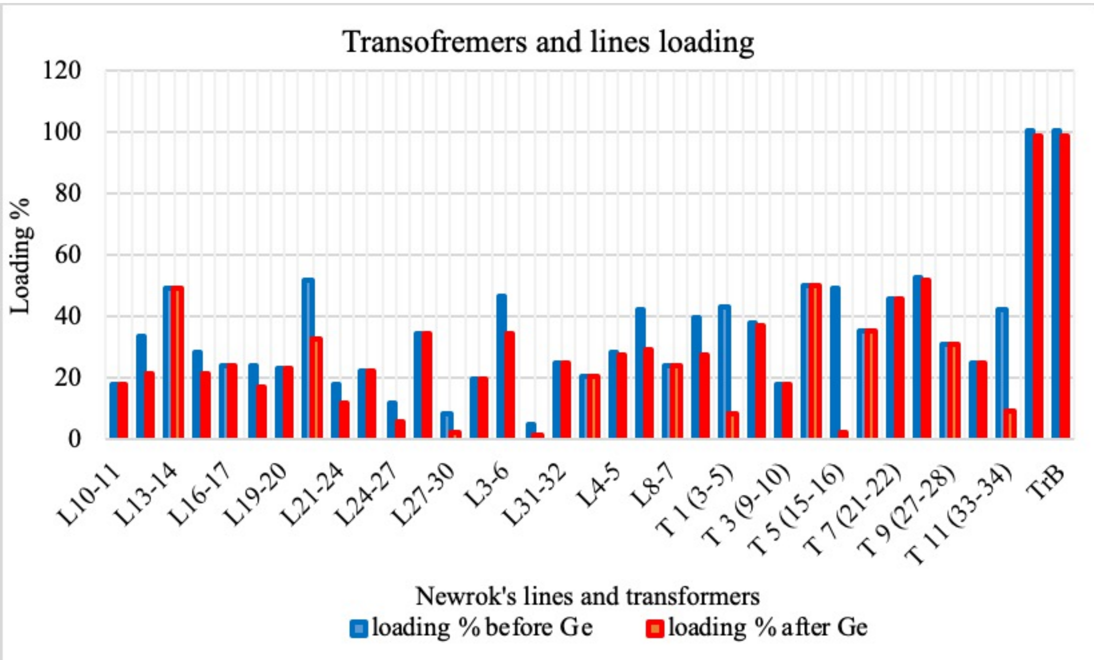

Figure 4-9 Transformers and lines loading with and without generators connected at buses 18, 22 and 24

4.8.1.2 Economic result:

After the generators are connected to the best places in the network, the economic analysis is performed using the algorithm presented in Figure 4-10.
It was estimated that the total cost of the electricity for three generators (0.2MW, 0.25MW and 0.3MW) is about £62.4/h as presented in Section 4.5.

It was found that the best saving for electricity price of £9.7/h occurs when the diesel generators 200kW, 250kW and 350kW are connected in the network at bus numbers 18, 22 and 24 respectively, see Table 4-5.

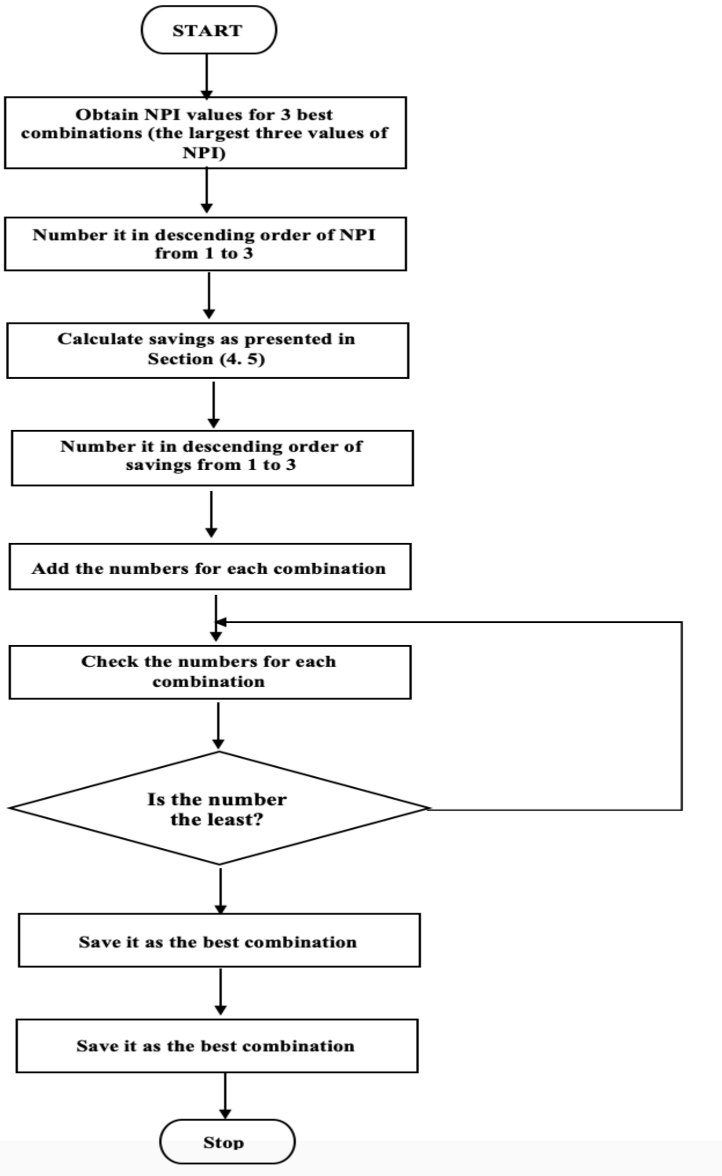

Figure 4-10 Flowchart for cost comparison

Table 4-5 The best location for three generators based on saving (in the decreasing order of the saving)

Savings Choice no:	Generator sizes	Bus No	Saving (£/hr.) = Base cost-total cost, see Sec. (4.5)	NPI	NPI Choice no:
1	0.20MW	18	9.7	0.5071	1
	0.25MW	22			
	0.30MW	24			
2	0.20MW	14	9.4	0.5037	2
	0.25MW	18			
	0.30MW	24			
3	0.20MW	14	8.72	0.4940	3
	0.25MW	18			
	0.30MW	22			

4.8.2 Scenario (2): the summer season of 2025 with the load increase by 80%

Integration of the diesel generators into the network is more important in the context of a significant increase in the load in the future. It is estimated an 80% increase of the load by 2025 based on [163]. Base on the optimisation study, the best location for the connection of diesel generators was found at buses 18, 21 and 24 and an increase in the load by 80%.

Figure 4-11 shows the voltage profile along with the radial network with and without diesel generators connection for the summer season of 2025. The minimum steady state voltage limit is 0.95 p.u. based on the distribution code in Iraq [150]. It was found that in the future, diesel generators in Iraq will play an important role in improving the terminal voltages (see Figure. 4-10).

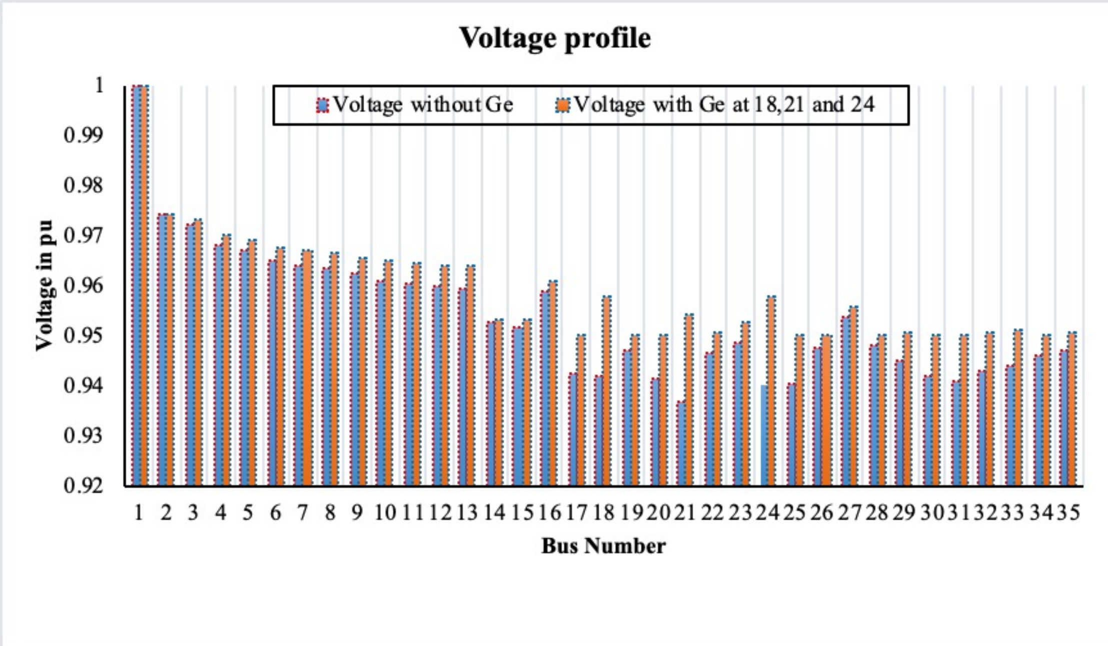

Figure 4-11 Voltage profile when the generators are connected at bus 18, 21 and 24

Figure 4-12 shows the impact of the diesel generators on the transformers and lines loading when the generators are connected to the buses 18, 21 and 24. It was found that the transformer T8 and the line L2-3 loading is close to 100% before the diesel generators are connected to the network. When the diesel generators are connected to the network at the best location, the loading of transformer and line is reduced to 45% and 75% respectively.

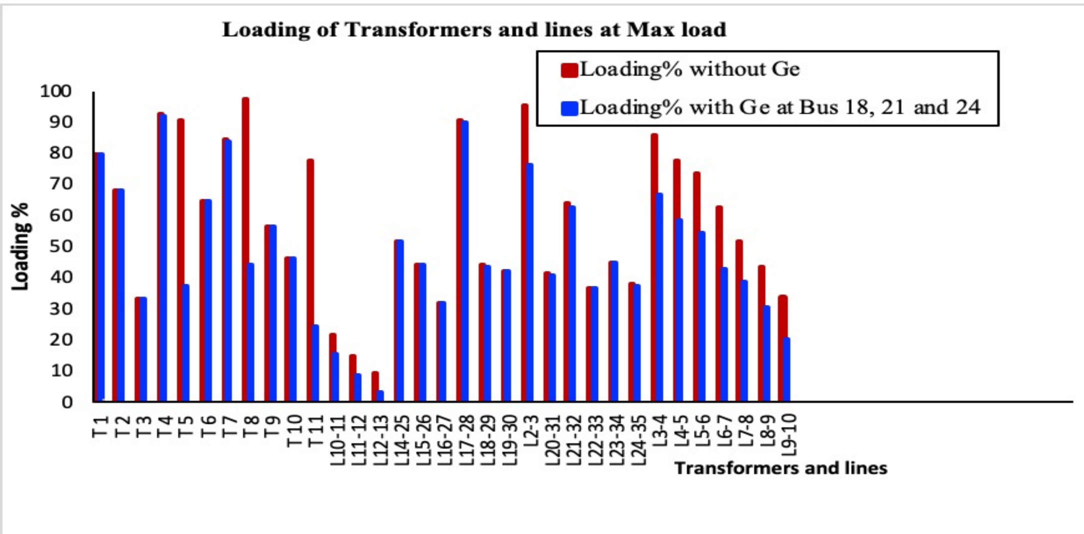

Figure 4-12 Transformers and lines loading with and without generators connected at buses 18, 21 and 24

The enhancement result in terms of loss reduction is also illustrated in Figure 4-13. It can be seen that the highest percentage of losses reduction on line L9-10 and line L6-7 was recorded at 62.2% and 51% respectively.

$$\text{Real power loss reduction in P}_{\text{L9}-10} = \frac{2.2 - 0.83}{2.2} = 62.2\%$$

$$\text{Real power loss reduction in P}_{\text{L6}-7} = \frac{3.5 - 1.69}{3.5} = 51\%$$

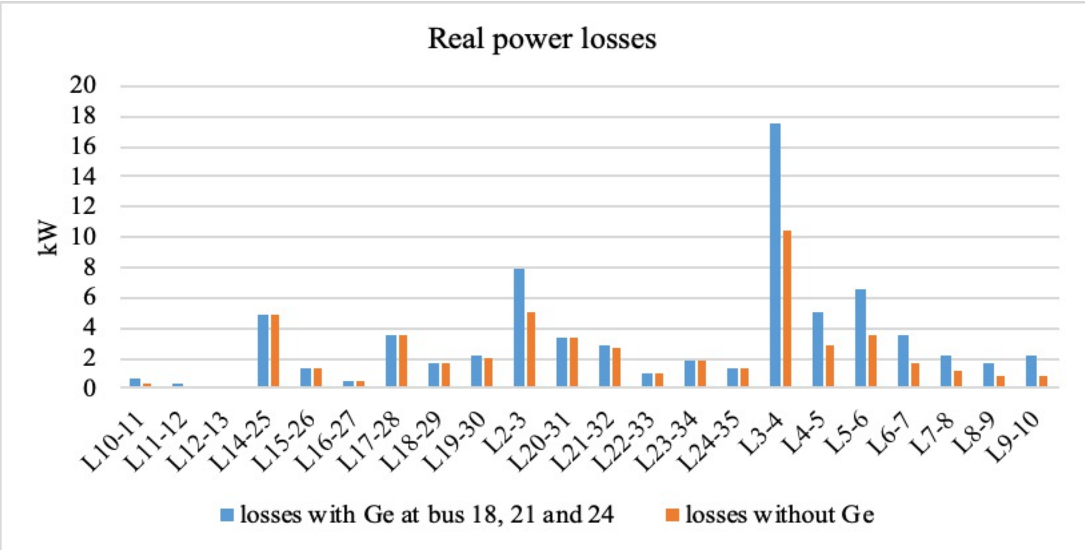

Figure 4-13 Real power losses of networks lines with and without generators connected at buses 18, 21 and 24

4.9 Conclusion

Due to the increase of the electrical consumption in Iraq, the diesel generators in the distribution network and the optimisation of their location and size have many advantages such as meeting the incremental demand, reducing the total real power losses and enhancing the network performance. This study presented an important challenge to the Iraqi power system and provides a feasible solution by integrating diesel generators in the distribution network. An optimisation algorithm was developed to find the best location and size of diesel generators at the peak load in a 35- bus radial distribution network has total maximum load of 2.0725MW with 377 consumers in Ziyounah district of Bagdad.

The optimisation process is solved by the combination of genetic algorithms (GA) techniques with power flow to evaluate the diesel generators impacts in savings of electricity and networks performance, including a reduction in real power loss and acoustic noise from the generators and improving voltage profile. The fitness evaluation function that drives the proposed method to the solution is the Network Performance Index (NPI). The objective is to maximise the capacity of the generator by knowing the total number of generation units that the power operator is interested to connect. The Network Performance Index (NPI) gives an indication of best busbars and capacity for generators. As evident from results, the selection of bus locations and corresponding capacities of generators based on the highest NPI leads to overall system improvement. The result has also shown that the determination of the best locations in the network for connection generators with the help of the proposed Network Performance Index (NPI) leads to savings in electricity due to real power loss reduction in the network.

Chapter 5

Load forecasting

5.1 Introduction

In this study, Linear Regression (LR) and Artificial Neural Networks (ANN) techniques are implemented to improve a decision of the daily and hourly peak demand during the summer and winter days 2020. The models were trained using historical load data to determine the model parameters for the LR model and the weights of the network for ANN. Then, the use of obtained weights or parameters allows the prediction of the output for a given input. Mean Absolute Percentage Error (MAPE) is considered to evaluate the model performance. After analysing the model prediction results, it was found that the LR technique offers a higher degree of prediction accuracy in daily peak load forecasting compared to the ANN technique. Whilst, hourly peak load forecasting result was less accurate than the result from ANN.

In Iraq, the temperature varies between the seasons, and the residential load is affected directly by the seasons, as shown in Figure 5.1. In Iraq, the seasons are:

1. Winter season: from 1st Dec to 28th Feb.
2. Spring season: from 1st Mar to 30th April.
3. Summer season: from 1st May to 30th Sep.
4. Autumn season: from 1st Oct to 30th Nov.

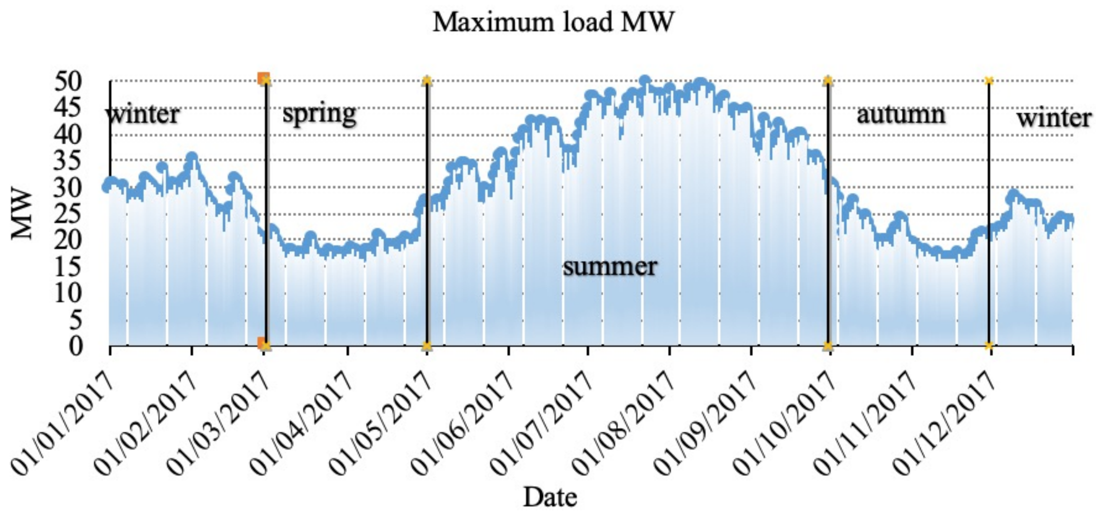

Figure 5-1 Daily peak loads of the Zeyonah area in Baghdad for different seasons of 2017. Ministry of Electricity of Iraq.

Figure 5-1 shows that the electric load consumed during a season is affected by weather fluctuations. The electric power consumed in hot summer due to the increase in the use of air conditioning equipment is higher relatively to the power consumed in cold winter which also increases due to the use of electrical heaters.

5.2 Linear regression method (LR)

Regression analysis is a well-known statistical technique used to identify the dependence between a given variable and one or more explanatory variables. It is often used in forecast estimates [164]. It can be used, for example, to examine the relationship between variables such as weather and time of the day and the variable being forecast. [165] studied the application of the linear regression method in STLF and concluded that this method provided reliable results under different conditions.

5.2.1 Simple linear regression analysis

Simple linear regression is a linear regression model with a single explanatory variable. In order to represent the relationship between a response variable (Y) and an explanatory variable (X), it is used a line of best-fit. The general form of the linear relationship between the dependent and independent variables can be expressed as follows [81]:

$$Y = B_0 + B_1 X + \varepsilon \tag{5.1}$$

Where Y is predicted by X and $B_0 and\ B_1$ are the model parameters to be estimated, and ε is the error of the estimate.

The scope of this analysis is to predict the daily peak demand in the winter and summer season of 2020. The historical training data required for the summer, winter and spring seasons for this analysis are presented in Appendix A.

5.2.2 Correlation and regression analysis by using a simple linear technique

Correlation analysis provides information on the strength and direction of the linear relationship between the daily peak demand and maximum temperature, while a simple linear regression analysis model estimates in a linear equation, as presented in Section5.2, that can be used to study the predicting values of one variable (maximum daily demand) based on the other.

5.2.2.1 Correlation coefficient (R)

As mentioned in Section 5.2.2, a correlation coefficient (R) is a statistical relationship between two variables that can describe the strength and direction of the linear relationship between the daily peak demand and maximum temperature. The correlation coefficient R in the range of -1 and 1. The sign of R corresponds to the direction of the relationship. If R is negative, then as maximum temperature increases, the maximum power tends to decrease. If R is positive, then as maximum temperature increases, the maximum power tends to increase. A perfect linear relationship (R=-1 or R=1) means that one of the variables can be perfectly explained by a linear function. The correlation coefficient (R) is expressed as:

$$\text{Correlation coefficient (r)}= \frac{\sum(x-\tilde{x})(y-\widetilde{y})}{Sqr(\sum(x-\tilde{x})^2 \sum(x-\tilde{y})^2)} \tag{5.2}$$

It was found that the correlation coefficient for summer, winter and spring is 0.8872, -0.904 and 0.1658 respectively. Regression coefficients for the three models (summer, winter and spring) are presented in Figure 5.2, 5.3 and 5.4.

In Figure 5-2, the correlation indicates a strong relationship between maximum loads and maximum temperature in the summer season as the daily peak load is proportional directly to the ambient temperature during this season. While in a winter season, the daily peak load is inversely proportional to the ambient temperature as shown in Figure 5-3.

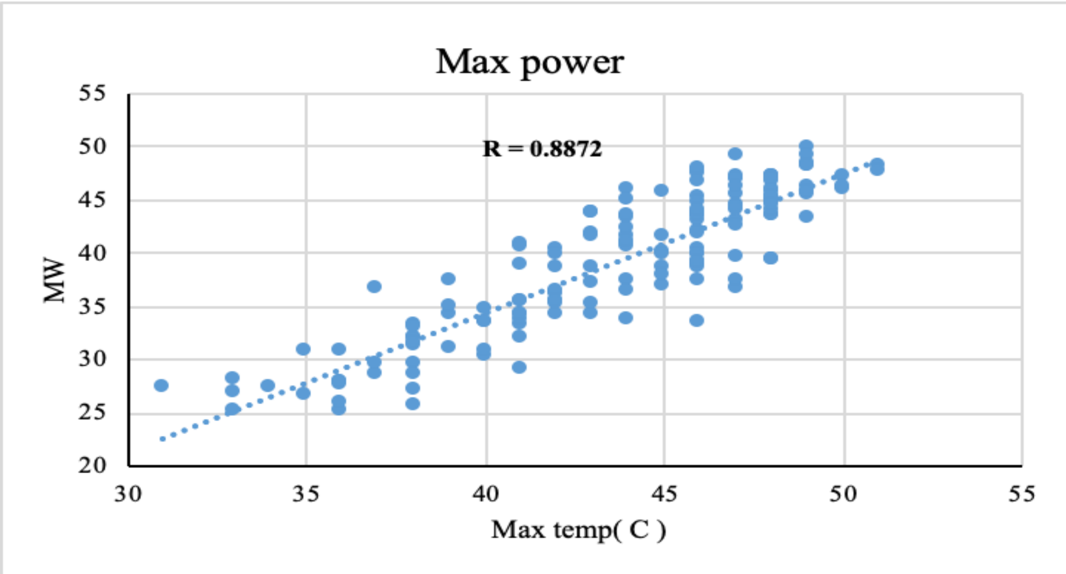

Figure 5-2 Correlation between daily peak loads and max temperature of Zeyonah area in Baghdad for the summer season

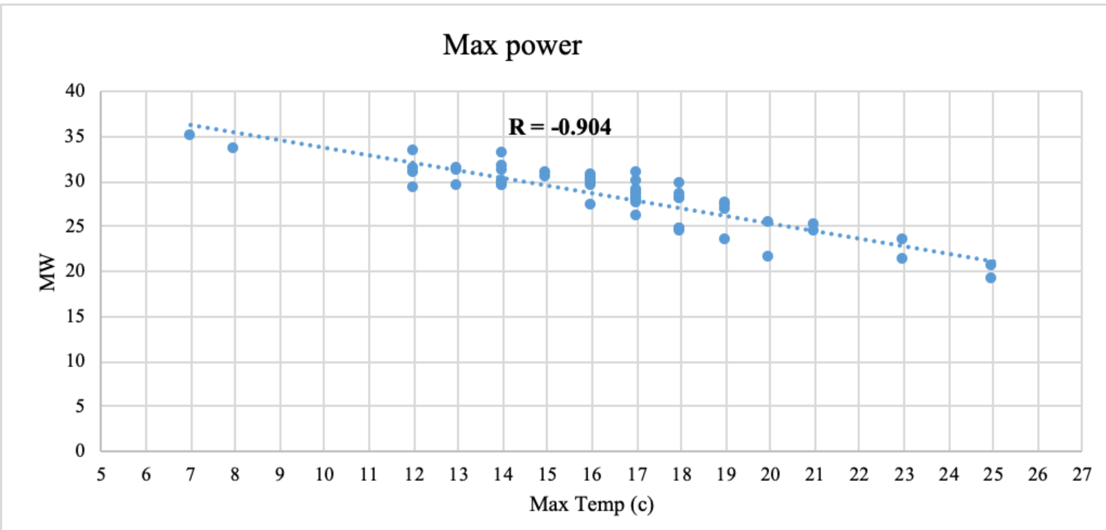

Figure 5-3 Correlation between daily peak loads and max temperature of Zeyonah area in Baghdad for the winter season

Figure 5-4 shows the strength of the relationship between loads and temperature in the spring season. In this model with coefficient ®=0.1658, the correlation has a weak relationship compared to the correlation coefficient in the summer and winter seasons. This means the demand is not affected significantly by the fluctuation of temperature during this season. This is because the majority of consumers are not using the air conditioner nor water heaters on spring days.

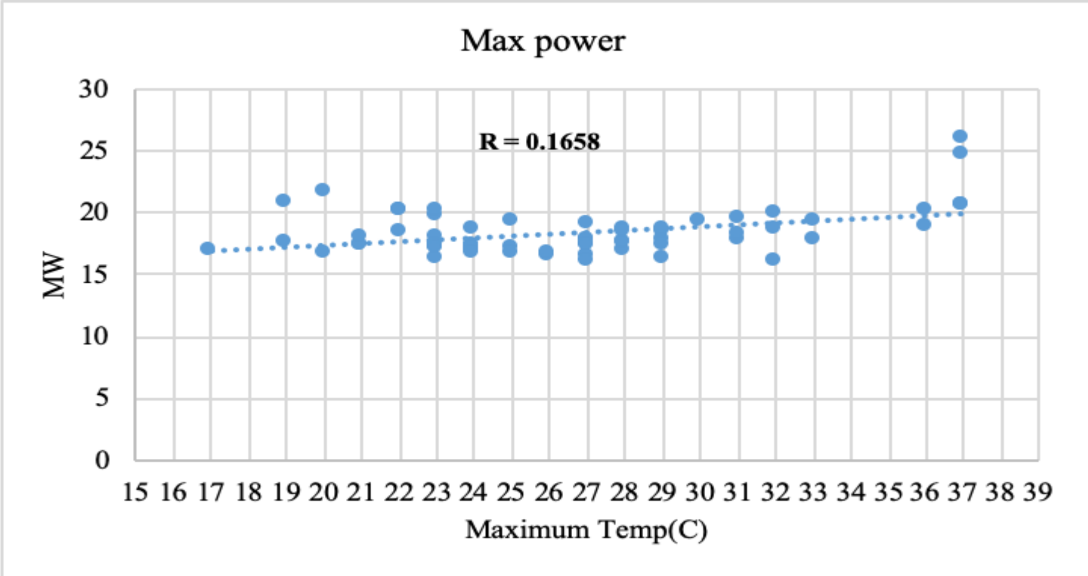

Figure 5-4 Correlation between daily peak loads and max temperature of Zeyonah area in Baghdad for the spring season

The correlation analysis results in this section show that the results are significant because the role of maximum temperature change having the greatest effect on maximum power demand during summer and winter seasons. In other words, the graphical results give support for our assumption that peak demand consumption in Iraq increases with maximum temperature in summer and decreases in winter while it has less correlation with the same temperature in spring.

This means the fluctuation of the maximum temperature cannot be ignored for summer and winter in this study because it is the most important affecting peak power demand.

5.2.2.2 Slope of maximum power against maximum temperature

The regression coefficients for the models are computed as:

$$B_0 = \tilde{y} - b\,\tilde{x} \tag{5.3}$$

$$B_1 = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2} \quad (5.4)$$

Which describes a line with slope B_1 and y-intercept B_0

The line slope B_0 represents the slope of maximum power against the maximum temperature. It was found that the slope for the summer, winter and spring is 1.3187, -0.84 and 0.1529 respectively. The coefficients regression for the models are presented in Figure 5-5, 5-6 and 5-7. That means, for an increase of 1°C temperature in the Ziyounah area of Baghdad, there will be an increase of 1.3187 MW, a decrease of 0.84 MW and an increase of 0.1529 MW electricity peak demand during summer, winter and spring seasons respectively.

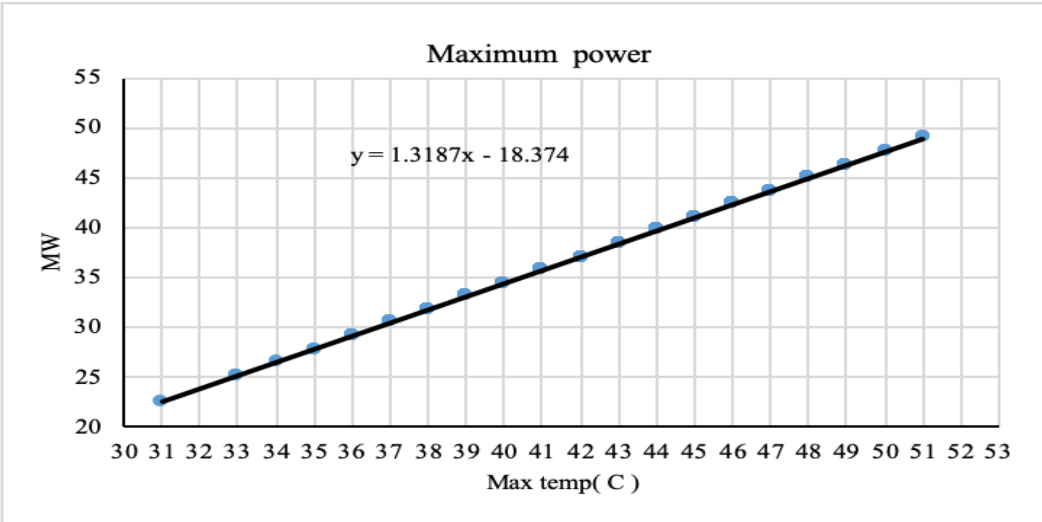

Figure 5-5 Slope of maximum daily power against maximum daily temperature for the summer season

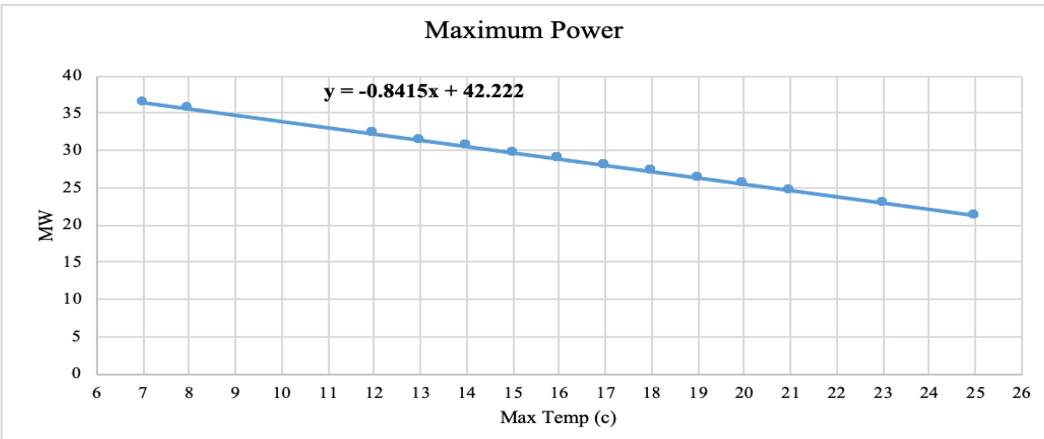

Figure 5-6 Slope of maximum daily power against maximum daily temperature for the winter season

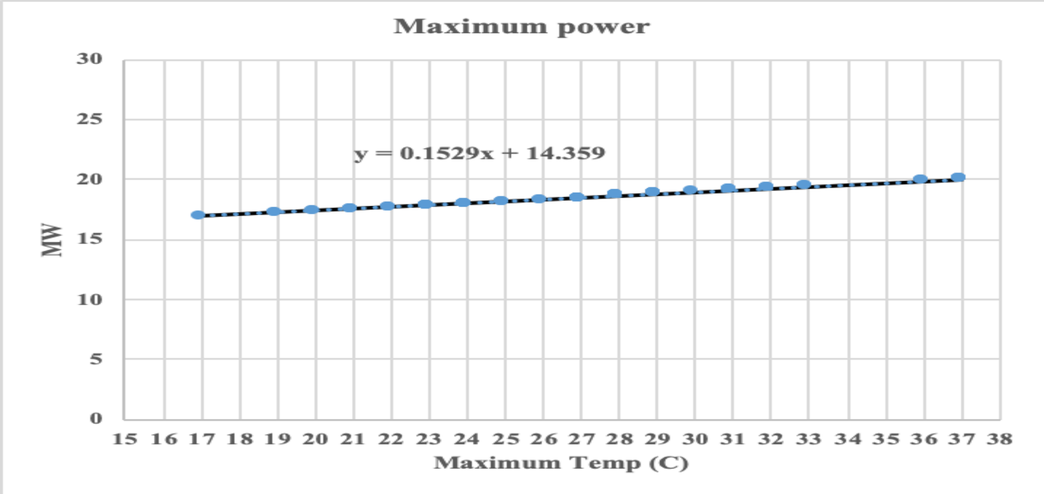

Figure 5-7 Slope of maximum daily power against maximum daily temperature for the spring season

5.2.3 Multiple linear regression analysis

A multiple linear regression model is a statistical technique that can use many explanatory variables to predict the outcome of a response variable. It is generally expressed by the relationship between a single outcome variable (Y) and some explanatory variables (Xi) presented as:

$$Y = B_0 + B_1 x_1 + B_2 x_2 + \cdots B_n x_n + \varepsilon \tag{5.5}$$

Where B_0, $B_1, \ldots B_n$ are the model parameters to be estimated, and n is the number of explanatory variables.

The scope of this analysis is to predict the hourly peak load in the winter and summer season of 2020. The historical training data required for the summer and winter season for this analysis are presented in Appendix B.

5.3 Artificial Neural Networks (ANN)

STLF based on the ANN technique is considered in this study due to its clear model, easy implementation, and good performance [67]. The other important feature of this technique is its capability of generalization and non-linear learning relationships between variables, as well as its capability to adjust the weights between layers [166]. ANN structure can be classified into two categories as single-layer and multi-layer network. The network that has only the input and output layer connected by the synaptic weights are known as a single layer network. While network with neuron layers between input and output layers are known as the multi-layer neural network. The hidden layer represents the layer between the input and output layer. Multi-Layer Perceptron (MLP) has been selected for this research as their networks have the ability to learn the complex relationship between the input and output patterns which are not possible in the case of single-layer networks [66]. Figure 5-8 shows a multi-layer ANN structure with four layers.

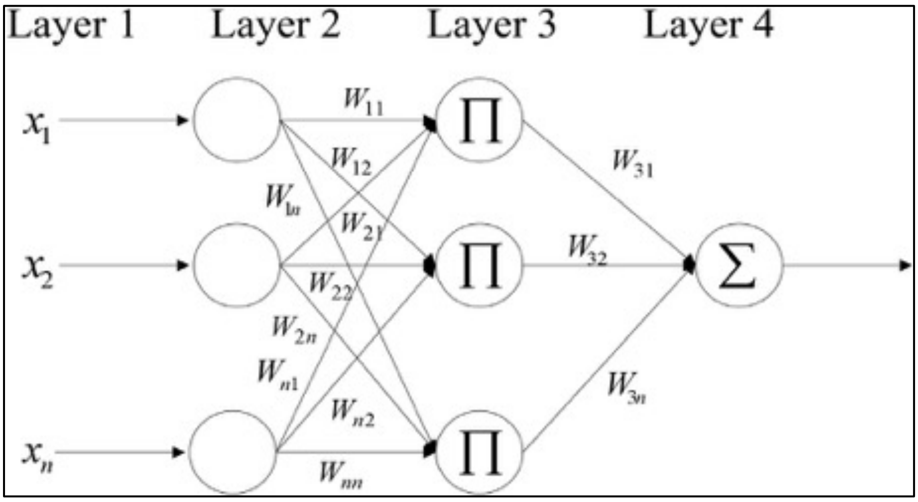

Figure 5-8 Structure of Multi-Layer Network [167]

5.4 Evaluation criteria

To investigate the forecast model performance, an intuitive measuring criterion is used. The percentage error is computed at every time step and the model performance is evaluated over the whole period. Many forecasting studies use Mean Absolute Percentage Error (MAPE) as an indication of model performance. This method is calculated with respect to data that is positive only, such as electricity load demand. MAPE is defined as the average of percentage errors and it is expressed as:

$$\text{MAPE}= \frac{\sum_{1}^{N}\left|\frac{Actual-Forecast}{Actual}\right|}{N} \tag{5.6}$$

where N is the sample size, the time samples in this study. The number of samples considered is the number of days in a month or hour in a day. The acceptable value of MAPE is 5% from a practical point of view [67] and hence the criteria of MAPE 5% will be used as a criterion for acceptable performance. This limit represents the average of all percentage errors among the forecast period. Generally, when different models are subjected to comparison, better performance is evaluated based on the least MAPE error.

5.5 The Methodology of Load Forecasting (LF)

A LF model based on Linear Regression (LR) and Artificial Neural Network (ANN) analysis were used to forecast future daily peak and hourly peak demand. Single linear regression analysis was considered to predict the daily peak demand, whilst multiple linear regression was implemented to predict hourly peak demand. In addition, daily and hourly peak load forecasting were obtained using the ANN method, taking into account the same historical data that are used for predicting the daily and hourly peak demand using LR method.

5.5.1 The Methodology of daily load forecasting

This section presents the forecasting process using simple linear regression and ANN for forecasting daily load.

For simple linear regression, the procedure is to train the model to estimate its parameters and then to use this forecast model to extrapolate the future daily peak demand. In the first step of the training process, which is used to find the parameters B_0 and B_1, historical data shown in Figure 5-10 and 5-11 are required for summer and winter seasons. For the second step, correlation analysis is applied to evaluate the relationship between a dependent variable and an independent variable to determine the correlation coefficient (r). It is important to find a strong relationship between independent variables and dependant variables. After the correlation is done, a simple linear regression is applied to estimate the model parameters or coefficients for a given model. Once the model is trained, it is ready for forecasting. For the daily peak demand forecasting, the testing set is the forecasted maximum temperatures provided from the Iraqi Meteorological Organization and Seismology (IMOS), see Figure 5-9. A common criterion of evaluation between different models is the Mean Average Percentage Error (MAPE).

For daily peak load forecasting, a set of historical data for 2019, i.e. daily peak demand as outputs and maximum temperatures recorded as inputs, is used to train the model for simple linear regression. The input and output data for training is selected for the time interval 01/January/2019 - 01/March/2019 for the winter season, and for time interval 01/May/2019 - 01/October/2019 for the summer season. The daily peak demand forecasting for this technique during the month of January 2020 is assumed as a representative month for winter season. While, the peak demand forecasting during the month of September 2020 is assumed as a representative month for summer season. Figure 5-10 and 5-11 show real historical data of daily peak loads with the maximum temperature were used to train the models for forecasting the daily peak demand for summer and winter seasons for Ziyounah district in Baghdad.

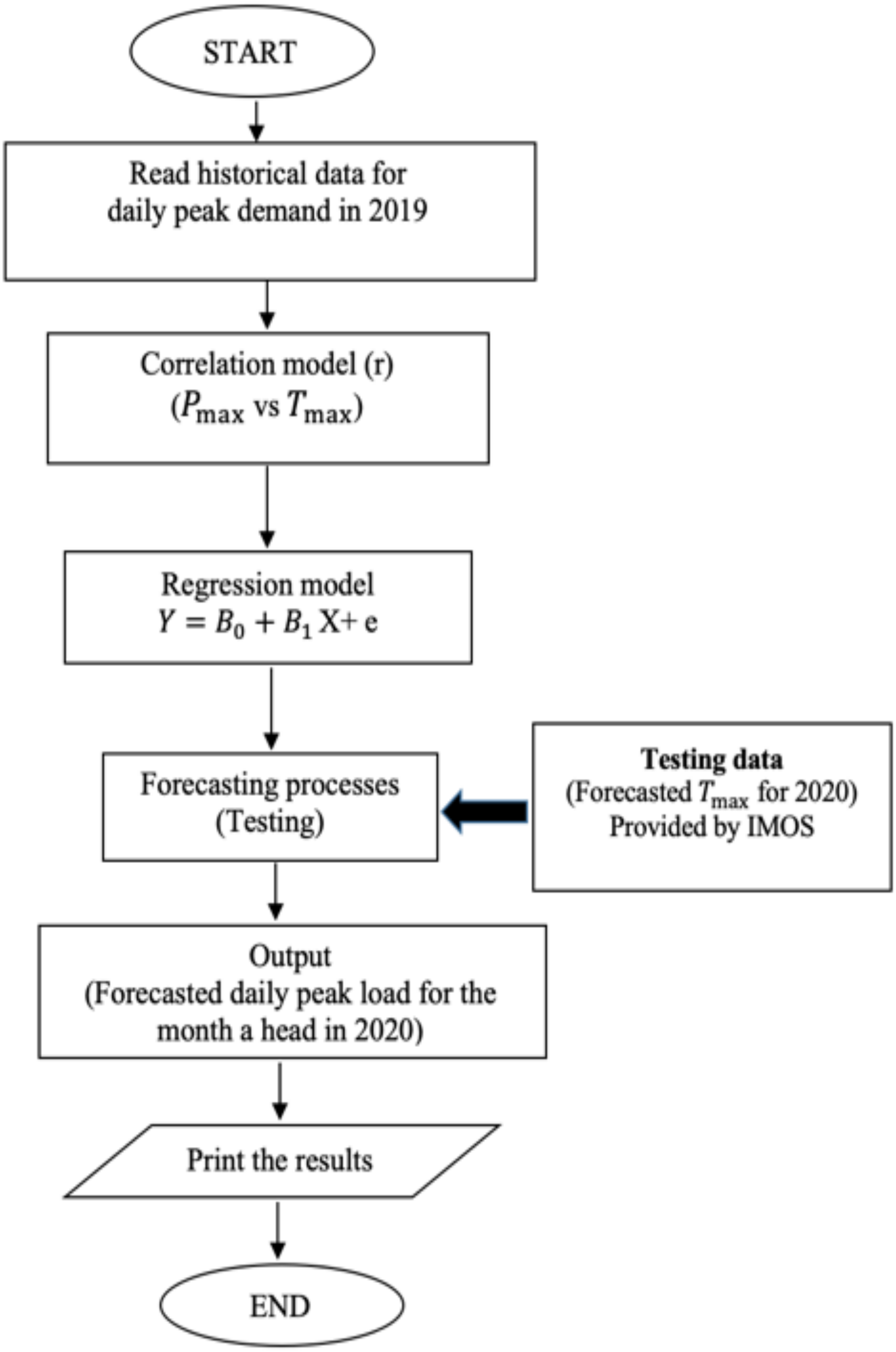

Figure 5-9 Flowchart of modelling and forecasting process for daily peak load using simple linear regression analysis

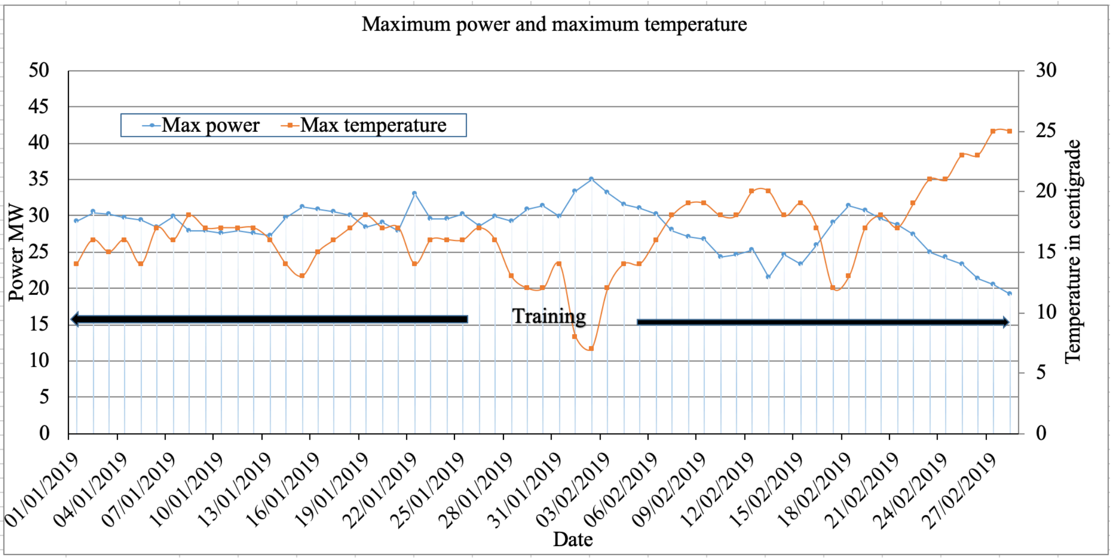

Figure 5-10 The training data required for forecasting the daily peak of the winter season

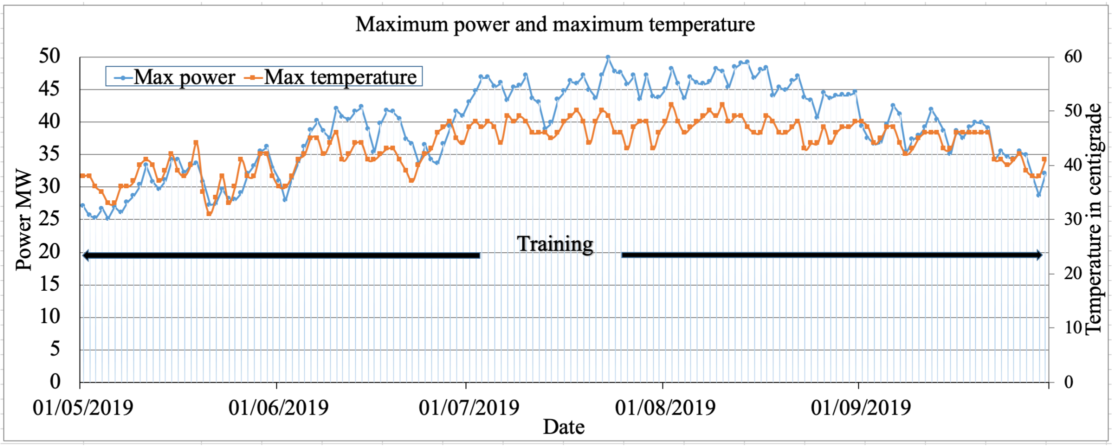

Figure 5-11 The training data required for forecasting the daily peak of the summer season

For daily load forecasting using ANN, the nature of electric consumption makes it difficult to be predicted accurately [66]. However, the development of artificial intelligence techniques, particularly the neural networks with their advantage of automatic learning from measured data can be successfully used for electric load prediction, which is extrapolated to the future without the need to add more information about the system [166].

The load forecast model-based ANN was implemented in the MATLAB Neural Networks Toolbox. The model was trained using the same data that are used for predicting the daily peak demand using the simple linear regression method shown in Figure 5-10 and Figure 5-11 to determine the weights of the network.

Then, the use of obtained weights allows the prediction of the output for a given input. The historical data used in predicting the daily peak demand was one input, which represent the daily peak load.

The target for training is one month ahead for the same season. The input and the desired output efforts were made to optimise network parameters during the training phase. The ANN algorithm tries to minimise the difference between the desired and actual output by adjusting the weights of the network. Tangent hyperbolic (tanh) activation function is used for the hidden, and linear activation function is used in the output layer. The output layer has only one neuron in its output layer, which contains the predicted value of the load during the month.

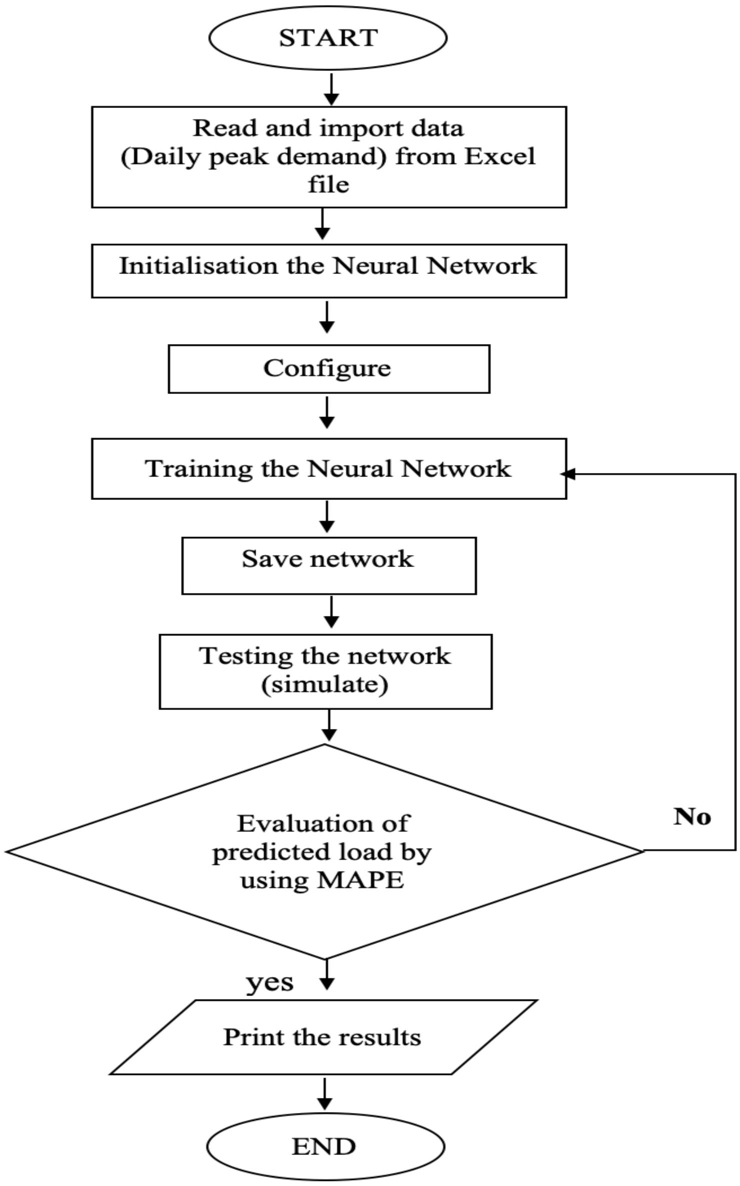

Figure 5-12 Flowchart of the neural network model to forecast daily peak load

The mean absolute percentage error in equation (5.6) is considered to evaluate the accuracy of neural network and the predicted load.
The flowchart of the proposed forecasting model is presented in Figure 5-12. The learning mechanism of this model is summarized as follows:

1. Read collecting data is the first step in designing load forecasting based ANN. In this section, the data represents the actual daily peak load of Ziyounah district for a certain month.
2. The neural network was initialised by using the function (Newff) for MLP which has one input layer, one hidden layer and one output layer. The transfer function has been chosen as “tansig" and "logsig"for hidden and output layers respectively.
3. At the training stage, the network was trained with historical data.
4. After the training process, the network was simulated or tested This process is run by calling the function "sim".
5. Finally, the best training result is obtained with a minimum value of Mean Absolute Percent Error MAPE (i.e. the lower the MAPE is, the more accurate the estimation is).

5.5.2 The Methodology of hourly peak load forecasting

This section presents the forecasting process using multiple linear regression and ANN for forecasting 24h load.

For the methodology of hourly peak load forecasting using multiple linear regression, the procedure is to train the model to estimate its parameters and then to use this forecast model to extrapolate the future hourly peak demand as shown in Figure 5-13. In the first step of the training process, which is used to find the parameters B_0, $B_{1,} \dots B_{\mathrm{n}}$, historical data shown in Table 5-1 and 5-2 are required. For the second step, correlation analysis is applied to evaluate the relationship between a dependent variable and an independent variable to determine the correlation coefficient (r). After the correlation is done, multiple linear regression is applied to estimate the model parameters or coefficients for a given model. Once the model is trained, it is ready for forecasting. For the hourly peak demand forecasting, the testing set is shown in Table 5-2. A common criterion of evaluation between different models is the Mean Average Percentage Error (MAPE).

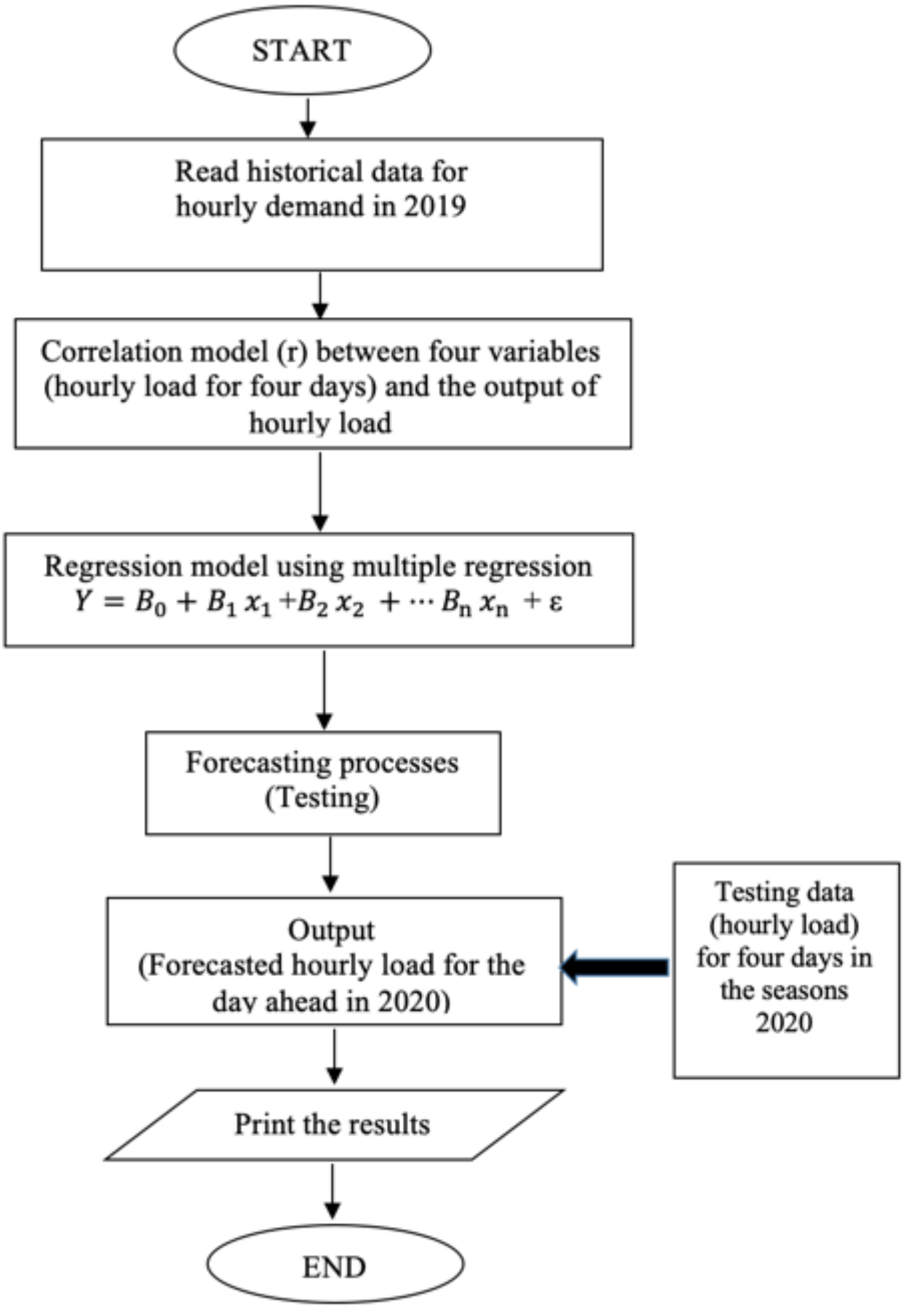

Figure 5-13 Flowchart of modelling and forecasting process for hourly peak load using multiple linear regression analysis

It was assumed that the 15th January 2020 and 11th July 2020 represent typical days in the winter and summer seasons, and it was selected as a representative day for hourly peak load forecasting based on multiple linear regression forecasting. Four independent variables, which represents 24-hour load profile for four days, were required to train and test the summer and winter season models as shown in Table 5-1 and Table 5-2. The target was assumed to be the 24-hour load profile of the fifth day, see Table5-1.

Table 5-1 Methodology of creating required data for training (historical data) for 2020

	Training (MW) from the past year 2019				Target (MW)
day / hour	X1= day1 (Sunday)	X2= day2 (Monday)	X3= day3 (Tuesday)	X4= day 4 (Wednesday)	Y= day5 (Thursday)
1	P1,1	P1,2	P1,3	P1,4	P1,5
2	P2,1	P2,2	P2,3	P2,4	P2,5
3	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.		.	.	.	.
24	P24,1	P24,2	P24,3	P24,4	P24,5

Table 5-2 Methodology of creating required data for testing for year 2020

	Input data for testing for year 2020				Forecast load (MW)
day / hour	X1= day1 (Sunday)	X2= day2 (Monday)	X3= day3 (Tuesday)	X4= day4 (Wednesday)	X4= day5 (Thursday)
1	P1,1	P1,2	P1,3	P1,4	P1,5
2	P2,1	P2,2	P2,3	P2,4	P2,5
3	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.		.	.	.	.
24	P24,1	P24,2	P24,3	P24,4	P24,5

For the methodology of hourly peak load forecasting using ANN, the load forecast model-based ANN was implemented in the MATLAB Neural Networks Toolbox. The model was trained using the same historical load data that are used in the multiple linear regression technique to determine the weights of the network, see Table 5-1 and 5-2. Then, the use of obtained weights allows the prediction of the output for a given input. The historical data used in predicting the hourly peak demand were four inputs or days as shown in Figure 5-14 which are the hourly peak power demand for the time interval 7th- 10th July 2019 for the summer season, and the hourly peak power demand in 11th- 14th January 2019 for the winter season, see Appendix B.

The target for training is one day ahead for the same week which is 11th July 2019 and 15th January 2019 for the summer and winter seasons respectively. The day of a week is suitably coded as an input to the network. The input and the desired output efforts were made to optimise network parameters during the training phase. The ANN algorithm tries to minimise the difference between the desired and actual output by adjusting the weights of the network. Tangent hyperbolic (tanh) activation function is used for the hidden, and linear activation function is used in the output layer. The output layer has only one neuron in its output layer, which contains the predicted value of the load during the day. The architecture of the proposed ANN model is shown in Figure 5-14.

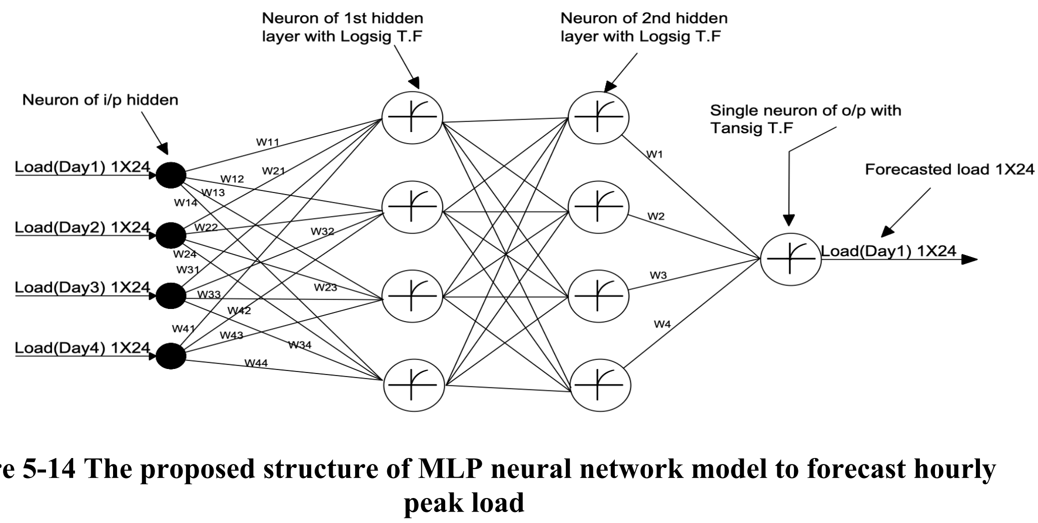

Figure 5-14 The proposed structure of MLP neural network model to forecast hourly peak load

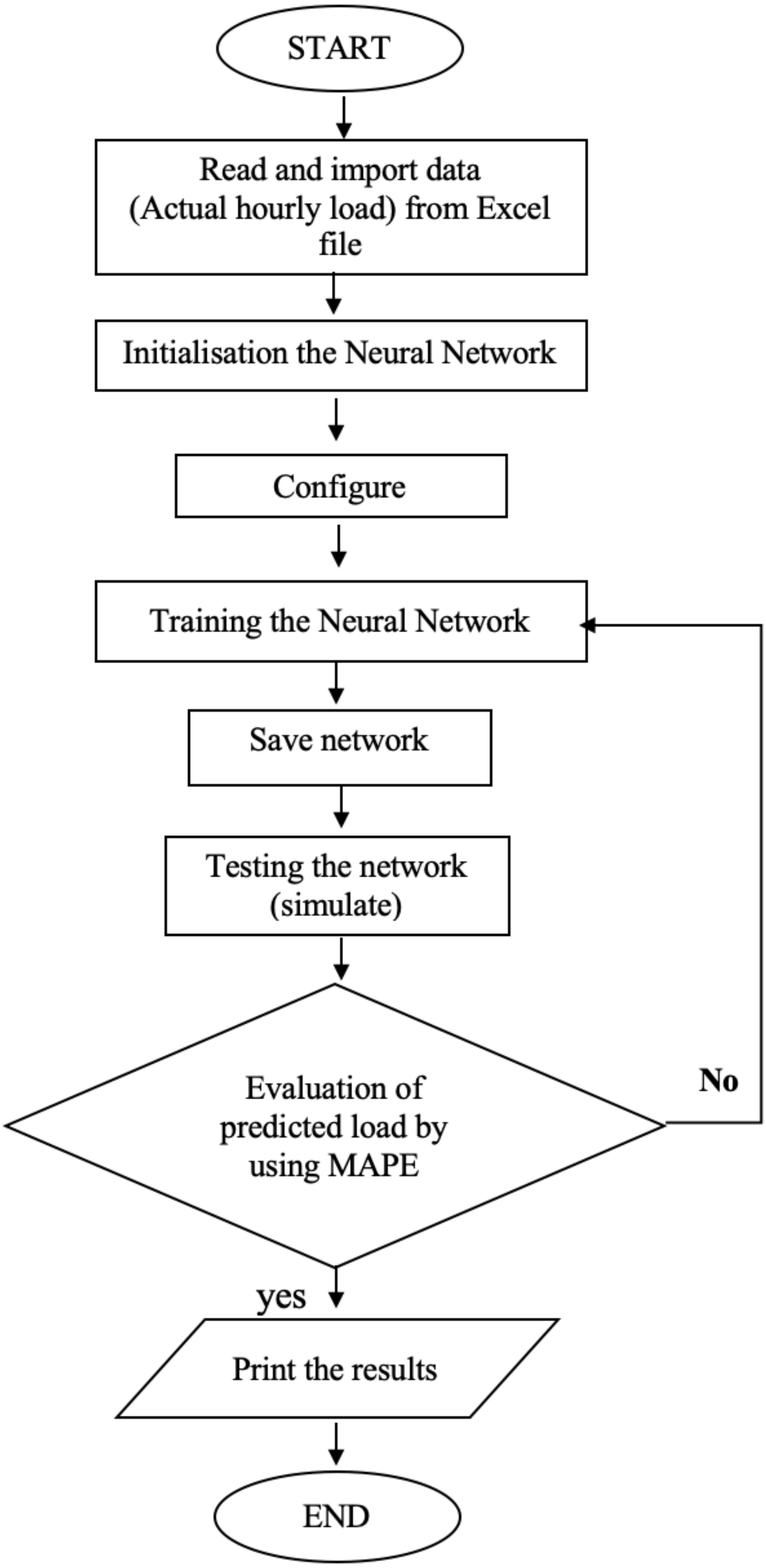

Figure 5-15 Flowchart of the neural network model forecast hourly peak load

The mean absolute percentage error in Equation (5.6) is considered to evaluate the accuracy of neural network and the predicted load.

The flowchart of the proposed forecasting model is presented in Figure 5-15. The learning mechanism of this model is summarized as follows:

6. Read collecting data is the first step in designing hourly peak load forecasting based ANN. In this section, the data represents the actual hourly peak load of Ziyounah district for a certain month
7. The neural network was initialised by using the function (Newff) for MLP which has one input layer, one hidden layer and one output layer. The transfer function has been chosen as “tansig" and "logsig"for hidden and output layers respectively.
8. At the training stage, the network was trained with historical data.
9. After the training process, the network was simulated or tested This process is run by calling the function "sim".
10. Finally, the best training result is obtained with a minimum value of Mean Absolute Percent Error MAPE (i.e. the lower the MAPE is, the more accurate the estimation is).

5.6 Data analysis

5.6.1 Daily peak load data analysis

In this study, daily peak demand for the Ziyouna area in Baghdad in 2019 was considered as historical data for training load forecasting based on LR and ANN to predict the maximum daily demand in 2020. This data represents the time interval from May 2019 -September 2019 for the summer season, see Figure 5-11. Whilst, the time interval from January 2019 -February 2019 represent the winter season, as shown in Figure 5-10. Figure 5-10 and 5-11 show the variation of the maximum daily temperature and maximum load with respect to the time during the seasons. It was assumed that the summer season in Iraq is starting from May to September, when the temperature is increasing during this time. Whilst, the winter represent only two months (January and February) because the weather during this period is the coldest in Iraq.

The testing set was the forecasted maximum daily temperatures for September 2020 (summer) to predict the maximum daily load in September 2020. The maximum daily temperatures for January 2020 (winter) was used to test the model to predict the maximum daily load in January 2020. This data was provided by the Iraqi Meteorological Organization and Seismology (IMOS).

5.6.2 Hourly peak load data analysis

Hourly peak load forecasting has been performed on weekdays during the summer and winter seasons using historical load data gathered for the time interval 7th- 11th July 2019, which represent the summer season. Whilst, the time interval 11th -15th Jan 2019 represent the winter season for Ziyouna area in Baghdad.

This data was collected in 2019 using SCADA system at 33/11kV power substation of the Ziyouna distribution network. The load values are representing the dominant residential type of load.

The testing set was the hourly peak load in 2020 gathered for the time interval 7th- 10th July 2019 to predict hourly peak load in 11th July (summer), and for the time interval 11th- 14th January 2020 to predict hourly peak load in 15th January(winter).

5.7 Forecasting Results

After training the models, testing was used for load forecasting using LR and ANN techniques to predict the daily peak load for one month ahead for summer and winter seasons of 2020. In addition, 24-hour load demand was predicted based the same techniques for one day ahead in summer and winter seasons of 2020, using the testing data in Appendix B. Once the testing data utilises the model, the forecasting result is presented here in this section. Mean absolute percentage error (MAPE) criteria are computed according to equation (5.6), and the model performance is evaluated over the whole period of time. It was assumed that the 15th January 2020 and 11th July 2020 represent typical days in the winter and summer seasons, and it was selected as a representative day for the LR and ANN forecasting. While, the month of January 2020 and September

2020 represent typical months in the winter and summer seasons, and it was selected as a representative month for both techniques.

Figure 5-16 shows the comparison between the results of daily peak demand for LR against ANN technique during the month of January 2020, which was assumed as a representative month for winter season. It was found that MAPE for LR and ANN models was 3.6% and 3.7% indicating that the forecasted load from the proposed model based LR is closer than that results from ANN. Looking at this result in more details, it can be seen that there is an inaccurate predicted demand by ANN which shown in red line in Figure 5.16 on 29th Jan 2020, i.e. the actual power is greater than the predicted power with approximately 4MW.

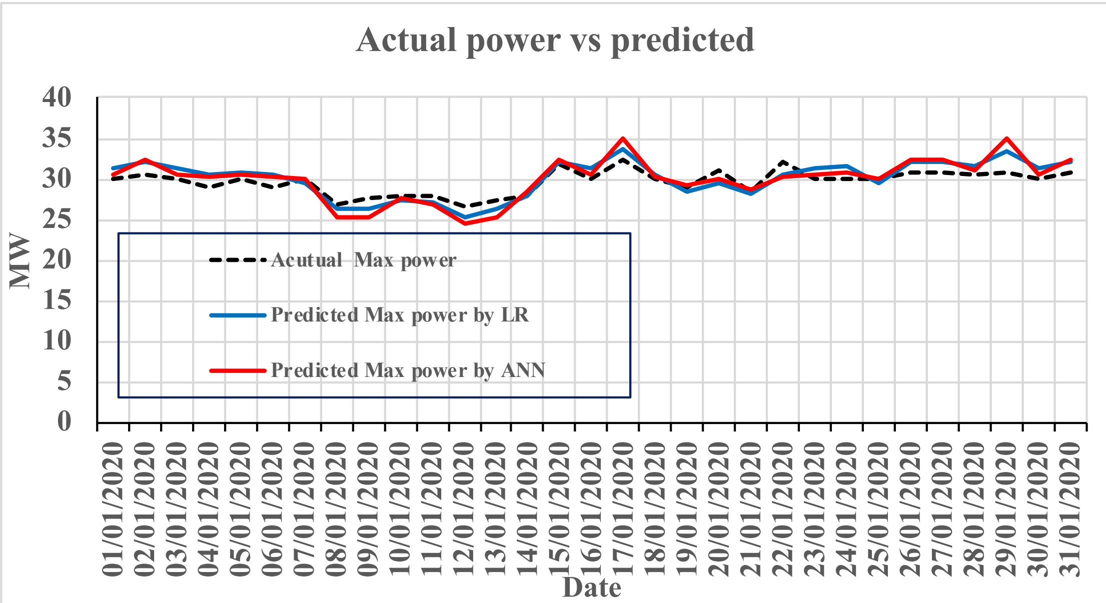

Figure 5-16 Comparison of daily peak demand predicted by LR and ANN, with MAPE=3.6%and 3.7%, against actual power for Jan 2020

Figure 5-17 compare the results of daily peak demand for LR against ANN technique during the month of September 2020, which was assumed as a representative month for summer season. It is obvious that the forecasted peak demand using LR technique with MAPE=3%, which represents in blue line is more accurate than the results from ANN with MAPE=3.8%. This means more backup generation units at peak time are required to supply the area based on that error during the month to match the actual demand and keep the system stable. However, there was an acceptable deviation between the actual and predicated, i.e. under-prediction or over-prediction of the maximum power load, see Figure 5-17.

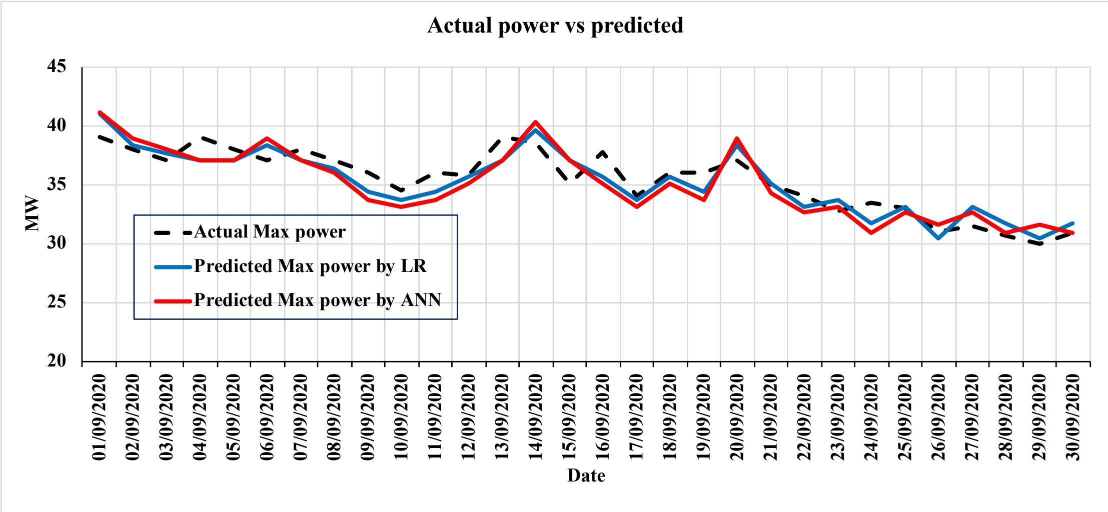

Figure 5-17 Comparison of monthly peak demand precited by LR and ANN, with MAPE =3%and 3.8%, against actual power for September 2020

Figure 5-18 illustrates the comparison between the result of predicted demand for LR and ANN against with actual power during 24 hours in 11th July which was assumed as a representative day for summer season. The recorded MAPE for LR and ANN is 5.7% and 3.7% respectively. Hence, the forecasted hourly peak load from the proposed model using ANN is performing well and the forecasted results are very close to the real demand data. Unlike the result by LR which shows inaccurate predicting during 24hours. Hence, the obtained results of forecasting performance reveal the effectiveness of the ANN model over LR. According to the MAPE results with 5.7% for LR and 3.7% for ANN, the author believes that power operators required more generation units which are 5.7% of peak demand for using LR or 3.7% of peak demand for using ANN. This can assist to avoid any mismatch between the supply and demand due to these errors.

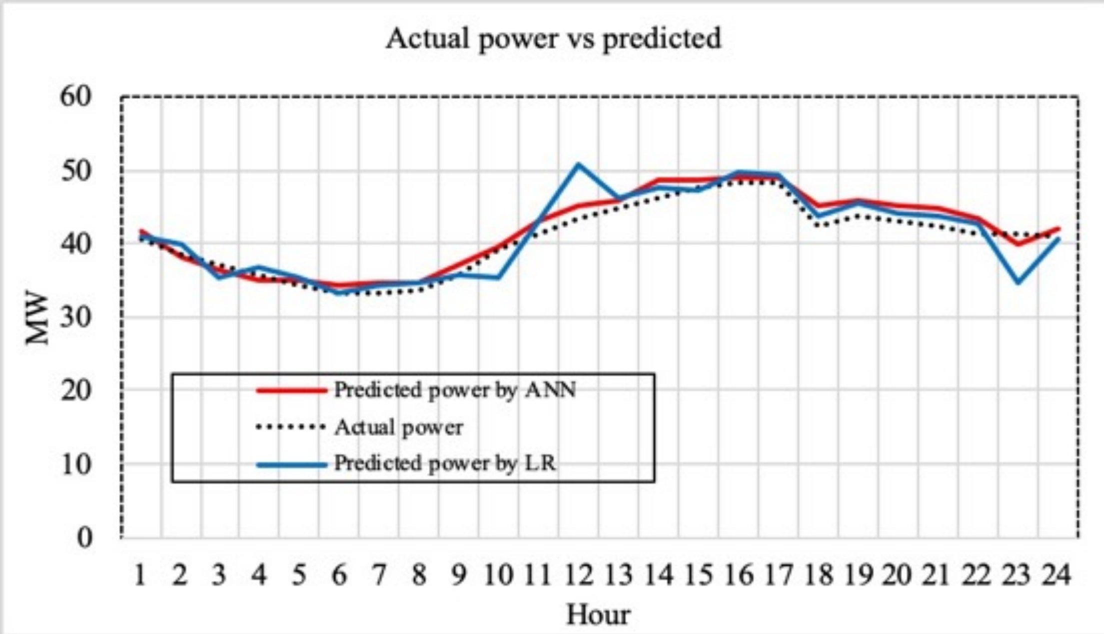

Figure 5-18 Comparison of hourly peak demand precited by LR and ANN, with MAPE =5.7%and 3.7%, against actual power for 11th July 2020

Figure 5-19 compares the results of hourly peak demand for LR and ANN techniques against the actual power during the day of 15th Jan 2020. This date was selected to as a typical day in winter season. The performance of the both techniques of LR and ANN are satisfactory at MAPE =4% and 3.1% respectively.

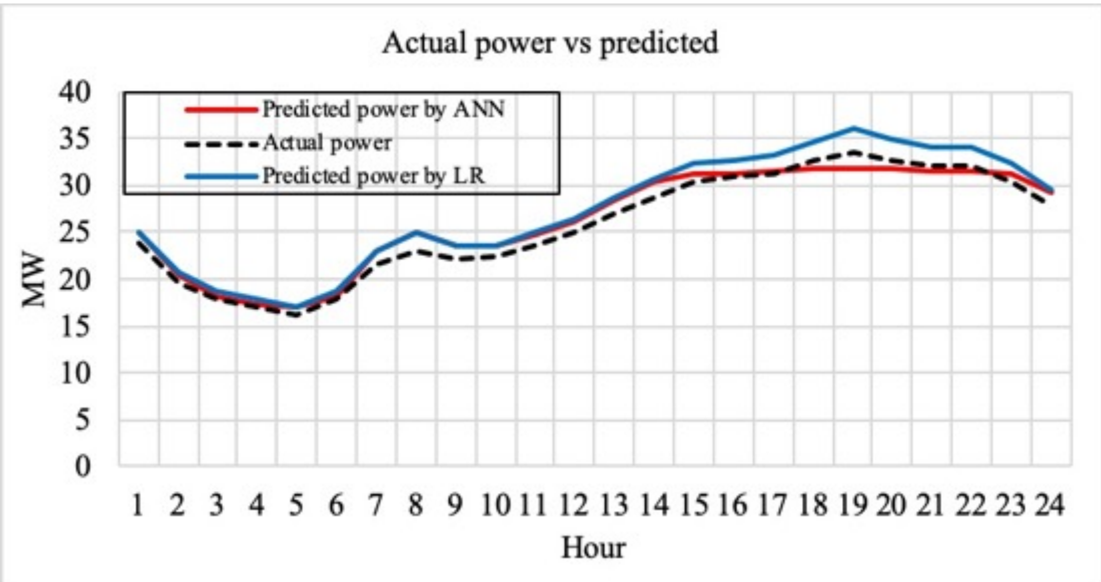

Figure 5-19 Comparison of hourly peak demand precited by LR and ANN, with MAPE =4%%and 3.1%, against actual power for 15th January 2020

5.8 Conclusion

Load forecasting using LR and ANN is implemented in this study to provides the power operator for Ziyounah in Baghdad with valuable information that can be used in chapter 7 for minimising the operational cost for integrated unit generations and accurately match electricity production to consumption in summer and winter seasons of 2020.

(MAPE) criteria were introduced to evaluate the model performance over the whole seasons. The difference error measures between the predicted and actual results provide useful insight into how the predicted can be used for a varying approach to the energy management for the distribution network of Zyonnah. Load forecasting models, in their present form, may be used in the following chapters for gaining predictive knowledge on the 24-hour load and peak demand forecasted of Zyounah ; which may then be used in achieving goals such as decreased overall operational cost and CO_2 emissions from the generation units that connected to the grid, as well as balancing the supply and demand. If load forecasting is advantageous for the operator to meet these goals or other motivation, it is vital to understand the limitations of the LR and ANN’s ability to accurately predict the demand.

According to the MAPE results, the author believes that load forecasting using LR provides predictions of peak demand that are accurate enough to be used in chapter 7 for planning the required generation units at peak time to supply the area based on the daily peak predicted demand during the month. This might be because of a strong correlation between the maximum temperature and the daily peak demand during the summer and winter seasons, i.e. the demand is affected significantly by the fluctuation of temperature during both seasons. It was found that the correlation coefficient for summer and winter is 0.8872, -0.904, respectively. The positive value of regression R at 0.8872 in summer means that the daily peak load is proportional directly with the ambient temperature during this period of time. Whilst, the negative value of regression R, at -0.904 in winter, indicates that the daily peak load is inversely proportional with the ambient temperature during this season. This attributed to a large number of usages of air conditioning in summer and water heaters in winter.

MAPE results for the ANN shows that this technique is more accurate than the LR technique in predicting 24-hour demand to control and scheduling the power system during the daytime. This because of its ability to deal with non-linear learning relationships between variables (hourly peak demand).

Due to the reasons outlined above, it is, therefore, load forecasting using LR in predicting peak demand for one month ahead (January 2020 and July 2020) and ANN in predicting hourly peak demand for one day ahead (15 January 2020 and 11 July 2020) is considered in this study.

Chapter 6

Economic power dispatch in Iraq power systems

6.1 Introduction

This chapter describes an optimal dispatch for the power operator of Ziyounah distribution network to calculate the optimal production schedule for connecting diesel generators and PV into the network in relation to the network's operating constraints. This approach can bring energy, environmental, and economic benefits not only to the power operator of Ziyounah in Baghdad but also to other power users whose generation suppliers do not meet their peak demands.

In this study, Economic dispatch analysis was carried out using Lagrange multiplier (LM) and linear programming methods (LP) and assisted by the MATLAB application based on forecasted demand in summer and winter seasons because operational decisions in power systems such as economic dispatch depends on the future behaviour of demand [168][169].

The overall objective is to determine the optimal dispatch power for various size of diesel generators including PV and grid import to reduce the total operating cost and CO_2 emissions simultaneously for the integrated generation units while meeting the peak during 24hour in the summer and winter season. To reflect the environmental effect for diesel generators, the calculation of CO_2 emissions from diesel generators can be calculated at any output power by using the Equations (3.5) or (3.6).

Results demonstrate that the proposed for LM and LP is a highly suitable and simple approach to determining the optimal dispatch in the power system with various types of generator sources subject to several constraints.

The environmental effect of diesel fuel led to using PV to meet the rising power demand[136]. In this context, the integration of PV to meet the demand of a given area is a promising scenario to overcome the Iraqi power system challenges. The main reason for support to PV technologies is that they are desirable technologies that must be supported because they are suitable for the environment and contribute to sustainability and energy security objectives. Though, for various legitimate reasons, they are still comparatively expensive sources and tend to disrupt the normal way that power systems are used to operate[18].

6.2 Operating cost of a diesel generator

The operating cost of a diesel generator plays a vital role in economic scheduling. It is equal to the fuel consumption of a diesel generator(litre/kWh) multiply by the price of fuel (£/litre). As mentioned in Chapter3, the fuel consumption depends on the size of the generator and the load at which the generator operates at. For example, a diesel generator size 250kW has an operating cost of about 0.1 £/kWh when the generator operates near 25% of its rated power. In contrast, the same generator operates approximately 0.078 £/kWh if it is operating at full load, see Table 6-1 and Figure 6-1.

Table 6-1 The operating (marginal) cost per kWh and the cost per hour for different sizes of diesel generators based on Iraqi fuel cost[6]

Generator Size (kW)	1/4 Load		1/2 Load		3/4 Load		Full load	
	Operating cost		Operating cost		Operating cost		Operating cost	
	£/kWh	£/h	£/kWh	£/ h	£/kWh	£/ h	£/kWh	£/ h
250	0.0994	6.213	0.0828	10.355	0.0790	14.824	0.0784	19.62
500	0.0959	11.99	0.0806	20.165	0.0767	28.776	0.0778	38.91
750	0.0947	17.76	0.0796	29.866	0.0761	42.837	0.0776	58.20
1000	0.0941	23.54	0.0793	39.67	0.0757	56.789	0.0775	77.49

[6] Cost for 1gallon of diesel in Iraq = £1.09 based on rate currency= 1666.67

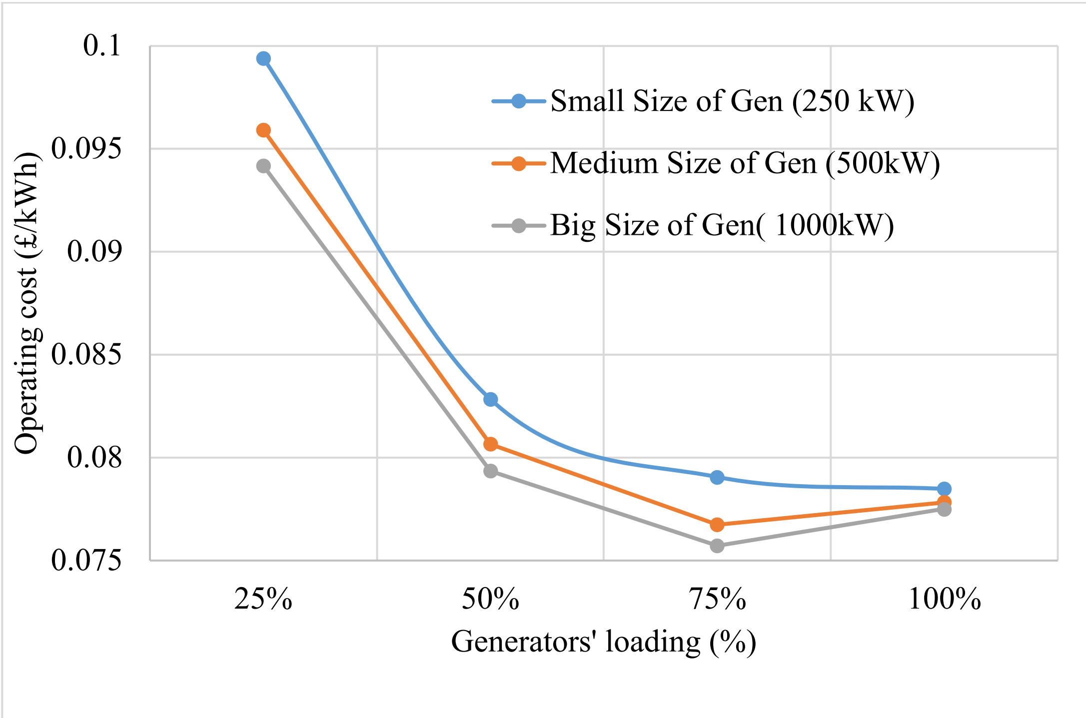

Figure 6-1 The operating (marginal) cost per kWh for 250kW, 500kW and 1000kW of diesel generators

6.3 Developing the operating cost model of a diesel generator

The input-output characteristics of a fossil fuel generating set plays an important role when the economic operation is considered [136]. Operating efficiencies of generators and fuel cost have a significant effect on operation cost of diesel generators. The fuel costs generated by these units are described using quadratic functions [8], [11], [13], [15].

In practical cases, the fuel cost of a diesel generator can be expressed as a quadratic function of real power generation[2], [121] [5], [6].

$$Ci = \alpha i + \beta iPi + \gamma i\, Pi^2 \quad £/\,h \tag{6.1}$$

Where: i= {1,2, 3, .., N}, N= the number of generation units; αi, βi, and γi are the coefficients for the cost equations of the ith generator; Pi is the power output of the ith generator.

To obtain the cost model for generators, Table 6-1 is used as an estimate of the quantity of fuel consumption uses during operation. From Table 6-1, the fuel cost of four groups of diesel generators is found by using a quadratic regression analysis which is a way to model a relationship between the output power (kW) and the operating cost (£/h). The result is a regression equation that is used to make predictions about the operating cost for the generators.

To find the coefficients of α, β and γ, we assumed that (x) represents the output power of generators and (y) represents the operating cost (£/h). The regression equations are presented here [174].

$$\alpha = \frac{[S(x^2y) * S(xx)] - [S(xy) * S(xx^2)]}{[(S(xx) * S(x^2x^2)] - [S(xx^2)]^2} \tag{6.2}$$

$$\beta = \frac{[S(xy) * S(x^2x^2)] - [S(x^2y) * S(xx^2)]}{[(S(xx) * S(x^2x^2)] - [S(xx^2)]^2} \tag{6.3}$$

$$\gamma = \frac{\sum y_i}{n} - \beta \frac{\sum x_i}{n} - \alpha \frac{\sum {x_i}^2}{n} \tag{6.4}$$

Where:

i= {1,2, 3, .., n}, n= the sample size

$$S(xx) = \sum {x_i}^2 - \frac{(\sum x_i)^2}{n}$$

$$S(xy) = \sum x_i\, y_i - \sum x_i * \frac{\sum y_i}{n}$$

$$S(xx^2) = \sum {x_i}^3 - \sum x_i * \frac{\sum {x_i}^2}{n}$$

$$S(x^2y) = \sum {x_i}^2\, yi - \sum {x_i}^2 * \frac{\sum yi}{n}$$

$$S(x^2x^2) = \sum {x_i}^4 - \frac{(\sum {x_i}^2)^2}{n}$$

Table 6-2 Coefficients of the cost equation for four size of diesel generators by using regression analysis based on Table 6-1

The coefficients of the cost equations	Units	G1	G2	G3	G4
α	£/h	2.351	5.0685	7.621	10.35
β	£/ kWh	0.06	0.052	0.05	0.049
γ	£/kW^2h	0.000052	0.000034	0.000024	0.0000185

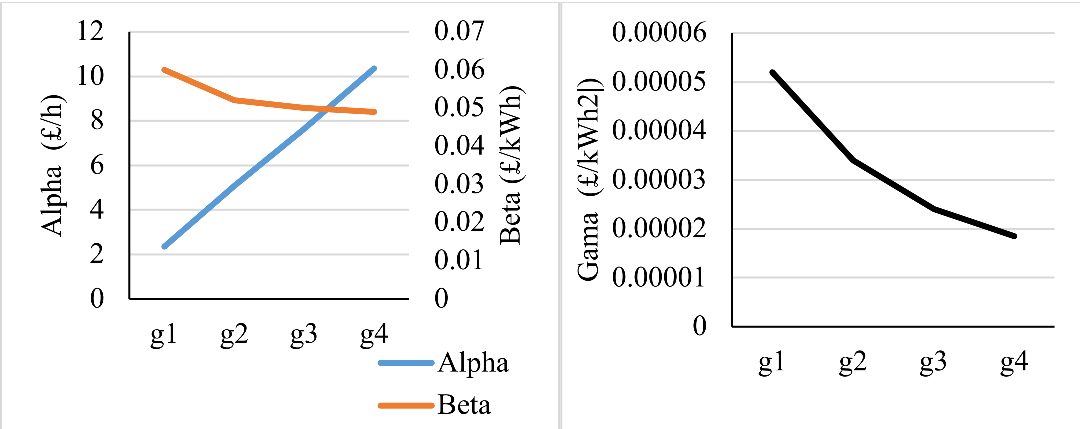

Figure 6-2 Coefficients of Alpha, Beta and Gama for cost equations for generators in G1, G2, G3 and G4

For calculating the fuel cost for diesel generators at various loading, the coefficients equation *α, β, and γ* are considered. The calculation is presented in Figure 6-3. by using Equation (6.1).

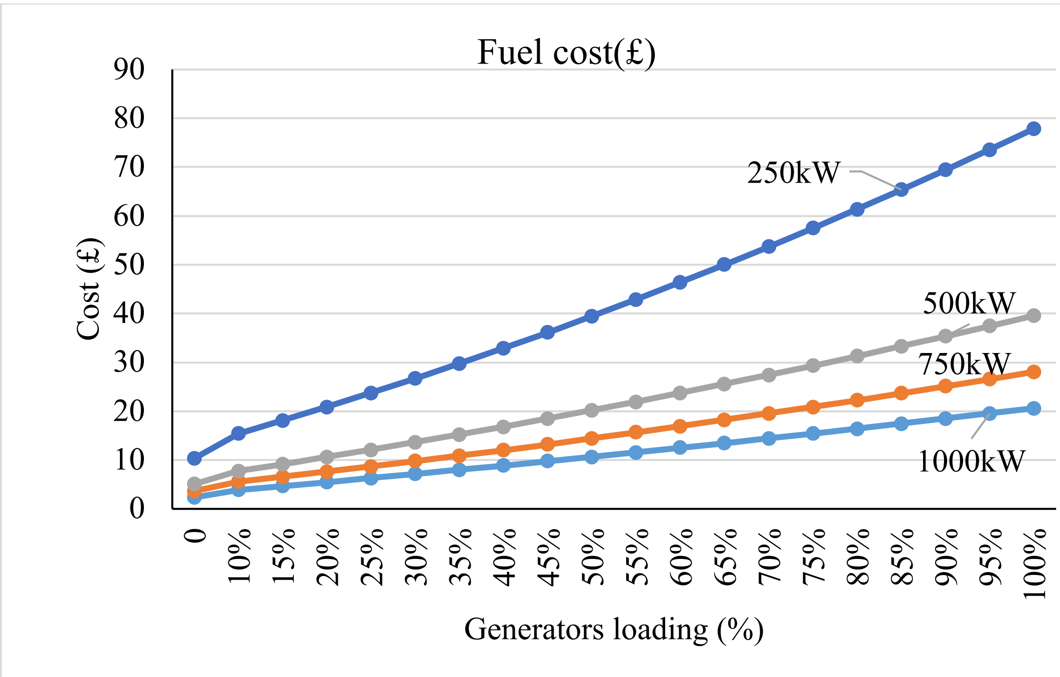

Figure 6-3 Graphs of fuel cost of four diesel generator types 250kW, 500kW, 750kW and 1000kW during operating

6.4 Assumptions

In this chapter, it is assumed that the electricity from the national grid should not exceed 77.5% of the peak demand. This allocation is calculated by the Ministry of Electricity for Baghdad Governorate which depends on several factors such as population and the size of demand for that area.

The assumptions are taken into account as:

The number of diesel generators distributed in Ziyouna region are:

- Group1: Ge1, Ge2, Ge3, Ge4, Ge5 and Ge6 = 250 kW 6 units
- Group2: Ge7, Ge8, Ge9, Ge10, Ge11and Ge12 = 500 kW 6 units
- Group3: Ge13, Ge14, Ge15 and G16 = 750 kW 4 units
- Group4: G17, G18, and G19 =1000 kW 3 units
- Total capacity of diesel power generations = 10,500 kW
- National electricity supply ≤77.5% of peak load (Source: Ministry of Electricity)
- Using renewable energy sources with high priority and when are available.
- The number of the PV system is 200 systems. Every system consists of 12 panels with total power rated of 10kW
- Cost for 1gallon of diesel in Iraq = £1.09, or 1 litre of diesel= £0.2397
- Neglecting line power losses in the analysis of total production cost
- It has been chosen that 12th July and 15th January are representative days for the summer and winter seasons in Iraq.

6.5 Calculations of the number of diesel generators

Calculation of the number of diesel generators is important every day with varying peak loads during the seasons. The minimum number of these units will be available and selected before applying the dispatch analysis.

Scheduling of generators can be divided into two separate parts: unit commitment and economic dispatch. Unit commitment takes place before the real-time operation and determines the set of generating units that will be available for dispatch. Economic dispatch is undertaken in real-time and determines the amount of generation required from each available unit[175]. In this section, a simple unit commitment is used to determine the minimum number of diesel generators required every day with varying peak loads, i.e. the number of diesel generators required is calculated before applying the dispatched power of the generation units. This calculation is simple to the problem and it can be conducted to impose priority order, wherein the most efficient units (the bigger size of diesel generators) are loaded first to be followed by the less efficient units (the smaller size of diesel generators) in order as the peak load increases. Therefore, if < PD, we increase the number of units otherwise, if > PD, we reduce the number of units. The best result occurs when = PD, taking into consideration that the bigger size of generators is the top priority

In the summer season, all the diesel generators are required to be integrated into the distribution network of Ziyounah due to a severe shortage of generation during this time. But in the winter season, the number of diesel generators required is calculated as shown in Table 6-3. This table shows the minimum number of diesel generators at peak load and the additional generation required to match the demand in the district.

The calculations are for January 2020 considering the predicted maximum demand. We assume that these generators are operating at full load. For instance, on the 15th January 2020, the power supply required is 8500kW, see Table6-3. Therefore, the numbers of required generators are:

Group4: 3X1000kW= 3000kW,

Group3: 4X750kW= 3000kW,

Group2: 5X500kW= 2500kW,

Group1: 0X250kW= 0 kW,

Total = 8500kW this represented the total output power of required generators operating at 100% to match the maximum load on the15th January 2020.

Table 6-3 Minimum number of diesel generators required for January 2020 for Ziyouna district/ Baghdad based on forecasting load

Day	Predicted maximum demand	Maximum Power supply required[7] to meet the demand in MW = 22.5% *Predicted	Number of Generators for group1- group4				Total maximum generation of diesel generators (MW)
			Gr1 250	Gr2 500	Gr3 750	Gr4 1000	
1	34.408	7.038	0	4	4	3	8
2	35.332	7.227	0	4	4	3	8
3	34.408	7.038	0	4	4	3	8
4	33.484	6.849	0	4	4	3	8
5	33.946	6.9435	0	4	4	3	8
6	33.484	6.849	0	4	4	3	8
7	32.56	6.66	0	3	4	3	7.5
8	28.853	5.901	0	2	4	3	7
9	28.853	5.901	0	2	4	3	7
10	30.25	6.187	0	2	4	3	7
11	29.788	6.093	0	2	4	3	7
12	27.929	5.712	0	1	4	3	6.5
13	28.853	5.901	0	1	4	3	6.5
14	30.712	6.282	0	2	4	3	7
15	35.574	7.515	0	5	4	3	8.5
16	34.408	7.038	0	3	4	3	7.5
17	37.191	7.607	0	5	4	3	8.5
18	33.484	6.849	0	4	4	3	8
19	31.262	6.3945	0	3	4	3	7.5
20	32.56	6.66	0	3	4	3	7.5
21	30.899	6.320	0	2	4	3	7
22	33.484	6.849	0	4	4	3	8

[7] The percentage of 22.5% assumed to be the gap between supply and peak demand, providing by Ministry of Electricity for Baghdad. This means about 77.5% of maximum demand can be supplied as permissible limit from the grid.

23	34.408	7.038	0	4	4	3	8
24	34.782	7.114	0	4	4	3	8
25	32.56	6.66	0	3	4	3	7.5
26	35.332	7.227	0	4	4	3	8
27	35.332	7.227	0	4	4	3	8
28	34.87	7.132	0	4	4	3	8
29	36.729	7.512	0	5	4	3	8.5
30	34.408	7.038	0	4	4	3	8
31	35.332	7.227	0	4	4	3	8

6.6 Optimal scheduling of generation using Lagrange multipliers

Since losses are neglected, the total demand PD is the sum of all generation outputs. Ci is assumed to be known for each generator. The problem is to find the real power generation for each generator such that the objective function (i.e., total production cost) as defined by the equation [176] [177].

$$Ct=\sum_{i=1}^{n} \alpha i + \beta iPi + \gamma i \; Pi^2 \tag{6.5}$$

is at a minimum

Where $\mathrm{Ct} = \mathrm{C1} + \mathrm{C2} + \mathrm{C3} + \cdots + \mathrm{Cn}$

subject to the constraint

$$\sum_{i=1}^{n} Pi = PD \tag{6.6}$$

Where Ct is the total production cost, Ci is the production cost of the ith generator. Pi is the generation of ith generator. PD is the total load demand which equal to the difference between the forecasting demand and allocated supply from national electricity, and n is the total number of dispatchable generating units.

The objective function is found by using the Lagrange multipliers [170], [172].

$$\mathrm{L} = \mathrm{Ct} + \lambda\,(\mathrm{PD} - \sum_{i=1}^{n} Pi) \tag{6.7}$$

The minimum of this unconstrained function is found when

$$\frac{\partial L}{\partial Pi} = 0 \tag{6.8}$$

$$\frac{\partial L}{\partial \lambda} = 0 \tag{6.9}$$

First condition, given by (6.8), results in

$$\frac{\partial \text{ Ct}}{\partial Pi} + \lambda(0 - 1) = 0 \tag{6.10}$$

Since $\text{Ct} = \text{C1} + \text{C2} + \text{C3} + \cdots + \text{Cn}$

Then $\frac{\partial \text{ Ct}}{\partial Pi} = \frac{d \text{ Ct}}{dPi} = \lambda$, therefore the condition for optimal dispatch is

$\frac{d \text{ Ct}}{dPi} = \lambda$ i=1, 2,….n

$$\text{Or} \quad \beta\text{i} + 2\gamma\text{i Pi} = \lambda \tag{6.11}$$

Second condition, given by (6.9), results in

$$\sum_{i=1}^{n} Pi = PD \tag{6.12}$$

To find the solution, (6.11) is solved for Pi

$$Pi = \frac{\lambda - \beta\text{i}}{2\,\gamma i} \tag{6.13}$$

The relations given by (6.13) are known as the coordination equations.

An analytical solution can be obtained by substitution for Pi in (6.12)

$$\text{Then} \quad \sum_{i=1}^{n} \frac{\lambda - \beta\text{i}}{2\,\gamma i} = \text{PD} \tag{6.14}$$

To find the optimal scheduling of generation, the value of λ, Coordination equation is presented here

$$\lambda = \frac{PD + \sum_{i=1}^{n} \frac{\beta i}{2\,\gamma i}}{\sum_{i=1}^{n} \frac{1}{2\,\gamma i}} \tag{6.15}$$

To demonstrate the concept of equal operating cost for optimal dispatch, Figure 6-4 can be used to determine the operating cost dC/dP graphically for each generator on the same graph[178]. Obviously, the load on the generator with higher dC/dP will be reduced by increasing the load taken by the generator with the lower dC/dP. This change is beneficial until the values of dC/dP for all generator are equal ($\boldsymbol{\lambda}$= dCi /dPi).

To obtain a result, various values of $\boldsymbol{\lambda}$ can be tried until one is found that produces $\sum_{i=1}^{n} Pi$ = PD. The horizontal dashed-line shown in this graph is moved down and up until at the optimum value when $\sum_{i=1}^{n} Pi$ = PD. Hence, for each λ, if $\sum_{i=1}^{n} Pi$ < PD, we increase λ otherwise, if $\sum_{i=1}^{n} Pi$ > PD, we reduce λ. For example, at maximum load with PD =9900kW, the optimal dispatch for generators in Ge1, Ge2, Ge3, and Ge4 are 6X240kW, 6X470kW, 4X702kW and 3X944kW respectively at λ =0.084£/kWh as shown in Figure 6-4

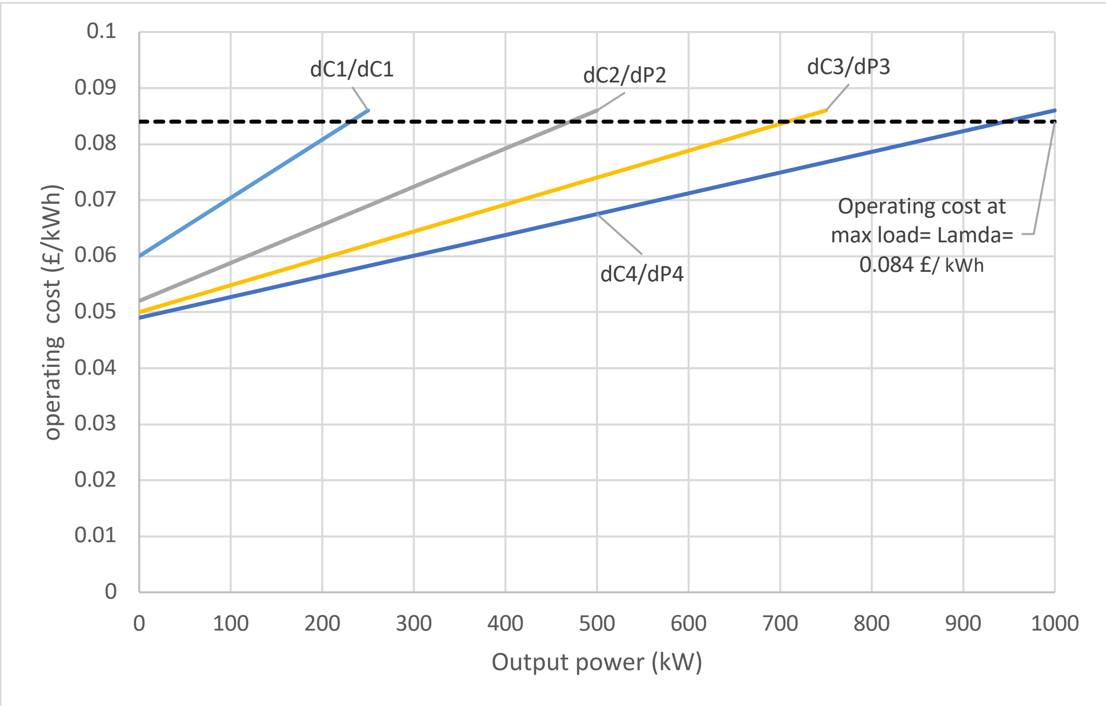

Figure 6-4 Graphs of incremental fuel cost against output for four diesel generators sharing a load for Ziyounah/ Baghdad

The solution steps for obtaining the optimal cost-effective allocation of generations and their minimum operationg cost are summarized in Figure 6-5.

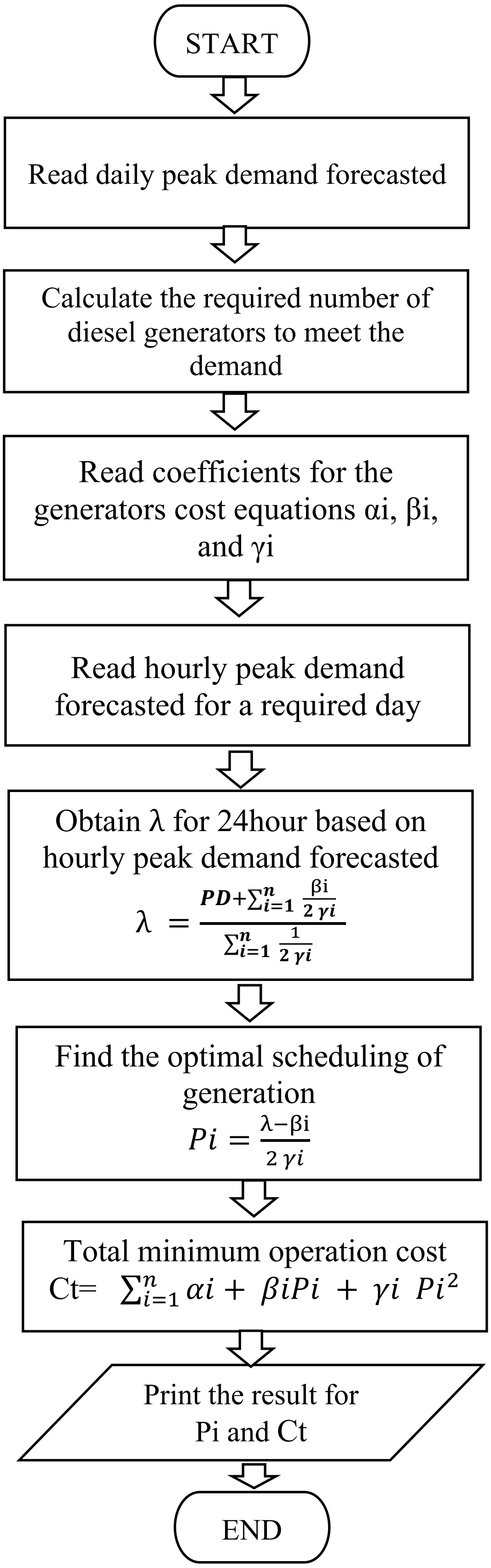

Figure 6-5 Flowchart for obtaining power schedule and minimum operation cost for diesel generators using Lagrange multipliers

6.7 Optimal scheduling of generation using the Linear Programming

The linear programming method is an optimisation technique for a problem of linear constraints and a linear objective function. The objective of linear programming is to find values of the variables that minimise or maximise the objective function. This technique has been considered widely to optimise the allocation of power resources[179]–[181]. In this section, the linear programming method is used for obtaining the optimum generation schedule for integrated generation units that minimises the total operation cost with given constraints.

6.7.1 Methodology:

To minimize cost of dispatching local generation

- Use renewable energy sources with high priority and when are available.

- Differentiate the four types of diesel generators by the cost of fuels
    1. The biggest size of generators can be generally considered cheaper
    2. The smaller size of diesel generators can be generally considered expensive

- Input profiles
    1. Demand profile is considered from the previous chapter (chapter5) based on the forecasting analysis.
    2. 24-hour output profile as shown in appendix A.

- Output profiles
    1. The optimal usage allocation of the five sources of generation as well as the optimal amount of grid import.
    2. The minimum operating cost of the five sources of generation as well as the optimal amount of grid import during the day. To reflect the environmental effect for diesel generators, the calculation of

CO_2 emissions produced from diesel generators can be obtained at any output power by using the Equations (3.5) or (3.6).

6.7.2 Mathematical formulation

Problem description

- Consider Hourly profile in one day – 24 data points $t \in [1,24]$.
- Input set: J = [1: PV, $x_1(t)$; 2: G250, $x_2(t)$; 3: G500, $x_3(t)$; 4: G750, $x_4(t)$; 5: G1000, $x_5(t)$ 6: grid import, $x_6(t)$].
- The cost of using $x_1(t), x_2(t), x_3(t), x_4(t), x_5(t),\ x_6(t)$ is set up as *[*$c_1(t)$, $c_2(t)$, $c_3(t)$, $c_4(t)$, $c_5(t)$*] with* $c_1(t)$ the lowest and $c_5(t)$ the highest.
- The production capacity limit of the four types of generation is set as $0 \le x_1(t) \le PV(t),\ Ib2 \le x_2(t) \le ub2,\ lb_3 \le x_3(t) \le ub_3,\ lb_4 \le x_4(t) \le ub_4, lb_5 \le x_5(t) \le ub_5$.

Therefore, the optimisation problem can be written as follows:

$$\min_{x_j} \sum_{j \in J} c_j(t) x_j(t) \tag{6.16}$$

$$\text{s.t.:} \begin{cases} lb_j \le x_j(t) \le ub_j \\ \sum_{j \in J} x_j(t) = D(t) \end{cases} \tag{6.17}$$

6.1.1 Mathematical formulation translated into MATLAB

Recall the standard linprog format in MATLAB as follows:

$$\min_x f^T * x \ \text{ such that} \begin{cases} A * x \le b, \\ A_{eq} * x = b_{eq} \\ lb \le x \le ub \end{cases}$$

Step1: Equations (6.16), (6.17) can be written as:

$$\min_{x_1(t),\, x_2(t),\, x_3(t),\, x_4(t),\, x_5(t)} \sum_{t=1}^{24} c_1(t) * x_1(t) + c_2(t) * x_2(t) + c_3(t) * x_3(t) + c_4(t) * x_4(t) + c_5(t) * x_5(t) \tag{6.18}$$

Subject to:

$$x_1(t) + x_2(t) + x_3(t) + x_4(t) + x_5(t) + x_6(t) = D(t)$$
$$0 \le x_1(t) \le PV(t)$$
$$lb_2 \le x_2(t) \le ub_2$$
$$lb_3 \le x_3(t) \le ub_3$$
$$lb_4 \le x_4(t) \le ub_4$$
$$lb_5 \le x_5(t) \le ub_5$$
$$lb_6 \le x_6(t) \le Inf$$

Step2: Combine variables into one vector

$$\begin{bmatrix} x_1 & \cdots & x_{24} \\ \vdots & \ddots & \vdots \\ x_{121} & \cdots & x_{144} \end{bmatrix} \begin{array}{c} <== x_1(t) \\ \dots \\ <== x_6(t) \end{array}$$

Step 3: Write the lower bounds vector (lb ≤ x)

$$lb = zeros(144, 1)$$
$$lb(49{:}72) = lb_3$$
$$lb(73{:}96) = lb_4$$
$$lb(97{:}120) = lb_5$$
$$lb(121{:}144) = lb_6$$

Step 4: Write the upper bounds vector (x ≤ ub)

$$ub = zeros(144, 1)$$
$$ub(1{:}24) = PV$$
$$ub(25{:}48) = ub_2$$
$$ub(49{:}72) = ub_3$$
$$ub(73{:}96) = ub_4$$
$$ub(97{:}120) = ub_5$$

$$ub(121{:}144) = Inf$$

Step 5: Write linear equality matrix and vector ($A_{eq} * x = b_{eq}$)

$$\begin{cases} x_1(1) + x_2(1) + x_3(1) + x_4(1) + x_5(1) + x_6(1) = D(1) \\ . \\ . \\ . \\ x_1(24) + x_2(24) + x_3(24) + x_4(24) + x_5(24) + x_6(24) = D(24) \end{cases}$$

That is,

$$\begin{cases} x_1 + x_{25} + x_{49} + x_{73} + x_{97} + x_{121} = D(1) \\ . \\ . \\ . \\ x_{24} + x_{48} + x_{72} + x_{96} + x_{120} + x_{144} = D(24) \end{cases}$$

A_{eq} is a matrix of size 24X144 and b_{eq} is a matrix of size 24X1.

Hence,

$$A_{eq} = zeros(24{,}144)$$

$$b_{eq} = zeros(24{,}1)$$

$$\begin{cases} A_{eq}(1, [1{,}25{,}49{,}73{,}97{,}121\ ]) = ones(1{,}6) \\ A_{eq}(2, [2{,}26{,}50{,}74{,}98, 122]) = ones(1{,}6) \\ . \\ . \\ . \\ A_{eq}(24, [24{,}48{,}72{,}96{,}120, 144]) = ones(1{,}6) \end{cases}$$

$$b_{eq} = D$$

Step 6: Write objective function vector

$$\text{Cost} = \begin{bmatrix} c_1(1) \\ . \\ . \\ . \\ c_1(24) \end{bmatrix} * [x_1 \quad \cdots \quad x_{24}] + \begin{bmatrix} c_2(1) \\ . \\ . \\ . \\ c_2(24) \end{bmatrix} * [x_{25} \quad \cdots \quad x_{48}] + \begin{bmatrix} c_3(1) \\ . \\ . \\ . \\ c_3(24) \end{bmatrix}$$

$$* [x_{49} \quad \cdots \quad x_{72}] + \begin{bmatrix} c_4(1) \\ . \\ . \\ . \\ c_4(24) \end{bmatrix} * [x_{73} \quad \cdots \quad x_{96}] + \begin{bmatrix} c_5(1) \\ . \\ . \\ . \\ c_5(24) \end{bmatrix}$$

$$* [x_{97} \quad \cdots \quad x_{120}] + + \begin{bmatrix} c_6(1) \\ . \\ . \\ . \\ c_6(24) \end{bmatrix} * [x_{121} \quad \cdots \quad x_{144}]$$

Hence, the objective function can be written as

$$\text{minimise Cost} = f^T * x = f(1) * x_1 + \cdots + f(144) * x_{144}$$

Therefore,

$$f = \text{zeros}(144{,}1)$$

$$f(1{:}\,24) = \begin{bmatrix} c_1(1) \\ . \\ . \\ . \\ c_1(24) \end{bmatrix}$$

$$f(25{:}\,48) = \begin{bmatrix} c_2(1) \\ . \\ . \\ . \\ c_2(24) \end{bmatrix}$$

$$f(49{:}\,72) = \begin{bmatrix} c_3(1) \\ . \\ . \\ . \\ c_3(24) \end{bmatrix}$$

$$f(73:96) = \begin{bmatrix} c_4(1) \\ . \\ . \\ . \\ c_4(24) \end{bmatrix}$$

$$f(97:120) = \begin{bmatrix} c_5(1) \\ . \\ . \\ . \\ c_5(24) \end{bmatrix}$$

$$f(121:144) = \begin{bmatrix} c_6(1) \\ . \\ . \\ . \\ c_6(24) \end{bmatrix}$$

***Step** 7: Call solver and obtain solution*

$$[x^*, \mathrm{fval}, \sim] = \mathrm{linprog}(f, A, b, A_{eq}, b_{eq}, lb, ub)$$

Therefore, the optimal solutions are as follows,

$$x_1^* = x^*(1:24)$$
$$x_2^* = x^*(25:48)$$
$$x_3^* = x^*(49:72)$$
$$x_4^* = x^*(73:96)$$
$$x_5^* = x^*(97:120)$$
$$x_6^* = x^*(121:144)$$

6.8 Simulation results

On the basis of the maximum hourly demand forecasted and the maximum available power generation of the diesel generators and PV, considering the operating constraints, we show the numerical results of the optimal dispatch using LM and LP techniques for the summer and winter seasons.

6.8.1 Summer result

Figures 6-6 and 6-7 show the optimal allocation of the four sizes of diesel generation as well as PVs and grid import to match the demand hour by hour in a stacked bar using LM and LP methods respectively. At each hour, the sum of the coloured areas is equal to the load in that hour. Obviously, the big size of the generators with the lowest marginal costs are more likely to operate at a high loading to satisfy the demand at a minimum operating cost. The result of economic dispatch using both techniques LM and PL reveal that the power supply from 19 diesel generators (total 10,500kW) and 200 PV(10kW each) in Zyounah area can meet the forecasted hourly demand on hot summer days with minimum operational cost.

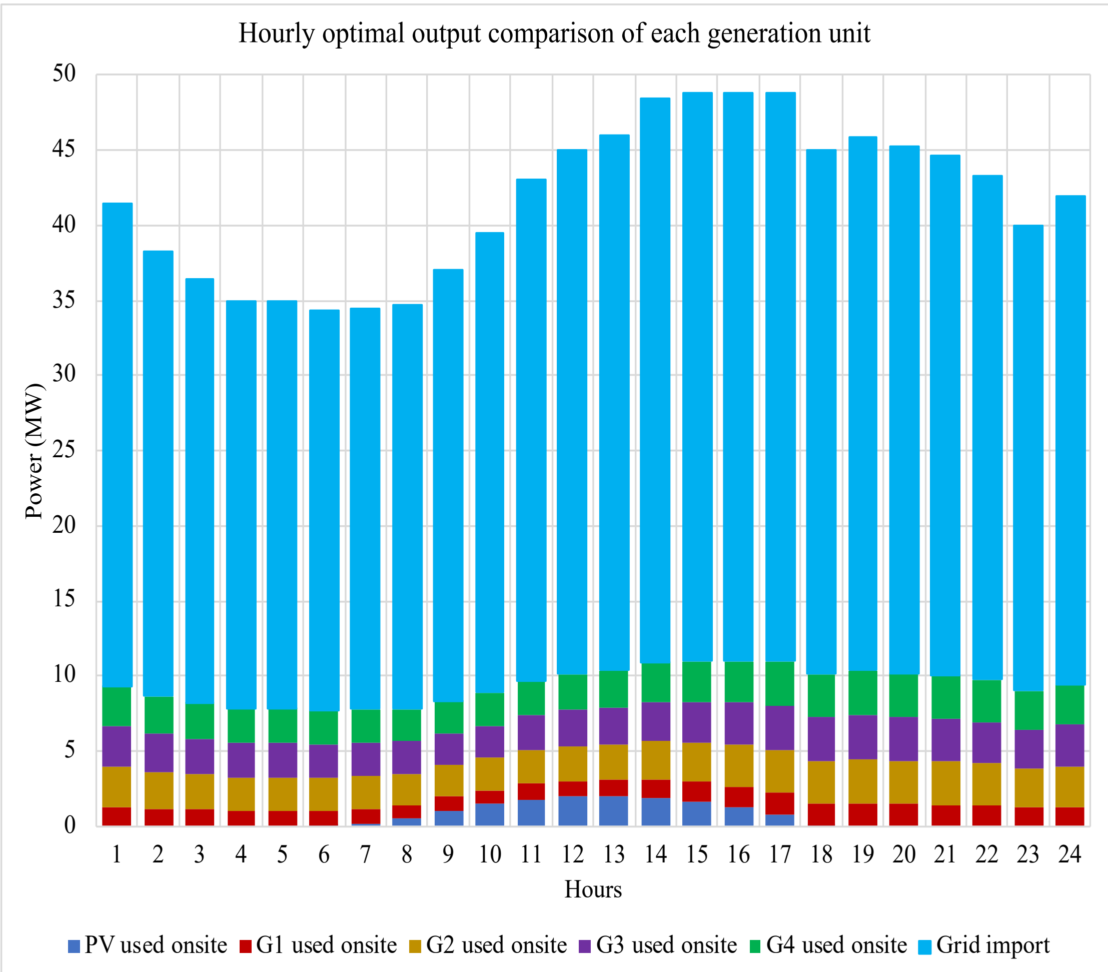

Figure 6-6 Optimal hourly usage comparison of each generating source on 12 July 2020, summer season using LM method

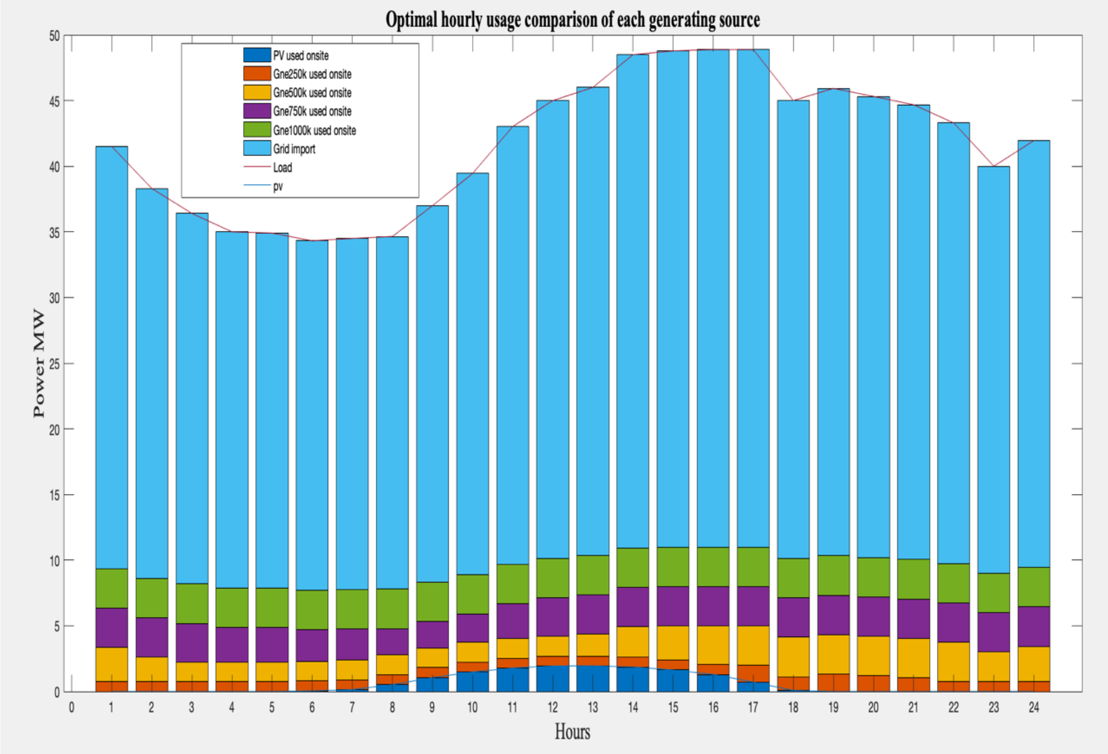

Figure 6-7 Optimal hourly usage comparison of each generating source on 12th July 2020, summer season using LP method

Figure 6-8 Compares the results of the total minimum operation cost of PVs, diesel generators, and grid import. It was found that the total operation cost for the total generation sources in 12th July 2020 using LM and LP methods is £77,955 and £78,814 respectively. However, between 13:00 to 17:00, electricity is the most expensive since the demand is at a maximum during this period.

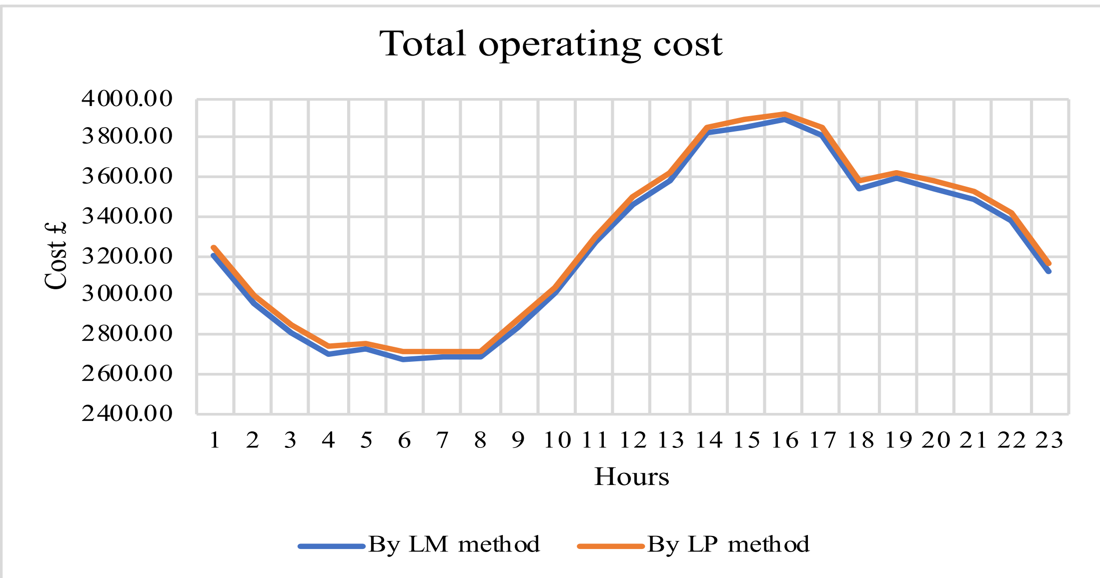

Figure 6-8 Comparison between LM and LP methods in total operation cost for generation supply in 12th July 2020 (summer)

6.8.2 winter result

As mentioned in section 6.5, the required number of diesel generators in 15th January2020 are:

G1= 0x250kW

G2= 5x500kW

G3= 4x750kW

G4= 3x1000kW

Figures 6-9 and 6-10 illustrate the optimal composition of each generating source at each hour in a stacked bar on 15th January 2020, highlighting the total available PV. The flexibility from these generating sources consists of the rest of the PV. This amount of flexibility can be exported to the grid, store in a battery energy storage system or participate in ancillary services in an optimal cost-effective manner.

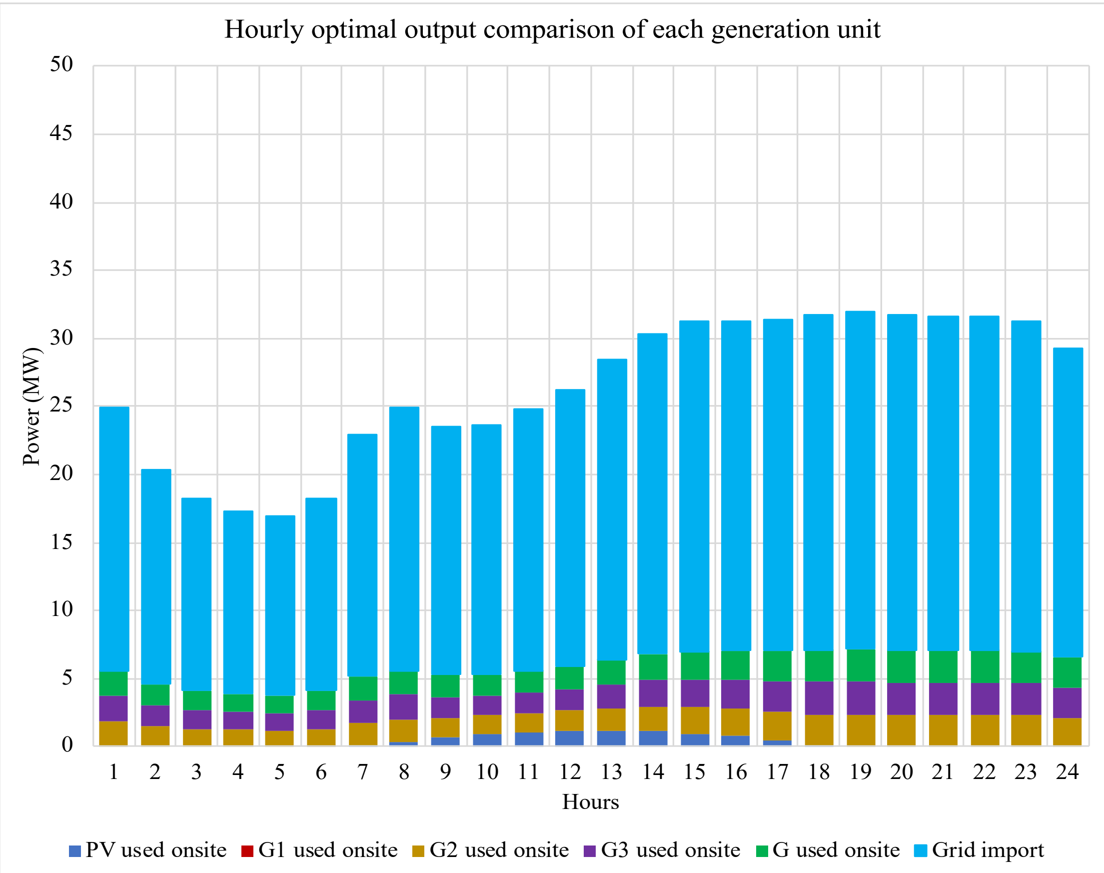

Figure 6-9 Optimal hourly usage comparison of each generating source in 15th January 2020, winter season using LM method

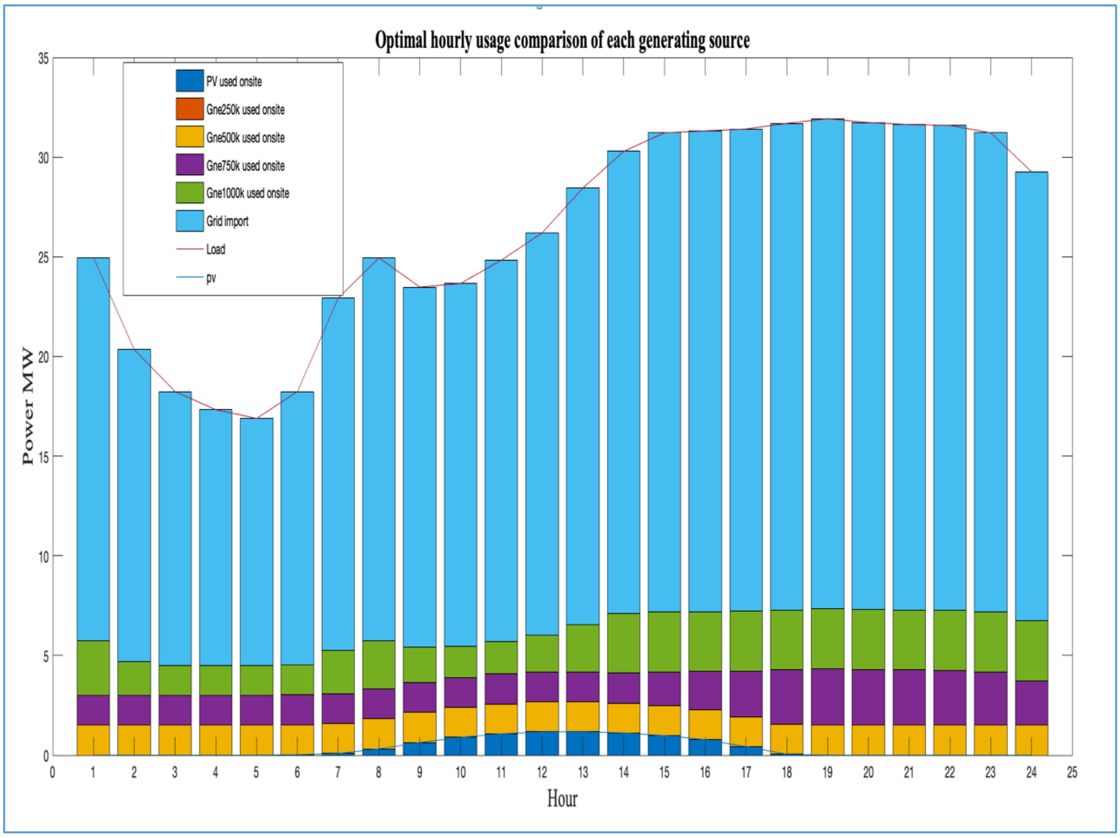

Figure 6-10 Optimal hourly usage comparison of each generating source in 15th January 2020, winter season using LP method

Figure 6-11 illustrates the comparison between the result of the total operation cost of all generation sources, including grid import for LM and LP methods during 24 hours on 11th July which was assumed as a representative day for the winter season. It was found that the results of the minimum operation cost for total generation sources in 12th July 2020 using LM and LP methods is £49,386 and £49,904 respectively.

The dispatch power using LM and LP succeed to obtain the approximate results of minimum operating cost while still meeting operators' constraints. Hence, the obtained results reveal the effectiveness of the LM and LP.

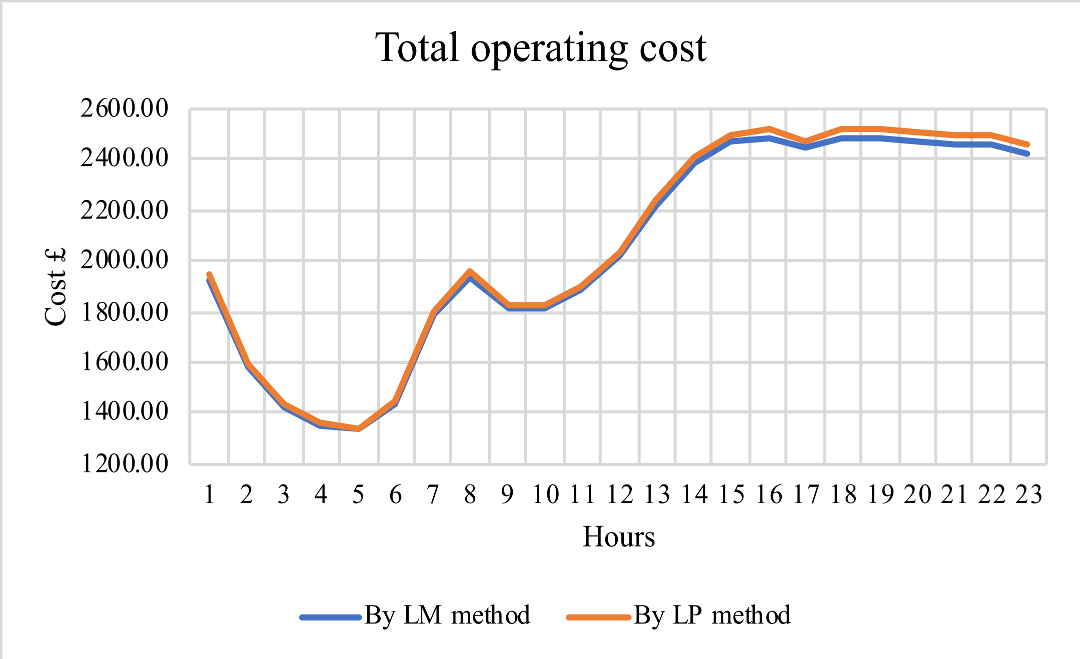

Figure 6-11 Comparison between LM and LP methods in total operation cost for generation supply in 15th January 2020 (winter)

6.9 Conclusions

Due to a severe shortage of generation in the Iraq power system (Ziyonah area of Baghdad), four groups of diesel generators with a10,500 kW total capacity and PV (200 systems 10kWeach) are assumed in section 6.4 to be integrated in the power system to overcome this problem. But The integrated generation units, including grid import need to be carried out by economics dispatch, which is how to get a minimum operating cost while still meeting operators' constraints. To solve this problem, it is necessary to design an optimisation tool for energy users or power operators to unlock their electricity flexibility of distrubuted generators and to assist in the decision-making process.

This chapter has presented two solution methodologies of economic power dispatch problems concerning the integration of distributed generation into electric power systems that are of most interest to the stakeholders planners and operators, policymakers and regulators, particularly for countries whose their power system facing a severe shortage of generation such as Iraq. Implementation is done using MATLAB programming, and the results of the optimal cost-effective allocation of generations and their total operation cost are presented.

LM and LP are optimasation tools that determine the optimal allocation of generation units are presented. The overall objective is to determine the optimal dispatch power for the diesel generators, taking into consederation that the bigger size of generators in the top priorty as their operating cost are cheaper, including PV and grid import to reduce the total operating cost for the integrated generation units to generate whenever is required to meet the peak during 24hour in the summer and winter season.

The importance of emission reduction is paramount in terms of environmental perspective and, hence the reduction of CO_2 emissions from diesel generators and penetration of more PV into the distribution network is encouraged.

The chapter has also presented the models of fuel cost for diesel generators at any loading based on the coefficients equation *α, β, and γ,* which are obtained using regression analysis in section 6.3.

Results demonstrate that the proposed for LM and LP is a highly suitable and simple approach to determining the optimal dispatch in the power system with various types of generator sources subject to several constraints.

Chapter 7

Conclusions and recommendations for future work

7.1 Introduction

This chapter reviews the conclusions of this research and summarises the key findings that answer the research questions. It provides a number of recommendations for power operators and policymakers in the context of the case study in Iraq for future work. This chapter also summarises the main limitations and outlines the contributions of the work.

7.2 Conclusions of the research

This study presents a comprehensive assessment of the use of diesel generators in Iraq. These were introduced due to the lack of electricity supply for a country that has suffered several decades of wars and international sanctions. The results of the case study in Baghdad describe a realistic situation to provide a clear picture and to address multiple directions of solutions, including future planning vision and to address current and future conditions.

In this research, existing off-grid diesel generators of the Zyounah region in Baghdad are investigated to provide an understanding of the challenges of these generators for the consumers in terms of their environmental and economic consequences. Models of both diesel fuel consumption and carbon emissions were created to determine the hourly fuel consumption, efficiencies and carbon emissions of a diesel generator during operation. The findings reveal that the efficiency of the diesel generator is inversely proportional to the fuel consumption rate, CO_2 emissions and rated power of the diesel generator with constant load demand. In other words, if the load is less than the generator's size, the generator's efficiency will drop, and the generator will consume a large amount of fuel and emit more CO_2 emissions. Hence, the rated power of a diesel generator should be close to the required load demand.

This study also presented an important challenge to the Iraqi power system and proposed the solution of integrating the diesel generators into the distribution network. The integration of distributed generation into electric power systems is of interest to the stakeholders; planners and operators, policymakers and regulators, particularly for countries whose power system faces a severe shortage of generation such as Iraq. It presents a methodology to find the best placement and the right size of the diesel generators in the distribution network of Ziyounah in the Baghdad area. The optimisation of their location and size has many advantages such as meeting the incremental demand, reducing the total real power losses and enhancing the network performance most effectively. The optimisation is solved by the combination of genetic algorithm (GA) techniques with power flow to evaluate the impact of the diesel generators on network performance, including through a reduction in real power loss and acoustic noise from the generators and improving the network voltage profile. The fitness evaluation function that drives the proposed method to the solution is the Network Performance Index (NPI).
The results in Chapter 4 showed that the determination of the best locations for connection generators with the help of the proposed Network Performance Index (NPI) leads to savings in electricity due to real power loss reduction in the network.

Load forecasting for maximum daily and hourly demand is implemented in this study using Linear Regression (LR) and ANN. Chapter 6 discusses minimising the operational cost of integrating the generators and accurately matching electricity production to consumption in the summer and winter seasons of 2020. A criterion of Mean Absolute Percentage Error (MAPE) was introduced to evaluate the model performance over the whole season. The finding reveals that the load forecasting using LR provides predictions of peak demand that are accurate enough to be used for planning the required generation units at peak times to supply the area based on the maximum daily peak predicted demand during the month. However, the result for hourly peak demand using ANN is more accurate than the LR technique according to the MAPE. The forecasted results for 24-hour demand produced from ANN technique is more suitable compared to the result from LR technique. Load forecasting using LR to predict peak demand one month ahead (January 2020 and July 2020) and ANN to predict hourly peak demand for one day ahead (15 January 2020 and 11 July 2020) was undertaken.

Due to the mismatch between generation and maximum demand (Ziyonah area of Baghdad), four groups of diesel generators with a 10,500kW total capacity and PV (200 systems 10kW each) are integrated into the power system to overcome this problem. The integrated generation units, including grid imports, were scheduled by economic dispatch, to get a minimum operating cost while still meeting operators' constraints. This research presented two solution methodologies of economic power dispatch, using Lagrange multiplier and linear programming methods.

Implementation is done using MATLAB programming, and the results of the optimal cost allocation of generators and their total operation cost are presented. The overall objective is to determine the optimal dispatch power for the diesel generators, including PV and grid import to reduce the total operating cost for the integrated generation units to generate whenever is required to meet the peak during 24hour in the summer and winter season. Results demonstrate that the proposed Lagrange Multiplier and Linear Programming are suitable and simple approaches to determining the optimal dispatch in the power system with various types of generator subject to several constraints.

7.3 Answering the research questions

RQ1: How do the third parties sell electricity from the diesel generators to Iraqi consumers?

Chapter 3 answered RQ1 by comparing the electricity tariff for the government supply and neighbourhood generators for lower-class households, i.e. these customers with 1500kWh of monthly consumption. The finding revealed that the cost from diesel generators is 47 times more expensive than the electricity provided by the government. Therefore, the efforts to reduce the contribution or costs of neighbourhood diesel generators could improve electricity affordability for most, if not all, families., The household might pay as much as £ 3000 per year to the operator of the neighbourhood generator as the generator charges are as much as £15/month per Ampere of capacity.

RQ2: How are carbon emissions and fuel consumption estimated for a diesel generator at any operating load?

A study described in chapter 3 was conducted to obtain models for carbon emissions and fuel consumptions for a diesel generator used linear regression analysis with two independent variables, which are nominal capacity and power output of the diesel generator based on the collected data in this research. It was found that the results of both models depend on the size (rating) of the generator and the load at which the generator operates at, i.e. depend on the efficiency of the generator.

RQ4: How would the integration of the stand-alone neighbourhood diesel generators into the Iraq power system provide technical and economic benefits with low environmental effect?

To answer this question, a study in chapter 4 was conducted to show the advantages of integrating diesel generators in Iraq's power system which is facing significant challenges due to the mismatch between generation and supply. The finding reveals that if these existing diesel generators were to be well-placed, they could provide benefits to the grid by helping to reduce the real power losses, stabilize the grid voltage, and improves the network performance. In addition, the integration of diesel generators in suitable locations in the power system based on the optimization in chapter 4 contributes to minimizing the level of acoustic noise from existing diesel generators that are installed at the neighbourhood location.

RQ5: Is there a strong relationship between the maximum power demand and the maximum temperature in Iraq during the days in the summer, winter and spring seasons?

A study using correlation and regression analysis has been conducted to provide information on the strength of the linear relationship between the daily peak demand and maximum temperature by using a simple linear technique in chapter 5. The finding reveals that the correlation indicates a strong relationship between maximum loads and maximum temperature in the summer season as the daily peak load is proportional directly to the ambient temperature during this season. In the winter season, the daily peak load is inversely proportional to the ambient temperature. In the spring season, the correlation has a weak relationship compared to the correlation coefficient in the summer and winter seasons. This means the spring load is not affected significantly by the fluctuation of temperature during this season. This is because the majority of consumers are not using either the air conditioner or water heaters on spring days.

RQ6: What are the techniques considered to predict the daily and hourly peak demand, which is required for planning and operating, for Ziyonah area of Baghdad based on the historical data collected in this research?

In chapter 5, Linear Regression (LR) and Artificial Neural Networks (ANN) techniques are implemented to improve a decision of the daily and hourly peak demand during the summer and winter days 2020. The models were trained using historical load data to determine the model parameters for the LR model and the weights of the network for ANN. Then, the use of the obtained weights or parameters allows the prediction of the output for a given input. Mean Absolute Percentage Error (MAPE) is considered to evaluate the model performance.

After analysing the model prediction results, it was found that the LR technique offers a higher degree of prediction accuracy in daily peak load forecasting compared to the ANN technique, whilst, hourly peak load forecasting result was less accurate than the result from ANN.

RQ7: Can the operator overcome the mismatch between demand and supply, i.e. what are the required numbers of diesel generators and PV to meet the peak daily demand for Ziyounah area of Baghdad in the summer and winter season of 2020? What is the method to calculate the number of diesel generators?

Chapter 6 has presented the minimum number of diesel generators required for Ziyouna district/ Baghdad based on forecasting load. In the summer season, all the diesel generators, 19 generators with a total capacity of 10,500kW which are assumed in chapter 6, are required to be integrated into the distribution network of Ziyounah due to a severe shortage of generation during this time. In the winter season, the number of diesel generators required varies and depends on the predicted maximum daily demand in chapter 5. This calculation is simple to the problem and it can be conducted to impose priority order, wherein the most efficient units (the bigger size of diesel generators) are loaded first to be followed by the less efficient units (the smaller size of diesel generators) in order as the peak load increases. Therefore, if < PD, we increase the number of units otherwise, if > PD, we reduce the number of units. The best result occurs when = PD, taking into consideration that the bigger size of generators is the top priority.

RQ8: In what ways can the operators for the Iraq power minimise the total operating cost for integrated generation sources during 24 hours while meeting the demand?

To achieve this goal, a study of the economic dispatch problem has been conducted in chapter 6 to obtain the optimal cost allocation of diesel generator, PV and Grid import power. In this research, economic dispatch analysis was carried out using Lagrange multiplier and linear programming methods and assisted by the MATLAB application to find forecast demand in the summer and winter seasons. It was found that this approach can allocate the power generation output so as to minimise the total operational cost while meeting the constraints of total load demand.

7.4 Research limitations

The most significant limitations shaping the scope of this study are as follows;

- Detailed data for diesel generators and power systems in the Iraqi context are not available or are difficult to obtain. This lack of data limited the depth of the case study information.
- The numerous interruptions and shutdowns in the national grid in most Iraqi regions was one of the major barriers that affect the accuracy of the collected data from the power operators or Ministry of Electricity in Iraq.
- Because of the current problems in Iraq, especially in terms of security, safety, and political instability, it was difficult to achieve some plans and obtain relevant national reports on current and future strategies. In particular, the selection of formal leaders and experts in face to face interviews via the validation stage often required official approval and specific meetings, this impacted on the selection procedure.

7.5 Contribution of the work

This study describes, a realistic problem for the power systems in the context of the case study in Iraq. Due to the lack of published information regarding the diesel generators and power systems in Iraq, which is faced with challenges, this work provides valuable and clear information for planners and researchers to enhance current and future conditions and reduce the research gap between this study and previous studies. This contributes to identifying multiple factors that must be considered by the study. The contribution of the work is summarised as:

- **The development of a model of diesel fuel consumption**

A model of fuel consumption was built for diesel generators whose capacities were in the range of 200kW to 1000kW. The proposed model was designed based on two variables (the rated and output power of a generator) to estimate the hourly fuel consumption of diesel generators during operation. The parameters of the model are found by using regression analysis. The model also can be used to estimate the hourly carbon emissions for the generators taking into consideration the carbon intensity or the emission factor for the fuel of the generator.

- **The development of optimisation tool of optimal locations for diesel generators in the distribution network**

The algorithm of the optimisation tool was developed to quantify the benefits of the integration of diesel generators in the real distribution network based on the Network Performance Index. This index was designed to represent a comprehensive improvement in the network performance such as real loss reduction, voltage profile improvement. In addition, the proposed algorithm was developed to consider the acoustic noise factor that affects the environment.

- **Investigating the correlation and regression between peak daily power demand and peak daily temperature**

Correlation and regression analysis were used for the case study of Iraq to describe the strong relationship between the daily peak residential demand and maximum temperature in the summer, winter and spring seasons. A mathematical model representing the correlation coefficient (R) and the regression coefficients B_0 and B_1 was presented in this study.

- **Build a method of daily and hourly peak demand forecasting for Iraq power system**

A model of predicting the daily and hourly peak demand was presented using simple linear regression analysis for the first time to provide the power operator for Ziyounah in Baghdad with valuable information that can be used for minimising the operational cost for integrated unit generations and accurately match electricity production to consumption in summer and winter seasons of 2020.

- **Calculating the minimum number of generators required**

The calculation of the minimum number of the required diesel generators was presented to meet the peak daily demand and help avoid or reduce the number of blackouts for the Ziyounah area of Baghdad.

- **The development of a model of fuel cost for diesel generators**

A model of fuel cost was built for diesel generators to estimate the quantity of fuel consumption uses during operation. Therefore, the proposed model can be used for optimal scheduling of generation using the Lagrange multipliers to obtain the minimum operating cost for diesel generators. The model coefficients α, β, *and* γ were calculated using linear regression analysis as a quadratic function.

- **The development of an optimisation tool using Linear Programming**

A linear programming method for integrated diesel generators, PV and import grid was developed to obtain the optimal cost-effective allocation of generations. The proposed model was implemented using MATLAB programming to minimise the operation cost for the integrated generation sources while meeting the operating constraints for the Iraq power system.

7.6 Recommendation for future work

The following future research work was identified to extend the work reported in this thesis:

- In this study, the load demand of Ziyonah area of Baghdad was uncontrollable. It hits its peak on hot summer days because the majority of consumers use air conditioning. With rapid smart grid technology development, the customer can actively participate in mutual information communication between the power operation company and the smart devices including air-conditioning appliances in real-time. If the power operator uses controllable domestic loads during specific time, i.e. air condition appliances, the money spent to procure these services may be used as incentives to attract the residential consumers to load control schemes. Therefore, the number of controllable loads available from these appliances can reduce the gap between the demand and the generation supply.

- In this work, diesel generators and PV are integrated into the Iraq power system to overcome the shortage of generation in the Iraq power system in cost-effective manner, but the outputs from these generation units are difficult to control in real time during the day. Therefore, it is necessary to develop other flexible solutions to manage the power system when integrating large amounts of small and dispersed generation sources. In this context, it is recommended to use a Virtual Power Plant to provide fast balancing services to the system in the active distribution system. To do this, each feeder in Zyounah distribution network (consists of 14 feeders) must have a control box and smart metering for collecting data from the consumers and automatic control of underlying devices. Control strategies of a Virtual Power Plant will be investigated, with a focus on active power control of distributed diesel generators, and the addition of renewable energy sources (PV plus storage systems) to support efficient and sustainable energy. Both economic and environmental objectives will be considered, e.g. minimise the operation costs of diesel and reduce CO2 emissions. Several parameters should be introduced into the controller design to consider the uncertainties of intermittent generation and increase the lifetime of storage systems. Although the power system is state-owned and managed, the Iraqi ministry of electricity awarded several Independent Power Producer (IPP) contracts in recent years, which lay the foundation for Virtual Power Plant operators to contribute to reducing the power deficit.

- Iraq has high solar irradiance values all year round, with Baghdad about 3,300h of bright sunshine annually, and this clean energy is yet to be exploited. Therefore, it is very important to integrate more PV into the power system with the diesel generators for dispatch power generation because they are suitable for the environment and contribute to sustainability and energy security objectives.

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Appendix A

This appendix describes the collected data of forecasted maximum temperature for the winter and summer seasons provided by IMOS.

Table 1: Forecasted maximum temperature in January 2020 for a winter season, providing by IMOS for Load forecasting

Date	Max temperature forecasted (input)	Date	Max temperature forecasted (input)
01/01/2020	13	16/01/2020	13
02/01/2020	12	17/01/2020	10
03/01/2020	13	18/01/2020	14
04/01/2020	14	19/01/2020	16.4
05/01/2020	13.5	20/01/2020	15
06/01/2020	14	21/01/2020	16.8
07/01/2020	15	22/01/2020	14
08/01/2020	19	23/01/2020	13
09/01/2020	19	24/01/2020	12.6
10/01/2020	17.5	25/01/2020	15
11/01/2020	18	26/01/2020	12
12/01/2020	20	27/01/2020	12
13/01/2020	19	28/01/2020	12.5
14/01/2020	17	29/01/2020	10.5
15/01/2020	12	30/01/2020	13

Table 2: Forecasted maximum temperature in September 2020 for a summer season, providing by IMOS

Date	Max temperature forecasted (input)	Date	Max temperature forecasted (input)
01/09/2020	45	16/09/2020	41
02/09/2020	43	17/09/2020	39.5

03/09/2020	42.5	18/09/2020	41
04/09/2020	42	19/09/2020	40
05/09/2020	42	20/09/2020	43
06/09/2020	43	21/09/2020	40.5
07/09/2020	42	22/09/2020	39
08/09/2020	41.5	23/09/2020	39.5
09/09/2020	40	24/09/2020	38
10/09/2020	39.5	25/09/2020	39
11/09/2020	40	26/09/2020	37
12/09/2020	41	27/09/2020	39
13/09/2020	42	28/09/2020	38
14/09/2020	44	29/09/2020	37
15/09/2020	42	30/09/2020	38

Appendix B

This appendix shows the training and testing data required for load forecasted in Zyounah for the summer and winter seasons.

Table 3: The training data required for the summer season for Zyonah district for Load forecasting

	Input data for training (MW) July 2019 (summer season)				Target for training (MW)
Hours	(Day1) Sunday 7 July19	(Day2) Monday 8 July19	(Day3) Tuesday 9 July19	Day4) Wednesday 10 July19	Day4) Thursday 11 July 19
1	40.32	40.6	41.2	41	40.698
2	38.4	38.64	38.72	38.9	39
3	35.9	36.3	37.1	35.4	36.3
4	35.52	35.742	34.4	35.89	35
5	34.08	34.293	34.36	34.435	34
6	33	33.327	35	33.465	33.5
7	33.12	33.327	34	33.465	34.5
8	33.6	33.81	33.88	33.95	33.91

9	35.52	35.742	34.9	35.89	36
10	38.88	39.123	38.7	39.285	38
11	41.28	41.638	42	41.71	41
12	43.2	43.47	43.56	44	43.7
13	44.64	44.919	45.3	45.10	44.9
14	46.08	46.36	46.46	46.56	47
15	47.52	47.81	47.91	48.015	47.96
16	48	48.3	48.45	48.51	49
17	48	48.3	49	48.5	48.45
18	42.24	42.504	43	42.68	43
19	43.68	43.953	44	45	44.08
20	42.72	42.987	43.07	43.165	43
21	42.24	42.504	42.59	42.68	41
22	41.28	41.538	41.7	41.71	41.5
23	41.3	41.7	40.2	41.71	40.6
24	40.8	41.055	41.2	41.3	39.9

Table 4: The testing data required for the summer season for Ziyounah district for Load forecasting

	Input data for testing (MW) July 2020 (summer season)				Predicted demand (MW)	Actual demand (MW)
Hours	(Day1) Sunday 7 July20	(Day2) Monday 8July20	(Day3) Tuesday 9July20	(Day4) Wednesday 10 July20	(Day5) Thursday 11July20	(Day5) Thursday 11 July20
1	41	41.4	42	42	41.5	40.488
2	39.04	39.08	39.2	40	38.3	38.56
3	36	36.5	36	37	36.4	37.114
4	36.11	36.14	36.15	37	35	35.668
5	34.64	34.68	34.68	35.5	34.91	34.222
6	33.67	34.1	33.71	34.3	34.32	33.258
7	33.67	33.70	33.71	34.5	34.5	33.258
8	34.16	34.19	34.2	35	34.65	33.74

9	36.11	36.6	36.7	37	37	35.668
10	38.2	39.56	39.57	40.5	39.45	39.042
11	41.96	42.011	43	43	43.02	41.452
12	43.92	42	43.97	45	45	43.38
13	45.38	45.4305	45.43	46.5	46	44.826
14	46.84	46.896	46.90	48	48.5	46.272
15	48.31	49	48.5	49.5	48.78	47.718
16	48.8	48.85	49	50	48.88	48.2
17	48.8	49	48.85	50	48.88	48.2
18	42.94	43	42.99	44	45	42.416
19	44.40	44.45	45	45.5	45.93	43.862
20	43.43	43.47	43.48	44.5	45.31	42.898
21	42.94	42.98	42.99	44	44.68	42.416
22	41.96	42.011	42.01	43	43.29	41.452
23	40	42.011	40	40.9	40	41.452
24	41.48	42	41.52	42.5	41.96	40.97

Table 5: The training data required for the winter season for Zyonah district for Load forecasting

	Input data for training (MW) July 2019 (winter season)				Target for training (MW)
Hours	(Day1) 11 Jan19	(Day2) 12 Jan19	(Day3) 13 Jan19	Day4) 14 Jan19	Day4) 15 Jan19
1	21.7	22	22.4	22.75	22.8
2	17.98	18.386	19	18.85	19.14
3	16.43	16.801	16.96	17.225	17
4	15.7	15.85	16	16.25	16.5
5	14.88	14	15.36	15.1	15.84
6	16.43	16.801	16.96	17.225	17
7	19.84	20.288	20.48	20.8	20.9
8	21.7	22.19	23	22.75	23.1
9	20.305	20.7635	20.96	21.2875	21

10	20.46	21	21.12	21.45	21.78
11	21.576	22.0632	22.272	22.62	21.9
12	22.94	23.458	23.68	24.05	24
13	24.8	25.36	25.7	26	27
14	26.35	26.945	27.2	27	28.05
15	27.9	28.53	28.8	29.25	29
16	29	28.847	29.12	29.575	30.03
17	28.52	29.164	29.44	29.9	30.36
18	29.76	30.432	30.72	31.2	31.68
19	31.5	31.7	32	32.5	33
20	29.977	30.6539	30.944	31.4275	31
21	29	30.115	30.4	30.875	31.35
22	29.295	29.9565	30.24	30	31.185
23	27.9	28.53	28.8	29	28.8
24	25.42	24.8	26.24	26.65	27.06

Table 6: The testing data required for the winter season for Zyonah district for Load forecasting

	Input data for testing (MW) July 2020 (winter season)				Predicted demand (MW)	Actual demand (MW)
Hours	(Day1) 11 Jan20	(Day2) 12 Jan20	(Day3) 13 Jan20	Day4) 14 Jan20	Day4) 15 Jan20	Day4) 15 Jan20
1	23.8	24.15	24.5	24.29	24.95	23.73
2	19.72	20.01	20.3	20.126	20.34	19.662
3	18.02	18.285	18.55	18.391	18.24	17.967
4	17	17.25	17.5	17.35	17.33	16.95
5	16.32	16.56	16.8	16.656	16.89	16.272
6	18.02	18.285	18.55	18.391	18.24	17.967
7	21.76	22.08	22.4	22.208	22.92	21.696
8	23.8	24.15	24.5	24.29	24.95	23
9	22.27	22.5975	22.925	22.7285	23.48	22.2045

10	22.44	22.77	23.1	22.902	23.66	22.374
11	23.664	24.012	24.36	24.1512	24.83	23.5944
12	25.16	25.53	25.9	25.678	26.20	25.086
13	27.2	27.6	28	27.76	28.45	27.12
14	28.9	29.325	29.75	29.495	30.29	28.815
15	30.6	31.05	31.5	31.23	31.22	30.51
16	30.94	31.395	31.85	31.577	31.32	30.849
17	31.28	31.74	32.2	31.924	31.41	31.188
18	32.64	33.12	33.6	33.312	31.69	32.544
19	34	34.5	35	34.7	31.93	33.5
20	32.878	33.3615	33.845	33.5549	31.73	32.7813
21	32.3	32.775	33.25	32.965	31.63	32.205
22	32.13	32.6025	33.075	32.7915	31.59	32.0355
23	30.6	31.05	31.5	31.23	31.22	30.51
24	27.88	28.29	28.7	28.454	29.26	27.798