AN OPTIMAL ENERGY MANAGEMENT SYSTEM FOR SUSTAINABLE CITY BASED ON RENEWABLE ENERGY SOURCES

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Prepared as
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I certify that in my opinion the thesis submitted by Mohamed Ali ELWEDDAD titled "AN OPTIMAL ENERGY MANAGEMENT SYSTEM FOR SUSTAINABLE CITY BASED ON RENEWABLE ENERGY SOURCES" is fully adequate in scope and in quality as a thesis for the degree of Doctor of Philosophy.

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Mohamed Ali ELWEDDAD

ABSTRACT

Ph.D. Thesis

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The present power generation system is confronted with difficulties such as reducing pollution, rising global energy consumption, high reliability requirements, energy cleanliness, and planning constraints. To achieve a sustainable and intelligent energy system, large and central generating stations are converted into small generating systems located close to residential buildings. Therefore, the design and installation of a micro grid lead to energy and cost savings. The micro grid consists of a number of loads, smart meters, communication system, traditional and alternative power generators, and storage systems. Energy management is necessary for the uninterrupted and reliable operation of a micro grid. Thus, energy management should be prioritized when developing multi-source system for economic and sustainable growth.

Optimum scheduling of power generators operation leads to proper utilization and optimization of available energy sources while maintaining a balance between supply and demand. Many programs and smart algorithms can be used to manage and control the production and consumption of energy generated in a micro grid in order to calculate operating costs, reduce harmful gas emissions, maximize the use of renewable energy, reduce the cost of energy storage, and respond quickly to high loads., reduce energy cost, and finally simulate the components of the micro grid while carefully considering the constraints.

This thesis aims to manage energy within the micro grid to supply residential loads effectively and cheaply. The first objective is to analyze six combinations of different energy sources to determine the best hybrid source in addition to improving the size and number of generation and storage units based on the cheapest total costs of the project. After that, obtaining the best energy source by comparing several economic and environmental factors help the decision-maker determine the best suitable combination for feeding a residential building to ensure optimal control of micro grids by considering reducing energy costs and reducing gas emissions as a main goal.

Three research stages were investigated to determine the best hybrid system in terms of cost and sustainability. The first stage is determining the best size and optimization of the proposed system; the goal of this section is to use multi criteria decision-making algorithms to select the optimal design of six energy systems for sustainable energy to supply some buildings located in Tripoli. In this part, the HOMER software results were used to select all of the criteria for decision-making analysis. At first, the study used Homer software to determine optimal energy systems that can meet load demand while minimizing net present cost and the cost of energy. The technical, economic, and environmental results are explored for the most suitable system companion. To select the best HRE system, two decision-making algorithms (Vikor and Topsis) were implemented. Following that, in comparison to the other HRES, the final scores proved that PV /WT/Batt/Diesel generators are the best micro grid component for supplying the building. This proves that significant investment in hybrid PV/WT/Batt/Diesel generator systems will give the Libyan residential sector an excellent chance of achieving sustainable power.

The second part of this study is a control strategy including "ON/OFF" operation of the available energy sources, including photovoltaic system PV- diesel generator, wind system, and energy storage banks using a Genetic algorithm. Then the output results from the algorithm are used as input data to machine learning models; in this phase, three algorithms were used to predict load and supply dispatch for the next 720 hours. The final part of the study compares the results obtained from the classification algorithms. The tables below show the high performance of the Decision Tree and Random Forest algorithms, where the accuracy reached 100% and 99%, respectively, in addition to the KNN algorithm, which was the worst with an accuracy of 90%.

Key Words **:** Renewable Energies, Micro grid, Hybrid Energy System, Energy Management System, machine learning Algorithms, Energy consumption predication, Cost, Emissions reduction.

Science Code : 90544

ÖZET

Doktora Tezi

YENİLENEBİLİR ENERJİ KAYNAKLARINA DAYALI SÜRDÜRÜLEBİLİR ŞEHİRLER İÇİN ENERJİ YÖNETİM SİSTEMİ OPTİMİZASYONU

Mohamed Ali ELWEDDAD

Karabük Üniversitesi
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Mevcut enerji üretim sistemi, kirliliğin azaltılması, artan küresel enerji tüketimi, yüksek güvenilirlik gereksinimleri, enerji temizliği ve planlama kısıtlamaları gibi zorluklarla karşı karşıya bulunmaktadır. Daha sürdürülebilir ve akıllı bir elektrik enerjisi sistemine geçmek için, merkezi üretim tesisleri daha küçük ve dağıtık üretim sistemlerine evrilmektedir. Sonuç olarak, bir grup yük ve farklı tipte yenilenebilir enerji kaynağı ve batarya grubundan oluşabilen dağıtık enerji kaynaklarının bir araya geldiği mikro şebeke uygulamaları olarak kabul edilen sistemler ortaya çıkmaktadır. Bir dizi dağıtık enerji kaynağının olduğu sistemlerde enerji yönetimi, mikro şebeke sisteminin güvenilir bir şekilde çalışması için gereklidir. Sonuç olarak enerji yönetimi, ekonomik ve sürdürülebilir kalkınma için mikro şebeke operasyonunun kritik bir bileşenidir.

Enerji üretim operasyonunun optimum zamanlaması ile arz ve talep arasında bir denge korurken mevcut enerji kaynaklarının uygun şekilde kullanılmasına ve optimizasyonuna da imkân sağlanmaktadır. Mikro ölçekli enerji üretim tesislerinde optimum çalışma noktasını bulmak belli durumlarda mikro şebekede mevcut olan enerjinin daha verimsiz kullanımına yol açabilir. Bu problemi çözmek için ele alınan çeşitli enerji yönetimi modelleri; mikro şebeke değişkenleri ve şebeke tasarımı ile hücresel enerji üretim sistemlerinin işletme maliyetlerinin, geleneksel üretim kaynağı emisyon maliyetlerinin, yenilenebilir enerji kaynaklarının maksimum kullanımının, batarya bozulma maliyetinin, talep yanıt teşviklerinin ve yük maliyetinin nesnel fonksiyonlarını içermektedir.

Bu tez, konutların enerji ihtiyaçlarını etkili ve ucuz bir şekilde karşılamak için mikro şebekedeki enerjiyi yönetmeyi amaçlamaktadır. İlk amaç, farklı enerji kaynaklarının altı kombinasyonunu en iyi hibrid enerji kaynak grubunu belirlemek için karşılaştırarak analiz etmek ve ek olarak projenin en ucuz toplam maliyete göre üretim ve depolama birimlerinin boyutunu ve sayısını iyileştirmeyi sağlamaktır. Ardından, bir konutun enerji maliyetlerini azaltma ve ana hedef olarak emisyonu düşürme önceliğiyle ve en iyi enerji kaynağını elde etmek için çeşitli ekonomik ve çevresel faktörleri karşılaştırarak mikro şebekenin optimal yönetimini sağlayacak alternatifi belirlemesi sağlanmıştır. Maliyet ve sürdürülebilirlik açısından en iyi hibrit sistemi belirlemek için üç araştırma aşaması yürütülmüştür. İlk aşama, önerilen sistemin en iyi boyutunu ve optimizasyonunu belirlemektir. Bu aşamada, Trablus'ta bulunan bazı binaları sürdürülebilir enerji ile beslemek için altı farklı enerji sisteminin optimal tasarımını seçecek çok kriterli karar verme algoritmaları kullanılmıştır. Bu kısımda, HOMER yazılım sonuçları, karar verme analizi için tüm kriterleri seçmek için kullanılmıştır. Çalışmada, mevcut maliyeti ve enerji maliyetini en aza indirirken yük talebini karşılayabilen optimal enerji sistemlerini belirlemek için teknik, ekonomik ve çevresel faktörler en uygun sistem tasarımını hedefleme algoritmasına göre çalıştırılmıştır. En iyi hibrit enerji sistemini seçmek için iki karar verme algoritması (Vikor ve Topsis) uygulanmıştır. Bunu takiben, diğer hibrit enerji sistemlere kıyasla, son değerler, FV/Rüzgâr/Batarya/dizel jeneratör tasarımının binayı beslemek için en iyi mikro sistem bileşeni olduğu kanıtlanmıştır. Bu sonuç, hibrid FV/Rüzgâr/Batarya/dizel jeneratör kapsayan sistemlerine yapılacak yatırımın Libya konut sektöründe sürdürülebilir enerji üretim tasarımı fırsatı sunulabileceği göstermektedir.

Çalışmanın ikinci kısmı, dizel jeneratör, güneş fotovoltaik -rüzgar türbini ve batarya Mevcut enerji üretim sistemi, kirliliğin azaltılması, artan küresel enerji tüketimi, yüksek güvenilirlik gereksinimleri, enerji temizliği ve planlama kısıtlamaları gibi zorluklarla karşı karşıya bulunmaktadır. Daha sürdürülebilir ve akıllı bir elektrik enerjisi sistemine geçmek için, merkezi üretim tesisleri daha küçük ve dağıtık üretim sistemlerine evrilmektedir. Sonuç olarak, bir grup yük ve farklı tipte yenilenebilir enerji kaynağı ve batarya grubundan oluşabilen dağıtık enerji kaynaklarının bir araya geldiği mikro şebeke uygulamaları olarak kabul edilen sistemler ortaya çıkmaktadır. Bir dizi dağıtık enerji kaynağının olduğu sistemlerde enerji yönetimi, mikro şebeke sisteminin güvenilir bir şekilde çalışması için gereklidir. Sonuç olarak enerji yönetimi, ekonomik ve sürdürülebilir kalkınma için mikro şebeke operasyonunun kritik bir bileşenidir.

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Çalışmanın ikinci kısmı, dizel jeneratör, güneş fotovoltaik -rüzgar türbini ve batarya dahil olmak üzere mevcut enerji kaynaklarının Genetik algoritma kullanarak "AÇIK/KAPALI" çalışmasını içeren bir kontrol stratejisini açıklamaktadır. Daha sonra algoritmanın çıktı sonuçları, makine öğrenimi modellerinde girdi verileri olarak kullanılarak, önümüzdeki 720 saat boyunca arz talep dağılımı üç farklı algoritma kullanılarak tahmin edilmiştir. Çalışmanın son bölümünde ise, en iyi performansı gösteren algoritmayı belirlemek için makine öğrenme tekniklerinin, yani Rastgele Orman (RF), Karar Ağacı (DT) ve K-En Yakın Komşuların (KNN) sonuçlarını karşılaştırılmaktadır. Sonuçlar, DT tekniğinin sınıflandırma uygulamasında %100 doğrulukla en iyi performansa sahip olduğunu göstermiştir. Ayrıca, RF yaklaşımının %99'e varan doğrulukla kabul edilebilir sonuçlar verdiğini ve KNN algoritmasının %90'lik bir değerle doğruluk açısından en kötüsü olduğunu göstermektedir.

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Anahtar Kelimeler : Yenilenebilir Enerjiler, Mikro Şebeke, Hibrit Enerji Sistemi, Enerji Yönetim Sistemi, makine öğrenimi Algoritmaları, Enerji tüketimi tahmini, Maliyet, Emisyon azaltımı.

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ABBREVITIONS

BESS	: battery energy storage system
BOS	: balance of system
COE	: cost of energy
DG	: distributed generation
EMS	: energy management system
FC	: fuel cells
GA	: genetic algorithm
PSO	: particle swarm optimization
GHG	: greenhouse gas
HOMER	: hybrid optimization model for electric renewable
HPS	: hybrid power stations
HRES	: hybrid renewable energy sources
ICC	: Initial capital cost
LCC	: life cycle cost
LPP	: loss of load probability
LOLE	: loss of load expectation
LOLR	: loss of load risk
LOPS	: loss of power supply
LPSP	: loss of power supply probability
LRIC	: long run ıncremental cost
MG	: micro generation
NPC	: net present cost
NPV	: net power variation
PV	: photo voltaic
RES	: Renewable energy source

KNN	: K-Nearest Neighbor
DT	: Decision Tree
RF	: Random Forest
ML	: Machine Learning
TOU	: time-of-use
WT	: wind turbine
PV	: PV modules (W)
APV	: area of the PV module (m2)
Npv	: modules number of PV modules
GPV	: efficiency of PV module (%)
Gbatt	: efficiency of battery (%)
Ginv	: efficiency of inverter (%)
Ewt	: efficiency of wind turbine (%)
RF	: renewable fraction (%)
DoD	: depth of discharge of battery storage (%)
Bsv	: battery storage voltage (V)
AI	: Artificial intelligence
P_{wout}	: the electrical power delivered by the turbine (W)
V_{cin}	: cut-in speed of wind turbine (m/s)
Vi	: instantaneous speed of wind (m/s)
Vr	: rated speed of wind turbine (m/s)
Vco	: cut-out speed of wind turbine (m/s)
Nturbines	: number of Wind turbines
Aw	: total swept area of wind turbine in (m2)
Mbatt	: the required battery system (A h)
Ad	: days of Autonomy (days)
nbatt	: number of required battery storage
Soc_{bat}	: state of Charge at time t (W h)
Soc_{min}	: minimum state of charge (W h)
Soc_{max}	: maximum state of charge (W h)
CO_2	: Carbon dioxide emission at time t (kg)
Ebatt	: out output energy from battery storage at time t (W h)
Egenout	: output energy from Generator at time t (W

PART 1

INTRODUCTION

1.1. HISTORY

The primary source of power generation is a fossil fuel, but this option negatively impacts the environment significantly with carbon and its pollutants. As a result, harmful emissions are the primary issue in the world today since they destroy the atmosphere's greenhouse system. Energy sources such as wind, solar, biomass, and hydropower can help solve this issue. Several countries today are dealing with concerns related to energy and environmental security. The world's population is expanding exponentially, which has resulted in a steady rise in energy demand, mainly for electricity. The rising trend in energy application is a 2.8% annual increase. Since the current configuration of energy sources cannot meet the increasing need for power globally [1]. Alternative sources are being considered because of the rising costs of conventional electricity and environmental damage. Hence, renewable energy systems can be grid-connected or off-grid. Off-grid hybrid sources with a diesel generator and battery unit power remote areas. The best off-grid system size is studied in the literature with relation to a maximum renewable fraction (RF), low (NPC), The lowest cost per kilowatt hour of energy (COE), and reduction of loss of power probability (LPSP) [2], [3]. Many papers have also been published on how to reduce co2 emissions, unmet load and maximize the employment creation factor [4], [5]. Earlier research also assessed the optimal hybrid system size regarding social, technological, and economic benefits using many objectives and criteria.

Accessibility to electrical power is vital to decreasing poverty in rural places where human progress is typically minimal [6], [7]. However, a considerable percentage of the global population, 17.8%, cannot access electricity, which indicates poor human advancement, according to a study in 2014 [8]. The population's living standards will rise, through efficient energy use, improving education, higher net incomes, and increasing use of electrical appliances, leading to new employment opportunities [10]. Several authors have considered the Job Creation factor when designing HRES [11]. Many economic jobs might be created by clean energy, and a number of these opportunities would stay in the area because they involve infrastructure construction. The economy can be enhanced by shifting funds from energy costs to infrastructure development, encouraging employment creation. According to many studies, increasing the use of energy-efficient technologies and sustainable power sources generates financial benefits by creating jobs and protecting the economy from the economic and political risks associated with an excessive reliance on fuel sources. This review focuses on power generation management because it is the most significant vital energy section developing quickly and is the location of most employment/job creation research [12]. In addition to other factors, the population, gross domestic product, and energy prices are all intimately related to energy consumption. In order to secure sustained economic growth, Power management contributes to self-sufficiency and cost-effectiveness. In order to plan for future demand, establish conservation strategies, determine the most valuable energy resources, optimize energy use, formulate plans for increased consumption management is necessary. In order to predict energy demand, energy models are created utilizing time series analysis. It supports developing and designing load management techniques [13].

This study focused more on the accuracy of the methods used in forecasting energy consumption. Its primary goal is to produce an energy usage predictive model for intelligent buildings utilizing various machine learning techniques. Advances in machine learning studies have dramatically impacted intelligent building energy management since it is necessary to lower consumption in residential and industrial buildings. Additionally, it helps industrial companies expect the development of their factories vs. load demand and predict the energy demand on their system over the long term.

Related literature review several studies have analyzed the best design of microgrids, taking into account sustainable energy and demand response approaches. The required sizing aims have a significant influence on optimal power scheduling. Cagnano et al.

[19] investigated the present principal design characteristics and defined several control methods required to enable microgrids' cost-effective, and stable operation. in [20], a detailed literature study of microgrid-sizing approaches was covered. The two basic sizing approaches are cost-based and non-cost-based. To achieve low energy costs and sustainability, the ideal microgrid was designed and sized using the Grasshopper Algorithm [21]. When establishing the appropriate size of the microgrid, the reference [22] considered the capital cost, renewable energy availability, electricity price variation, and $C0_2$ emissions. To decrease initial and annual operation costs, The authors in.[23] used an evolutionary model to alculate optimal scale of distributed energy sources. In ref. [24], the enhanced hybrid optimized genetic algorithm was used to specify HRES cost and varying load levels for efficient and optimum microgrid sizing. Integrating microgrids into the electricity utility improves microgrid sustainability. [25] described a method for developing grid-connected generating units that improve dependability while supplying the demand at a minimal cost. A grid-connected system that uses sustainable energy was effectively managed by using the enhanced bat algorithm in reference [26]. The microgrid was optimized by [27] using Homer and particle swarm methods.

To enhance RE, the design of the electricity system should be upgraded first [14]. Conventional energy production systems or batteries for storing energy are commonly used as decision variables in the present investigation to obtain power demand balancing. Ref. [15] suggested a power management system that includes day-ahead production forecasting and optimum capacity modification. The corresponding system framework includes a wind generator (WT), a PV systems, and a storage system (Batt), all of which are derived from the Matlab software and use Mixed Integer Programming to simulate and optimize the capacity of the PV, WT, and battries system to reduce capital costs. Referencing [16] as the goal function predicts the appropriate size of the system comprising renewable and thermal generation and control its scheduling operation. The outcomes indicate that the proposed system can save alot of money over 20 years while generating thousands of kw of installed energy from renewable sources. The study [17] aimed to analyze a reactive power compensation system that considers solar, wind energy, and rechargeable batteries inside a remote area. According to the analysis results, the system architecture can reduce surplus energy production. The publications described above all present clean energy sources such as wind and solar to generate energy using different methods. However, the established systems have insufficient use of renewable energy, so a sustainable plan for energy management and optimal configuration sizing is necessary for the best possible design of HESs. Choosing an appropriate energy management strategy is essential because it influences the system's operation by controlling power flow and prioritizing each system component [18]. So, an effective management plan may increase the system's stability, guarantee the power generation's quality, reduce the cost of energy (COE), and prevent components from damage. Furthermore, in grid-connected systems, the energy management strategy is essential for metering and controlling energy flow to and from the grid [19]. Several innovative strategies are carried out using various economic and technical criteria, relying on the system architecture and the optimization goals. These techniques can be more accessible or complex, enabling more straightforward or more difficult optimization algorithms [20].

1.2. ENERGY MANAGEMENT OF OFF-GRID MICRO GRID SYSTEM

In MG systems, numerous power management strategies are employed. For instance, several studies applied linear programming (LP) to improve MG operating, optimizing, and forecasting renewable energy production using artificial intelligence (AI). Reference [21] summarizes the studies that utilized these approaches. For a standalone PV/battery micro grid, reliability problems, optimal sizing, and intelligent power control aspects are discussed [22]. A hybrid system with a Photovoltaic, a wind turbine, and storage batteries as a backup source was first presented by Ismail et al. For a remote Palestinian village, the authors established an innovative method for managing energy. In this situation, the study examined the heat released by the micro turbine and the generated electricity through Distributed generation [23]. Kilic investigated the effectiveness of two alternative energy management techniques in a fuel cell, solar, wind, and off-grid system. These techniques aim to improve the performance of fuel cells (FC) and guarantee the flow of power in the micro grid. [24]. In different study the authors modeled and analyzed a diesel-wind combination for a remote area. The system aims to provide energy to colleges, hospitals, and other rural institutions. In this system, the turbine is the primary energy source, with storage batteries supplying surplus power. When battery storage systems are completely drained, a diesel generator (DG) provides electricity [25]. The HOMER software has been used in several projects to optimize configurations. For example, Bhakta et al. utilize this tool in Northeast India to optimize, and make economic study of the system including (PV-WT-battery). Off-grid systems are a practical choice for consumers in rural locations, according to the HOMER examination [26]. Many off-grid systems were proposed, and HOMER was used to analyze them for different scenarios.

1.3. COMMONLY USED ALGORITHMS

The optimization of particle swarms (PSO), a traditional optimization technique, as well as artificial intelligence (AI) techniques like neural networks, fuzzy logic, ant colony optimization, genetic algorithms (GA), and others have been used in many studies on power management over the past decade. This section reviews AI investigations, including one PSO, GA, and fuzzy-logic study. Azizipanah suggested an algorithm to enhance management methodology and dispatch at a cheaper cost. The algorithm aims to determine the appropriate battery size for MG with HRES. The technique determined the cost function and maintenance costs before defining the optimization problems. The suggested approach proved it could solve that problem rapidly [31]. Kumar et al. recommends optimization technique for (hybrid PV-WT) system to achieve optimal system effectiveness. The authors evaluated the findings with HOMER and PSO algorithm [32]. Ali et al. reduced operation costs and improved techno-economic effectiveness of hybrid micro grid using GA techniques. The maximum system efficiency is obtained, and excess power for supplying different loads is controlled by switching to low peak periods [33]. Figure 1.1. presents the commonly used algorithms for energy management.

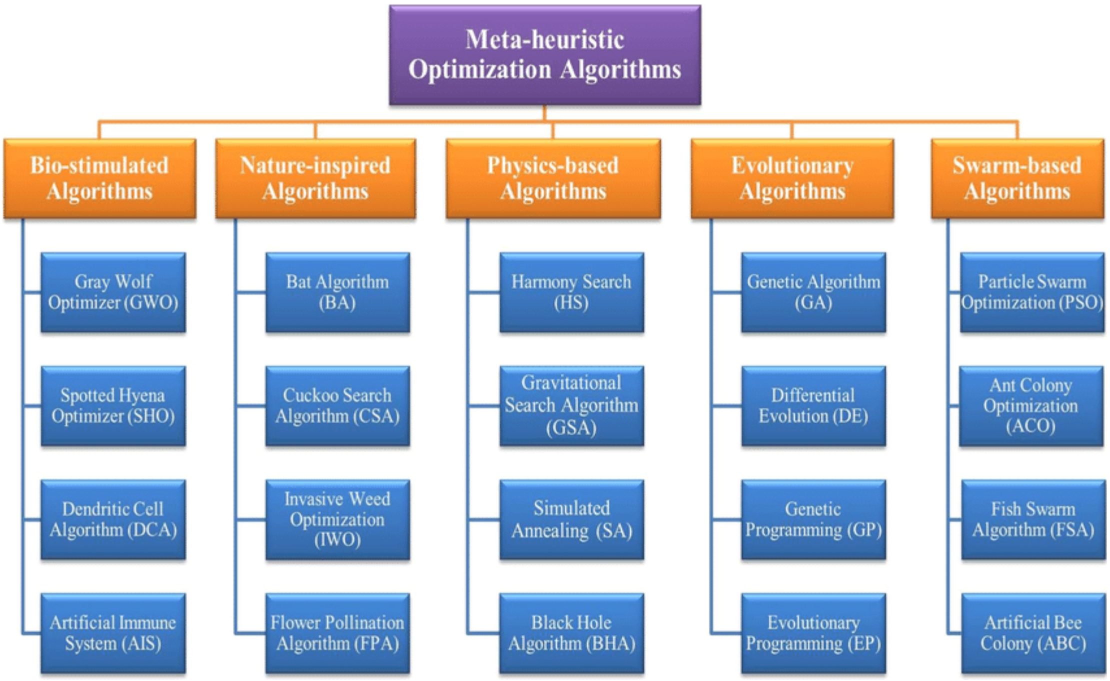

Figure 1.1. The commonly used algorithms in micro grid management.

1.3.1. Genetic Algorithm

It is an effective and reliable technique for solving and improving problems that bases its search strategy on evolution and natural selection principles. As can be seen in Figure 1.2, it is commonly used for finding optimal solution to complex problems which need perfect and accurate results. It is widely used in many fields, including optimization, research, and machine learning. For example, a heuristic tool based on a genetic algorithm and simulated annealing is developed to fix the problem of identifying and determining the appropriate size of storage systems within an LV system. To overcome overvoltage challenges caused by increased PV penetration, this is used to investigate various energy storage designs and structures [34]. solar irradiance, temperature, wind speed, and demand are utilized in the predictive model control of the combined photovoltaic-wind-diesel-battery system [35]. The five control parameters' optimal set positions determine the best control approach for every hour. This study aims to improve the PV system's design using solar tracking, which involves improving the PV unit's component characteristics to maximize efficiency and minimize energy loss. Intelligent methods for studying and optimization obtained from natural evolution are known as evolutionary algorithms (EAs) [36]. In order to reduce pollution and save money, a hybrid system was developed [37] that includes photovoltaic panels, hydropower, energy storage tank, and a diesel generator. The system comprises different components, including solar, wind generators, and battery. According to the study results, using the proposed technology can reduce operating costs by about 10% compared to DG [38].

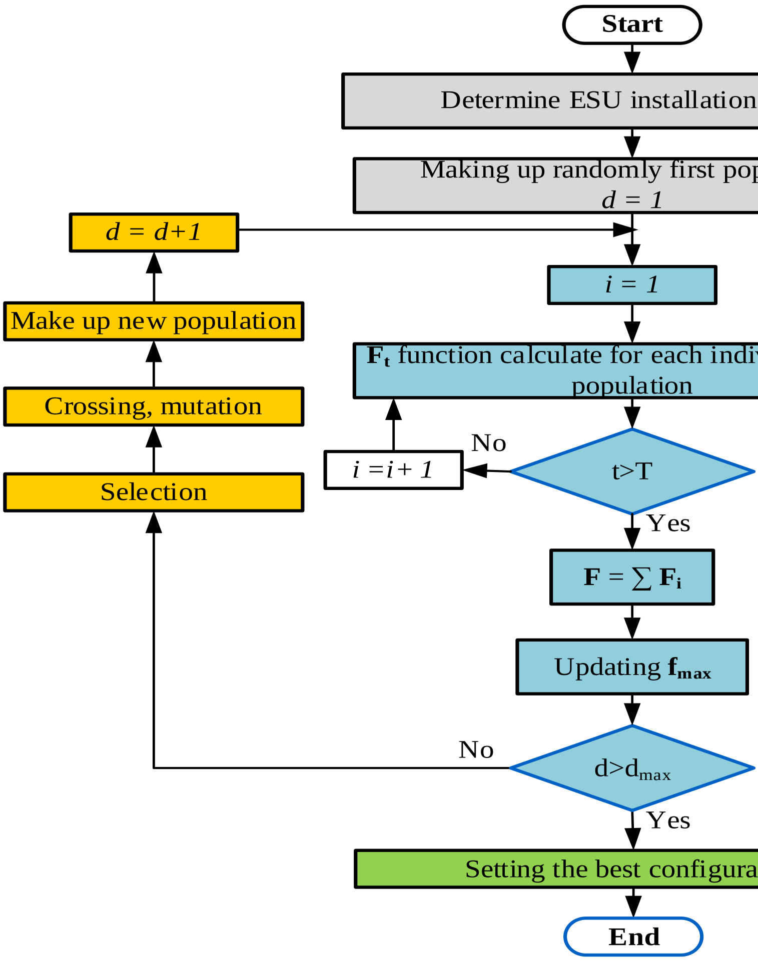

Figure 1.2. The flow chart of genetic algorithm [117].

1.3.2. Fuzzy-Logic

Borni et al. discuss the methods used to simulate MG that is connected to a utility grid. A fuzzy Technique controls the speed of a wind generator, and a PSO fuzzy algorithm controls the output of a PV [39]. The study proposes a new method to control the production of solar cells with rechargeable batteries. This method reduces the dynamic stress of the battery, which makes the battery live longer. This strategy reduces the power conversion rate, peak current, and battery power drawn [40]. In another study, the author designed a microgrid containing a PV, a fuel cell, and an extensive storage system. The PI controller was used to design the process of charging and discharging the batteries from the energy generated from the solar cell, in addition to controlling the value of the energy withdrawn to feed the loads [41].

In reference [42], the author established fuzzy logic for a simple power generation system. The interchange between the solar and fuel cells allows the control of the power flow level and the amount that needs to be stored, as shown in Figure 1.3.

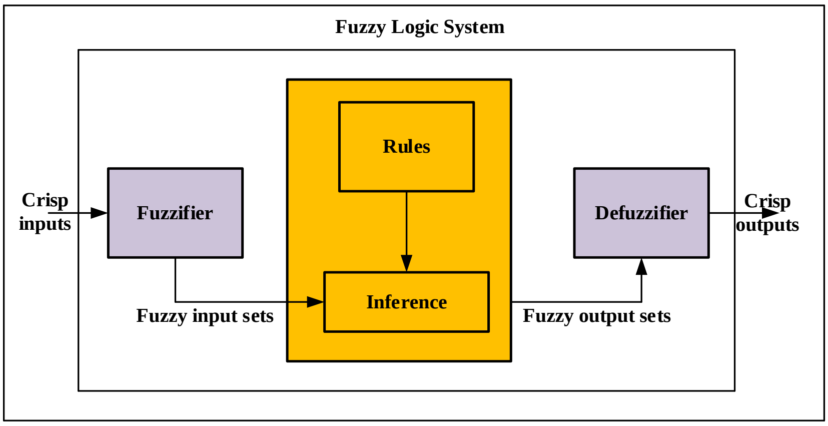

Figure 1.3. Fuzzy logic system architecture [117].

In a different article, Saravanan et al. suggested a novel approach to power management using an intelligent controller. Compared to a single renewable energy source, the control method achieves higher stability and optimizes the operational conditions of the Photovoltaic, wind, and fuel cell systems [43].

1.3.3. PSO Algorithm

The PSO algorithm is one of the more popular traditional approaches for developing MG systems based on clean energy sources with a mix of generators and storage configurations. The investment cost, unmet load, and gas emissions are reduced using the constraints mechanism. PSO simulation is used to tackle the multi-objective optimization problem [44]. PSO is utilized to handle the dynamic control problem of power-producing units like hydro, wind, and solar energy, and reliable outcomes are achieved [45]. A modified PSO technique for solving objective function, taking into account how battery total capacity and uncertainty affect economic dispatch [46]. A "PV-wind turbine" system connected to the grid is designed with multiple objectives in mind to generate enough energy [47]. This study outlines a novel approach to optimal prediction for a standalone system that can supply an energy-starved tiny village in southern Libya. By considering the regulated power constraint and the appropriate number of Photovoltaic panels, backup generators, and batteries, the bat algorithm is utilized to reduce the system's yearly cost [48]. Solar station charging in smart cities uses the best energy management strategy [49]. In another study, the charging method has been created using pso algorithm, and MATLAB has performed the modeling of the EV battery charging operation [50]. Figure 1.4. shows the flow chart of PSO algorithm.

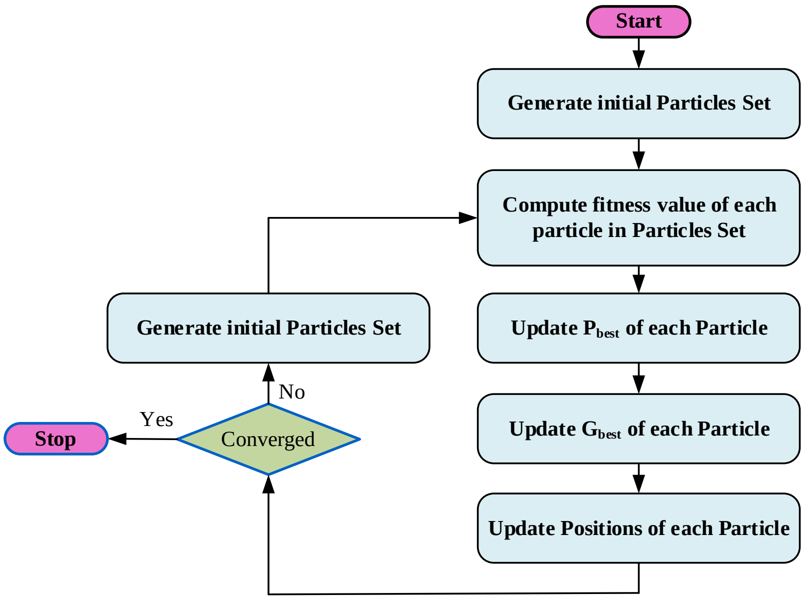

Figure 1.4. Flow chart of PSO algorıthm [117].

1.4. CLASSICAL ENERGY MANAGEMENT APPROACHES

Traditional techniques such as mixed integer linear and nonlinear programming are used in several EM optimization methods. These techniques can be considered practical ways of controlling micro grids depending on goals and limitations. To prevent frequency loss due to distributed energy production and load shifting, Rezae et al. proposed an accurate power flow controller for automated micro grid [51]. Information decision theory deals with the variable and essential factors in power generation in MGs, such as temperature change, wind speed, solar radiation, and loads. In another context, the article [52] presents several optimization options for a hybrid system containing hydrogen storage devices. The system consists of three generating units: photovoltaic panels, wind turbines, and gas generators. The simulation results are implemented in MATLAB / Simulink with the gas generator as a backup power source. The control algorithm has been calibrated, and the power flow management results are presented in the paper [53]. The control scheme is developed to assure proper power management and power suitability between all different resources in the micro grid. In the study [54], MG with distributed generation is investigated. Environmental and economic considerations are specified as decision variables. The power management structure is assumed to be multi-objective problem. To manage MG excess power Dynamic programming method is applied, and simulation results are used to evaluate the algorithm's efficacy. The authors of [55] have put forth another piece of work, presenting a MILP to control energy consumption across several consumers. The model was proposed based on detailed information on the power transformer, batteries, clean energy generators, thermal units, in addition to the diesel generator to obtain the best scheduling and operation of the MG units. In order to reduce operation costs, the algorithm is built around the AC power flow, taking amplitude and power flow limits into account. Implementing MILP to decrease operating costs and take into account power dispatch management as a limitation on MG operation [56]. In [57], The authors presented an accurate MPC algorithm to improve the economical operation of small MGs. In addition, residential load building designs were developed in literature. Finally, using MILP for several case studies, issues including lowering energy usage, gas, and electricity costs.

1.5. MACHİNE LEARNİNG RELATED REVIEW

1.4.1. Machine Learning in HRES

In both the generating and consumption fields, efficient energy management has been achieved using machine learning (ML) technologies. Furthermore, ML approaches can be applied to stand-alone or grid-connected renewable resources depending on the specifications of the type of barriers. Figure 1.5 shows the fields where techniques based on machine learning can be applied to forecast electricity, forecast demand, manage renewable energy systems, and improve system performance. The following paragraphs briefly describe the main applications of ML approaches in HRES.

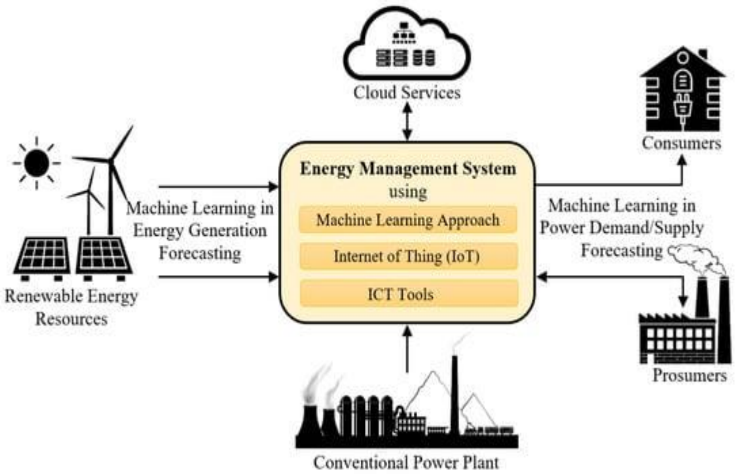

Figure 1.5. Using machine learning in energy management system [66].

- Forecasting how much renewable energy will be produced. Predicting energy generation is a critical challenge with renewable energy sources and machine learning.
- Identifying the Location, Design, and Size of Renewable Power Resources. A difficult task in HRES is determining the best size for renewable energy facilities. The power station site and other criteria, such as weather, geography, availability, and costs, depending on various variables. These decision-making processes may be enhanced by machine learning approaches [32].
- Overseeing the RE Integrated Smart Grid's General Operations.
- Predicting the energy demand. The demand-supply scheme must be balanced correctly for electricity consumption estimation to guarantee the reliability of the power source [84]. The actual power consumption and demand estimation can be sorted using ML algorithms.
- Producing materials for renewable energy. The ability of machine learning to improve material selection is growing. Other energy-related industries that can benefit from it include crystal creation, catalysis, solar panels, and batteries [87].

It is a difficult to forecast energy demand accuratly. Because time series data are complicated and contain random periodic components. The periodic components contain overlapping periods on a daily basis due to the fluctuations in the use of electricity in household loads, and differences due to weather changes, economic effects, and inaccuracy of measurement data [58].

Electricity load forecasting is essential for adequately operating, maintaining, and planning electrical power systems. Electrical load forecasting can be classified into four categories, according to the time period: Long term: for several years. Mid-term: from one month to a year; short-term: estimates for today or next week; And a concise term: a few minutes to an hour before electricity consumption. Long and medium-term expectations are important for strategic planning in developing energy systems, which includes intelligent grid design, maintenance scheduling, and long-term demand measurement, all of which are quickly done using machine learning and artificial intelligence [59].

Exact demand forecasts are critical for efficient electrical system operation, although the electricity load is complex and unstable. Forecasting such complicated variables necessitates the use of appropriate prediction tools. Forecasting techniques can be classified into artificial intelligence (AI) and statistical data methodologies. As illustrated in [61], black-box algorithms are also classified as linear autoregressive. There are three types of power forecasting models: white box, gray box and black box [60]. Data-driven black-box and gray-box algorithms consider an irregular part whenever appropriate climate and energy usage data are available

Probabilistic forecasting techniques compare the energy required for their correlational effects on mathematical algorithms. ANN, SVM, evolutionary models, and fuzzy logic are examples of AI-based approaches. Such techniques include Kalman filters, multiple regression techniques, and autoregressive moving averages [62]. Forecasting and scheduling are two essential parts of successful systems to manage energy (EMS). EMSs are critical to the overall stability of the SG. They are all in charge of controlling the SG parts' energy to decrease expenses and increase quality [63]. Estimating the electricity consumption of various devices is a critical component of the SG approach.

Power consumption can be represented as a nonlinear period with different complicated variables [64]. A significant number of studies published show various techniques to forecast the electricity consumed by different appliances. Elkonomou suggested an artificial neural network-based prediction approach [65]. The multilayer perceptron algorithm performed experiments to determine which design provided the best prediction. Real input and output data were utilized throughout the training, validation, and testing processes.

The ability to forecast future energy demand is still a concern for power enterprises because of the increasing size of the world's population. Scientists predict that if energy usage is not controlled, there will be an energy crisis within the next few years. There are two ways to deal with the energy shortage: increase energy production or decrease energy use while cutting waste. Energy generation is an expensive, time- and resource-intensive solution, but power consumption may be decreased by taking what is needed to be effective [66]. Scientists and other academics are also interested in forecasting and managing electricity use in residential buildings in order to ensure the sustainability of IoT-based intelligent home systems. Predictions using statistical evaluation and algorithms for learning applied to electricity information on energy usage are conventional energy-saving techniques [67]. The study's (68) objective is to forecast electricity usage every 10 minutes or every hour to identify the most effective method. To that purpose, we will contrast four standard machine learning models: the support vector machine for regression (SVR) with radial basis function kernel, the random forest, and the feed-forward neural network with the back-propagation algorithm method. Fazil Kaytez et al. [69] compared regression analysis, neural networks, and least squares support vector machines in estimating Turkey's power usage. Linear regression, fuzzy modeling, and models based on neural networks were all investigated by Henrique Pombeiro et al. [70] to forecast the amount of power used in a commercial building. Based on support vector machine technology, Subodh Paudel et al. [71] projected the energy consumption of low-energy buildings. Hamid R. Khosravani et al. [72] evaluated neural network-based prediction models for energy use in a bioclimatic building. The objective of data mining in this field is to enhance the operating performance of building energy systems. Data mining may significantly analyze information and data from various buildings [73]. Buildings can be regarded as intelligent structures that promote the quick adoption of sustainable technology and lower operating expenses, productivity, welfare, and comfort levels while reducing carbon emissions [74]. Battery-powered energy storage (BES) and thermal storage (TES) are two types of storage used to decrease energy usage in the building. BES is a tool for energy storage that enhances system performance. This is the most widely used method for generating combined energy in structures. The distribution of thermal force inside the limitations of the energy storage system controls TES, which is dependent on it [75]. A. Tsana s et al. used a machine learning framework to examine the relationship among input and output parameters [76].

To analysis the important factors that are related to households. linear regression algorithm is used. This technique makes use of random forest approaches and nonlinear non-parametric approaches. Two outcome parameters were derived from a data simulation on 769 buildings. In this research, heating load and cooling load serve as output results . Ashori et al. [77] presented a strategy for decreasing energy usage. The end goal of this method is to build a structure with deficient power needs (an efficient building). It serves as a standard for home construction. This analysis shows consumers how much energy they are consuming due to inefficient load management. The building model is simulated with the help of an algorithm that utilizes neural networks and clustering methods. When choosing buildings, the classifications with the minimum energy consumption are prioritized. Using machine learning techniques like decision trees and random forests, Smarra et al. [78] suggested a novel approach to predictive control. They employed this strategy, which they labeled the Data-Based Predictive Model (DPC), in three separate experiments. These three tests aimed to show how well DPC performs, how easily it can be scaled, and how efficient it is. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Decision Trees are the three most common machine learning algorithms used for building energy prediction (DT). In order to train and analyze these algorithms [[79], [80], [81]], data from more than one thousand buildings have been used. Reviewing the use of ANN for daily sustainable building predictions, Runge and Zmeureanu (2019) found that the ANN method gives excellent results in single and multi-step forward forecasting [83]. Using a data set consisting of two 6-story houses, Neto et al. compared the prediction accuracy of ANN and the software package EnergyPlus, which is used for energy simulation. The findings demonstrated that data-driven approaches (ANN) are superior for energy load prediction in buildings [82]. Bagnasco et al. investigated the feasibility of using multi-layer perceptron ANN to forecast electricity demand at a specific hospital according to weather input and daytime time. The ANN forecasting improved during the winter after deployment [80]. With nonlinear data, Decision Tree (DT) typically does not outperform neural networks. However, its rapid adoption is because it is simple to implement and yields predictive models with easy-to-understand frameworks [83]. It was discovered by Yu et al. [84] that the decision tree method was capable of correctly categorizing building energy consumption ranges. Tso and Yau compared the efficacy of three methods for forecasting a household's daily electricity use: a decision tree, a neural network, and a regression model. With a root of average squared error of 38.36 [85], decision trees and neural networks performed considerably better than the regression technique.

Furthermore, power consumption data is classified daily, seasonally, and monthly to forecast short, medium, and long-term productivity. For futre power prediction, four supervised algorithms are used: I Binary Decision Tree; ii) Regression Gaussian Process; iii) Stepwise Gaussian Processes; and iv) Linear Regression Model. The inputs include constrained external environmental information, day-type/hour-type, and the total power consumption of different load types. The result is the overall energy requirement of the building's power consumption[86]. [87] analyzes the efficiency of different methods based on deep learning in automatic generation information for improving building calculations. Completely autoencoders, convolutional autoencoders, and generative adversarial networks create three types of deep learning-based features. Their ability to predict building energy has been explored and compared to standard methods.

1.6. MULTI CRITERIA DECISION ANALYSIS (MCDA)

Decision analysis is a helpful method for resolving problems that are characterized by various criteria and purposes, as was already mentioned in the introduction part. The decision maker's preferences, options, criteria, and results are the five elements that make up most MCDM topics. Multiple Criteria Decision Making (MADM) depends on the number of options being considered; if not, both have comparable properties. Using vectors of input values as specified limitations, MODM can be used to evaluate continuous alternatives [88]. The effectiveness of one or more targets is compromised while a combination of objective functions is optimized, taking the limitations into account. In MADM, fundamental criteria regarding examining limited choices make the evaluation and prioritizing more challenging. The results are determined by comparing various alternatives regarding each feature taken into account [89].

In order to achieve the objectives of various actors, energy planning is a complicated strategic activity that involves a wide range of interrelated activities, including power generation, transmission, and distribution [10]. In the investigations on energy planning, many objectives and multiple criteria are commonly utilized in the decision-making process. These methods can produce excellent outcomes by effectively achieving several frequently competing goals or objectives. [90].

There are two primary MCDM techniques, subjective and objective processes, for determining the criteria weights and alternative values. In the subjective techniques, the alternatives' scores and the criteria weights are determined by pairwise comparisons of the decision makers' evaluations and opinions. The Analytic Hierarchy Process (AHP), created by Saaty, is one of the most extensively used subjective techniques [91]. Despite its widespread use, the use of AHP has regularly come under fire when there is confusion brought on by a lack of knowledge and difficulty caused by the differing opinions of decision-makers. One of the most common solutions to the complexity issue imposed by a lack of knowledge is the extension of AHP by connecting it with the theory of fuzzy sets. Moreover, random modeling can be combined with fuzzy AHP techniques to account for unpredictability from different decision-makers points of view. Sitorus et al. [92] showed that FSAHP algorithm might resolve the problems and, in addition to producing more accurate findings than AHP and its variations, also improved the reliability of decisions made in the face of confusion by using decision-making.

Environmental, cultural, scientific, and economic aspects are just some of the factors that go into making the best choice when it comes to renewable energy technology

[93]. In order to make well-informed decisions, decision-makers require methodological tools that combine quantitative and qualitative evaluations of the various evaluation standards. So, the most effective resources should be used by decision-makers to assess the efficiency of sources of clean energy. Thus, selecting the most appropriate energy source to implement is a Multiple Criteria Decision Making (MCDM) challenges due to competing factors [94]. Wang et al. [95], Kumar et al. [96], and several other researchers have reviewed the available literature and found that MCDM approaches can be successfully applied to the selection of power sources (96).

According to [97], the appropriate power supply option must take into account social, commercial, and environmental considerations. Therefore, power production techniques in the German downtown [98], and Niger country [99], were evaluated using the "Preference Ranking Organization Technique and AHP, respectively. Reference [100] has provided a framework for choosing new renewable generation plants and has brought down the price of establishing the sustainability of power. To choose the optimal solution, it is vital to consider both the social and environmental aspects. The study's primary objective is to find the attributes for choosing a renewable power source. The ELECTRE (elimination and choice expressing reality) approach was used to implement energy planning by Beccali et al. [101]. The study offers alternatives from 14 clean energy sources and three models for protecting the environment, economics, and energy. Kay suggested a simplified fuzzy TOPSIS algorithm in [102] to choose the optimal energy option.

In the energy industry, MCDM approaches were effectively used to select on- and off-grid hybrid solar, wind, and biomass power sources using integrated TOPSIS/EDAS/MOORA (103), to select the best design for solar, wind, and diesel power sources while integrating battery capacity using an integrated Fuzzy-VIKOR (104), and to choose the sources of clean energy using Fuzzy TOPSIS (105). The main areas of study for energy optimization in the literature are the location selection challenge, structured cabling, distribution of resources, energy modeling, and decision-making. Investigations on energy design commonly use multi-objective, decision-variable, and multi-criteria approaches. Previous studies' most often used approaches are the PROMETHEE Method, ELECTRE (Elimination and Choice Expressing Reality), fuzzy logic, and AHP [106].

1.7. NOVELTY OF THE STUDY

This study contains three related stages, each depending on the other results: First, an investigation and analysis of the micro grid components in terms of economic feasibility and the size of each generating unit are discussed. Using HOMER Pro software to optimize the system to reach the optimal and best combination with low cost and energy sustainable leads to the optimal system size. Then, a decision-making model (MADM) was created using two reliable methods TOPSIS and VIKOR to determine the best combination of energy sources based on the results obtained from the simulation in the first stage. After determining the best sources, we need to schedule the energy sources so that the available and cheapest power sources are turned on every hour. The operating schedule for the selected power system is managed using the genetic algorithm in the MATLAB environment. The algorithm was successfully used to manage the power within the micro grid to obtain the high utilizing of renewable energy, in addition to obtaining the cheapest energy source as a priority, for an entire month, 720 hours. Thirdly, a prediction model based on supervised machine learning is proposed to build an intelligent operation control model. This model aims to operate the best available energy source, so that the energy demand always is satisfied, that is, to determine the time to turn on or off the three sources (solar energy, wind energy, diesel generator) based on the data obtained from the genetic algorithm. Then we presented how efficient the proposed algorithms by comparing the results and calibrating the model using some matrix tests to evaluate the algorithm's reliability. According to our knowledge and based on the previous studies that have been read, this study has not been done before in a similar way.

1.8. OBJECTIVES

Based on the results of previous studies, the most important factor for the success of designing any hybrid system that contains clean energy sources is determining the appropriate location in terms of abundance of solar radiation, wind speed, and sufficient space. Therefore, the first objective of this study is to find a hybrid system capable of feeding residential loads at any time, at the lowest cost, and with the least emission of harmful gases such as carbon dioxide. The second objective is to design a system with less capital cost to obtain a small cost per kilowatt hour. The third and most important goal is to create an intelligent model using machine learning algorithms that is able to predict the available energy sources, variable loads, and the best combination of power sources that can feed the growing demand. In general, the three goals mentioned above will lead to using hybrid energy sources effectively, economically, and in a more environmentally friendly manner. In this thesis, different technologies have been used to achieve these goals.

1.9. SIGNIFICANCE OF THE STUDY

This study is essential for several reasons:

- Determine the appropriate energy sources to feed the loads at the target site to obtain the optimal and cheapest operation and ensure the continuity of power flow and non-interruption.
- Machine learning algorithms can be used to predict the energy consumption and the sources that need to be operated for a specific residential building, and then these ready-made models can be applied to another building under the same weather conditions and the same components of the energy system.
- Based on the results obtained, the model can choose the best suitable power source for each hour based on the input data, such as temperature, wind speed, and solar radiation.
- This model will provide a reliable and high-accuracy program for designing energy sources for other buildings in the same area to shorten time and effort.
- It should be noted that the Libyan state has set the goal of using renewable clean energy sources only to cover most of its energy consumption by the year 2050. The plan includes replacing some fuel and gas stations with renewable energy systems. These systems will be built in several country cities, especially in remote villages. Accordingly, we preferred to study the possibility of

applying intelligent systems to control and predict the available alternative energy.

1.10. THESIS STRUCTURE

The thesis was divided into five chapters as follows:

Chapter 1-The first chapter reviews the relevant previous studies to form a sufficient idea of the research, the most important results obtained, the algorithms and techniques used in the past, and their effectiveness.

Chapter 2-The second chapter explains the microgrid and its renewable and conventional power generator components. In addition, it displays different designs for small networks to be connected to the main network or not. The chapter begins with an explanation of energy management, its principle of operation, and its methods. Then it gives a brief idea about renewable energy production and the crucial factors in designing these systems.

Chapter 3-The third chapter explains alternative energy and diesel generator system components and their mathematic representation. In addition to how to use the Homer pro program and the critical inputs to simulate and study the hybrid system and improve the size of power generators, and then explain the method for making the appropriate recognition using MCDM methods. In addition, the chapter explains energy scheduling using the genetic algorithm, the characteristics of the algorithm, and the important mathematical equations. It also provides an explanation of the machine learning algorithms used in predicting the use of energy resources. Moreover, it proposes three classification algorithms, explaining their working method and how to use them in research.

Chapter 4- demonstrates and discuss the most important results.

Chapter 5- presents conclusions and future work.

1.11. CONTRIBUTION TO THE LITERATURE

In comparison with previous studies, the methods and techniques used in related research, we conclude that many authors used different algorithms to control, improve and manage power generation and consumption. Therefore, this study suggests the use of classification algorithms for energy management based on the results of the genetic algorithm in scheduling the operation of generation units, unlike some authors who focused on managing energy generation (production) and scheduling loads (demand) to achieve a balance between generation and consumption, our research used three classification algorithms, which are as follows (RF, KNN, and DT) to intelligent control the energy production and consumption in residential buildings and predict how many energy sources should be operated together at the same time. The link between Homer's results, decision-making methods, and energy scheduling using the algorithm, in addition to machine learning prediction, formed a smart and reliable strategy compared to some studies in the field.

PART 2

INTRODUCTION

The combination of different power generation units, batteries used to store excess energy, and residential, commercial, and industrial buildings in one place leads to the design of a microgrid capable of covering different loads at the lowest costs. Unstable production of clean energy sources and increased demand may cause a decrease in the reliability of the mini-grid. The closeness of the microgrid to residential communities contributes to the decrease in the costs of transmission and distribution lines and the transmission of high-voltage power over long distances, in addition to supporting the local energy market at low prices. In order to reach the stability and reliability of the network, the energy management model must be applied with intelligent methods to control generation units within the small network, in addition to controlling consumption by scheduling loads and applying a demand response program. This study established an Energy Management System (EMS) to ensure optimal management of interconnected generation systems such as solar energy, wind energy, diesel generators, and others. Generators can be controlled by a smart program that senses all crucial variables, such as temperature, wind, solar radiation, demand fluctuation, and technical problems within the network. Accordingly, energy management reduces operating and maintenance costs, fuel, and harmful emissions. It is important to know that improving operational efficiency will be brutal without using optimization using algorithms. Optimized artificial intelligence in the mini-grid. In the following sections, the concept of energy management in microgrids will be explained, which contributes to an understanding of our research and the work that has been done.

2.1. ELECTIRCITY SYSTEMS

The Generation, transmission, and distribution make up a power system. Generation is the method of producing energy from natural resources, whether conventional or renewables . From power plants to distribution systems, power travels through high-voltage electrical wires. In order to allow consumers to use the electricity, step-down transformers are used in the distribution process, which includes reducing high-voltage power to low-voltage electricity. Because system dependability is essential to the overall efficiency of the electrical grid, electricity companies must maintain the stability and reliability of the system. Energy suppliers should also guarantee that there will be enough electricity produced in the future. In addition to growing fuel costs, supply disruptions, technical developments, and supply instability risk, additional costs caused by climate change will increase the cost of operating existing resources [108]. Figure 2.1. presents the overview of electric power system.

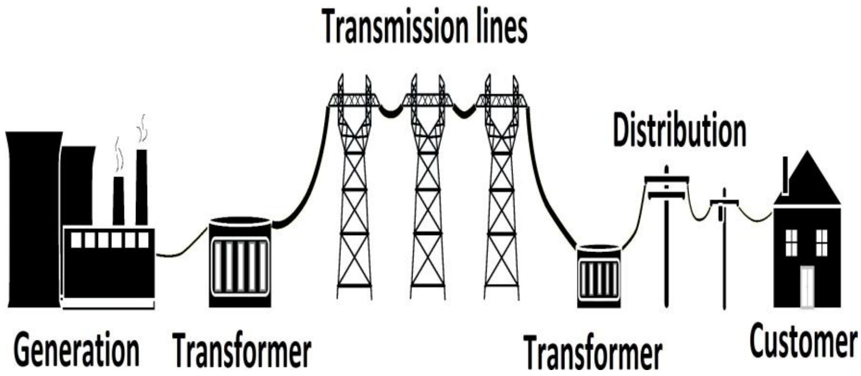

Figure 2.1. Overview of electric power system [66].

2.2. ENERGY MANAGEMENT SYSTEM

It can be challenging to develop a management system for microgrid. It works for unreliable energy sources, which are common in residential buildings and are required to deal with power interruptions. Several systems may be used for microgrid management. A system of decentralized and centralized management. Tiny grids are given objectives such as failure minimization, voltage and frequency regulation, and power management. A process is a planned theory or action of numerous systems that work together to achieve desired results. The process must complete the task for each system or unit to go forward and come to a close. We can see that a mini-operations network correlates to the activities it must carry out to fulfill the demands imposed upon it. Complex control and optimization systems are created to benefit from the mini-grid.

The purpose of power management is to provide the microgrid with self-control, to act independently on and on and off the distribution network to exchange electricity with the generating units. Power control must be in the connected mode reliably and efficiently, support the grid, and participate in the operation of the power market. The mini-grid control system comprises software and hardware and can be centralized or distributed. A Microgrid control system describes the control of several generating units and loads at a specific location using communications and intelligent devices [109]. Figure2.2. depicts the energy management system process.

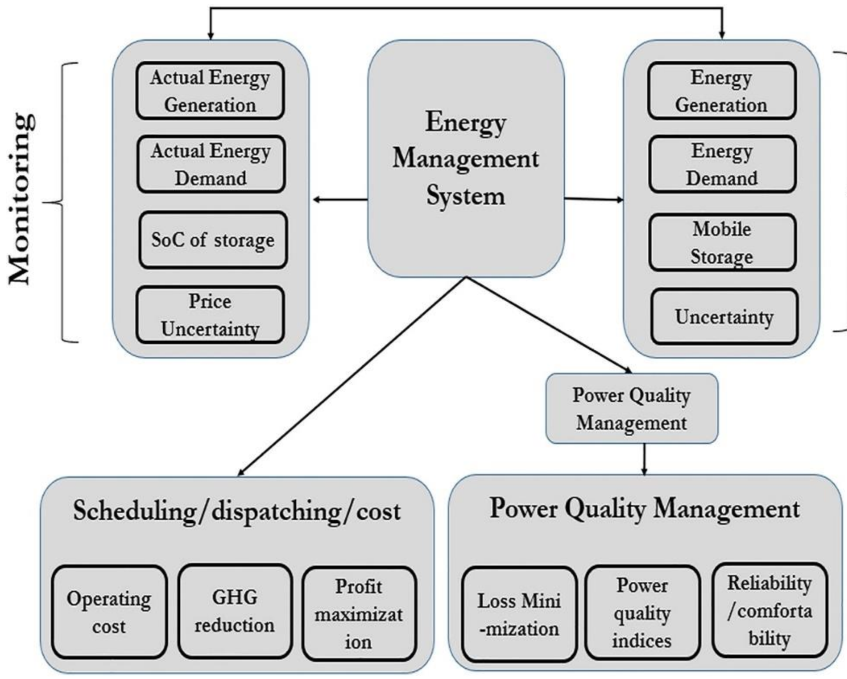

Figure 2.2. Energy management system process [118].

2.3. MICROGRID

The mini-grid produces continuous long-term electrical energy in order to contribute to creating sustainable energy. This dramatically ensures the energy requirements of groups of buildings. It is based on hybridization by creating conventional generation units and alternative energy together [110]. This system was developed to ensure reliable production to increase cheap energy and solve problems faced by the traditional electrical system, such as increased losses in distribution grid systems. The main objective is to transform the site of energy consumption into a production site using generators of different systems (microturbines, fuel cells, solar energy, wind generators, etc.) with storage systems that can operate interconnected or separate from the main grid. Small grids use load management to balance generation and consumption. So that consumption efficiency can be improved while providing flexibility and controllability to increase economic efficiency. Power management improves the stability and constant monitoring of the microgrid; Figure 2.3 depicts a schematic diagram of the microgrid system device. A microgrid can be designed with many benefits, such as increasing reliability, reducing costs, or preventing accidents that cause outages. Moreover, small networks are classified according to their operational objectives [109] as follows:

- Increased stability and durability
- Supplying remote areas with energy at a low cost
- Reduce transportation and distribution costs
- Prevention of environmental disasters

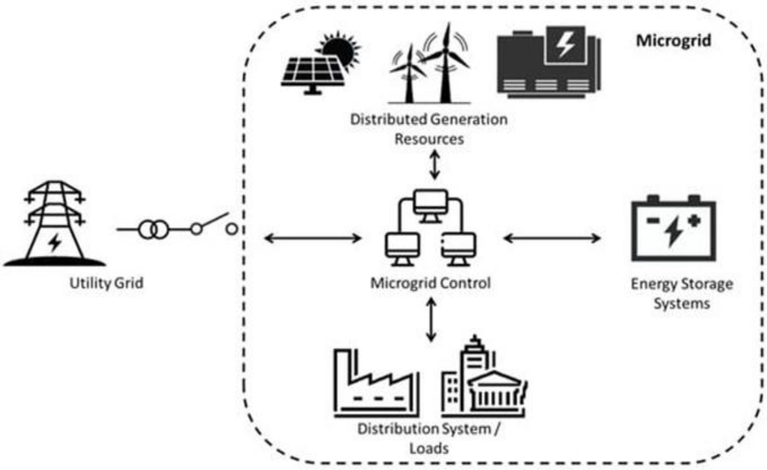

Figure 2.3. Power generation units in microgrid [119].

2.4. ENERGY MANAGEMENT İN MİCROGRİD

The management system microgrid uses a set of parameters and commands that contribute effectively to maintaining the sustainability of energy flow without deficiency or problems. Energy management aims at the appropriate scheduling of the production process in the short and long term by using generators and batteries as well as loads that can be controlled to cover the increasing demand and reduce costs. The management system creates a schedule for the commitment of each generation unit to obtain reliable results. Figure 2.4 shows the general scheme of the microgrid energy managment[110]. Using smart systems to schedule the operation and maintenance of generators in an effective manner. It includes monitoring the amount of power generated and overloads, in addition to determining the Unit Commitment (UC) and Best Economic Expedition (ED) for each generator. The unit commitment determines the best schedule for each power generation unit based on accurate information from sensors and measuring devices as well as on operating constraints, including reserve capacity and expected loads over short and medium periods of time.

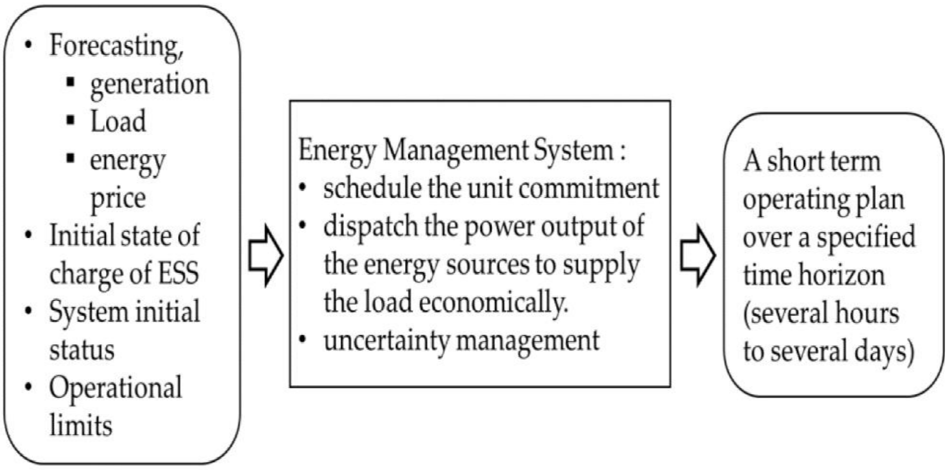

Figure 2.4. The general scheme of the micro grid energy managment.

2.5. TOPOLOGY OF MICRO-GRIDS

As previously stated, microgrids can operate in two modes: switched on or off connected [6]. Furthermore, the microgrid is supplied with small generation sources that create electricity for local usages, such as solar and wind power systems, a hydropower plant and etc. The small grid can also absorb any excess demand. The small grid's electricity consumption can come from residential, commercial, or industrial sectors. Using renewable resources is one of the advantages of the microgrid. However, there is one reason to be concerned: renewable energy is not constant. As a result, the mini-grid must have an adequate storage system, such as batteries, to minimize changes in wind speed and solar radiation. Smart meters, sensors, protection systems, and high-accuracy control devices are included in the microgrid. Based on that, it may use this advanced technology to determine each consumer's energy profile. The microgrid uses advanced communications technologies to deliver and receive data between consumers and power companies via data cable or wireless connection, and it can interface with smart devices in consumers' households to manage them (on/off) as needed or to schedule their operation to reduce energy demand during peak hours [6].

2.5.1. The Stand-Alone Generation

Off-grid generation is the ideal option for a house or community of homes when the area that needs to power is far from the main grid. Making the best size decisions is the first task to maintain supply regardless of weather or demand. Photovoltaic panels and micro wind turbines are the most suited production sources since they may be installed and maintained by a single customer. Also, in order to reduce the costs of transmission and distribution of energy from one city to another, it is better to build hybrid generating stations near residential and commercial buildings. Storage units are essential for storing excess energy and maintaining a balance between generation and consumption in the event of a shortage in access to energy and an increase in demand. The size of the small network units and the storage system is adjusted to have good flexibility and the ability to cover loads at peak times. Usually, in these systems, diesel and gas generators are used because it contributes to maintaining a balance between supply and demand, regardless of the price of fuel.

2.5.2. Control Systems Used in microgrid EMS

Centralized, decentralized, and hierarchical control approaches can all be used to develop the MG EMS control system [110]. Power generation, load profiles, electriity prices, weather information, etc. are all received by a single central controller in centralized system. A central controller makes the best microgrid energy scheduling decisions based on the inputs and then send those decisions to all operators in the control room. Figure 2.5 depicts the fundamental architecture of centralized system. But, if the central control system fails, the whole system might collapse. A decentralized control system differs from centralized control-based EMS; as shown in

Figure 2.6, it only uses local microgrid unit data to determine the property control decisions.

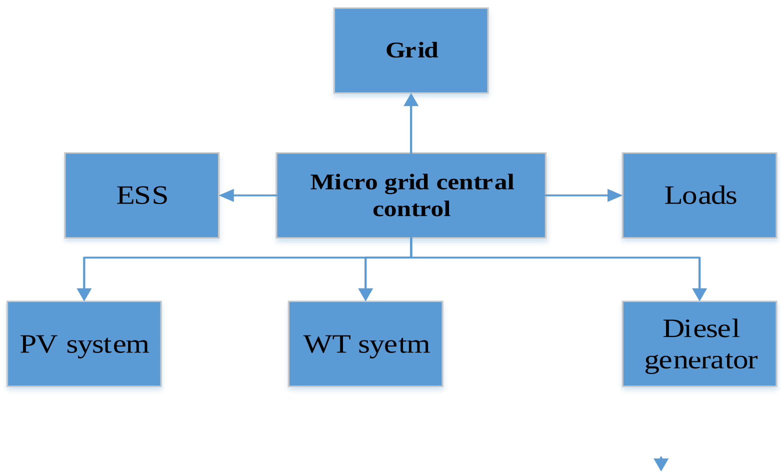

Figure 2.5. Centralized energy control system.

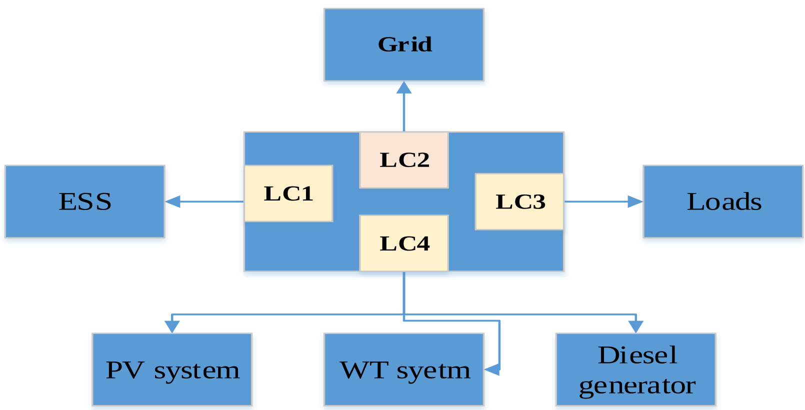

Figure 2.6. Decentralized energy control system [119].

2.5.3. Uncertainties in Microgrid Energy Management

The problem with green energy production is the intermittent and unpredictable during the days, weeks, and monthes. The energy sources, such as solar and wind ,etc are among the most accessible and frequently used in developing micro-networks. However, it is always tricky because wind speed and solar radiation are inconsistent. Since solar energy can only be used during the day, it is also affected by other elements like temperature and shade. The weather has an impact on wind speed. Additionally, consumer loads fluctuate regularly and randomly, and these changes may get more complicated with the integration of the request-response. Dealing with the unreliability of renewable energy supply and the rise in energy consumption is one of the significant challenges with microgrids.

As a result, it is crucial to create a suitable model, be aware of the issues, and find solutions to simulate small-scale systems accurately. Challenges, including wind power, increasing load demand, variation electricity costs, solar power generation, electric vehicle demand, etc., are considered by researchers [111]. The instability of RE and load demand are significant considerations in MG EMS. Therefore, modeling renewable resources and loads becomes the essential stage in the hybrid system's core to manage these components since proper modeling significantly impacts operational costs. There are numerous methods used for simulating microgrids and their applications.

2.6. MICROGRID SYSTEM STRUCTURE

Based on international classifications, there are three combinations of microgrids such as direct current (DC), alternating current (AC), and a mixture of both(AC/DC).

2.6.1. DC Microgrid

This technology is used to supply DC loads, transmit energy over very long distances, and charge energy stores in industrial and commercial buildings. In this system, the power supplied by several sources is gathered on a single combined DC bus. Therefore, in the end, these systems use voltage rectifiers to convert the direct current into alternating current. One of the most critical features of this system is the simplicity of the control and protection process between its components. Its efficiency could be low due to batteries and losses in the converter [62]. Figure 2.18 represents the schematic of this DC system [14].

2.6.2. AC Microgrid

Flexible AC-generating systems can be built by integrating the microgrid multiple generating units.in this option, renewable and traditional energy sources can work together. To fulfill the growing demand needs, the system may be expanded by adding generators [62]. With this setup, each output may be controlled separately, and the voltage can be increased or decreased with a step up and down transformer.

2.6.3. Decentralised Generation

The distributor generates power from low-voltage networks and small substations. Distributed generation uses renewable energy with diesel and small gas turbine generators. Due to the liberalization of energy markets and lower electricity prices, this technology has become more attractive [47]. As a result, independent electricity producers can sell in competitive energy marketplaces. Due to governmental pressure to promote energy independence and minimize greenhouse gas emissions, increase in distributed generators and renewable energy in the global energy market. Distributed generation benefits residential, industrial, and commercial consumers [13]. Some advantages can be taken, such as the following 1. Local energy production decreases bills. 2. Decentralized generator-control center cooperation improves distribution networks during peak hours and gives small networks greater flexibility.3. Distributed generation helps consumers in buildings far from the distribution network. 5. improves suppling power to the critical loads.

When designing any power generation system, production must always exceed consumption; However, due to the instability of renewable energy output may negatively affect system reliability. Poor power quality is considered one of the biggest problems facing operators and electricity companies, in addition to the difficulty of predicting the increase in loads in any event, so it is essential to place distributed generators as support for the network in areas of weakness and under protection from damage [39]. These distributed generators are often installed on a small grid, which contributes to a large surplus of energy, leading to a balanced market in terms of energy prices. Connecting batteries and other storage systems to the small grid will lead to the establishment of flexible stations for any sudden change of loads, which is the most appropriate solution to the problems of energy shortages and electrical power quality problems.

2.7. RENEWABLE ENERGY SYSTEMS USED IN MICROGRIDS

To maximize the utilizaton of clean energy that can be used in a microgrid, two conditions must be met: first, it must be possible to absorb the required power while maintaining the generator easily, and second, it must be more reliable economically than using a conventional grid.

2.7.1. Wind Energy

The generation of energy from wind turbines is one of the most important sources of clean energy, and it is widely available in some countries of the world. Some governments have focused on developing them because they contribute significantly to covering energy needs. In the last two decades, wind energy has become a preferred source for many consumers, with more than 592 TWh produced worldwide in 2020. Wind turbines can reach tens of meters in height, depending on the location, availability of wind, and the required space [48] In addition, there are small types that produce limited amounts of energy that are adapted for domestic use and can be installed near residential and commercial buildings.

2.7.2. Types of Wind Turbines

Vertical and horizontal axis wind turbines are widely used due to their low cost and excellent resistance to mechanical stress. Horizontal axis turbines have been the preferred use in recent years. These blades produce torque that drives the turbine to generate electricity. One or more blades can be used depending on the design. The three-blade rotor is the most popular design because it balances power factor, cost, and rotational speed [53]. Turbines are usually oriented in such a way that wind can flow through them quickly. This can be accomplished with a compass and the study of wind direction, such as leeward turbine, rudder, and dynamic balance.

2.7.3. Photovoltaic Solar Energy

Solar energy systems are the most widespread and preferred by many consumers, including individuals, factories, and buildings. Where solar energy is produced by exposing the panels to solar radiation and converting this energy into direct current using semiconductors such as silicon; these panels and cells can release electrons when they are exposed to high external energy and can decouple their constituents as energy is released when photons hit electrons and release them from the bonding force of the nucleus. As a result, a light current is generated to charge the batteries or feed the loads directly through the inverter. Sometimes these systems are connected to the primary grid, contributing significantly to covering the energy deficit. It all depends on the design of the system to be built. [8]. The performance of solar cells depends on several factors, the most important of which are the orientation of the panels, their quality, humidity, and, finally, the temperature.

2.7.4. Storage Stoarge System

The storageof power is the process of storing a sufficient amount of energy for future. It is essential to relevant problems, either to maximize energy sources or to enhance system performance. It reacts to different goals, allowing for an arrangement between consumption and production, achieving a real-time balance. When demand exceeds generation, however, this imbalance is resolved by compensation of the energy that stored in battreis. However, to deal with renewable energies' intermittency and unpredictable generation. It is necessary to have an auxiliary system, namely a battery, that will develop into a robust system [57].

2.8. HYBRID ENERGY SYSTEMS

Hybrid systems combine several energy production sources, such as wind generators, solar panels, hydro, and conventional fossil fuel-powered machines, to generate electricity. The above systems can be large enough to supply an entire city or island or smaller enough to feed just one household. Many rural areas of the developing world will have electricity available due to hybrid energy sources because the power grid is not feasible or cost-effective in these locations [43].. The Figure 2.7. presents schematic diagram of hybrid energy systems.

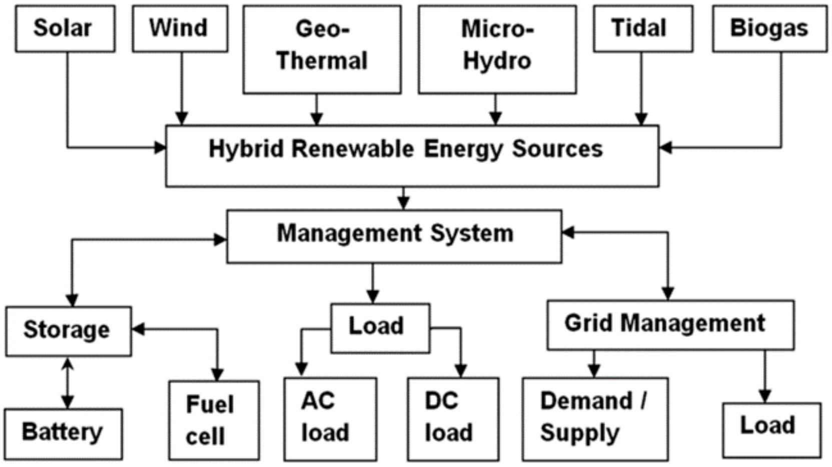

Figure 2.7. Schematic diagram of hybrid energy systems.

2.9. TYPES OF HYBRID ENERGY SYSTEM

Small-scale systems mainly supply power to rural and distant places. The growth of the microgrid has correlated with price declines in solar, wind, and converter systems. These systems are classified as grid-tied or off-grid, depending on their interconnection with the electric grid [88].

2.9.1. Off-Grid Systems (Stand-Alone System)

Off-grid systems make up the majority of small power systems that are created and optimized to supply the energy needs of isolated regions. A system that is off-grid is not connected to the main grid. theses systems come in a wide range of sizes and functions. The Off-grid hybrid system is presented in Figure 2.8. [88].

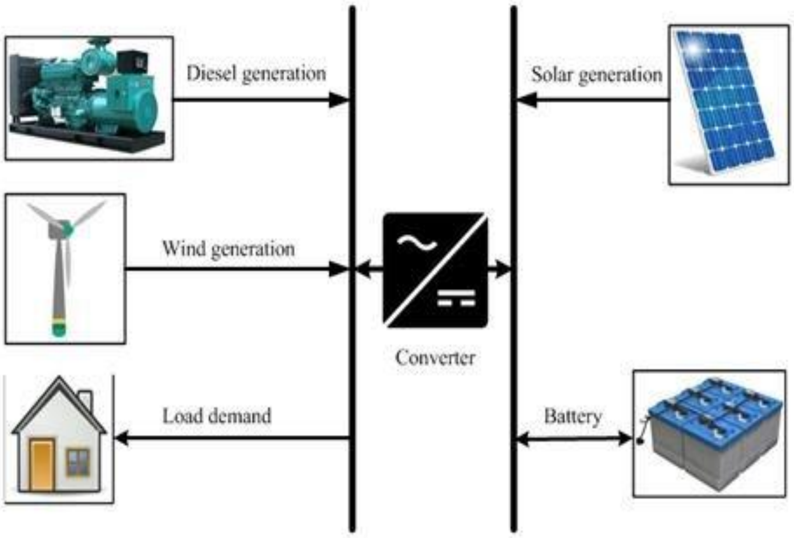

Figure 2.8. Off-grid hybrid solar-wind –diesel generator system with battery backup.

2.9.2. Grid Tied System

A system connected to the utility grid provides power directly into the distribution network. In this case, A synchronizing grid-tie inverter is necessary to convert the direct current (DC) to alternating current (AC) before electricity can be fed into the grid. Figure 2.9 shows the diagram grid connected of hybrid system [88].

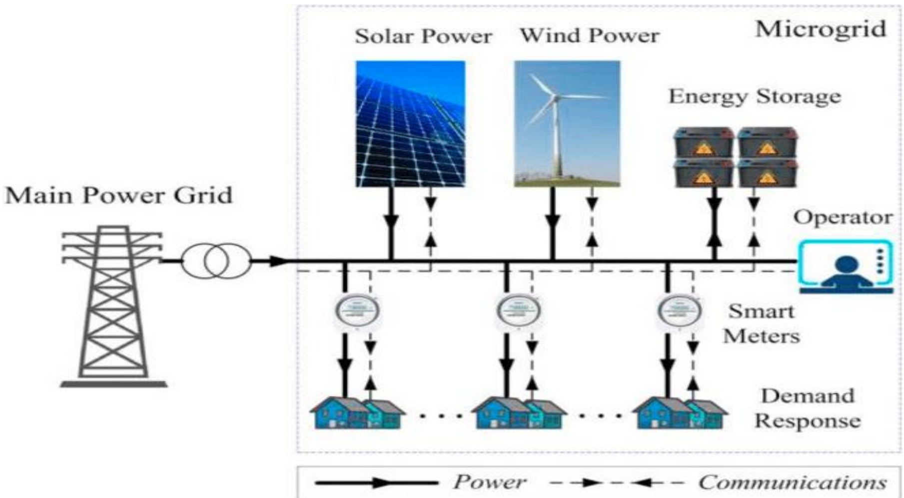

Figure 2.9. Grid connected of hybrid system.

2.10. DESCRIPTION OF THE PROPOSED HYBRID SYSTEM

This work analyzes a hybrid system including of a solar energy system, wind system, generator, and energy storage system. Usually, the energy obtained from the generation units in this system must cover the demand needs at all times, especially the unexpected critical loads. If the consumption is less than the production from renewable sources, the surplus energy will be preserved inside the battery. If the power demand needs exceed the electricity generation output, the battery or the grid will supply the gap. In the hybrid model, the generator is primarily responsible for recharging the battery and fulfilling the load requirements. To save electricity costs, green sources may recharge the battery during off-peak hours and then release it to the demand or the power grid during peak hours. The primary source of energy to meet demand was anticipated to be alternative energy sources like solar and wind energy. The energy store will offer the appropriate alternate source to fill the gap if these sources are unstable and unable to produce energy. In this case, the batteries' charge value is monitored to ensure they can provide energy. If the charge falls below 20%, one of the system's energy sources recharges the batteries until they are fully charged. If the charging procedure is complete and the battery is connected to the load to discharge its energy and help compensate for the power shortfall, the control unit disconnects the battery from charging.

2.10.1. Advantages of Hybrid Systems

Many villages in isolated locations, especially in poor nations where connecting to the national power grid is not economically or technically possible, can rely on hybrid systems to fulfill their energy needs. Here are some of the benefits of hybrid systems that utilize clean sources of energy [17]:

- Depending on the availability of resources, two or more renewable energy sources can be combined into a single system.
- The renewable energies used in a hybrid system do not contribute to global warming in any way.
- It is modular, simple to set up, and unsuitable for home use.

- Hybrid systems have the advantages of being less expensive than conventional ones and more straightforward than massive systems.
- The hybrid system is ideally suited for providing electricity in areas not connected to the primary power grid. Electricity generated by hybrid systems is not affected by fluctuations in fuel cost because the source is unlimited and free.

PART 3

MATERIALS AND METHODS

3.1. BACKGROUND

The main goal of any established generation system is to produce energy continuously and without interruption and technical problems. The most important achievement in our research is to rely on clean energy as an essential part that depends on it in feeding the loads. Accordingly, two sources of the best alternative energy options that are abundantly available in Libya have been combined. Wind and solar energy in addition to making use of the diesel generator in some critical times. Solar energy can be generated from sunrise to sunset, unlike wind energy, as it is available at most times of the day, according to wind speed and direction. Based on many studies and reports, most of the electrical loads come from residential buildings. We have focused on a suitable location containing several residential buildings, where the study was conducted on them to benefit from the results in real life and build new buildings based on these models and results.

- Power generation side Production*:*
  a. PV system.
  b. wind system.
  c. Non-renewable energy (Disel generator).
- Power Consumption side*:*
  a. Residential building.

3.2. THE PROPOSED SYSTEM COMPONENTS

This part explains the mathematical representation of the generation units used in this study, in addition to the target function, system limitations, and important inputs to the simulation. Below are the generating units from Alternative Energy and Generator.

3.2.1. Wind System Modeling

Wind speed and shaft height are among the most critical factors in power generation in this system, in addition to the characteristics of the turbine, such as wingspan and maximum output power. Therefore, the generated energy can be calculated using the following equations [20]:

$$u(h) = u(h_g) \tag{3.1}$$

In the previous equation, u (h) represents the speed at different heights (h), and the symbol u (hg) refers to the wind speed obtained from the anemometer (hg), while α symbolizes the roughness factor that gives an important reading and varies according to the place. Depending on the turbine information, the plates, and the generator characteristics, the following equations are used to determine the output power.

$$0 \leq P_W(t) \leq P_w^{max} \tag{3.2}$$

$$\begin{aligned} Pw(t) &= 0 \ \text{ if } v_f < v_{ci} \text{ and } v_f > v_{co} \\ Pw(t) &= P_{rated} \text{ if } v_r \leq v_f \leq v_{co} \\ Pw(t) &= P_{rated} \times \frac{v_f - vci}{vr - vci} \ \text{ ifvci } \leq v\_f \leq vr \end{aligned} \tag{3.3}$$

Where Pw is output power, the cut-in speed is denoted by V_{ci}while V_{co} denotes the cut-off speed. The characteristics of the turbines utilized in the simulation model are listed in Table 1. The turbine's output of power production is estimated using the above equation

Pw in the previous equations represents the output power, and the cut-in speed Vci, which is important with Vco that refers to the cut-off speed, both determine the ability of the generator to produce power. The turbine's power output is estimated using the below equation

$$P_{wind\ out} = P_w \times A_w \times \eta_g \tag{3.4}$$

Where η_g is the generator efficiency and any additional electronic equipment coupled to the turbine, and Aw is the overall swept surface (m^2). The number of turbines required for the power demands was calculated in this study using the above equation

$$N_{turbines} = \frac{P_L \times SF}{P_{wind\_out}} \tag{3.5}$$

Here, SF represents the safety factor, which is typically 120 %, and $P_{wind\ out}$ is the amount of power that a wind turbine produces in watts.

Table 3.1. Wind turbine details.

Turbine Details	Value
Output power (kW)	50
Cut-in speed (m/s)	3
Cut-off speed (m/s)	25
Hub height (m)	30
AC voltage (V)	220/380

3.2.2. PV System Modeling

The generated power from the photovoltaic system (P pv) is calculated based on the solar radiation, ambient temperature, and PV panel characteristics. [116].

$$P_{pv} = H_t(t) \times PVA \times \mu_c(t) \qquad 3.6)$$

Thus, H_t represents the tilted panel, and $\mu_c(t)$ represents the immediate Photovoltaic modules efficiency, its calculated using the cell temperature $T_c(t)$, as expressed in the following equation (7):

$$\mu_c(t) = \mu_{cr}[1 - \beta_t \times (T_c(t) - T_{cr})] \tag{3.7}$$

The symbols β_t, T_c, and T_{cr}, respectively, are used to represent variables such as temperature factor, actual cell temperature, and the critical variable standard cell temperature, which is set at (25 °C).

PVA represents the total area of the panels that is required to satisfy the load. using Eq. (8), we can determine the PVA: [116].

$$PVA = \frac{1}{8760}\sum_{t=1}^{8760}\frac{P_{L,av}(t)F_S}{H_t\eta_c(t)V_F} \tag{3.8}$$

where F_S represents the safety factor and V_F donates the variability factor of radiation fluctuations, η_c is the efficiency system [21]. Table 2 provides the key details of the solar PV module used in the study.

The number of solar panels in the solar system is significant in calculating the energy generated and the cost of the system, and the appropriate number can be determined using the following equation.

$$N_{pv\_modules} = \frac{P_{pv}}{S_{peak\_power}} \tag{3.9}$$

Where S_ (peak_energy) represents the maximum power that can be generated from the system, it can be accurately calculated using the following equation.

$$P_{pv} = W_{PV}f_{pv}\left[\frac{G_T}{G_{STC}}\right]\left[1 - \alpha_p(T_c - T_{C,STC})\right] \tag{3.10}$$

In the previous equation W_{PV} denotes the output power in (kW), f_{pv}represents the derating factor (%) and $\alpha_p$represets the temperature coefficient, G_T denotes the solar radiation (1 kW/m2), G_{STC} refers to the radiation energy at 25 C , and the temperature of the panel is represented by Tc . [116].

Table 3.2. PV Module Details.

PV system	specification
output power	350 W
Voltage	31 V
Current	8.5 A
Lifetime	25 years

3.2.3. Storage System Modeling

When renewable generation is included into residential buildings, it is more challenging to sustain an energy balance and prevent frequency deviations. Energy storage systems (BAT) are important for preserving the equilibrium between supply and demand and providing power quality correction in the case of sudden voltage changes. The ESS rating is affected by a number of factors, including battery type, backup duration, heat, battery size, depth of discharge, and the required reserve energy. The battery's charging and discharging cycle is expressed by equations (11) and (12) [116].

$$P_{BES}(t) = P_{ch}(t) \;\; if P_{PV}(t) + P_{WT}(t) \geq 0 \tag{3.11}$$

$$P_{BES}(t) = P_{dch}(t) \;\; if P_{PV}(t) + P_{WT}(t) < 0 \tag{3.12}$$

P_{ch} and P_{dch} illustrate the energy of batteries in charging and discharging modes, respectively, while P_{PV}, P_{WT} represents the output power of solar and wind energy systems.BAT can only operate in one mode—either charging or discharging—at any particular time. The voltage used to charge and discharge the battery is calculated as follows:

Charging mode:

$$E_{ch}(t) = \left(\frac{P_{WT}(t)+P_{pv}(t)}{\eta_{conv}}\right) * \Delta t * \eta_{ch} \tag{3.13}$$

E_{ch} is the hourly charged energy, and η_{conv} represents the charging cycle efficacy

$$SOC(t) = SOC(t-1)(1-\sigma) + E_{ch}(t) \tag{3.14}$$

Discharging mode:

E_{dch} is the hourly discharged energy, and η_{conv} donates discharging cycle efficacy

$$E_{dch}(t) = \left(\frac{-P_{WT}(t) - P_{pv}(t)}{\eta_{conv}}\right) * \Delta t * \eta_{ch} \tag{3.15}$$

$$SOC(t) = SOC(t-1)(1-\sigma) - E_{ch}(t) \tag{3.16}$$

Soc(*t*): represents state of charge
Soc (*t* – 1): represents charge of the batteries at time t – 1

3.2.3.1. Sizing of the Battery

Determining the storage capacity is very important to know the amount of energy that will be stored from clean energy sources and how many hours the battery can store excess energy. The following formula can be used to calculate the necessary storage capacity in Ampere hour (Ah):

$$M_{batt} = \frac{A_d \times E_L}{\eta_{batt} \times \eta_{inv} \times DoD \times V_s} \tag{3.17}$$

here A_d is the number of days that the batteries can provide energy without being recharged againe, DoD represents the max depth of discharge allowed for the batteries, and V_s donates the charging voltage in (v). Table 3 shows the battery specification [116].

Table 3.3. Battery system details.

Battery	specification
Nominal capacity	12 V/1000
depth of discharge	90%
efficiency	86%
Voltage range	160–230 V
Lifetime (Years)	5

3.2.4. Power Convertors

The power converter became necessary in the planned Hybrid system to maintain a constant power flow between the power supply and the load. DC-AC converter output power is determined by the converter's efficiency factor [60]. Equations (3.18) and (3.19) illustrate how the efficiency of the converting system modeled in HOMER which can be defined below.

$$P_{inv,out} = \eta_{inv} P_{DC} \tag{3.18}$$

$$P_{rec,out} = \eta_{rec} P_{AC} \tag{3.19}$$

where $P_{inv,out}$represents the output power from the converter (kWh); P_{DC} depactis the dilevered power to the converter (kWh); $P_{rec,out}$ donates the rectified (DC) power from the converter; and P_{AC} represents the AC output power in (kWh) [20].

3.2.5. Disel Generator Modeling

The generator will be a backup option if the solar and wind energy sources are unable to satisfy the energy requirement. The diesel generator is operated as a backup in the micro grid system. The fuel consumption can be calculated by using Ref. [20].

$$F_{DG} = B_G P_N - DG + A_G P_{out} \qquad 3.(20)$$

Where F_{DG} refer to fuel consumption (L/hr), $P_N - DG$ is the nominal power of diesel generator (kW), P_{out} is the output power (kW), A_G = 0.246 and B_G = 0.0814, A_G and B_G are the dieselconsumption coefficients (Load/kW h).

By using the equation below (3.21), it is possible to predict the maximum power that the generator can produce per hour.

$$\mathrm{E_{EDG}(t) = P_{DEG} \times \eta_{DEG} \times t} \tag{3.21}$$

The peak electricity demand typically determines the size of a diesel generator. For example, a 100 kW capacity is needed because the residential area's peak consumption is 250 kW. The generator's surplus will cover the spinning reserve, which could handle future load increases.

Due to the lack of solar power during the day and the higher load demand at night, the generators work primarily at night. The generator will switch on if the solar, wind, and battery systems cannot satisfy the load during the day. The machine's initial and replacement costs were estimated at $50,000 and $40,000, respectively. It was assumed that the operating and maintenance costs would be relatively high, at $ 0.5/hour. It is a result of the location under investigation being far away. Hence, when maintenance is required, and that would subsequently raise the cost, difficulty in the transportation problem arises. The generator was projected to operate for 15,000 hours in total.

3.3. INPUT DATA

3.3.1. Load Profile For Selected Site

This study analyzed the daily power profile and energy requirements of five residential buildings over a 30-day period. For the study to be more accurate, real information was obtained from the daily consumption of 5 buildings. Measuring devices were used to measure the monthly energy consumed per hour. The aim is to use these data in building a hybrid system of several generating units to feed loads effectively and reliably based on actual consumption values. The figure below shows the daily load for 24 hours. Figure 3. 1 presents the input load data to homer pro software.

The hybrid system in this study consists of clean energy units such as solar modules (PV), wind turbines (WT), and a conventional diesel generator (DG), in addition to using sufficient storage units to save the surplus energy generated from solar and wind sources, as well as the power converter that very important in the system composition, which must be carefully chosen to obtain the maximum conversion power without interference. Weather data for the chosen location is essential for calculating the generated energy, including solar irradiance, wind velocity, and temperature. Using the tripoli city latitude and longitude coordinates, the (NASA) database was queried for information on solar irradiance and wind speed [120].

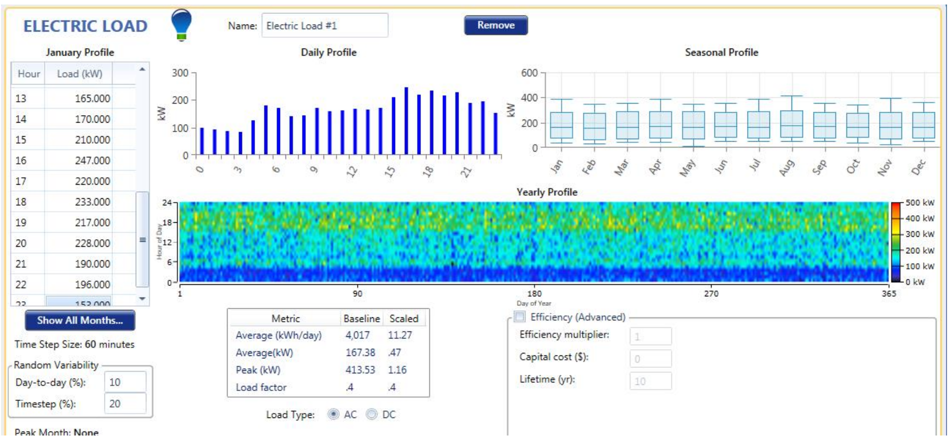

Figure 3.1. Ahourly Load profile in summer day.

Calculating the components of the hybrid system needs real weather information, which, based on it the output power of the solar and wind generator can be calculated. Figures 3.2, 3.3, and 3.4 show the difference in temperature, solar radiation, and wind speed values in the chosen location for a year because the highest value of wind speed and solar radiation must be known. The average annual solar radiation is 6 kilowatt-hours / m^2/ day. The average temperature is moderate in some months of the year at 25 C. Usually, the maximum temperatures in the site are in July and August, and the sunlight is abundant in these months. Figure 4 shows the average wind speed at a height of 50 meters, ranging from 2.6 to 7.9 m/s, at the given location. The months with the lowest wind speed are June and July, while the months with the highest wind speed sufficient for efficient power generation are January and February.

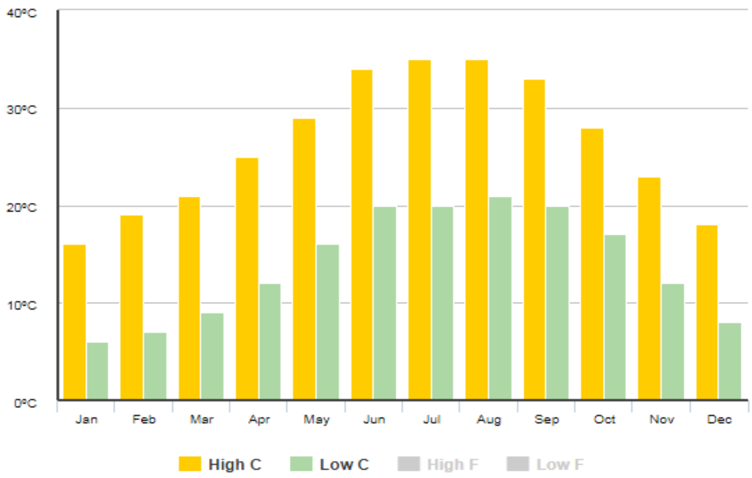

Figure 3.2. Monthly average high an low temperature [120].

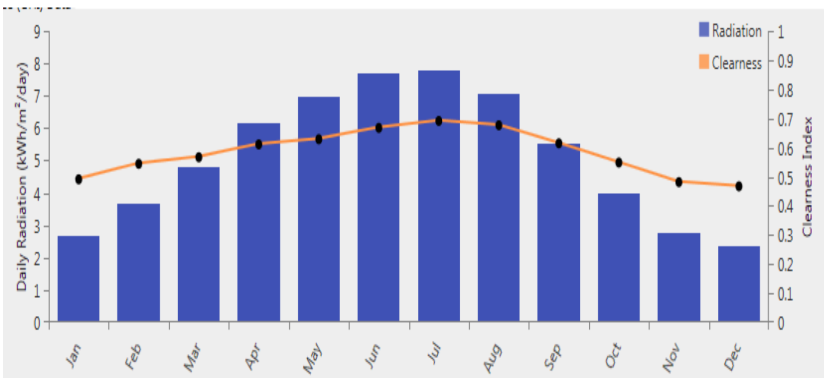

Figure 3.3. Monthly average daily solar irradiation, and clearness index [120].

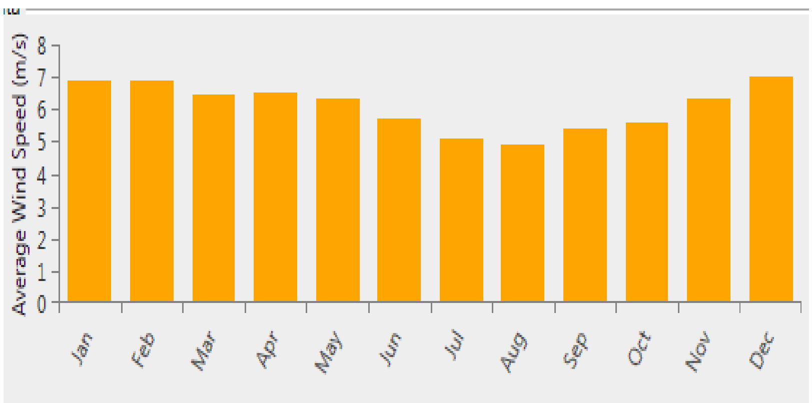

Figure 3.4. wind speed data [120].

Changes in the weather affect the energy produced, which happens throughout the year. Therefore, the basic idea is a hybrid system that must check weather information and electrical loads accurately to obtain the appropriate amount of renewable energy, reduce the cost of building, operating, and designing the energy system, in addition to obtaining very low levels of greenhouse gases (GHG).

3.4. SYSTEM DESCRIPTION

This study investigates a hybrid system that utilizes two renewable energy sources. Wind energy with a maximum output of 150 kW, and a solar power system with a 70 kW capacity. Priority is given to using these sources to feed the loads, but additionally a 100 kW diesel generator is also available to help maintain the power on and the buildings supplied. Furthermore, battery storage units are used to store excess energy produced during times of high generation and use it during times of low generation or peak demand. Figure 3.5 and Table (1) detail the specifications and components of the system

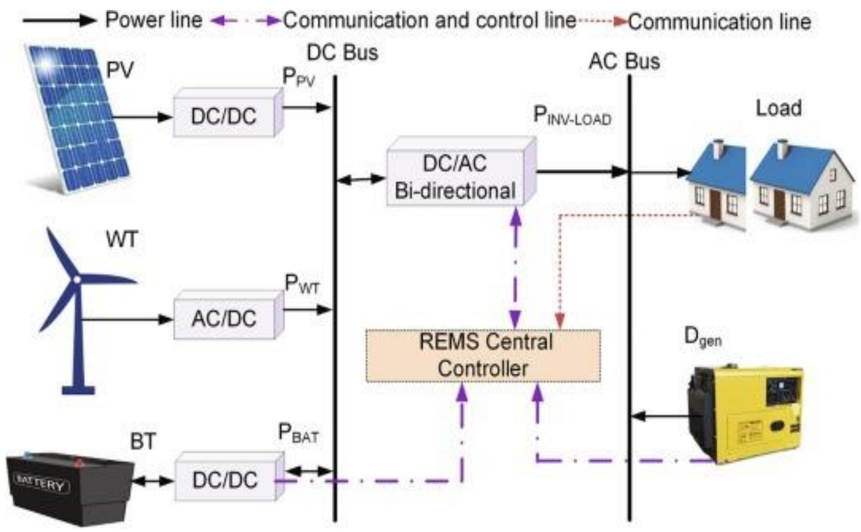

Figure 3.5. Components of the micro grid system [121].

The details of system components.

Table 3.4. Micro grid parameters

Generation units	Specifications
DG (kW)	Output power range: 100kW. fuel consumption is 0.3 L/h/kW capital cost: 35000$ replacement 35000$ operation, maintenance is $0.04/hour. Lifetime: 15,000 h.
Solar system	Output power 70 kW. Operating temperature 47 ◦C and 0.4%/ maintenance ,operation cost $10/year. Capital cost $800/kW, replacement cost $800/kW Lifetime: 25 years.
Wind system	Output power 150kW. Hub Height: 30 m. operation, maintenance cost $5000/year capital cost $220000, replacement cost $220000 Lifetime:25 years.
Battery stoarge sytem	Discharge 0 to 1000Ah. charging voltage 24 V Efficiency: is 85%. capital cost $80 per unit replacement $80 per unit operation and maintenance $150/year. Lifetime: 5 years.
Converter/(kW)	Power range: 0 to 150 kW. capital cost: 30000$ operation and maintenance $100/year.

3.4.1. Site Descriptıon

The study site was chosen in tripoli city with coordinates, (32°00′17″N 11°19′51″E), and it contains several residential buildings, and five buildings were chosen as a case study. Theses buildings contain 70 apartments. In total, they consume a maximum of 250 kilowatts of energy in the summer, which records the highest levels of daily energy consumption. There are 260 people from 70 families living in the buildings mentioned. The chosen location suffers from power outages for long hours. To create a reliable model and obtain accurate results, we used the hourly data of the consumed energy in one month.

3.4.2. Description of The Residantal Building (case study)

The target buildings of the study are located in the city of Tripoli in one of the residential neighborhoods in the south of the city, with a population of (260 people). Each building contains 14 apartments, and the total area of each apartment is about 200 square meters. The two walls on one side of the building occupy 20% of its total area, while on the other side, they occupy 15%. Where the thickness of the external walls of the bricks is 20, the internal walls are 10 cm, and all the walls were covered with cement. Unfortunately, all walls and ceilings do not use thermal insulation or other energy-saving materials, which causes a lot of energy consumption, such as cooling loads in summer and heating in winter.

3.5. RESARCH METHOLOGY

This study is divided into four tasks as follows

- Determine the optimal size and appropriate group of microgrid components (Using Homer)
- Selecting the optimum energy system by using decision-making techniques (using Topsis and Vikor)
- Energy scheduling using Genetic algorithm
- Energy classification and predication using machine learning algorithm

3.5.1. Optimal Planning and Design of Microgrid

Planning and designing a reliable microgrid that produces high-quality energy continuously in an area that suffers from problems in obtaining energy requires the availability of several vital factors that help in the success of this task. First, we must always focus on the use of sustainable energy and study several variables carefully, such as the number of energy sources required, the capital cost and the final energy price for the consumer, the amount of harmful gases, and methods to reduce them to the lowest level, the nearest suitable location so that the connection is made with the consumer and the main grid, in addition to excess energy during generation and how to store and preserve it. Accordingly, all the factors mentioned above have an impact on the system proposed in our study, and we will discuss the results obtained to improve this system.

3.5.1.1. Methodology Description

Choosing the number and size of the generation units is a complex task because it is related to varying electrical loads and changing weather, in addition to the restrictions imposed on the hybrid system, which consists of the wind and solar systems, in addition to the diesel generator and a sufficient energy storage system using batteries. In order to provide a residential area with sustainable and cheap energy for loads ranging between 86kW and 250kW, there are four sections to work on interconnected depend on each other. First, the system's optimization, modeling, economic analysis, and calculation of the necessary costs are carried out using HOMER software to evaluate the technical and economic feasibility. Secondly, the best alternative energy source is selected, and the appropriate decision is made using two multi-criteria decision-making methods (MCDM), which compare all hybrid energy combinations and rank the best option based on the exact calculation equations. Thirdly, the genetic algorithm is used to schedule the four energy sources, and the priority is always for clean and cheaper energy. This stage includes entering weather data such as solar radiation, wind speed, temperature, and monthly demand (720 hours). The algorithm calculates the power generated by renewable energy sources and the battery's charge level. Then, the program will choose the most suitable energy source to supply the demand per hour, considering the available energy and the lowest cost per kilowatt hour. Fourth, the results of the genetic algorithm are used as inputs to the classification model, where three machine learning algorithms are used, which are explained in detail in this section. The model is trained on these load value data, available power, weather data, and energy sources that must be turned on per hour. Finally, the model will understand these inputs and use them to predict the sources required to supply the hourly load in other buildings under the same conditions. Figure 6 shows the methodology of the study. The following subsections describe the simulations and calculations in detail.

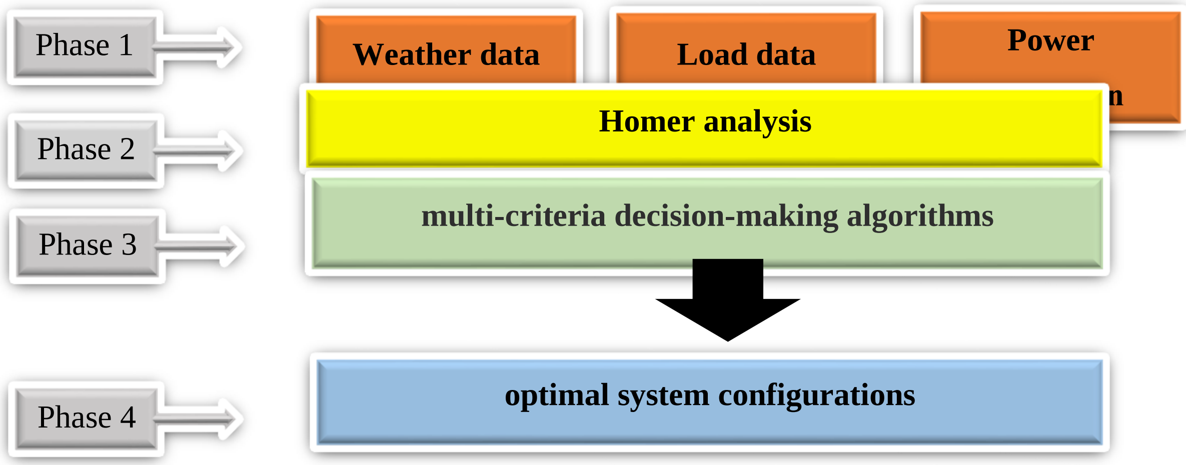

Figure 3.6. The detail of work procedure.

3.5.1.2. System Sizing And Simulation

Step 1. HOMER Simulation and Optimisation

The HOMER software is considered the best in microgrid design based on years of experience building and implementing distributed energy systems and microgrids that combine renewable energy sources, storage, and oil-gas-based systems. With the assistance of HOMER, it is possible to estimate the system performance and lifespan cost, which considers both initial, total and operation costs. The program's main objectives are modeling and optimization of hybrid systems that include renewable and conventional energy sources, as well as sensitivity analysis. In addition, it aims to tackle microgrid studies and planning issues, such as uncertainty factors suh as load demand , weather data, and future fuel costs changes. It can be determined whether the system is economically efficient and cheap through important measurement factors such as the total annual cost of the system (NPC) and the cost of energy to the consumer (COE).

In this initial step, the simulation was implemented to achieve the best size and technical and economic outputs. HOMER is fed with all input parameters, including meteorological data, load, generation unit size, fuel cost, renewable energy sources, and other economic factors. This study compares the best size and power generation from several hybrid renewable energy sources (HRES). For optimizing the design system, this software compares several energy sources with various sensitivities and limitations. The system's technical parameters and Life Cycle Cost (LCC), including installation, operating, maintenance, energy, and initial capital costs, are evaluated. The objective is to reduce the LPSP, NPC, COE, TCC, and CO_2 emissions. NPC contains all costs associated with the system, including replacement costs, capital, operation and maintenance costs, and fuel consumption. Figure 7 presents how homer softwre is working.

According to Figure 5, the system configuration including of a wind system, PV arrays, batteries, a converter, and a charge controller. By considering the lowest energy cost and the availability of renewable energy supplies, the optimization algorithm of the software provides fast techno-economic analyses of alternative energy options.

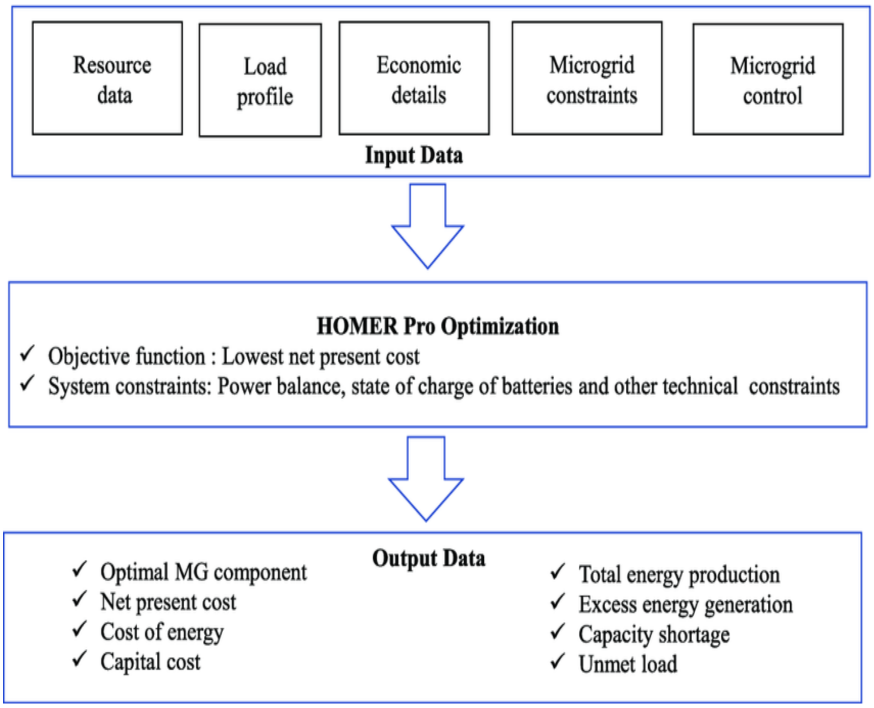

Figure 3.7. HOMER simulation flowchart.

In the folowing scenarios configuration of hybrid energy system that are propsed in this study

- (combinations 1) PV/wind/Diesel generator/battries .
- (combinations 2)PV/diesel generator / battries

- (scenario 3) wind/ diesel generator / battries
- (scenario 4)diesel generator/ battries
- (scenario 5) PV/ wind / battries
- (scenario 6) PV/ battries

3.5.2. Economical Model

3.5.2.1. Net Present Total Cost

It represents the life cycle cost of all system components, which is the present value of all the costs of building and operating the system over the life of the proposed project, subtracting from it the current revenues earned over the system's life. With high accuracy, HOMER calculates the net cost for each generating unit separately and for each system, and this helps decision-makers choose the appropriate and cheapest installation. Therefore, selected sizes must achieve the lowest NPC [119].

$$\mathrm{NPC} = \frac{\mathrm{C_{ann,tot}}}{\mathrm{CRF_{iN}}} \tag{3.22}$$

Wher $C_{ann,tot}$ is the annual cost.

N is the the system lifetime

3.5.2.2. CRF

capital recovery is important factor and can be calculated as follow[119]:

$$CRF_{(i,N)} = \frac{i(1+i)^N}{(1+i)-1} \tag{3.23}$$

The overall annual costs $C_{ann,tot}$, takes into account the system initial, maintenance, and operation costs. Also batteries , converter, the replacement costs are included. The follwing equation calculateds the salvage value [92]

$$SV = C_{rep}\frac{R_{rem}}{R_{comp}} \tag{3.24}$$

Where C_{rep}: is the replacement cost, and R_{rem}: represents the rest of system lifetime [119],

R_{comp}: refers to the system lifetime

3.5.2.3. Cost of Energy

Another important factor of the system design is the COE, which is used to evaluate the system's economic feasibility. Equation(3.25). is used to compute it. [92]:

$$COE = \frac{NPC}{\sum_{t=1}^{t=8760} P_{load}} \times CRF \tag{3.25}$$

Technical optimization model

3.5.2.4. Loss of Power Probability

LPSP is the performance of the system and a measurement of the unsatisfied load.number (1) indicates that the load is not supplied, while (0) means the load is completely satisfied. It is determined by Equation (3.26) [119].

$$LPSP = \frac{\sum(P_{load} - P_{pv\,out} - P_W + P_{bat_{min}} + P_{DG\,out})}{\sum P_{load}} \tag{3.26}$$

3.5.2.5. Greenhouse Gases Emission

Another crucial factor to take into account when establishing a hybrid system is the greenhouse gases that it releases (GHG). The system's environmental impact will increase as more GHG are released into the atmosphere. The DG, which mainly produces CO_2, SO_2, and N_{ox}, is the system most responsible for this emission [19]. In order to determine the system's TGE, we apply the following equation [53].

$$:TGE = \sum_{t=1}^{8760} (\alpha_{co2} + \alpha_{so2} + \alpha_{Nox}) \times P_{dg\_out} \tag{3.27}$$

where TGE represents the Total Greenhouse gases Emission, α_{co2}, α_{so2} and α_{Nox} represent the emission factors of the gases CO_2, SO_2, and N_{ox} respectively, P_{dg_out} is the diesel generator rated power [53].

3.5.3. Optimal Decision Making Techniques for Selecting The Best System Configuration

3.5.3.1. Multicriteria Decision Making Methodes (MCDM)

At this stage, two techniques are used to accurately make decisions based on several system variables and using a set of equations that will be explained in this section. To determine the best energy source, two models were combined to build a decision matrix based on the criteria of system components derived from homer results, including technical results, economic and environmental costs. This part explains the mathematical equations needed for decision-making. First, some equations are solved to calculate the standard weights for each hybrid system combination. This contributes to measuring the importance of each energy system. After that, other equations are used to calculate the degree of importance and preference of different energy sources and to choose the optimal source accurately.

Figure 8 shows the research plan that has been proposed using (MCDM). The results from homer are used to give several important factors when selecting an energy source. The process figures out the importance of the evaluation criteria so that the best choice can be made from the available options

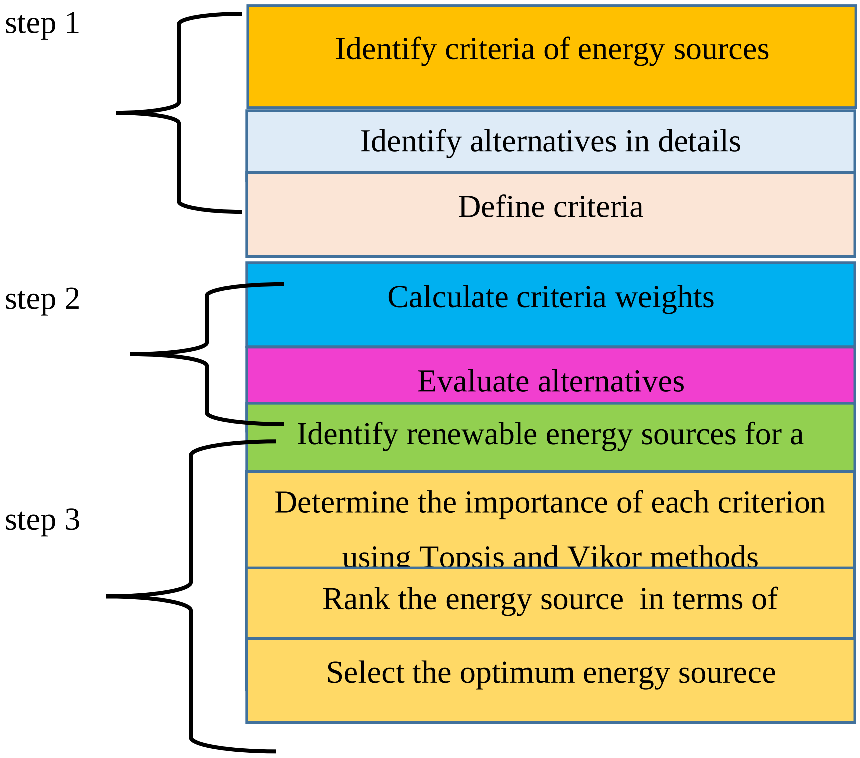

Figure 3.8. Proposed framework for energy sources selection

3.5.3.2. Methodology implementation

Vikor-TOPSIS methodology are applied to evaluate and select the optimum green energy sources for sustainable energy planning by taking multiple criteria into account. The problem is initially organized into a hierarchy model, beginning with the study's goal, as seen in Figure 3. 9, and the last step is the alternatives choices. Firstly, it demonstrates how the aim, criteria, and decision alternatives are related to each other. The best option for each is selected based on the criteria values indicated in Table 2. The decision criteria is described in the following subsection.

The crucial pairwise matrix is build based on data from hybrid system specifications, this provides the information of priorities for various criteria. Then, based on system parameters, the simulation result provides the performance score for each criteria for all alternatives.

The final step involves weighing all criteria to determine the opinions of each system component. The sum of all the individual weights for each criteria gives the overall score for each option. The values for the criterion are then combined. In the end, the best alternative choice with the maximum performance score compared to the other options is selected the best.

The decision-making process can be summed up in several points as following

- Determine the problem;
- Set goals;
- Identify options;
- Specify criteria
- Chose a decision - making framework
- Evaluate options with criteria;
- Examine solutions against research objectives.
- Select the optimal choice

The table below explains the criteria and their meanings that were used in building the decision-making matrix. Six different criteria are illustrated in table 3.5 The criteria includes cost of energy, Net present,Operating, capital costs ,Renewable fraction and Carbon dioxide emissions .

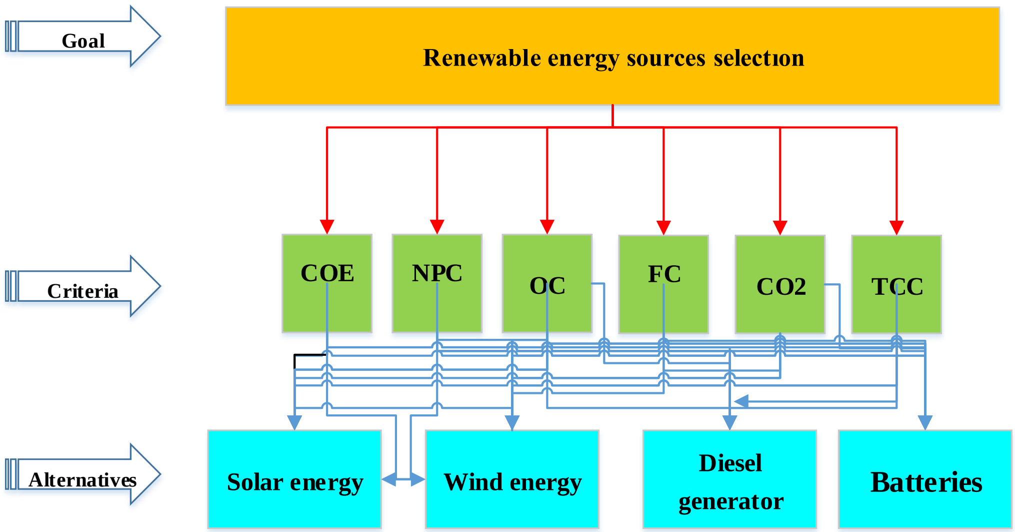

Figure 3.9. decision-making methodology for selecting energy source

Table 3.5. List of criteria and their meanings

Criteria	Index	Significance
Cost of energy (USD/kWh)	C1	It describes the generated power cost .
Net present cost (USD)	C2	refers to all costs associated with installing and operating the system during its life cycle
Operating cost (USD/yr)	C3	means the operating costs required for all generation units over the project lifespan
Initial capital cost(USD)	C4	This is the initial investment necessary to begin the hybrid power system deployment.
Renewable fraction (%)	C5	It presents the percentage of power delivered to a load comes from only renewable sources.
Carbon dioxide emissions (t/yr)	C6	refers to the amount of CO2 emitted by the microgrid over its lifetime.

3.5.3.2. Topsis Technique

Topsis is a method based on mathematical calculations to compare a set of alternatives and choose the best option. Simply, the solution is to find the nearest distance from the positive point and the farthest distance from the negative point. The distance between the positive and negative point is calculated after solving several mathematical equations as follows

- Build a decision matrix
- Calculation of weights for all six criteria
- Create the Unified Matrix
- Create a normalization matrix to calculate the distance between the alternatives.
- Calculate the matrix of idealized positive and negative values
- Measure the distance between the positive and negative points of each substitution.
- Calculate the relative coefficient for all six alternatives.

- And finally, arranging energy sources and determining priority.

The TOPSIS procedures as below [70]:

step 1. Establishing the decision matrix X

$$X = [X_{ij}] = \begin{bmatrix} X_{11} & . & . & . & X_{1n} \\ & & . & & \\ . & & & & . \\ & & . & & \\ X_{m1} & . & . & . & X_{mn} \end{bmatrix} \tag{3.28}$$

xij indicates the attributes values where j = 1, 2, 3. .4 . , n and, i = 1, 2, 3. 4. . , m

step 2. Normalizing the values of attributes using the following equation

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \\ 1 - \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}, \end{cases} \tag{3.29}$$

step 3. Establishing the normalized matrix using the equation(3.30)

$$R = [r_{ij}] = \begin{bmatrix} r_{11} & . & . & . & r_{1n} \\ & & . & & \\ . & & & & . \\ & & . & & \\ r_{m1} & . & . & . & r_{mn} \end{bmatrix} \tag{3.30}$$

rij indicates the normalized values of the the attributes

step 4. Calculating criteria weight [71]:

E = (e1, e2, . . . en), where: E means an entropy vector,

$$e_n = \frac{-1}{lnm} \sum_{i=1}^{m} Z_{ij} \ln Z_{ij} \tag{3.31}$$

Where $Z_{ij} \ln Z_{ij} = 0$ and $Z_{ij} \ln Z_{ij} = 0$

$$w = (w_1, \;\; w_2, \dots \dots .. w_n)$$

$$\sum_{i=1}^{n} w_j = 1, w_j \quad \in [0,1], \tag{3.32}$$

The criteria weight is represented by wj in the previous formula. If all criteria are correct, the weights can be calculated using the formula:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{3.33}$$

step 5. The normalized indicator numbers were weighted using the equation given below

$$v_{ij} = r_{ij}.w_j \tag{3.34}$$

step 6. The decision matrix V was generated using each attribute's weight:

$$V = \lceil v_{ij} \rceil = \begin{bmatrix} v_{11} & . & . & . & v_{1n} \\ & & . & & \\ . & & & & . \\ & & . & & \\ v_{m1} & . & . & . & v_{mn} \end{bmatrix} \tag{3.35}$$

where: vij represents the weighted and normalized values

step 7. Then the model generates the positive (A +) and negitive (A −) values

$$A^{+} = (v_1^{+}, v_2^{+} \;, \dots \dots v_m^{+}) \tag{3.36}$$

$$A^{-} = (v_1^{-}, v_2^{-} \;, \dots \dots v_m^{-}) \tag{3.37}$$

Step 8. using the equation (3.38) it can be calculate the positive distance (d_i^{+}) for each attribute and the negative distance (d_i^{-}) is calculated using the formula(3.39)

$$d_i^+ = \sqrt{\sum_{i=1}^{m}(v_{ij} - v_j^+)^2} \quad (3.38)$$

$$d_i^- = \sqrt{\sum_{i=1}^{m}(v_{ij} - v_j^-)^2} \quad (3.39)$$

here: i = 1, 2,3 .4 .. . , m.

step 9. calculating the relative coefficient (RCi) for each alternative

$$RC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (3.40)$$

where relative coefficient should be between 0 and 1 , 0 ≤ RCi ≤ 1, i = 1, 2, 3. 4. . , m.
step 10. By utilising the formula(3.41), it can rank the different options and give each one a final score

$$RC_i' = \frac{RC_i}{\sum_{i=1}^{m} RC_i'}, (i = 1.2 \dots \dots, m) \quad (3.41)$$

step 11. Select the optimal and best choice

3.5.3.3. VIKOR Method

VIKOR is one of decision making techniques that prioritizes the best option found relative to the closest ideal solution. The distance from the ideal solutions is then used to evaluate the stages in the ranking process. In order to find the optimal option, the VIKOR technique uses linear normalization. Normalization of the matrix as above.

$$\mathrm{R_{ij}} = \frac{(\mathrm{X*j} - \mathrm{X_{ij}})}{\mathrm{X*J} - \mathrm{X'j}} \quad (3.42)$$

Where Xij is Value of sample i and the criteria j

(J = 6 criteria)
X*j is the best value

X'j is the worst value

- Then determining the values of S and R

$$S_i = \sum_j^n wj \times (R_{ij}) \tag{3.43}$$

Where Wj represents the weighting criteria. The values of S are determined by combining the results of multiplying the weighted criterion by the numerical value of each alternative.

Ri= Max j [wj x Rij]

- Ri is the greatest value obtained by multiplying the criteria weights by the normalized data of each alternative.
- Calculates the final ranking

Compute the values Qj; j = 1, 2..., m,

$$Qj=\left[\frac{Si-S'}{S*-S'}\right]\times V+\left[\frac{Ri-R'}{R*-R'}\right]\times(1-V) \tag{3.44}$$

Where the S' is the smallest value of S, and S* is the largest value of S Rrepresents the smallest value of R and R* is the largest value of R

3.5.4. Optimal Sceduling of Energy Sources Using (Genetic Algorithm)

3.5.4.1. Metheology Description

The system proposed in the study is a hybrid of different generation units not connected to the main grid. This system relies heavily on renewable energy such as solar and wind energy and the traditional diesel-powered generator to obtain sustainable, uninterrupted, and cheap energy for the consumer. Figure 1 shows the components of the system. A residential building receives power from the system. 250 kW is the highest demand side, and 86 kW is the lowest demand. Throughout the entire month, the HES sources have scheduled over 720 hours. There are two sections to the study, the first of which is a model for an energy scheduling using genetic algorithm. The program first estimates the building's electricity demand for a month (720 hours) and the weather information. Next, the state of charge of the battery and the power generated from renewable sources per hour is determined accordingly. The algorithm will choose the most appropriate energy source for each load and the lowest cost per hour based on the changing demand, always considering the available and stored energy and the least cost in terms of operation. Then the scheduling results for 720 hours will be obtained and entered as data into the machine learning model. Then the model will be trained on this data so that the algorithms understand the scheduling results depending on the variable loads and the sources used to feed and meteorological data. Finally, the model will calculate the energy required per hour in new buildings under the same weather conditions, building size, generating unit size, and in the same city on all these inputs. The research methodology is shown in Figure (3.10) below. The following sections provide a detailed explanation of the management and forecasting process. To complete the objective of the study, the results of three machine learning techniques used in classification - Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbors (KNN) - are compared to find out the best algorithm in terms of performance and results.

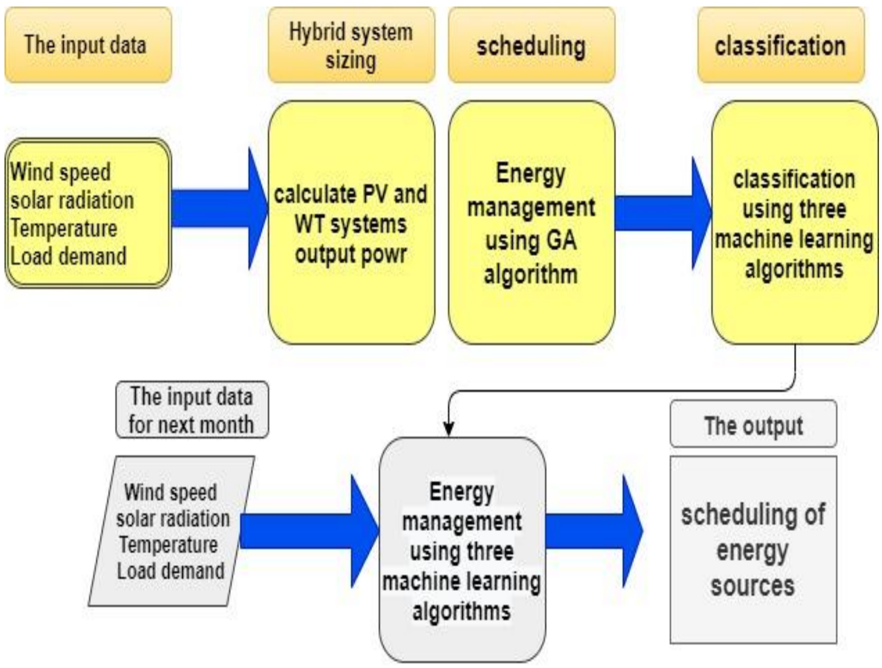

Figure 3.10. The microgrid scheduling and prediction methodology.

3.5.4.2. Details of The Generation Units In Microgrid

The hybrid system comprises a 150-kW wind (WT), 70-kW PV capacity, 100-kW diesel generator, and battries for energy storage. Based on various hourly weather and demand loads, an Energy Management strategy is suggested to control the share of power among the three sources. The EMS is handled by the Genetic algorithm GA approach, which makes its choice based on the availability of energy sources and the system's operational costs. The scheduling process is explained in the subsequent steps.

- The majority of the load demand is supplied by photovoltaic and wind energy..
- When renewable energy sources produce more power than is needed, the surplus is delivered to the BAT.
- When the output power from the PV array and the WTs is insufficient, the BAT discharges.
- When a maximum consumption occurs or renewable output varies, the BAT delivers a part of its energy.
- The generator will swich on when output power of PV and WT systems are insufficient.
- In case the generated energy exceeds the load demand and the BAT is completely charged ,the extra energy is sold to the main grid.
- The priority always for the lowest cost source.

Below are the restrictions that must be followed when applying energy management between generation units in the microgrid, as shown in equation (3.45). A balance must be maintained between generation and consumption continuously.

$$\mathrm{P_L = P_{PV} + P_{WT} + P_{Batt} + P_{DG}} \tag{3.45}$$

The excess and deficit energy are represented by equations (3.46) and (3.47), respectively.

$$P_{EX}(t) = \left[P_{pv}(t) + P_{wt}(t)\right] - P_L(t) \tag{3.46}$$

$$P_{Def}(t) = P_L(t) - \left[P_{pv}(t) + P_{wt}(t)\right] \tag{3.47}$$

$$P_{DG}(t) \leq P_{DG\,max} \tag{3.48}$$

Where $P_{PV}(t)$ is the PV power, $P_{Wt}(t)$is the wind system power, $P_L(t)$represents the demand power , $P_{Bat}(t)$ is the obtained energy from the battery, $P_{DG}(t)$is the power delivered by the diesel generator, $P_{EX}(t)$ is the the surplus power and $P_{Def}(t)$is the deficit power.

In the previous equation P_PV (t) represents the output of the solar power system and P_wt (t) refers to the wind power output, while P_L (t) represents the electrical loads of the residential buildings, P_bat (t) is the energy stored in the battery, P_DG (t) represents the output power of the generator, P_ex (t) is the redundant energy generated by the wind and solar systems and P_def (t) represents the deficit and lost energy.

3.5.4.2. The Proposed Scheduling Algorithm

3.5.4.2.1. Genetic Algorithm

The genetic algorithm is a frequently used algorithm due to the accuracy of its results. It is mainly used in optimization, scheduling, and solving mathematical equations. Its classified as exploratory, looking for solutions closest to the ideal. The main step is to generate the population randomly, then evaluate the fitness function, and after that generate anew group to obtain better results. The chromosomes are randomly generated, which can be a practical solution to the problem as fitness is evaluated with each cycle. Then each individual in the group is evaluated to provide a near-perfect solution [30].

The reproduction process consists of three critical stages: selection, crossover, and mutation. The parents' generation is chosen based on their fitness level and survival ability. The crossover process is the process of generating new offspring with better characteristics. Then the genes are randomly recombined to produce new offspring.

The mutation process changes one or more values to generate a new population different from the initial one. The process is repeated n times to get the best solution, then the algorithm stops searching and gives us the final result.

Objective functions with limitations, variables, and constants have been defined in M-file to solve the optimization problem (MATLAB code). The energy system's microgrid, PV, WT, BAT, and DG components are regarded as four independent variables. The fitness function of the optimization problem has been determined using the toolbox for genetic algorithms. It was found that accurate outputs with a low generation cost were regarded as specified functions. The procedures of crossover, mutation, and selection were only applied to find optimal components.

Figure 11 outlines some of the stages in the technique of the proposed GA-based energy scheduling methodology. The suggested algorithm has the advantage of including various renewable energy sources.

- input initial parameters
- input 720-hours load demand.
- input solar irradiance , wind speed data
- calculating the output power from renewable sources.
- enter the generator size
- scheduling avilable energy sources.
- determine the best solution for the system every hour.

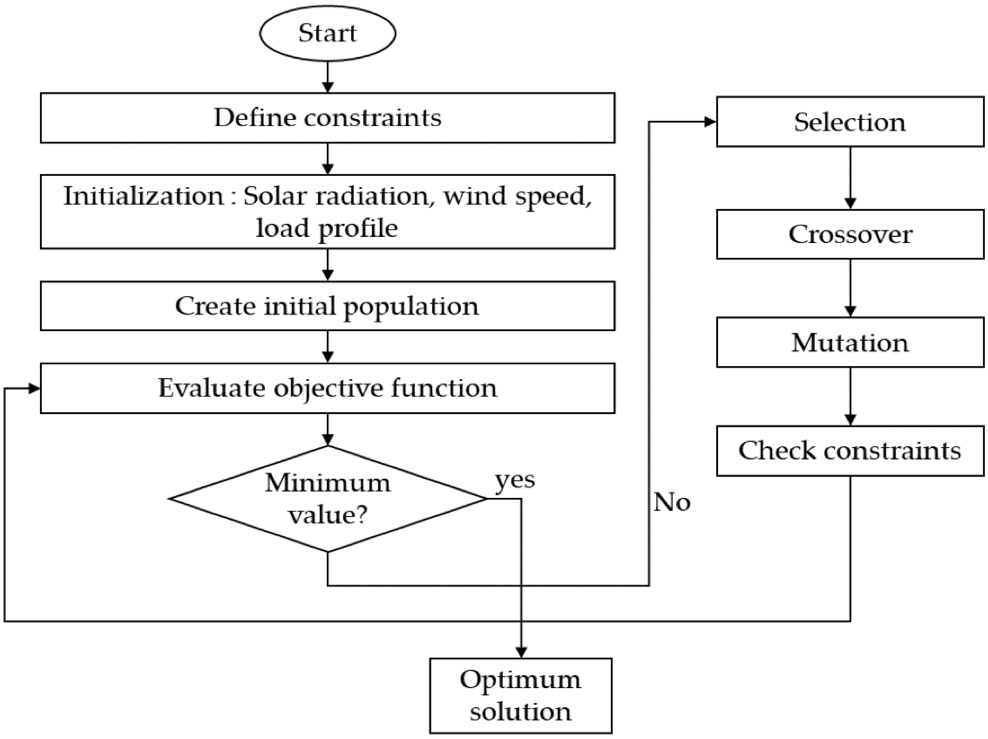

Figure 3.11. The Genetic Algorithm flowchart

3.5.4.3. Objective Function

The Objective Function is minimizing the TC(Total cost) of the proposed system. The TC includes capital (C_{cap}), maintenance (C_{main}), replacement costs (C_{rep}) for all generation units. The price of energy per kilowatt-hour is related to the cost of building, operating and maintaining the PV and WT generation units and the diesel generator, in addition to the cost of energy storage and the number of batteries required [54].

$$Min\ TC = C_{ap} + C_{main\ and\ op} + C_{rep} \tag{3.49}$$

The initial cost required for the installation of system is determined by the following[54]:

$$\mathrm{C_{cap}} = \mathrm{C_{PVc}} \times \mathrm{N_{PV}} + \mathrm{C_{WTc}} \times \mathrm{N_{WT}} + \mathrm{C_{Battc}} \times \mathrm{N_{Batt}} + \mathrm{C_{con}} \times \mathrm{N_{con}} + \mathrm{C_{DGc}} \times \mathrm{N_{DG}}$$
(3.50)

The costs of maintaining and operating the system are shown below[57]:

$$\boldsymbol{C_{m\,and\,op}} = \text{PWA} \times (\boldsymbol{C_{PVm}} \times \boldsymbol{N_{PV}} + \boldsymbol{C_{WT\,m}} \times \boldsymbol{N_{WT}} + \boldsymbol{C_{Batt}} \times \boldsymbol{N_{Battm}} + \boldsymbol{C_{con}} \times \boldsymbol{N_{con}} + \boldsymbol{C_{DGm}} \times \boldsymbol{N_{DG}}) \quad (3.51)$$

And the replacement cost is defined as follows[57]:

$$\mathrm{C_{rep}} = \mathrm{K} \times (\mathrm{C_{PVr}} \times \mathrm{N_{PV}} + \mathrm{C_{WTr}} \times \mathrm{N_{WT}} + \mathrm{C_{Battr}} \times \mathrm{N_{Batt}} + \mathrm{C_{con}} \times \mathrm{N_{con}} + \mathrm{C_{DGr}} \times \mathrm{N_{DG}}) \quad (3.52)$$

The equations above, Ccap, Cmain, and Crep represent the capital, the operation and maintenance, and replacement costs respectively. The numbers NPV, NWT, NBat, Ncon, and NDG represent the number of solar panels, wind turbines, battries, and diesel generators. Subsystem capital costs are shown by CPVc, CWTc, CBatc, Cconv, and CDGc. Component operating and maintenance costs are shown by CPVm, CWTm, Cbatm, Cconv, and CDGm. The system replacement costs are shown by CPVr, CWTr, Cbatr, Cconr, and CDGr..

3.5.4.4. Constraints

3.5.4.4.1. Battery Bank Capacity Constraint

To overcome the power deficit, which is determined as in equation(3.53) , a rechargeable battery is suggested.

$$\mathrm{E^t_{gap}} = \frac{\mathrm{E^t_{Dmd}}}{\eta_{\mathrm{inv}}} - \mathrm{P^t_w} \times \mathrm{N_w} \times \Delta\mathrm{t} - \mathrm{P^t_{pv}} \times \mathrm{N_{pv}} \times \Delta\mathrm{t} \quad (3.53)$$

where $\mathrm{E^t_{gap}}$ is the power gap at time *t* and $\mathrm{E^t_{Dmd}}$is the power demand at time *t;* $\boldsymbol{\eta_{inv}}$ represents the converter efficiency. Two cases, with $\mathrm{E^t_{gap}}\geq0$ and $\mathrm{E^t_{gap}}\leq0$, are considered in the operation of the microgrid system, therefore, the formula below can be used to determine the battery's available energy.

$$E_{batt}^{t} = \begin{cases} E_{batt}^{t-1} \times (1-\sigma) - E_{gap}^{t} \times \eta_{batt}^{c}, & \text{if } E_{gap}^{t} < 0 \\ E_{batt}^{t-1} \times (1-\sigma) - E_{gap}^{t}, & \text{if } E_{gap}^{t} \geq 0 \end{cases} \tag{3.54}$$

where E_{batt}^{t} and E_{batt}^{t-1} are the residual amounts of energy in the battery at times *t* and *t*−1, respectively. All batteries are considered to have an initial charge of 20% of their rated capacity, σ is the rate of self-discharge per hour, and η_{batt}^{c} is how effectively the battery bank charges.At any time, the amount of charge in the battery system should be within the range of what the batteries can hold.

$$E_{batt}^{min} \leq E_{batt}^{t} \leq E_{batt}^{max} \tag{3.55}$$

$$E_{batt}^{min} = (1 - DOD) \times E_{batt}^{max} \tag{3.56}$$

where E_{batt}^{max} represents the maximum limit of the charging energy, which is determined by the amount of the battery bank's rated capacity, and E_{batt}^{min} is the minimal capacity of energy storage, which is determined by the deepest point of discharge (DOD).

3.5.4.4.2. Energy Supply Constraint

The energy supply constraint for this system is specified in order to manage the microgrid power generation, which should be greater than the daily load demand.

$$\sum_{t=1}^{24}(P_{pv}^{t} \times N_{pv} \times \Delta t + P_{w}^{t} \times N_{w} \times \Delta t + E_{DG}^{t}) \geq \sum_{t=1}^{24} \frac{E_{Dnd}}{\eta_{inv}} \tag{3.57}$$

Three energy sources are used to generate power (PV, wind, and diesel) in palance. The rechargeable battery is an energy storage system that stores extra energy generated by renewable energy.When the battery gets low, and a power outage occurs, the diesel generat or serves as an emergency backup. Generally, the generator is operated at 20 to 100% of its nominal power[[17].

3.5.4.4.3. System Component Size Constraints

The following is the capacity constraints of hybrid overall system.

$$PminWT \leq PWT \leq Pmax\ WT \tag{3.58}$$

$$PminPV \leq PPV \leq Pmax\ PV \tag{3.59}$$

$$PminBat \leq Pbat \leq PmaxBat \tag{3.60}$$

$$Pmin\ DG \leq PDG \leq Pmax\ DG \tag{3.61}$$

3.5.4.5. The Power Sharing Strategy In Side Microgrid

The schduling strategy is described as follows:

- PV wind systems provide enough power to meet the demand. The extra power will be stored in the stoarge uints (batteries) .
- In case that, the energy generated from renewable sources is inadequate, the batteries will discharge its energy to compensate the power deficit. It is supposed that the battery system has the highest capacity at the initial stage.
- (3) In this case, the power from solar panels, wind turbines, and batteries might not be enough. So the diesel generator makes up for the battery's shortfall.
- The power management approach is typically very complicated due to the intermittent of renewable energy. Many scenarios included in this methodology are explained briefly below:

Case 1: The battery will start charging when all renewable sources have satisfied the demand.
Case 2: When renewable sources are unable to satisfy the load's needs, the battery will back up.
Case 3: When renewable sources and the storage battery aren't enough the generator will turn on to supply the loads

Case 4: Once the batteries are completely charged, then the surplus energy will be sold to the main grid.

In the scheduling stage, several scenarios have been proposed to ensure the optimal use of alternative energy and the sustainability of energy flow are stated as follows:

case 1: microgrid including PV, WT, Batteries and DG
case 2: microgrid including PV, WT and Batteries
case 3: microgrid including only DG

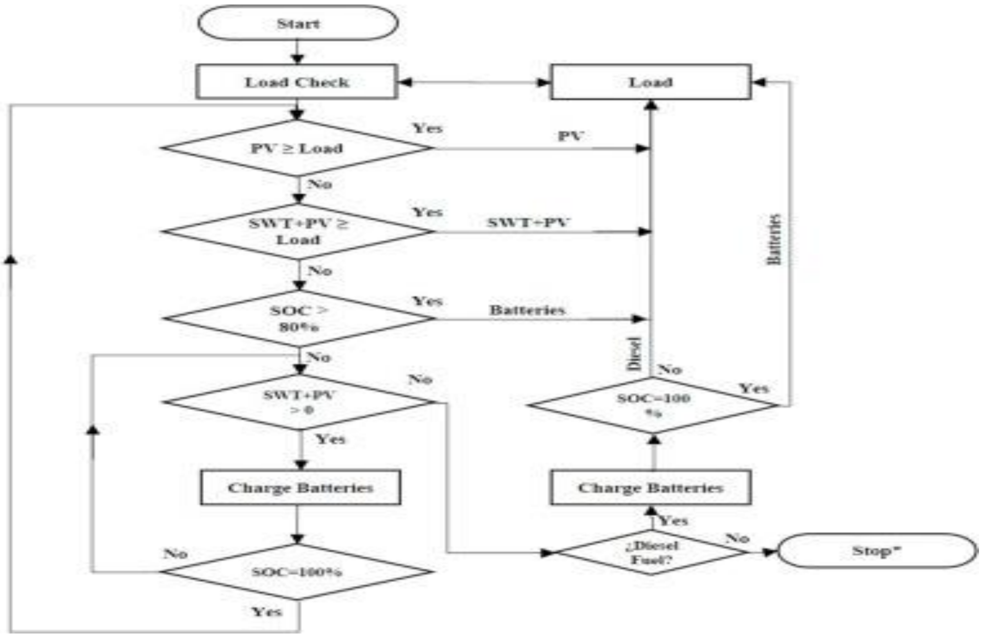

Figure 3.12. The power schduling strategy

3.5.5. Energy Sources operation Prediction using Machine Learning Algorithms

3.5.5.1. Prediction Based On Machine Learning

The most important applications of machine learning are classification and prediction based on historical data. ML has a variety of applications, including classification, and its divided into two primary categories: supervised and unsupervised [23]. In this study, we used supervised algorithms, which derive predictions from data sets containing specific input information and experience, to discover outputs directly related to the input data [24]. The supervised ML method aims to determine the relationship between the input variables (independent variables) and the output (dependent variable)[25]. Furthermore, classification is regarded as a reliable technique for predicting future information extraction. Although there are many techniques related to machine learning, only classification belongs to our research. Figure 1 depicts the classification of machine learning (ML) techniques.

3.5.5.2. Data Analysis

There are 720 cases in the scheduling dataset for period of one month, which include 7 features, 1 output variable, and 4 input variables. Hybrid energy source scheduling uses the 4 variables as inputs: solar power, wind power, hourly demand, and storage capacity. There are different attributes of classes. The encoding for these components is displayed in Table 2.

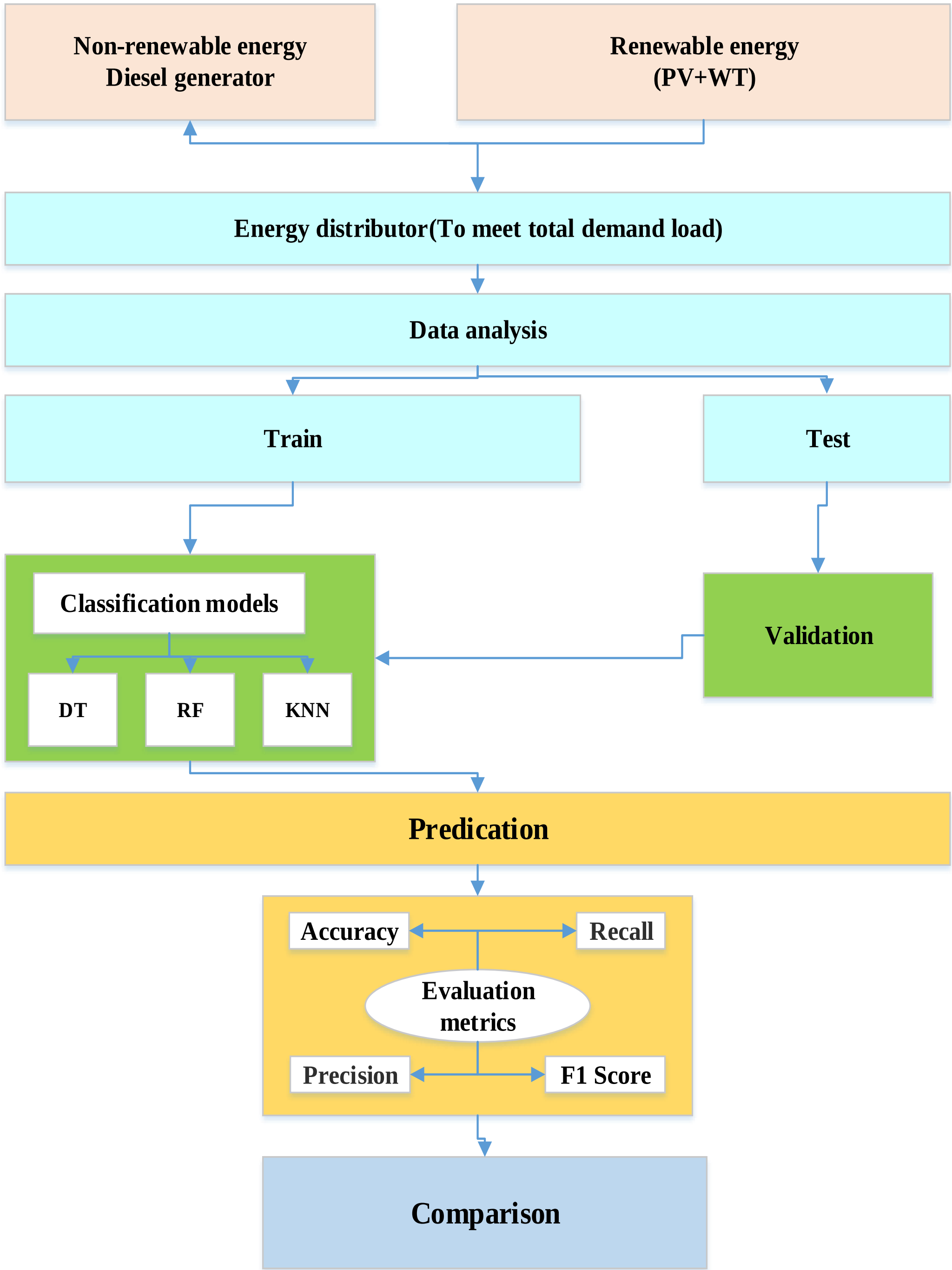

Figure 3.13. Flowchart of the classification process

Table 3.6. Encoded classes for all energy sources

Class	Class Encoding
WT + batt	1
WT +DG	2
WT+PV+Batt	3
WT+PV	4
PV+WT+Batt+DG	5
WT+Batt+DG	6
DG	7

3.5.5.3. Random Forest (RF) Algorithm

An collective supervised learning which is suitable for classification, regression, and other applications is the RF algorithm. Throughout the training process, several decision trees are created. In regression tasks, individual tree predictions are given back as the average predictions. The class that has the largest trees is what the RF produces when used to classification and prediction. RF is a classifier i.e., {h(x, Θ_k), k = 1,...}, where k is an independent vector. Multiple decision trees are created using different subtrees from the input data. Each decision tree classifies the data in a separate way from the other. Predictions are made through the use of data classification process. Data is classified based on some common features and a specific characteristic or numbers. The results of each tree can be different depending on the value of k which affects the classification accuracy and read all data without loss [27]. Figure13 shows RF flowchart.

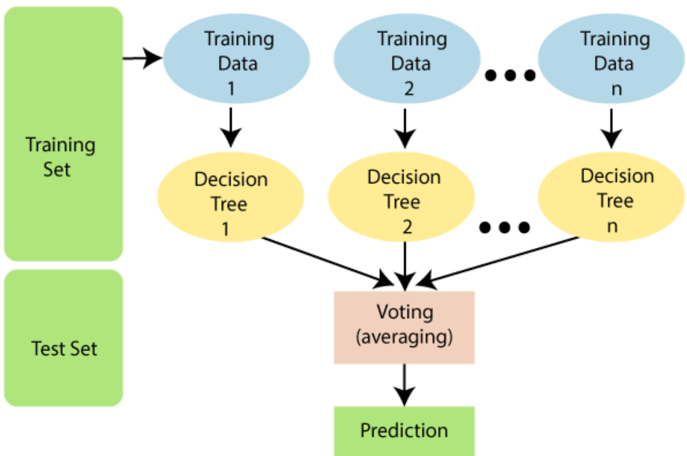

Figure 3.14. RF algorithm working principle

3.5.5.4. Decision Tree

The DT decision tree is a supervised technique commonly used in classification issues because it is simple to use, produces reliable results, and assists in decision-making when the data is large. The method is a tree, with internal nodes representing data attributes, branches representing decision-making rules, and terminal nodes representing the result and final outcome. The decision node and the leaf node are the two nodes, with the decision node contributing to any choice and having multiple branches that branch out from the origin. The leaf node, on the other hand, is the result and does not include the expansion of other branches.Based on specific variables and features, a graphical representation of alternative solutions to any problem. The algorithm generally asks a question and divides the tree into multiple sub-trees based on the answer (yes/no) until it finds the desired answer. The process employed in the decision tree is presented in the diagram below

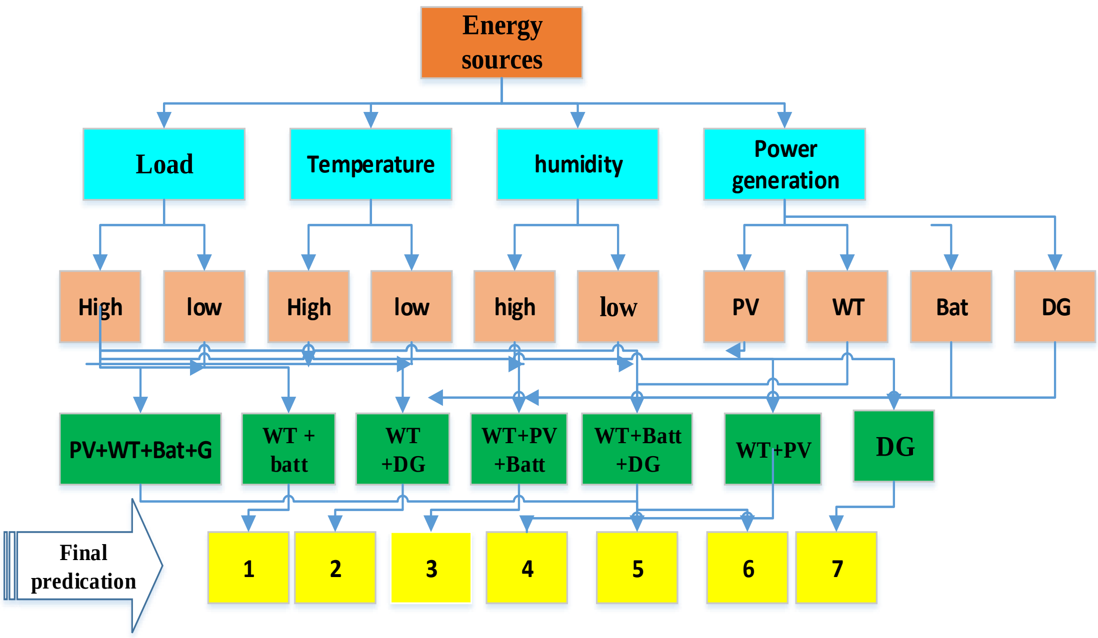

Figure 3.15. DT algorithm architecture

3.5.5.5. Nearest Neighbors Algorithm

Due to its simplicity and flexibility, KNN is widely used algorithms in the field of machine learning. KNN takes time to read and memory to store because it uses all of the training data. [29] gave a detailed overview of the benefits and drawbacks of the KNN approach. Regression and classification are both possible with KNN. The input data for both applications is a set of the k-closest training examples. KNN classification results in a class label. The object is allocated to the class with the greatest number of members among its k nearest neighbors (k is a small positive integer). If k = 1, the item is only assigned to the classes of its nearest neighbor.

The approach is effective in cases when there is no linear relationship between the independent (x) and dependent (y) variables. The process of KNN is presented in the flowchart below Figure 3.16.

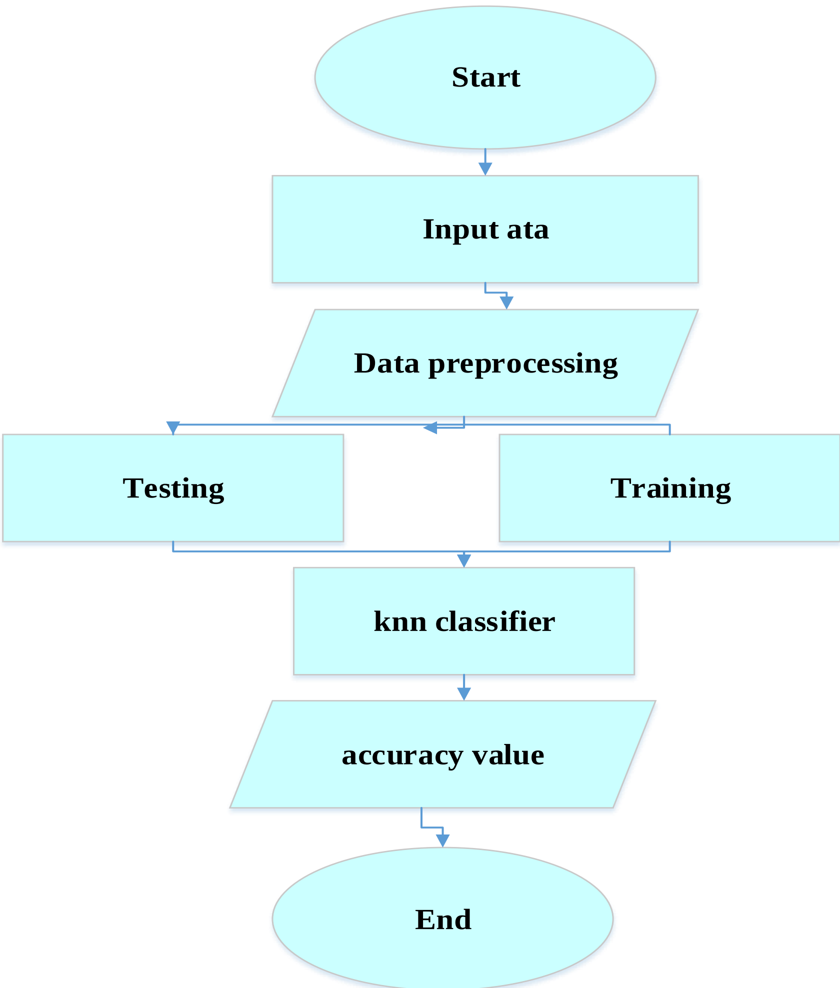

Figure 3.16. KNN algorithm flowchart

3.5.6. The Algorithms Evaluation

Performance evaluation is an important final stage in building a machine-learning model. This can be achieved by using a variety of metrics and measurements. The performance and accuracy of the model are validated in the following four steps.

Accuracy: It is a standard technique for evaluating classification problems, and it is calculated using equation (19): [32]:

$$\text{Accuracy}=\frac{\mathbf{TP+TN}}{\mathbf{To}} \tag{3.62}$$

TP denotes true positive, TO refers to classes number, and TN denotes true negative in this equation. The TP measurement is used if the expected value compared to the real value is "Yes", while if the two are not correct, the TN measurement is used. When data consists of imbalanced values, overall classification accuracy could be better for assessing the model's performance [38]. Additionally, because the algorithm can only detect one or two classes instantaneously, one class might be chosen over others. The following is a list of the best model performance evaluation metrics for input data that are imbalanced:

Precision: It is simply, a fraction of TP samples that are forecasted of specific classes. According to Equation 13, the precision is calculated by dividing TP by the summation of TP and FP [32].

$$\text{Precision}=TP/(TP+FP) \tag{3.63}$$

Recall: It refers to dividing the correct classified samples (TP) (belonging to a part of the real data) by the sum of the TP and FN measurements [32].

$$\text{Recall}=\frac{\mathbf{TP}}{\mathbf{TP+FN}} \tag{3.64}$$

F1 Score: It displays the accuracy, robustness, and balance between recall and precision of a model. This can be expressed mathematically as following [32].

$$\text{F1-score} = \frac{\mathbf{2}}{\frac{\mathbf{1}}{\mathbf{precision}}+\frac{\mathbf{1}}{\mathbf{recall}}} \tag{3.65}$$

PART 4

DISSCUTION AND RESULTS

4.1. BACKGROUND

In order to deal with the problems associated with renewable energy sources, such as overload, voltage instability, and poor power quality, an energy storage system, such as a battery (BESS), can be added as an essential type of energy balance, with the appropriate use of renewable energy sources (PV and WT). [10] [16]. Because the cost of BESS per kilowatt is proportional to capacity and cycle life, powering loads with 100% reliability using only renewable energy sources and BESS can be prohibitively expensive. Furthermore, because the energy stored in the battery is based on intermittent renewables, it is possible that the output of the renewables and battery becomes insufficient to satisfy the load while the MG is working. A dispatchable source, such as a diesel generator (DG), must also provide effective and affordable load feeding. On the one hand, distributed generation has several disadvantages, including high operating and maintenance costs and environmental degradation from greenhouse gas (GHG) emissions. Renewables and batteries, on the other hand, have high initial investment costs, low operating costs, and zero gas emissions. The high cost and gas emissions make it unsuitable for residantal , commercial and industrial applications. As a result, developing a strategy to control generation and energy consumption is critical in any system that including renewable energy sources, BESS, and DG. The amount of energy produced per hour was determined by developing mathematical models for wind and solar energy systems using weather inputs, the size of each generation unit, and the limitations applied.

4.2. HOMER SOFTWRE RESULTS

HOMER analyzes the hybrid systems for power generation from an economic point of view, the impact on the environment, and the appropriate size for each generation unit. It gives the results and several options for the same system. The software then helps the researchers to choose the best micro-network configuration based on the lowest TNPC cost; it then chooses the best configuration of the six proposed combinations. Tables 4.1 and 4.2 at the bottom present the results obtained from the software, which contain a detailed economic analysis of the proposed system. The Scenario (1) which contains a solar and wind energy system and a diesel generator in addition to storage units A1 (PV / W / DG/BAT), has the lowest TNPC cost with the maximum clean energy use of 62%. While Scenario A5 contains alternative energy as the primary source of energy (PV/wind/battery), and Scenario A6 depends entirely on solar energy and batteries (PV / battery). This system has the highest cost record TNPC due to the increase in the cost of batteries and solar panels, as it requires a large number of panels and batteries. It is also noted that systems use renewable energy by 100%. However, using 100% renewable energy makes the combination the best choice based on its positive environmental impact. The table found that the most hybrid combination in terms of the total cost of the project is A6, as it requires high construction and establishment costs (TNPC) with a value of ($ 460,756). The least expensive TNPC combination was the system (PV/WD/DG/BAT) which cost $254,874. Table 2 includes the details of the technical and economic criteria that assist the decision-maker in choosing the appropriate combination of several energy sources. Accordingly, these results will be used in the second phase of the research during the implementation of multi-criteria decision-making methods, the results of which will be explained in the next section. Figure 4.1 shows the six hybrid systems that were studied using Homer.

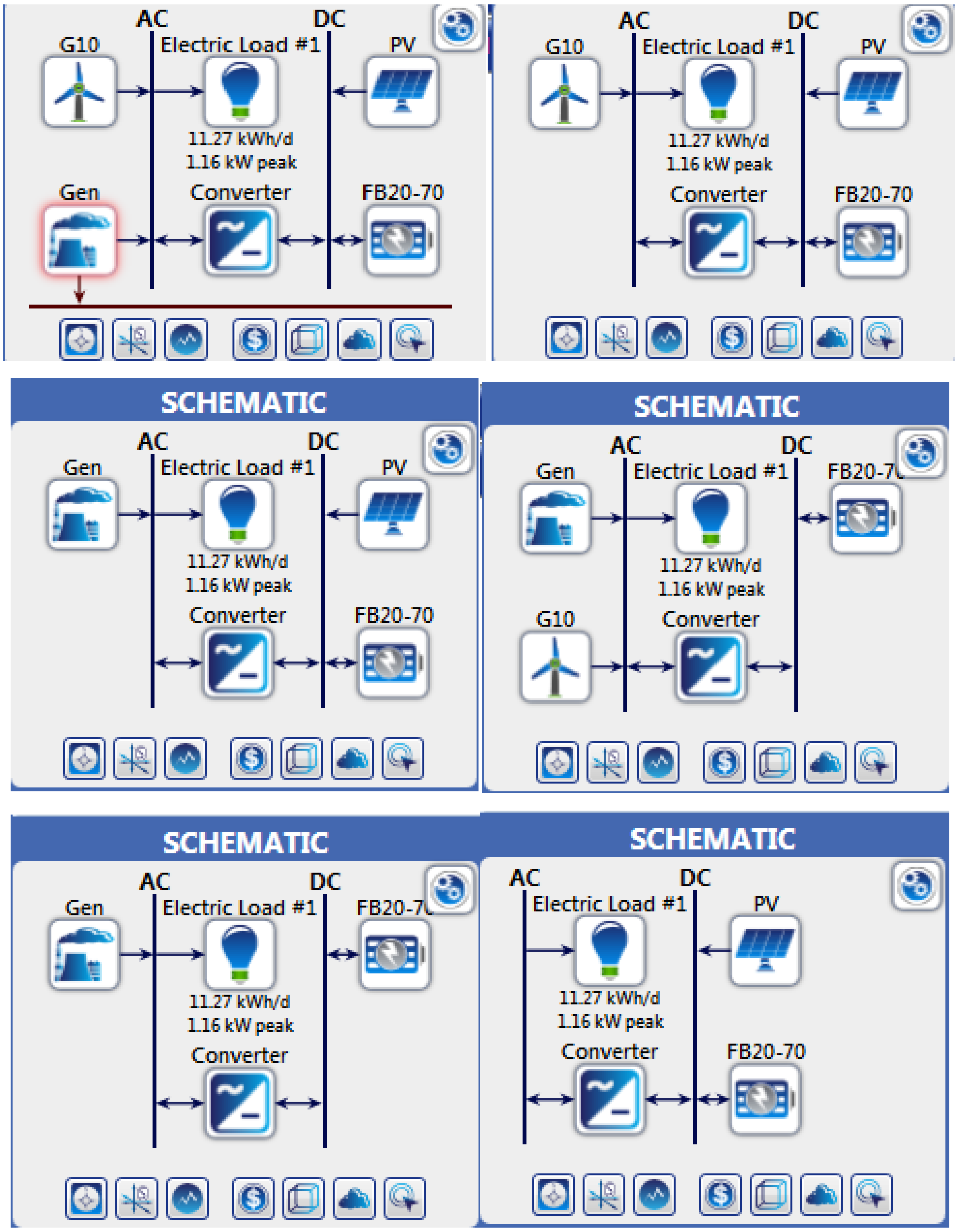

Figure 4.1. presents six energy combinations for all case studies.

The MG design incorporating different renewable and conventional energy sources depends on the low capital cost . Geographical specifications varies from site to site depending on available natural resources , load demand and their behavior. Different combinations of energy generators and Battries can be selected based on geographical location and demand needs. It is also important to study the economic feasibility of each energy source and its ability to supply the loads efficiently and sustainably.

Practical factors should be analyzed to design reliable power source. As shown in Table 4.2, Initial capital cost ($), Cost of Energy COE, Total O&M Cost ($/yr), CO2 emissions(t/yr), and Fuel cost ($/yr).From the table system A1 has low initial capital cost than other choices ,also the cost of energy(0.476) which is an essential factor in determining the size and components of the microgrid. the operating costs are also lower(2,645) This makes it the best choice compared to the rest of the scenarios. The renewable fraction is an important factor that explains the percentage of renewable energy use in the system to the total production. The highest value of this factor is (100%). The system in which the factor is 100 depends entirely on renewable energy only such as A5 and A6. For the rest of the scenarios, the percentage of involving clean energy varies according to the need and the increase in the load. For example, scenario (1) has 62%, scenario (2) shares 43% of the power generation, and scenario (3) was 52% of the total power generation. The table shows that the systems that contain only wind and solar energy require the highest construction and capital cost due to the high price of wind and solar systems, such as scenario 6 (PV/BAT) costs 355,865$. In general, the Homer selects the system based on total NPC and energy cost. Hence, system 1(PV/WD/DG/BAT) is selected as an optimum choice for our case study.

The important inputs required for the software in terms of capital, establishment, operation and maintenance costs were according to the current prices in the Libyan market. In addition to economic data, sensitive parameters such as the nominal discount rates (%) per generating unit and for the system as a whole range from 4% - 17%, and the price of diesel fuel that is set. 0.4 $/L, measured solar radiation 5-7 (kWh/m2), and finally measured wind speed 2-8 (m/s).

The following are the six scenarios of the mini-grid obtained from the Homer simulation.

Scenario1 (PV/WT/DG/BATT)
Scenario2 (PV/DG/BATT)
Scenario3 (WT/DG/BATT)
Scenario4 (DG/BATT)
Scenario5 (PV/WT/BATT)

Scenario6 (PV/BATT)

Table 4.1. HOMER Technical results for the energy systems.

Hybrid system	PV/WT/DG/BATT	PV/DG/BATT	WT/DG/BATT)	DG/BATT	PV/WT/BAT	PV/BATT
Wind turbine (kW)	150	0	200	0	200	0
PV (kW)	70	140	0	0	140	300
Diesel Generator (kW)	100	100	100	100	0	0
Battery (kWh)	150	100	100	150	180	200
Converter (kW)	150	120	150	50	250	250
Unmet Load (kWh/yr)	0	0	0	0	13	37
Renewable fraction (RF) (%)	0.64	0.43	0.52	0	1	1
Dispatch	cc	cc	cc	cc	cc	cc

Table 4.2. HOMER Economic results for the hybrid systems.

Hybrid system	PV/WD/DG/BAT	PV/DG/BAT	WD/DG/BAT)	DG/BAT	PV/WD/BAT	PV/BAT
Total NPC ($)	254,874	289,657	322,867	344,546	422,756	460,756
Initial capital cost ($)	193,567	112,756	260,756	280,865	340,756	355,865
Cost of Energy COE (USD/kWh)	0.476	0.487	0.576	1.765	0.687	0.712
Total O&M Cost ($/yr)	2,645	2,965	3,265	3,567	1,123	895
Fuel cost ($/yr)	2035	3065	2,565	6,756	0	0
Fuel consumption (L/yr)	11350	15678	12,657	37,756	0	0
CO2 emissions(t/yr)	2.435	3,785	2.956	5,756	0	0

4.3. MULTİCRİTERİA DECİSİON MAKİNG ANALYSİS RESULTS

Determining criteria for each choice is necessary to select the best energy source from a collection of hybrid energy sources. Therefore, making choices requires understanding essential information about each energy source and allocating weights to each criteria. The priority of the systems is based on the weights given to each criterion. Therefore, the weights significantly impact which systems are chosen over others. Table 4.3. shows the six power generation scenarios. And the weights assigned to each calculated criterion are shown in Table 4.4. The MCDM algorithms use weights to establish the rank of the systems. Table 4.4 demonstrates that the sum of the criterion weights is 1. The table below shows an example of alternatives and corresponding criteria values (based on previously specified criteria in Table 2), with costs stated in thousands of dollars and production energy in kW.

Table 4.3. Alternatives for six power generation systems.

Alternatives	Energy source
S1	PV-WT-BATT-DG
S2	PV/DG/BATT
S3	WT/DG/BATT
S4	DG/BATT
S5	PV/WT/BATT
S6	PV/BATT

Table 4.4. Estimated criterion weights

Criteria	Index	weights
Net present cost	C1	0.31
Initial capital cost	C2	0.10
Cost of energy	C3	0.04
Total O&M cost	C4	0.13
Renewable fraction	C5	0.28
CO2 emissions	C6	0.16

4.3.1. Vikor Method for Selecting The Optimal Renewable Energy Copmanation

Table 4.5 displays the performance scores from the simulation for each criterion. The greater the score, the more favorable the alternative compared to another. For example, the criterion 'capital cost' displays the lowest score for the PV+Batt alternative and the highest for the DG-PV-WT-Battery option. This indicates that the A1 option is a better choice for capital cost need and Net present cost when compared to other options. The Renewable portion criterion has the most weight in the system, followed by CO2 emissions and the 'Initial capital cost criteria. This criterion weighs 0.10 because the A1 (DG-PV-WT-Battery) system requires less capital than other alternatives.

Similarly, the capital and NPC costs for six cases (PV/BAT) are higher than for the other four possibilities since the battery and PV request a higher capital and O&M cost. The criteria of NPC, Cost of energy, and capital cost have approximately similar performance scores (0.45626),(0.34072), and (0.45763) .for the second choice, the PV/DG/BAT scenario. The system architecture of the WT/PV-Battery option indicates that a larger battery bank be added to handle higher levels of PV and wind penetration. Compared to the other alternatives, this system has the highest weight for renewable share (100%) in the generation and the highest weight for Renewable fraction (0.28).

Step 1 : Establish decision matrix

Table 5 displays a normalized decision matrix (as in Eq. (21)) in the previous chapter, a set of alternatives with different weights for all criteria (where 6 is the total number of all criteria).

Table 4.5 .The normalized decision matrix

alternatives	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
S1	0.02381	0.45626	0.19354	0.12183	0.27218	0.11234
S2	0.40825	0.45763	0.16036	0.12867	0.7384	0.11032
S3	0.55318	0.34072	0.18342	0.17830	0.26183	0.05432
S4	0.38692	0.26348	0.29863	0.38226	0.34361	0.32172
S5	0.62348	0.00342	0.40831	0.37643	0.318751	0.54216
S6	0.15673	0.10087	0.21762	0.10127	0.32712	0.41412

Step *2*: calculate the best f_i^* and the worst f_i^- values of all criterion functions.

Table 4.6. Shows the values of all criterion functions

max	**0.62183**	**0.45342**	**0.48483**	**0.38481**	**0.34841**	**0.54276**
min	0.02134	0.00187	0.19625	0.10271	0.20368	0.04214

Step 3. calculate the values of S_j and R_j, j = 1,2,3.4…,J

Step 4*:* calculate the values of Q_j

Values for QS, QR, and Q are shown in Table 4.7 according to their respective Eqs. Q is provided for the compromise parameter (strategy coefficient) m (m = 0.25) in equations (22) and (23).

Table 4.7 ranks the energy systems based on these values, and the (WT/PV/DG/Bat) system comes out on top. This is because most criteria, such as (c1, c2, c5), significantly affect the value of QR. The first (A1) and sixth (A6) choices stand in vital difference from each other. The final option in the table has high up-front costs due to the high price of batteries and solar panels but lower total project costs.With incredibly high impact scores for two of the six impact criteria (c1 and c2) and an overall ranking advantage over other options, these criteria could be recommended for final selection.The results demonstrate the viability of applying multicriteria decision-making techniques to sustainable energy design.

Table 4.7. Vikor methode final results

Si	**Ri**	**Qi**	**Rank**	**Optimal enery source**
0.796513	0.302143	0.956	1	PV-WT-BATT-DG
0.730431	0.272341	0.806	6	PV/BATT
0.677403	0.302211	0.827	2	PV/DG/BATT
0.677044	0.302314	0.826	3	WT/DG/BATT
0.666781	0.302316	0.811	5	PV/WT/BATT
0.650739	0.302241	0.821	4	DG/BATT

The above steps show the simplicity of VIKOR in facilitating the decision-making during designing and selecting the best energy sources based on selected criteria.By using different values of the weights - it can calculate the order of alternatives by linking between inputs consisting of economic and environmental parameters and outputs represented in the cheapest energy source that can be chosen. The VIKOR method has advantages and disadvantages, but overall it is a reliable tool by which the decision maker can rank the best among several different energy sources. To evaluate the results of VIKOR and to increase the reliability of the decision-making process, another method of decision-making was used, which is called Topsis, and the following are its results.

4.3.2. TOPSIS Method Results

1: Calculate Normalized Matrix

First, create decision matrix ($\bar{X}_{ij}$) by dividing each value in a column by the sum of its columns using Equation (1). Normalization is required to compensate for differences in the values of the criteria associated with the metrics. This step is significant in building the initial decision-making matrix.

$$\overline{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}^{2}}} \qquad (4.1)$$

2-Determining the weighted Normalized Matrix

Equation (2) is used to create the weighted matrix after normalizing the matrix To create the weighted matrix in this stage, AHP weights (Table 4) are added:

$$V_{ij} = \bar{X}_{ij} \times W_j \qquad (4.2)$$

3- determining the best and worst ideal values

Equations (3) and (4) are used to determine the best performance s+ and worst performance s- for each ideal criterion. TOPSIS depends on measuring distances, so the optimal option is close to the positive solution(s+) and far from negative solution (s-). This is achieved utilizing Equation (8) and Equation (9), respectively:

$$S_i^{+} = \left[\sum_{j=1}^{m} \left(V_{ij} - V_j^{+} \right)^2 \right]^{0.5} \qquad (4.3)$$

$$S_i^{-} = \left[\sum_{j=1}^{m} \left(V_{ij} - V_j^{-} \right)^2 \right]^{0.5} \qquad (4.4)$$

4-Calculate Performance Score

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{4.5}$$

Table 4.8. The Normalized Matrix

Alternative	**Net present cost(NPC)**	**Initial capital cost(ICC)**	**Cost of energy(COE)**	**Total O&M cost**	**Renewable fraction**	**CO2 emissions**
PV-WT-BATT-DG	0.303237	0.344583	0.224054	0.297043	0.491303	0.067115
PV/BATT	0.227427	0.258436	0.358487	0.346553	0.070187	0.536924
PV/DG/BATT	0.303237	0.043072	0.448113	0.297045	0.070185	0.536923
WT/DG/BATT	0.682287	0.215363	0.134432	0.297042	0.350932	0.067113
PV/WT/BATT	0.303238	0.43075	0.448113	0.346551	0.56146	0.536924
DG/BATT	0.227428	0.43075	0.358487	0.396058	0.421115	0.335576

After calculating the weights for all standards, the next step is to calculate the weighted normalized values, where this matrix is obtained by multiplying the normalized values in the previous step by the weights wj values. The results of this step are shown in Table 4. 9

Table 4.9. The weighted normalized values.

Alternative	**(NPC)**	**(ICC)**	**(COE)**	**(TOC)**	**(RF)**	**(CO2)**
PV-WT-BATT-DG	0.030328	0.057434	0.037314	0.049506	0.081883	0.011187
PV/BATT	0.037904	0.043076	0.059746	0.057756	0.011696	0.089486
PV/DG/BATT	0.05057	0.007175	0.074687	0.049505	0.011697	0.089486
WT/DG/BATT	0.113713	0.035895	0.022407	0.049505	0.058488	0.011185
PV/WT/BATT	0.050547	0.071786	0.074686	0.057756	0.093581	0.089484
DG/BATT	0.037907	0.071786	0.059746	0.06603	0.070185	0.055931

Step 4: By using the equation, the positive (S +) and negative (S-) ideal values are calculated. These values affect the order of the alternatives. Where the alternative is closest to the positive and far from the negative values, it is the best choice as seen in Table 4.10.

Table 4.10. calculating positive(S+) and negative (S-) solutions

S+	**0.113714**	**0.071787**	**0.074683**	**0.06602**	**0.093583**	**0.089486**
S-	0.037904	0.007178	0.022405	0.041257	0.011697	0.011185

5-Using the two equations (3) (2), the distance between each option and the ideal positive solution and ideal negative solution was computed in this step. The findings are shown in Table 4.11.

Table 4.11. The results of The distance calculation

Alternatives	**S +**	**S -**
S1	0.110143	0.088895
S2	0.116482	0.095323
S3	0.123057	0.095354
S4	0.107964	0.093965
S5	0.063713	0.142043
S6	0.087427	0.107725

6- Determining the closeness to the desired Solution

The table below shows the values that have been calculated in the next step, which is a very important step for choosing the best hybrid energy source. Using Equation 5, the distance to the negative solution can be divided by the total distance to the negative and positive solutions, denoted by the symbol (Pi), where Pi is the final output of the ideal topics steps. Based on the values obtained from the table, the hybrid energy sources are arranged as shown in Table 4.12.

In the final step, the hybrid system is chosen based on the largest value of (Pi) in the following table, where the system that consists (PV+DG+WT+BATT) of is determined as the best suitable option to provide the buildings with sufficient energy.

Table 4.12. Final ranking of hybrid energy sources with the use of (Pi)

Alternatives	**pi**
S1	0.69034
S2	0.44661
S3	0.5532
S4	0.46534
S5	0.45007
S6	0.43656

High Pi values (0.69034) indicate that the alternative is more likely to be the best choice.

According to Table 12, the option with the highest score value is (PV-WT-BAT-DG) system, and the remaining options are evaluated according to how closely they resemble the ideal solution . for example ,(PV/DG/BAT) which has a value of 0.5532 is the second option. And the system (WD/DG/BAT) with a value of 0.46534 is the thirthd one. It is evident from a comparison of the two techniques (Vikor and Topsis) that both chose the PV+WT+BAT+DG structure as the optimal choice. İts noted that Net present value and capital cost has high impact in the selection procedure. By comparing tables and final results all standards are converted to a standardized range using TOPSIS vector normalization and VIKOR linear scale normalization. VIKOR technology offers a compromise option based on the highest level of collective benefit. TOPSIS always chooses the solution closer to the ideal solution than the negative one. The calculated results are examined using the VIKOR and approache. For every method, the calculations provide index values to obtain the optimum solution , in case , by using the VIKOR approach, which has the shortest index value, whereas the TOPSIS method has the biggest index value. Finally, both methods are accurate and reliable, and helped us determine the best power system. In the next section, we will explain the results obtained from scheduling the power units to supply energy to buildings using the genetic algorithm. In view of the results of the second stage, the decision-making methods were very effective.Table 4. 13 presents the final results of Topsis methode.

Table 4.13. Topsis final results

Alternatives	pi	Energy source	Ranking
A1	0.69034	PV-WT-BAT-DG	1
A2	0.44661	DG/BAT	6
A3	0.5532	PV/DG/BAT	2
A4	0.46534	WD/DG/BAT	3
A5	0.45007	PV/WD/BAT	4
A6	0.43656	PV/BAT	5

4.4. ENERGY SCHEDULING AND MANAGEMENT RESULTS

The EMS is managed by the Genetic algorithm technique, which decides depending on the system's operating expenses. Figure 4.2 depicts the management plan that was established. The suggested methodology enables the operator to manage the power supply to the loads based on one of the three scenarios specified below. In the initial scenario, renewable energy is given priority for power supply; batteries and generators are supportive sources. In contrast, in the second scenario, energy from renewable sources only provides the entire building's energy needs. Furthermore, the third scenario supposes that the diesel generator is the only power source. All three options are then economically evaluated to determine the best feasible option regarding energy costs for Libya's residential sector.

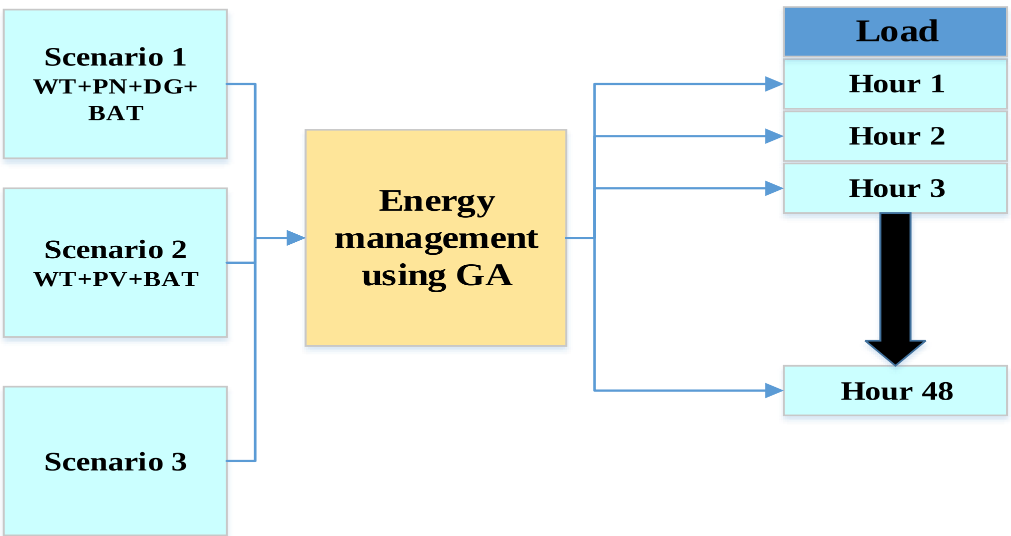

Figure 4.2. The energy management methodology (included three scenarios).

4.4.1. Scenarios 1

The following subsection analyzes only 24-hour data to give sufficient information into the management and scheduling of power sources. Using the genetic algorithm, a hybrid PV-WT-DG system was suggested for powering the needs of residential loads. The study utilized a typical load profile with a maximum load of 250 kW. Energy production systems are designed to supply peak demands effectively. Still, the fluctuating nature of RES and customer habits may impact the reliability and sustainability of the energy supply. The load curve and energy production graphs for a building are shown in Figure 4.3. As can be seen, the load fluctuates during the day, reaching periods of highs and lows. In order to meet consumption during the peak hours (from 7 pm to 12 pm and from 6 am to 8 am), energy producers must increase their output. The operators need more production capacity when energy consumption exceeds the average to meet unanticipated increases. Due to a reduction in the use of batteries and diesel generators, energy costs will go down. The cost of producing energy is frequently reduced by using renewable energy. Customers can take advantage of lower energy costs when energy prices are lower, from 9 am to 7 pm.

In some cases, load demand is higher than the combined output power of wind and solar systems. Therefore, at this time, the generator and battery storage will be connected to the load to compensate for the lack of energy. On the opposite, there are hours when the output power of renewable systems is greater than the load; in this case, the batteries will be charged with the surplus energy. Always the generator is kept on standby during these times to reduce running costs and ensure the sustainability of power generation. The optimal combination of the sources was determined to make energy balance between the sources and demand Figure 4.3 shows the energy obtained from solar and wind sources and the diesel generator. The solar energy system starts producing energy at sunrise at 08:00 and continues to generate for several hours until evening, based on the intensity of the solar radiation, where the rays are concentrated and intense at 14:00. :00, from 12 pm to 3 pm, the solar panels can produce effectively, as the highest value of the generated energy reaches 68 kilowatts, and this also applies to generating energy from the wind system, as energy can be generated throughout the day due to the availability of wind at different times, we note from The figure shows that the total energy provided by the generating units is sufficient to supply the demand with sufficient and sustainable energy. To compare the energy obtained from the generation units, we find that during the first three hours of operation (from 01:00 am to 04:00 am), the wind system efficiently supplies the demand without the need for a generator or the solar system, as the total generation reached 238 kilowatts. During these hours, the energy stored in the batteries was used as a backup.

Depending on the consumption data, the highest value was at 5:00 pm, when the loads were supplied with a sharing between the energy sources as follows: PV (42 kW), WT wind system (100 kW), diesel generator (31 kW), and energy from The storage system was (37 kW). On the contrary, the lowest load was measured at 4 am 86 kW, as it was fed only by WT and BATT. Generally, the amount of energy produced and consumed is always balanced, and all constraints are achieved. The main factors that determine how power is shared are the cost and amount of the energy source. If the amount of energy needed is more than what can be produced using renewable sources, the generator is the only choice, despite how much energy costs at that time.

Batteries are considered to be fully charged at 100% SoC, with a maximum allowed discharge level of 20%. When the battery energy value decreases below 20%, and the energy provided by renewable systems is inadequate to feed the loads, the generator must be operated. The illustration clearly shows that due to a lack of sufficient energy from the wind turbines, the generator runs from 04:00 to 07:00 in the morning to support the system while also charging the batteries. In this situation, the battery charge level exceeds 70%. Thus, the energy consumption rises between 08:00 and 10:00 a.m., as the batteries serve as an auxiliary power source for wind and solar systems, providing 59 kWh. Following that, with a drop in load from 11:00 to 15:00 due to the exit of the majority of the population from their houses, where consumption values range from 159 to 165 kilowatts, as renewable energy systems alone can meet the energy demand efficiently without using the battery or generator.

From 11:00 in the morning until 3:00 in the evening, it mainly relied on renewable energy only. At this time, the batteries were recharged with excess energy, as the energy generated from the wind turbine was 621 kilowatts, and the total energy generated from the solar system was 235 kilowatts. During this period, surplus generation is sold to the main grid to contribute to feeding critical and unexpected loads. The batteries are discharged from 4:00 pm until 7:00 pm until they reach less than 20%, then they are charged again at 20:00 for two hours. The maximum power from the generator was used for an hour, 21:00 to 10:00 pm (100 kW), and the support was obtained from the wind generator (110 kW), in addition to fully discharging the batteries to reduce pressure on the generator, reduce fuel consumption, and harmful gas emissions. Also, it is clear from the figure that the consumption from 9:00 pm to 11:00 pm reaches 635 kilowatts. To meet this load, the wind generator was operated and supported by batteries, as shown in the Figure 4.3.

The generator launches between 8 and 11 p.m. to make up for the 648 kilowatts of extra demand while the batteries charge. At night, the BATT and WT share their power until they reach minimum SOC limit, to reduce the pressure on the generator to minimize the fuel costs. The GA provides that during the hours of 8 a.m. and 4 p.m., the generator is off, and schedule the power between the two sources (WT+PV) and the batteries, and charging the batteries to avoid load shifting or power disruptions in the next few hours because RESs are unstable. In addition, the battery can operate at lower DOD values to increase its lifespan. The batteries used in the micro grid are expected to have an initial state of charge (SOC) of 100%.

The total cost of power at each time unit is depicted in Figure 4.4. The highest cost of $ 120 was recorded at 5 a.m., while the lowest cost of $ 38 was acquired at 4 a.m. This is caused by the current significant share of renewables and the generator.

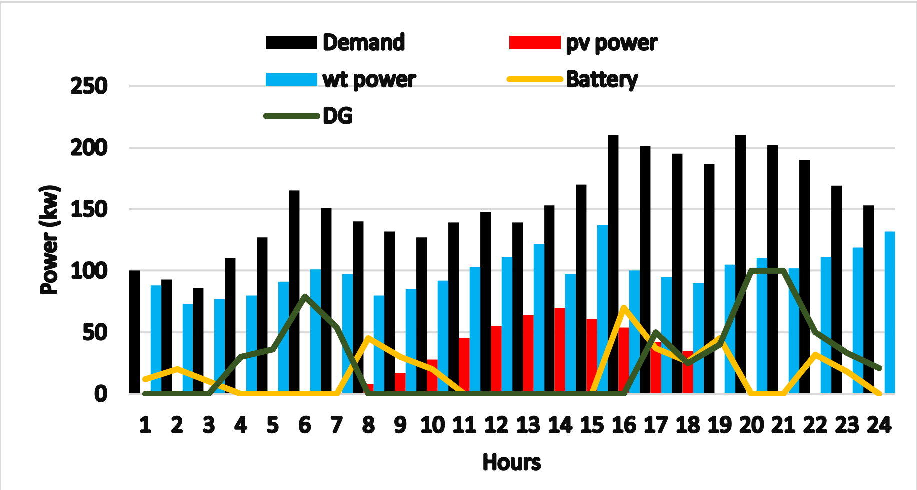

Figure 4.3. Generated power from each energy source (case 1).

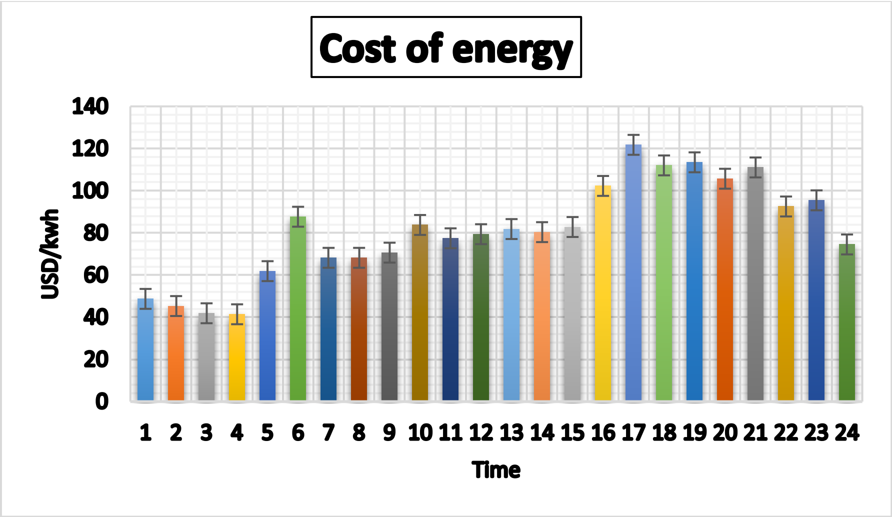

Figure 4.4. The power generation cost for 24 one day (case 1).

During the day, the charging and discharge of batteries affect the energy cost overall. In this case, the batteries are charged between 3 a.m. and 7 a.m., 11 a.m. and 3 p.m., and 8 p.m. and 10 p.m., so their electricity can help make energy during high demand, making the generator and wind system less critical. When batteries (BATT) are added to the system, the algorithm can share energy between the source and the load more cost-effectively, which means the generator does not need to run continually. In general, storage systems can make a balance when there is an unexpected change in demand.

4.4.2. Scenarios 2

This scenario supposes that the household demand is entirely supplied by renewable energy RE sources, i.e., PV+WT, without a diesel generator. Figure 4.5 depicts the algorithm results for this situation. The graph displays the percentage of power generated by each renewable unit. WT serves as a base generator, supplying electricity at all times. Due to its highest power output, the solar PV system is the only additional supplier to WT between 11:00 and 15:00. Moreover, WT, on the other hand, is supplementing source at some times. The chart demonstrates that the WT generates energy ranging from 73kW to 148kW, with the most significant values occurring between 13h and 21h. The most significant notable dependency was on this unit, particularly during hours when no solar energy was generated. Because there was enough energy, the WT unit closed down from 11 to 15 hours to extend the system's lifetime and reduce maintenance and operation costs. Furthermore, the maximum power generated by the solar system from 9 a.m. to 6 p.m. is 68 kW, which was collected at 2 p.m. Figure 4.6 depicts the hourly cost the other hand. Because of the more significant capital cost of the wind system, the higher price is (169$ daily) at 5 p.m., while the lowest price is 59$ at 4 a.m. This cost reduction is due to a significant decrease in load, which was 85 kW.

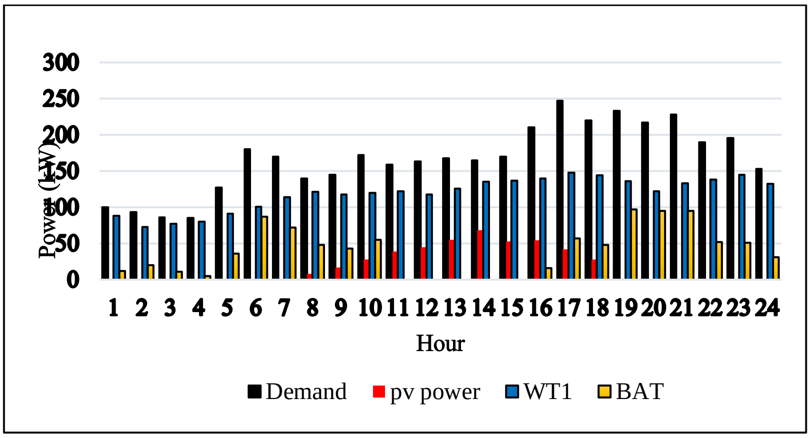

Figure 4.5. Generated power from each energy source (case 2).

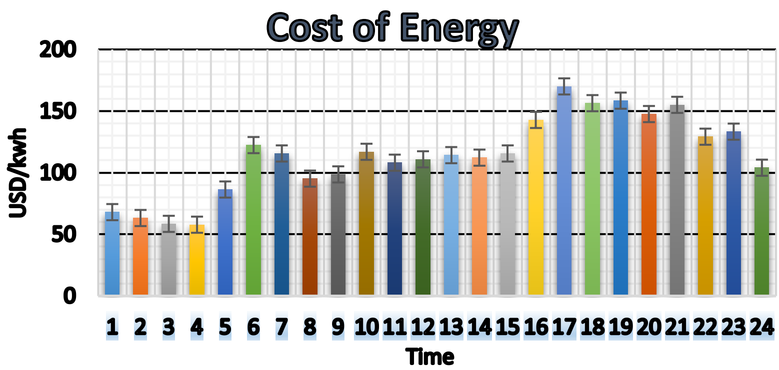

Figure 4.6. The power generation cost for 24 one day (case 2).

4.4.3. Scenarios 3

The third scenario assumes that the conventional electricity from the utility grid completely meets the required load demand. The total energy imports amounts to 4017 kWh throughout the day, as shown in Figure4.7. The hourly energy cost variation for the generator electricity is illustrated in Figure 4.8. the third scenario is the most expensive option compared to the other scenarios with the implication of renewable sources. In the third scenario, the highest hourly cost is at 17:00 with 485$ and the lowest was 167 $at 4 am morning.

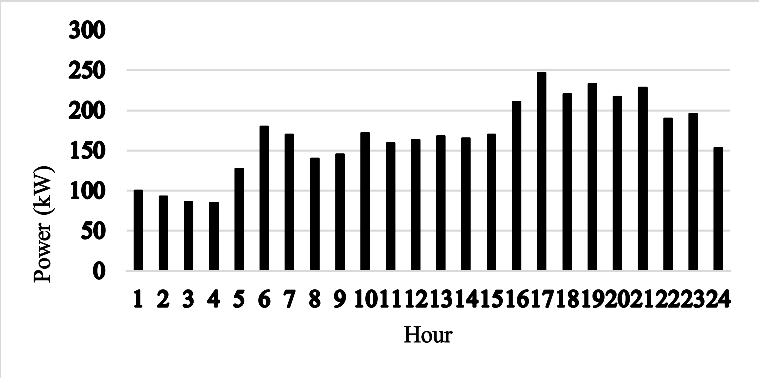

Figure 4.7. Generated power from diesel generator (case 3).

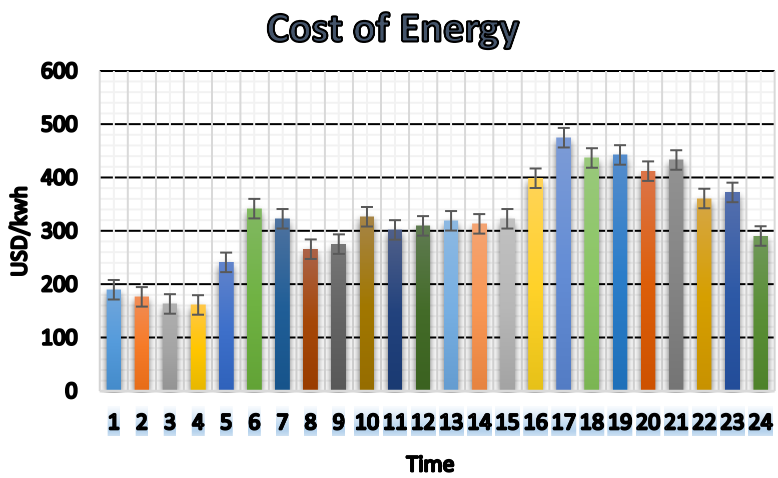

Figure 4.8. The power generation cost for 24 one day (case 3).

This option provides excellent reliability in the continuity of energy and supplying loads but at a higher price than the first and second cases. Based on the results in the three cases, we conclude that the first case (PV+WT+DG+Bat) produces energy at the lowest price and is considered the best option for the consumers in terms of the hourly price and also in terms of the total costs of establishing the system.

4.5. ENERGY CLASSIFICATION AND PREDICATION RESULTS

This part will explain the results of the machine learning algorithms used to predict the energy sources that should operate related to the hourly consumption value. In this last part of our study, we will present an accurate prediction of energy consumption using classification algorithms. First, the data were divided into two groups: 70% for training and 30% for testing, and the total is 720 samples. The most important step in building the model is to train the algorithm on the input data obtained from the genetic algorithm. For example, system data is entered from generation units, electrical load data for a month, and weather data such as solar radiation, wind speed, temperature, operating hours of energy sources, and the number of sources used. After the model understands the data classification and classifies the four energy sources used accordingly, it can easily classify the sources used to feed the loads and predict them in any other building with the same specifications and size of the generating units. Comparison of three machine learning algorithms used to confirm the accuracy of the results. Below is an explanation of the results.

4.5.1. Data Analysis

The dataset consists of 720 cases, seven features, one output variable, four input parameters, and one output variable. Hourly demand, wind power, and solar power are the mentioned inputs; hybrid energy source scheduling is the output. There are six attributes in the class type. The encoding of these items is displayed in Table 14.

Table 4.14. Encoded classes

Class	Class Encoding
WT + Batt	**1**
WT +DG	**2**
WT+PV+Batt	**3**
PV +WT	**4**
PV +WT+Batt+DG	**5**
WT+Batt+DG	**6**
DG	**7**

Figure 15 depicts the monthly power supply schedule based on dispatching hours using machine learing algorithms. After the GA algorithm determined the optimal energy output by selecting energy combinations in order to receive the cheapest amount of power supplied by the microgrid.then the classification algorithms will predicte the energy sources that shoud be swieched on hourly.

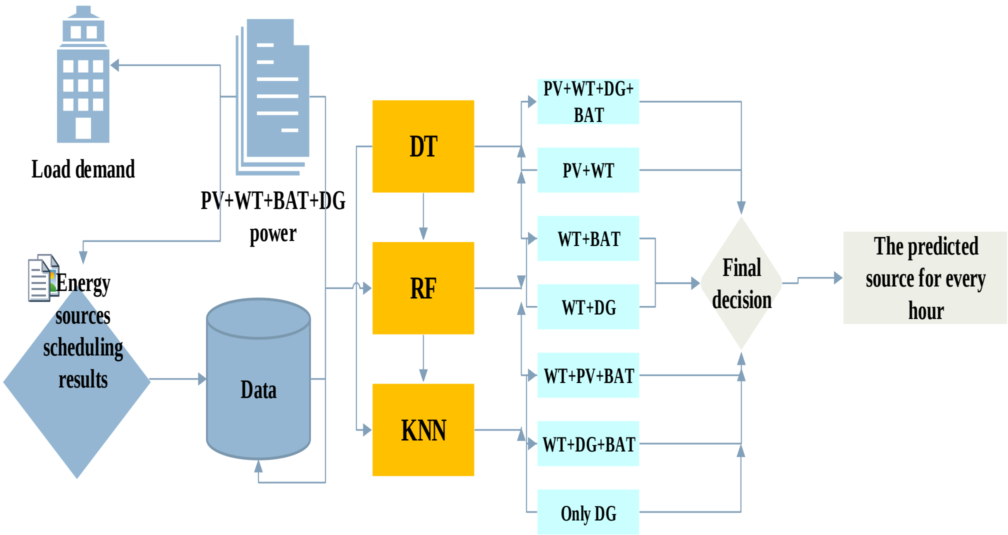

Figure 4.9. General schematic diagram of predication uding machine learning.

Figure 16 depicts how frequently energy sources are turned on over the course of a month using machine learning. The figure shows the best hourly mix of power supplies chosen using algorithms to ensure all loads are fed and there is never a power shortage. It is noted that the Bat-WT formula is the most widely used (160 hours) within 720 hours. Usually, renewable energy is available in abundance in the middle of the day due to the high production of solar cells, and this helps to dispense with the generator and, at the same time, charge the batteries. In addition, wind turbines are used in most periods of the day and night due to the availability of wind at different times. However, in the night hours, the dependence is on the generator and batteries significantly to support the wind turbines in providing energy. From the results of the classification algorithm, it is clear that the operation of (WT + DG) occurs 150 hours per month, which is considered excessive use of the generator, which causes an increase in the cost of energy for the consumer. On some days and in the night period, the Bat + WT combination cannot feed the load efficiently, so in this case, a generator runs for 45 hours to back up the power. As for the solar energy system's results show that it operates for 330 hours during the month, at an average of 10 hours per month. This is an excellent and ideal use of the system, which contributed to the stability of the energy flow at a low price and the reduction of harmful gas emissions from the combustion of generator fuel. In general, the results confirmed that the classification technique efficiently predicted the energy sources that supply residential buildings with electricity. Accordingly, this model can be used in any new building with the same four energy sources. Also, this procedure will facilitate the construction of a small network that includes renewable energy sources and a generator to serve a residential area or commercial.

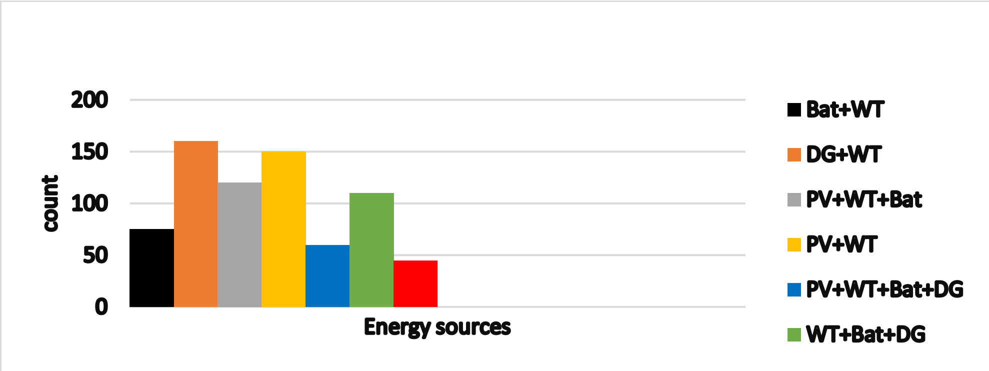

Figure 4.10. Operating hours for each (energy source) class.

5.6. ALGORITHMS PERFORMANCE EVALUATION

The model's performance is evaluated and analyzed in that stage, and the results are compared for validity. Figures 4. 11 to 4.13 show the precision, F1-score, and recall measurements used to evaluate the performance of the ML techniques. According to the results, DT is the most efficient algorithm with 100% accuracy. The KNN algorithm, on the other hand, has the lowest accuracy. Figures indicate that the algorithms DT and RF outperform the KNN algorithm in terms of overall performance across all classes. It is important to remember that for an effective classifier, the recall must be as high as feasible, preferably one. That is only achievable if the numerator and denominator of the formula 20 are the same, indicating that FN is zero. The recall value drops as the factor FN increases as well; as a result, a reliable classifier should ideally achieve a precision of 1. Just when FP = 0, the precision value equal 1. The F1-score produces similar performance indicators as the precision and recall measures, as seen in Figures below. The obtained findings demonstrated that the KNN method did not classify efficiently.

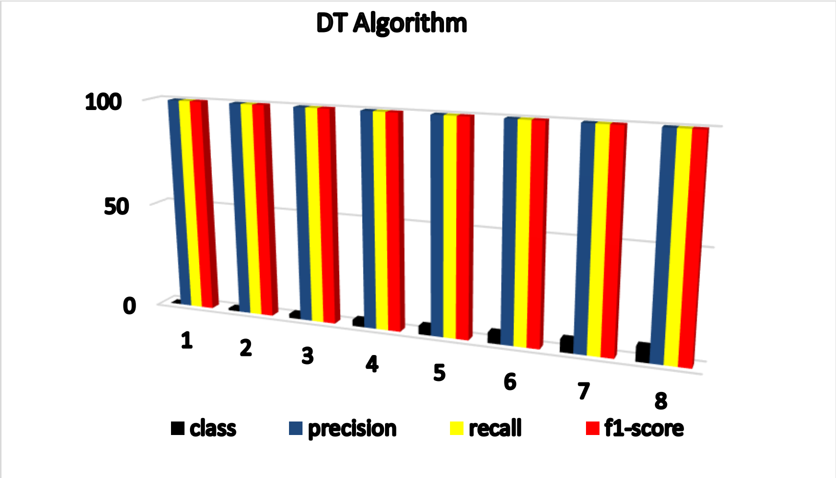

Figure 4.11. The evaluation measures for DT algorithm.

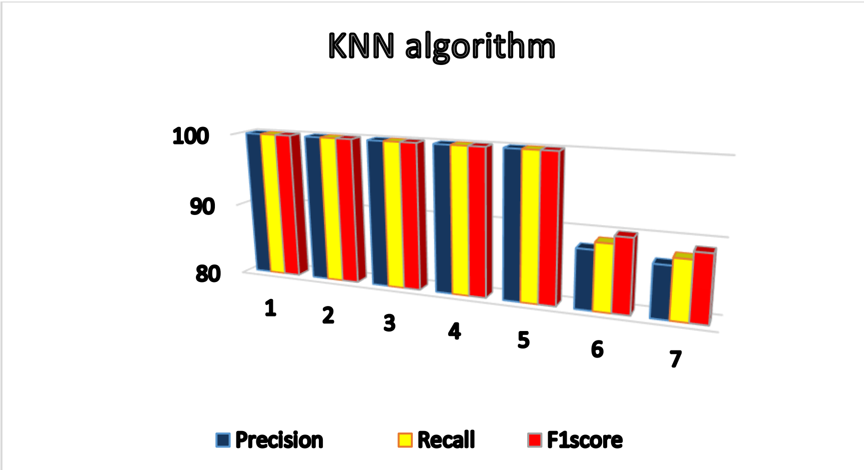

Figure 4.12. The evaluation measures for KNN algorithm.

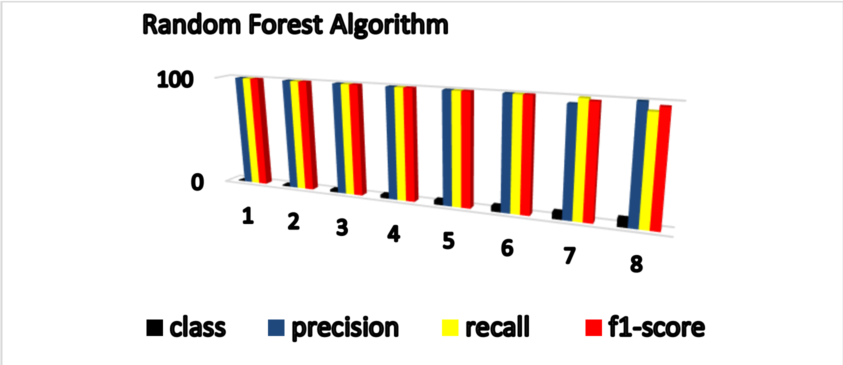

Figure 4.13. The evaluation measures for RF algorithm.

RF Algorithm

The algorithm first builds small, branched decision trees trained on the data components and then combines the different results to form the final branch, representing the final prediction. To achieve the best results, entropy was used as an indicator of the accuracy and performance of the algorithm. Overall, the results show that the RF was very accurate, with a rate of 98% regarding the classification of similarities in the data. The results of the analysis are as follows: Precision 1.00 for the first six classifications and 0.96 for the sixth classification. Table 4.17 shows that the return is 1.00 for all results, and the F1 score is 1.00 for six classifications and 0.99 for class number 6. The results are generally considered good, and the algorithm performs high. Below are the results of the second algorithm.

DT Algorithm

The algorithm includes several nodes and variables before it reaches its leaves to predict classes. We utilized the entropy metric for speed. Because of this, the DT technique provides 100% accuracy, the highest accuracy of any classification algorithm. The accuracy, recall, and F1-score for each class that was obtained are listed in Table 4.16, with high measured values for most classes being around 1.00.

KNN Algorithm

Determining the distances between points enables the classifier to perform Accurately. This algorithm labels data by locating closest neighbors (k) and combining similar and nearby values. The length of the distance and the value of the k factor influence the effectiveness and precision of the algorithm's output. As depicted in the figure below, we must first determine the optimal value for k, which ranges from 1 to 20, to improve the algorithm's precision. According to the initial results, the accuracy decrease as the number and distance of neighbors increases. The algorithm's overall accuracy was 90% smaller than the other algorithms (DT and RF). As shown below, the results of the evaluation matrices are not adequate and accurate. Table 5 displays each class's recall, F1 score, and accuracy measurements. The evaluation results were generally imporoved , for example, Precision in class (1) differs from 0.88 to 1, recall in four classes (1, 2, 3, 4,5) is 1 and this is good result, but un other classes are les than 1 for example class number 6 and 7 and the scores for the left three classes are (0). classes (1,2,3,4,5) have the highest value of F1-score with value of (1), while all other classes are less 0,90 ,0.89, which very similar to recall results.

Table 4.15. Testing classification report of KNN algorithm

Class	Precision	Recall	F1-score	Support	Accuracy
1	1	1	1	39	90
2	1	1	1	12	
3	1	1	1	24	
4	1	1	1	10	
5	1	1	1	26	
6	0.88	0.89	0.90	3	
7	1	0.91	0.89	20	

Table 4.16. Testing classification report of DT algorithm

Class	Precision	Recall	F1-score	Support	Accuracy
1	1	1	1	39	100
2	1	1	1	12	
3	1	1	1	24	
4	1	1	1	10	
5	1	1	1	26	
6	1	1	1	3	
7	1	1	1	20	

Table 4.17. Testing classification report of RF algorithm

Class	Precision	Recall	F1-score	Support	Accuracy
1	1	1	1	40	99
2	1	1	1	14	
3	1	1	1	26	
4	1	1	1	13	
5	1	1	1	25	
6	0.96	1	0.99	23	
7	1	0.94	0.98	17	

The heat map in Figure 4.14 demonstrates a relationship between inputs and outcomes. The map shows the correlation between parameters on a scale of 1 to -1, with 1 being the strongest correlation and -1 being the weakest. There is no relationship between the variables if the correlation coefficient is 0, presenting a low reliance between model inputs and expected outputs. Consumption load, temperature, speed of the wind, solar radiation, wind power, and solar power are all analyzed parameters in the map. Correlation variables demonstrated that when both irradiance and wind speed were high, and obtain the maximum power from both sources of renewable energy (wind and photovoltaic systems).

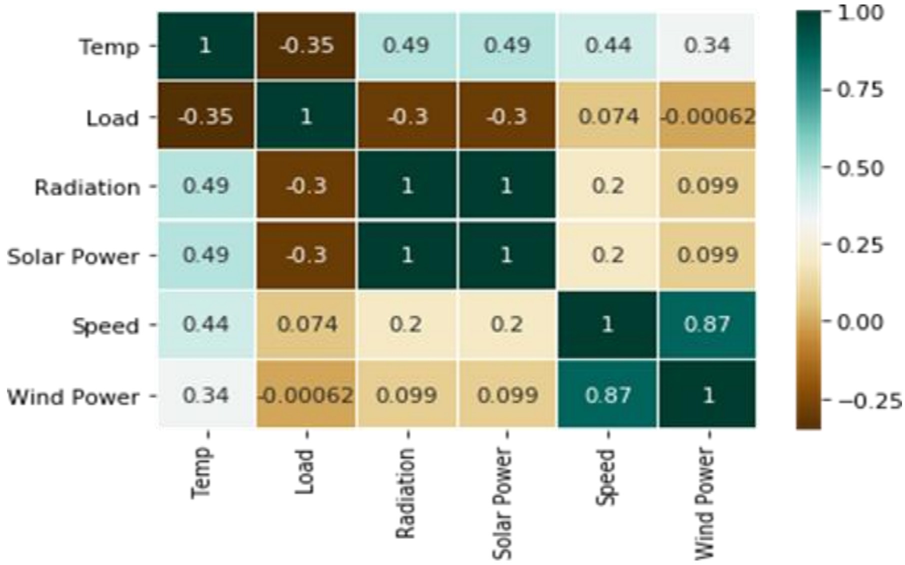

Figure 4.14. Heat map.

The map illustrates direct and indirect relationships between the parameters by showing positive and negative correlations for certain classes. For example, the map displays a strong connection (above 1) between solar output power and sun radiation and an accepted correlation (about 0.49) between temp and radiation from the sun. Furthermore, by reaching 0.87, the relationship between wind energy's generated energy and wind speed is excellent. A model will frequently be developed by improving the correlation between each significant feature. Every input and output variables include positive and negative correlation coefficients; however, the correlation matrix analysis shows that these connections are not always strong.

Confusion matrices were used to understand the results further and evaluate the performance of the algorithms, which are usually used to determine the accuracy of the model, as shown in Table 4.18 . The below matrices summarize the overall performance of the model. Where the columns represent the actual results while the matrix rows represent the predictions, the table shows that the correct predictions are in red, and the rest of the elements wrapped in black represent the real data. Through the matrix, the number of correct and skewed predictions produced by the three classifiers can be counted. Generally, the exact model contains large values in the diameter and smaller values in the rest of the array elements. Successful matrices show that the diagonal elements are large. At the same time, the rest of the cells have a value of zero, which means that the model is accurate and has succeeded in reading and classifying all data elements with an accuracy of up to 100% in the DT algorithm and 98% in the RF algorithm. While in the case of the KNN algorithm, the numbers in the diagonal and the rest of the matrix are close and greater than zero, which is evidence of the poor ability of the algorithm to identify data elements and classify similar ones. For example, the first, sixth, and seventh columns contain values greater than zero, which indicates that the model is inaccurate and does not recognize all classifications.

Table 4.18. Confusion matrix results

Class	**3**	**4**	**6**	**8**	**10**	**12**	**14**	**16**
3	40	0	0	0	0	0	0	0
4	0	14	0	0	0	0	0	0
6	0	0	0	0	0	5	4	0
8	0	0	0	10	0	0	7	0
10	0	0	0	0	26	1	0	0
12	0	0	0	0	0	4	6	2
14	0	0	0	0	0	2	8	3

A. The confusion matrix of k-nearest neighbors algorithm

class	**3**	**4**	**6**	**8**	**10**	**12**	**14**	**16**
3	40	0	0	0	0	0	0	0
4	0	14	0	0	0	0	0	0
6	0	0	26	0	0	0	0	0
8	0	0	0	13	0	0	0	0
10	0	0	0	0	25	0	0	0
12	0	0	0	0	0	23	0	0
14	0	0	0	0	0	0	20	0
16	0	0	0	0	0	0	0	14

B. The confusion matrix of random forest algorithm

class	**3**	**4**	**6**	**8**	**10**	**12**	**14**	**16**
3	40	0	0	0	0	0	0	0
4	0	14	0	0	0	0	0	0
6	0	0	26	0	0	0	0	0
8	0	0	0	11	0	0	0	0
10	0	0	0	0	24	0	0	0
12	0	0	0	0	0	3	0	0
14	0	0	0	0	0	0	20	0
16	0	0	0	0	0	0	0	15

The confusion matrix of decision tree algorithm

PART 5

CONCLUSION AND FUTURE RESEARCH

5.1. CONCLUSION

Energy production and management are essential challenges for all countries. As a source of energy, renewable energy sources are increasingly utilized. In such situations, microgrids that operate as completely operational power systems in several places are becoming an attractive option. To successfully implement a microgrid design, it is necessary to accurately forecast the power consumption of large consumer populations, such as residential ones. The aim of this study sought to develop a standard predicting model for switching on and off power sources. The goal of this study is to come up with the best microgrid design for the specified location. This design should ensure that power is always available at the lowest cost by using the best energy management system. The suggested best design for the microgrid is examined and evaluated at different comparisons, considering all possible scenarios and conditions. The proposed system comprises a photovoltaic system, a diesel generator, a wind system, a battery, and a power converter. This is the best combination of power sources to meet the energy needs of a residential building at the lowest cost over the next 25 years, with 62% of the energy derived from renewable sources. This helps make green and clean energy and reduces greenhouse gas emissions. To get the maximum benefit out of the microgrid, its size and how well it works are of the highest priority. Because of this, the suggested microgrid is designed, simulated, and optimized with the HOMER software. After carefully examining the economy, energy demand, and weather forecasts, the best mix of energy sources has been chosen to provide continuous energy at the lowest cost. In the end, a 70-kW PV power source, a 100-kW diesel engine, a 150-kW wind system, and a 0-250-kWh energy storage unit were the best for the selected load profile.

This thesis' second section explains how the genetic algorithm estimates energy consumption and identifies the best power source to meet demand. By offering predictive models for energy supply and demand, this strategy enables end users to connect with the market for intelligent electricity systems and renewable energy sources. This study was focused on a standalone system with flexible components (such as demand loads, renewable energy generation, an energy backup system, and a diesel generator). The study focused on the power management procedure used in that microgrid. In the first stage, a rule-based system was created to choose the proper use of energy sources based on predictions for renewable resources. Considerations include decreasing operating costs, increasing reliance on clean energy sources, and exchanging power with diesel generation.

Compared to single-source energy systems, hybrid power systems are more reliable and have lower production costs. We performed a techno-economic analysis to evaluate the hybrid system, in which the electric power is generated either by diesel engines or by renewable sources. In these situations, the cost of diesel fuel makes diesel-only generating uncompetitive with hybrid diesel/photovoltaic/wind generation. As well, the system that enables them to be turned off during the day and has energy storage offers the lowest energy cost.

The results of scheduling different energy sources show how effectively the algorithm manages the energy available in the small grid to feed the loads efficiently. It is possible to build on these results and design a model to predict the energy consumption and the energy sources required to operate. In order to predict the sources that must be switched on for a month, essential factors were introduced to determine the sufficient source, such as the value of the load per hour, the energy generated for each source, and weather information. Using machine learning algorithms such as Decision Tree (DT), K-Nearest Neighbors (KNN), and Random Forest (RF), the feeding sources were classified for a month, and then the three models were compared to select the optimal model. After evaluating the results, it was discovered that the DT method was the best in accuracy and efficiency, while the performance of the KNN algorithm was insufficient. Moreover, the results showed that the RF and DT algorithms are accurate and robust, and this is through the results of the evaluation matrices and the measurement equations used for that. To obtain the best model, the parameters of the algorithms were optimized for accuracy, which resulted in enhanced system reliability and reduced training time.

In general, the proposed models obtained different percentages. The DT algorithm obtained the best accuracy (100%), followed by the RF algorithm (98%), while the KNN method gave the least accuracy (28%). Moreover, the results of accuracy and recall, the DT algorithm works better than the rest. Finally, the results show the classifier's success in predicting energy sources for 720 hours. This research allows the optimal use of hybrid systems and benefits in developing an accurate prediction model; Thus, the operator can determine the time of use to achieve the best results in terms of reducing costs and continuity of energy flow. Moreover, unlike complex and difficult algorithms, the classification methods are simple and easy to use and implement.

5.2. FUTURE WORK

In the future, comparing grid-connected and off-grid plans for different places will be conducted. Also, hybrid systems that include other renewable resources like biomass, wind, and geothermal could be used to determine the best source.

The effect of building design and orientation and increasing loads on energy consumption will be studied. In addition, the effect of consumer consumpation behavior and electric devices effecincy on increasing demand will be analyzed.

Secondly, one of the most important factors that increase the demand for cooling and heating in the building is the materials and insulators that are used. Therefore, it is important to study the effect of using thermal insulators to reduce energy consumption in the building.

The majority of studies cited in the literature depend on conventional load and climate profiles. Frequently, these profiles are simulated artificially and may not reflect actual conditions. Due to the high costs of housing, building homes in Libya is restricted by installation area limits. As a result, using case study analysis, the possibility of a HES system for residential buildings is investigated. Using profiles from weather regions, we try to overcome the lack of hourly load-profile data for the Tripoli region in this study. In addition, we suggest an approach for optimizing and analyzing the multiple objectives of a solar–wind–diesel generator HES system by taking into account the various economic factors. This study suggests an overall structure for the multi-objective optimization of the NPC, Total capital cost (TCC), cost of energy (COE), and total CO_2 emission objectives for a 20-year project lifecycle.

A fitness evaluation technique with a balancing decision strategy is presented for optimal system design to increase energy savings from the HES system whereas maintaining CO_2 emissions below the "No-hybrid system" level. Utilizing the suggested balanced strategy to select an unbalanced HES configuration, residential building users can find sustainable energy in rural areas, according to the results of the case study. The case study demonstrates that wind generation is important for minimizing total CO_2 emissions and decreasing reliance on diesel generators, despite a limited installation area. However, individual electricity users cannot use wind turbines without government support due to the higher NPC costs. The case study also demonstrates that a HES system comprised of a PV - WT-DG system and small-size battery storage provides the optimal equilibrium between economics and environmental issues.

Finally, to build a accurate prediction model , comparison must be made with several algorithms, in addition to use a large number of data, up to a one year of electrical loads, to reach accurate results.

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APPENDIX A.

PUBLICATIONS


TIIAME
TASHKENT INSTITUTE OF IRRIGATION AND AGRICULTURAL MECHANIZATION ENGINEERS
Politechnika Krakowska
im. Tadeusza Kosciuszki
KARABUK
UNIVERSITY
Research Institute of Forestry
Gulistan State University
Certificate
of Participation
14-16 October, 2021, Tashkent
ICECAE 2021
This certifies that
Mohamed Elweddad
actively participated in ICECAE 2021
Awarded on October 16, 2021
In recognition of his/her active and invaluable participation during the "2nd International Conference on Energetics, Civil and Agricultural Engineering (ICECAE 2021)"
Prof. Dr. Bakhadir MIRZAEV
1st Vice-rector of TIIAME
Prof. Dr. Obid TURSUNOV
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This is to cerrify that
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Energy Management Techniques in Off Grid Energy Systems: A review
for her/his attendance and delivery of an oral presentation in the 6th International Conference on Smart City Applications
27-29 October 2021
Virtual Safranbolu, Türkiye
SCA 2021
Prof. Dr. İsmail Rakıp KARAŞ
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Intelligent Energy Management and Prediction of Micro Grid Operation Based On Machine Learning Algorithms and Genetic Algorithm

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Abstract- Micro grid energy management has become critically important due to inefficient power use in the residential sector. High energy consumption necessitates developing a strategy to manage the power flow efficiently. For this purpose, this work has been divided into two phases: The first is the "ON/OFF" operation, which has been executed using a genetic algorithm for the hybrid system, including diesel generator, solar photovoltaic (PV), wind turbine, and battery. Then, in the second phase, the output results were used as input in three algorithms to predict load and supply dispatch one month ahead. This study has two objectives; the first is to decide which energy source should meet the load one month ahead. The second is to compare the outcomes of machine-learning techniques, namely Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbours (KNN), to determine the one that performs the best. The results indicated that the DT technique has the best performance in the application of classification with an accuracy of 100%. The findings also show that the RF approach gives acceptable results with an accuracy of up to 98%, and the KNN algorithm was poor in terms of accuracy with a value of 28%.

Keywords Renewable energy, Power management, Load classification, Machine learning algorithms.

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Research article Designing an energy management system for household consumptions with an off-grid hybrid power system

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Abstract: This paper analyzes the effect of meteorological variables such as solar irradiance and ambient temperature in addition to cultural factors such as consumer behavior levels on energy consumption in buildings. Reducing demand peaks to achieve a stable daily load and hence lowering electricity bills is the goal of this work. Renewable generation sources, including wind and Photovoltaics systems (PV) as well as battery storage are integrated to supply the managed home load. The simulation model was conducted using Matlab R2019b on a personal laptop with an Intel Core i7 with 16 GB memory. The model considered two seasonal scenarios (summer and winter) to account for the variable available energy sources and end-user electric demand which is classified into three demand periods, peak-demand, mid-demand, and low-demand, to evaluate the modeled supplydemand management strategy. The obtained results showed that the surrounding temperature and the number of family members significantly impact the rate of electricity consumption. The study was designed to optimize and manage electricity consumption in a building fed by a standalone hybrid energy system.

RESUME

Mohamed Ali ELWEDDAD, he completed primary and elementary education in Tripoli, of Libya. In 2001, he graduated from Electrical and Electronic Engineering Department, the higher institute for engineering techniques- Tripoli. After that, he worked at libyan center for plasma research in the period 2002 to up to now. In 2016, he got his MSc degree in Electrical and Electronic Engineering at türk hava kurumu üniversitesi in ankara -Turkey. In the period 2017-2018, he worked as part-time lecturer in some institutes in Libya. In the end of 2018, he got a scholarship to continue PhD education in Turkey. He registered in Department of Electrical and Electronic Engineering and started his PhD academic program at Karabuk University. His research area focuses on renewable energy systems and energy management.