Management and Control of Hybrid Renewable Energy Systems

by

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Dalhousie University is located in Mi'kma'ki,
the ancestral and unceded territory of the Mi'kmaq.
We are all Treaty people.

Dedication

To my father, who has consistently stood by my side as my unwavering pillar of strength, ever-watchful protector, and dearest confidant. I am eternally grateful for your immeasurable impact in shaping my life.

To my mother, whose unwavering love and encouragement have always motivated me to pursue excellence, show kindness, and greet others with a smile. She instilled in me the belief that I can achieve anything I set my mind to and that no challenge is insurmountable. Her unwavering faith in my capabilities has always given me a sense of empowerment, and I have cherished her every word. Furthermore, she emphasized that these accomplishments can only be realized through hard work. She has served as an outstanding role model and a source of inspiration for our family.

To my previous supervisor, Dr. Mohamed El-Hawary, who expertly guided me through challenges, unwaveringly supported me and consistently made himself available to provide invaluable assistance.

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Abstract

There is a big attraction towards renewable energy sources like wind, solar, and biomass because of concerns about greenhouse gas emissions and the limited supply of fossil fuels. While fossil fuels still comprise much of the world's energy supply, many countries are moving toward renewable energy to lessen their environmental impact. This Ph.D. dissertation aims to promote sustainable energy practices by combining wind, solar, and biomass energy in power generation. The research aims to reduce the use of traditional fuels, lower carbon footprints, and improve energy system performance through these key goals:

1. **Standalone Hybrid Energy System Design**
   A hybrid renewable energy system was designed using HOMER Pro software for a coastal city in Libya. Optimization techniques were applied to maximize system performance, minimize costs, reduce emissions, and enhance energy reliability. The analysis identified a hybrid system comprising wind turbines, a generator, and battery storage as the optimal solution.
2. **Multi-Criteria Decision-Making for Renewable Integration**
   Advanced multi-criteria decision-making (MCDM) techniques, including VIKOR and COPRAS, were employed to select the optimal renewable energy solution for a Libyan city with abundant wind and solar resources. The findings underscore the potential of integrating renewable energy into Libya's grid to address energy demands, improve power quality, and reduce carbon emissions. A hybrid wind-solar plant emerged as the most suitable option.
3. **Biomass Integration and Optimization in Power Systems**
   Biomass energy was introduced into an IEEE 30-bus system with six generating units. Optimization algorithms, including SA, BAT, QPEICC, and Modified Ant Lion Optimization (MALO) were utilized to minimize power losses and fuel costs. The MALO algorithm demonstrated superior performance to other techniques, highlighting its effectiveness in optimizing energy system energy.
4. **Novel Control Scheme for Hybrid Renewable Systems**
   A novel control strategy was developed for the automatic generation control of a multi-area hybrid renewable energy system comprising wind, solar, and biomass. The proposed GA-Fuzzy logic self-tuning PID controller outperformed traditional heuristic-based optimization methods, achieving improved settling time, overshoot, and undershoot.

This dissertation bridges key control, optimization, and decision-making domains to advance renewable energy integration, contributing to the development of sustainable, efficient, and resilient power systems.

List of Abbreviation and Symbols Used

ABC .... Artificial Bee Colony.

AC .... Alternating Current.

ACE .... Area Control Error.

AD .... Anaerobic Digestion.

AGC .... Automatic Generation Control.

AHP .... Analytic Hierarchy Method.

AHPS .... Autonomous Hybrid Power System.

ANFIS .... Adaptive Neuro-Fuzzy Inference System.

ANN .... Artificial Neural Network.

ANP .... Analytic Network Process.

BBO .... Biogeography-Based Optimization technique.

BFB .... Bubbling Fluidized Bed Boilers.

BFPSO .... Butterfly Particle Swarm Optimization.

BWOA .... Binary Whale Optimization Algorithm.

CEQ .... Carbon Emission Quantity.

CFB .... Circulating Fluidized Bed Boilers.

CHP .... Combined Heat and Power.

COE .... Cost of Energy.

COPRAS .... COmplex PRoportional Assessment.

CSP .... Concentrated Solar Power Systems.

DB .... Disturbance Behavior.

DC .... Direct Current.

DDPMSG .... Direct Drive Permanent Magnet Synchronous Generator.

DEA .... Data Envelopment Analysis.
DEMATEL .... Decision-Making Trial and Evaluation Laboratory.
DFIG .... Doubly Fed Induction Generator.
DG .... Distributed Generation.
DPTP .... Developed Power Transformer Protection.
DPVPS .... Photovoltaic Power Stations.
DWPCHS .... Distributed Wind Power Coupled Hydrogen Storage.
ELD .... Economic Load Dispatch.
ELED .... Economic Load and Emission Dispatch.
FAHP .... Fuzzy AHP.
FMCDM .... Fuzzy Multi-Criteria Decision-Making Methods.
FNIS .... Fuzzy Negative Ideal Solution.
FPIS .... Fuzzy Positive Ideal Solution.
GA .... Genetic Algorithm.
GDB .... Gain Droop Behavior.
GECOL .... General Electricity Company of Libya.
GIS .... Geographic Information System.
GRC .... Gain Repeatability Control.
GW .... Gigawatt.
GWO .... Grey Wolf Optimizer.
HES .... Grey Wolf Optimization.
HOMER .... Hybrid Optimization Modeling for Electric Renewable.
HRES .... Hybrid Renewable Energy Systems.
HS .... Harmony Search.
IAE .... The Integral of Absolute Error.
IEEE .... The Institute of Electrical and Electronic Engineers.
ISE .... The Integral of Squared Error.
ITAE .... The Integral of Time-multiplied by Absolute Error.
ITSE .... The Integral of Time-weighted Squared Error.

kW .... Kilowatt.

kWh .... Kilowatt hour.

LFC .... Load Frequency Control.

MALO .... Modified Ant Lion Optimization algorithm.

MAMT .... Multi-Agent Modeling Technique.

MCDM .... Multi-Criteria Decision-Making Techniques.

MJ .... Megajoules.

MSW .... Municipal Solid Wastes.

MW .... Megawatt.

MWth .... Megawatt thermal.

NASA .... National Aeronautics and Space Administration.

NREL .... The National Renewable Energy Laboratory.

NPC .... Net Present Cost.

OM .... Operating and Maintenance.

NS .... Nova Scotia.

OWPS .... Offshore Wind Power Station.

PID .... Proportional–Integral–Derivative Controller.

PROMETHEE Preference Ranking Organization Method for Enrichment Evaluation.

ps .... Pattern Search.

PSO .... Particle Swarm Optimization.

PV .... Photovoltaic.

QPEICC .... Quadratic Programming and Equal Increment Cost Criterion.

RKF .... Recurrent Kalman Filter.

RCI .... Random Consistency Index.

SA .... Simulated Annealing.

SFL .... Shuffled Frog Leaping technique.

SMA .... Slime Mould Algorithm.

SOA .... Sailfish Optimization Algorithm.

TBtu .... Trillion British Thermal Units.

THPPs .... Thermal Power Plants.

TLBO .... Teaching Learning-Based Optimization.

TOPSIS .... Technique for Order Preference by Similarity to Ideal Solution.

TS .... Tabu Search.

UN IPCC .... United Nations's Intergovernmental Panel on Climate Change.

VIKOR .... VIseKriterijumska Optimizacija I Kompromisno Resenje.

WPCC .... Wind Power Curtailment Control.

WPPs .... Wind Power Plants.

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I am deeply thankful for the guidance and support I have received during my Ph.D. journey. Firstly, I am grateful to God for providing me with unwavering guidance these past few years. His presence has been a constant source of strength, particularly during challenging times. Secondly, I would like to thank Dr. Mohamed El Hawary. His unwavering support was invaluable, and his passing deeply affected me. Thirdly, I am indebted to my supervisors, Dr. Timothy Little and Dr. Hamed Aly, for their mentorship and assistance in completing my thesis. Their guidance was instrumental in my success. Lastly, I extend my heartfelt thanks to my wife, Safia Ethabit, my children, family, and friends for their endless support and encouragement throughout this journey.

Chapter 1

Introduction

Conventional energy sources, such as fossil fuels, are finite and contribute to environmental degradation and climate change. On the other hand, renewable energy sources like biomass, wind, and solar power offer a sustainable and long-term solution to our energy needs. These abundant sources can be replenished, making them environmentally friendly alternatives to traditional fuels. This dissertation delves into the practical applications of biomass, wind, and solar energy as substitutes for conventional energy sources, addressing the pressing concerns of climate change, reducing carbon emissions, and lessening our reliance on non-renewable fuels.

1.1 Problem definition

Incorporating biomass, wind, and solar energy into the power generation mix is part of the broader global energy transformation agenda. This shift is spurred by the recognition that the world's dependence on traditional fuels is no longer viable and contributes to global warming, environmental degradation, and geopolitical concerns. Conversely, utilizing these renewable sources offers a promising alternative that can help reduce the impact of greenhouse gases and foster sustainable development.

Fossil fuels have been the primary energy source for decades, but they are limited resources that contribute to greenhouse gas emissions, air pollution, and other environmental issues. In contrast, biomass, wind, and solar energies are abundant, clean, and have a significantly smaller carbon impact. This dissertation explores replacing conventional fuels with the aforementioned energies to mitigate the effects of climate change, enhance air quality, and promote sustainable development.

1.2 Research Gap and Contribution to the Libyan Energy Context

Despite the growing global interest in renewable energy systems, Libya's renewable energy sector remains underexplored due to several challenges, including limited infrastructure, inadequate data availability, and a reliance on fossil fuels. While existing studies globally address hybrid renewable energy systems (HRES), their application and feasibility within Libya's unique geographical, economic, and social contexts are insufficiently studied. Specifically:

- **Limited Assessment of HRES Feasibility:** Existing research focuses on single-source renewable systems like solar PV or wind energy in Libya. However, the potential of hybrid systems, which combine resources to address intermittency and improve reliability, has been explored very limitedly.
- **Absence of Systematic Performance Metrics:** Few studies compare Libya's hybrid versus single-source renewable systems' economic, technical, and environmental performance. This research addresses this gap by evaluating cost-efficiency, energy output, and carbon emissions, providing a comprehensive performance comparison.
- **Neglect of Socioeconomic Benefits:** The role of renewable systems, particularly HRES, in addressing Libya's energy crisis, reducing dependency on fossil fuels, and supporting sustainable economic development has not been systematically studied.

This research contributes to the field by:

- **Evaluating HRES in the Libyan Context:** It demonstrates the feasibility, reliability, and environmental advantages of HRES tailored to Libya's unique climatic and geographic conditions.
- **Providing Comparative Insights:** This study delivers actionable insights for policymakers and investors to optimize renewable energy strategies by comparing hybrid and single-source systems.
- **Focusing on Sustainability Goals:** It aligns with Libya's strategic goal of

generating 30% of its electricity from renewable sources by 2030, providing a clear pathway to achieving energy security and sustainability.

- **Addressing Data Deficits:** Using localized data and advanced modelling tools, the study bridges gaps in resource assessment and system optimization for renewable energy development in Libya.

By addressing these gaps, the research sets the foundation for more effective deployment of renewable energy systems, aiding Libya's transition to a sustainable energy future.

1.3 Research Objectives

This study focuses on integrating renewable energy sources into the power generation mix by assessing their economic feasibility, environmental impact, and technical integration into the electric power system. The specific objectives are as follows:

- Evaluate the feasibility of implementing a hybrid off-grid renewable energy system for Dar Tellil Resort in Sabratha, Libya, to ensure a reliable and continuous power supply.
- Assess the potential for incorporating renewable energy sources into the existing grid in Msallata City, aiding GECOL in managing rising electricity demand and achieving its carbon reduction goals.
- Explore using biomass as an energy source to reduce fuel costs, minimize emissions, and enhance power efficiency within economic load and emission dispatch (ELED).
- Analyze the benefits and challenges of integrating renewable energy sources—such as solar, wind, and biomass—into automatic generation control technology. This includes evaluating impacts on grid stability, frequency regulation, and overall system efficiency and examining implications for traditional power generation and grid resilience.

1.4 Research Methodology

This Ph.D. dissertation aims to contribute to the advancement and adoption of renewable energy technologies, addressing energy security challenges and fostering a sustainable future through the following approaches:

1. **Standalone Hybrid Power System Analysis**
   - Use HOMER Pro software to analyze, assess, and recommend an optimal standalone hybrid power system for providing reliable electricity to a resort in Sabratha City, west of Tripoli, Libya.
2. **Multi-Criteria Decision-Making for Hybrid Systems**
   - Apply advanced multi-criteria decision-making techniques to evaluate site-specific factors and select the best hybrid renewable energy system for Msallata City, southeast of Tripoli, Libya.
   - Validate the proposed solutions using HOMER Pro to ensure accuracy and feasibility, focusing on the availability and utilization of renewable energy resources.
3. **Economic Load and Emission Dispatch with Biomass Integration**
   - Develop an algorithm to analyze economic load and emission dispatch within an IEEE 30-bus test system comprising six generating units.
   - Progressively integrate biomass energy to reduce dependency on conventional fuels while meeting growing energy demands, laying a foundation for sustainable and environmentally friendly power generation practices.
4. **Automatic Generation Control with Self-Tuning PID Controller**
   - Design an innovative self-tuning proportional-integral-derivative (PID) controller for automatic generation control in a multi-area hybrid renewable energy system. The system incorporates wind, solar, and biomass power plants.
   - Use advanced optimization techniques, including metaheuristic algorithms, to fine-tune the controller and enhance the overall system's performance, ensuring grid stability and efficiency.

This research spans three interconnected domains—control, optimization, and decision-making for system management. By integrating biomass into multi-area control systems and leveraging self-tuning PID controllers, the study develops operational strategies that maximize the potential of renewable energy resources while addressing the challenges of modern power systems.

1.5 Thesis Outline

This work is divided into seven Chapters: **Chapter 1** serves as the introduction; **Chapter 2** delves into various renewable energy sources; **Chapter 3** is divided into two sections: The first section features a published IEEE conference paper titled "Generating Heat and Power from Biomass – An Overview." In contrast, the second section showcases a published IEEE conference paper titled "Using HOMER Software to Investigate, Size, and Apply Renewable Energy Sources in a Convention Center in Sabratha, Libya."; **Chapter 4** highlights a published IEEE journal paper titled "Hybrid Renewable Energy Resources Selection Based on Multi-Criteria Decision Methods for Optimal Performance."; **Chapter 5** presents a published IEEE conference paper titled "Modified Ant Lion Optimization Technique for Economic Emission Dispatch Including Biomass."; **Chapter 6** spotlights a published MDPI Energies journal article titled "Automatic Generation Control of a Multi-Area Hybrid Renewable Energy System Using a Proposed Novel GA-Fuzzy Logic Self-Tuning PID Controller."; Finally, **Chapter 7** contains the conclusion and outlines future work.

Chapter 2

Renewable Energy Systems

2.1 Abstract

Renewable energy resources are environmentally clean and abundant in nature; consequently, they are gaining extreme emphasis worldwide. Two Stanford University professors [1] predicted that renewable energies alone (with enough storage) could provide all energy needs anywhere globally. Another study by the UN IPCC anticipated that renewable resources could supply 50% of the total world energy by 2050. Wind and solar resources are essential to meet the growing energy demand and mitigate global warming [2].

2.2 Wind Energy

The world has vast wind energy resources, currently the most economical "green" energy. According to Stanford University, only 20% of available wind energy can supply the world with all the electricity needed. Wind and PV energy are especially attractive to one-third of the world's population, who are not connected to electric grids [2]. China and India have large expansion programs for wind energy. Regarding the percentage of energy consumption, Denmark is the leader with 25% wind energy and is expected to increase to 40% by 2030. China is now the leader in installed capacity, followed by the US (close to Germany and Spain). One disadvantage of wind energy is that it is intermittent and needs backup power plants or energy storage systems. Surplus wind energy can be stored for later utilization [2].

2.3 Photovoltaic (PV) Energy

Sunlight can be converted directly into electricity through PV devices. The generated DC is converted to AC to connect it to the grid. In autonomous systems, battery banks are usually installed to backup energy sources. PV devices have the advantages of being static, safe, reliable, environmentally clean, and needing less maintenance than conventional fuels [2]. However, PV energy is currently more expensive than wind energy, depending on the installation cost and utilization factor. The IEEE predicts that by 2050, PV will provide 11% of the global electricity demand. The lifetime of a PV panel with the commonly used thin-film amorphous silicon is typically 20 years; conversion efficiency is typically 60%. They are installed on rooftops, off-grid remote applications, and grid-connected systems. Recently, China has been manufacturing PV cells very economically. Unfortunately, like wind energy, PV power is intermittent; therefore, backup energy storage systems are needed [2].

2.4 Biomass

Biomass is a stored solar energy source that plants collect during photosynthesis. Carbon dioxide is caught and converted into plant materials, primarily lignin, cellulose, and hemicellulose. Biomass covers many organic materials lately extracted from plants and animals that feed on plants. This biomass can be gathered and converted into bioenergy. It is not limited to forest and wood process residue; it also includes crop residues, animal wastes, food processing wastes, . . . , etc. [3].

Conventional biomass in the form of dried dung and fuelwood (often collected and scavenged) has long been used as an energy source for heating and cooking, and it is still so for about one-third of the world's population. When agriculture was produced about 10,000 years ago, cultivated crops provided humans and animals with food, were used as fibre for cloths, and were a source of construction materials and paper production [3].

Using industrialized agricultural technologies to harvest food and fibre crops left primary residues in the forest or the field. Secondary residues emerge from food, fiber, some material processing, and animal wastes (from livestock and poultry). Tertiary residues emerge using other waste materials such as demolished timber, sewage sludge, and municipal solid waste, see **Figure 2.1**. Since these include applicable energy values, they can be used as biomass feedstocks [3].

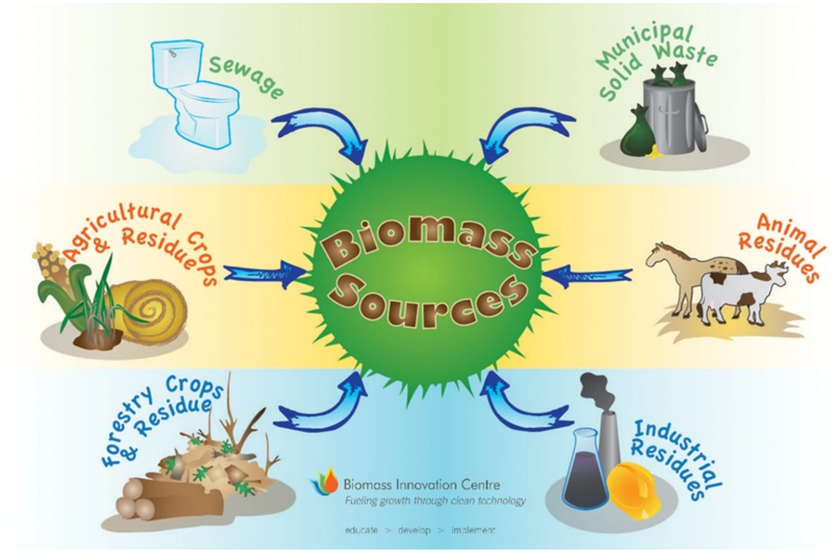


Figure 2.1: Examples of biomass resources [4]

There are several technologies to convert the solid and liquid biomass feedstock into solid fuels (such as wood chips, pellets, and briquettes), liquid fuels (such as methanol, ethanol, bio-oil, and biodiesel), or gas fuels (hydrogen, biogas, and synthesis gas). It can be converted into heat directly, see **Figure 2.2**. Many chemical products, such as oil, gas, and coal, can be co-produced from biomass. Bio-refinery development to get multi-products from a single feedstock has a promising future [3]. Polymers and furfural, which have high chemical value, could be produced in small volumes. On the other hand, some other products that include beneficial heat and energy at lower values could be produced in large volume outputs [3].

Large-scale multi-product plants exist, such as pulp mills, rice mills, commercial sugar mills, etc., where the main product is paper pulp, rice, or sugar. Their waste black liquor, husks, or bagasse could produce heat and power [3]. Biodiesel is usually produced in vegetable oil processing plants to produce a high protein meal to feed, among others, livestock or kernels appropriate for combustion to produce heat or pulp, and glycerol, which can either be upgraded to glycerin for cosmetics and explosives usage or could be used as another energy feedstock when it has low value [3]. Biomass is considered a renewable energy source, widely applied to produce heat and power in Canada and worldwide. With the commitment from many governments to lower the carbon footprint caused by burning fossil fuels, biomass is considered one of the options to replace them. However, some obstacles facing replacing fossil fuels with biomass include the availability and sustainability of biomass feedstocks, the feasibility and scalability of biomass conversion technologies, and the need for some policies and regulations to support applying biomass.

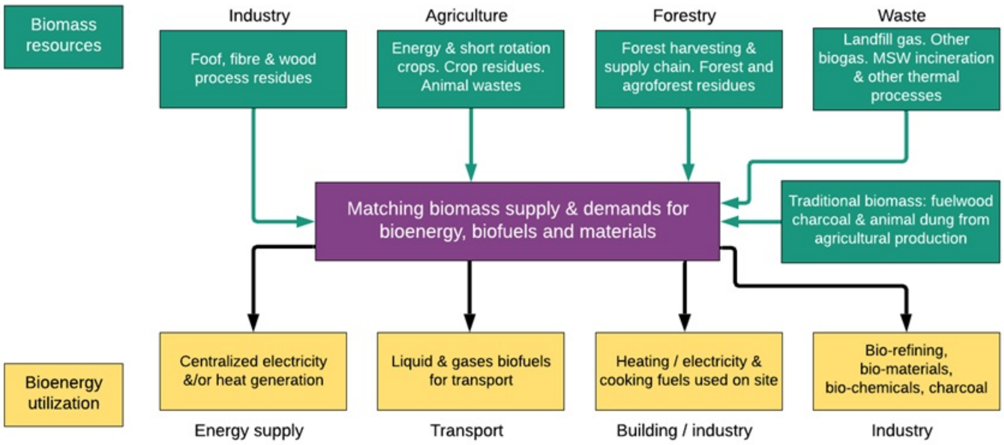


Figure 2.2: Biomass resources converted to bioenergy carriers.

2.4.1 Biomass Categories:

Biomass can be categorized into the following types:

1. Energy crops: These crops, like corn, sugarcane, and switchgrass, are grown specifically for use as fuel.
2. Agricultural residues: They are by-products of some agricultural processes, like corn stover, rice husks, and wheat straw.
3. Forestry residues: By-products of forestry operations, like wood chips, sawdust, and bark.
4. Industrial waste: By-products of industrial processes, like food processing waste and paper pulp.

5. Municipal solid waste: Household waste includes organic waste, like food and yard waste.
6. Biodegradable waste: Any organic material that can disintegrate by microorganisms, like manure and sewage sludge.
7. Aquatic biomass: Any organic material found in bodies of water, like algae and seaweed.

Each biomass category has distinctive characteristics and potential uses and can significantly generate heat and/or power and reduce reliance on fossil fuels.

2.4.2 Biomass to Electricity Conversion Technologies:

Generating power from biomass relies on the technology applied; the most famous three examples are:

- Combustion: Biomass is burned to produce electricity, like generating power from fossil fuels.
- Gasification: Biomass can be converted into gas using gasification technology, which can then be used to generate power.
- Anaerobic digestion: Anaerobic digestion can also convert biomass into biogas, which can then be used to produce power.

Combustion technology, gasification, and anaerobic digestion can be cost-effective ways to generate electricity, specifically when combined with energy efficiency measures and emissions controls. Some challenges facing them may include the need for a reliable and steady biomass supply, air pollutants emissions, and possible impacts on local communities and ecosystems. The results of producing heat and power from biomass show that it is possible to produce electricity from a renewable and local energy source. Careful consideration should also be given to the types and sources of biomass utilized for energy generation to ensure that they are sustainable and do not compete with other significant uses, such as food production or ecosystem services.

2.5 Literature Review, Research Gap, and Comparative Analysis between Hybrid Renewable Energy Systems and Single-Source Systems

2.5.1 Literature Review

The demand for biomass is increasing rapidly within the Maritime provinces and globally, driven by decision-makers to support biomass energy [5] or renewable energy sources in general [4]. Global biomass energy consumption is anticipated to increase between 0.6 and 2.3% annually until 2030 [5]. 19% of the global energy production in 2012 was predicted to be renewable, and 9% of this energy was estimated to come from traditional biomass use (i.e., cooking and heating). Electricity generation from biomass is relatively low at about 1.8% of the total energy generation [6]. Electricity generation from wind, in comparison, was a bit higher at approximately 2.9% of the global energy generation [6]. The electricity generated from biomass in NS has increased significantly. In 2013, NSPI inaugurated a new 60-megawatt capacity biomass power plant in Port Hawkesbury and acquired an additional 30 megawatts from the NS government for a biomass energy plant in Brooklyn. These developments resulted in a total of 90 megawatts of generated energy, contributing to about 4% of NS's electricity.

In New Brunswick, a total of 159.6 MW of electricity is generated from four biomass electric generating facilities, namely, Twin Rivers Paper, Irving Pulp & Paper, AV Nackawic, and AV Cell Inc., with capacities of 87 MW, 30 MW, 25 MW, and 17.6 MW, respectively [7]. According to a report from the K.C. Irving Chair in Sustainability at Moncton University in 2012, the province of New Brunswick has the potential to produce a total net generation capacity of 463 MW of power from biomass. This can be achieved by burning 15.5 million green tonnes of harvested wood annually. The New Brunswick government issued a bid in 2010 to harvest about 1.3 million tonnes of biomass for energy usage [7]. Prince Edward Island does not utilize forest biomass for electricity generation. Nonetheless, the region runs a modest 1.2 MW electric power facility that uses a blend of waste wood and oil as a fuel source. [6].

The driving forces to increase forest biomass power generation encompass reducing carbon emissions, foreign fossil fuels reliance reduction, creating job opportunities, developing rural areas, and energy costs reduction. From an economic feasibility viewpoint, the driver of these forces that forest biomass energy provides is carbon emission reduction. Since it is considered renewable energy, forest biomass energy producers are qualified for government incentives to make it economically feasible [8]. Relative to wind energy and because it can supply base-load power, power utilities also favourably consider biomass energy. It can provide any predicted amount of energy needed. Because biomass-generated electricity is more expensive than fossil fuel and wind-based, power utilities and some private energy providers need government incentives under different renewable energy promotion policies to develop it [8]. Regarding solar energy, two different technologies generate electricity from solar energy: photovoltaic (PV) and concentrated solar power (CSP) systems. Compared to PV systems, in the case of thermal energy storage technologies, CSP systems are used to store energy to generate electricity on cloudy days or overnight [9]. Much research was conducted to study Hybrid energy systems (HES) composed of two or more renewable energy resources.

In [10], a techno-socioeconomic criterion has been developed to determine the optimal grouping of sources for an autonomous hybrid power system (AHPS). A particle swarm optimization (PSO) algorithm has been applied to specify the optimal sizing for each piece of equipment. M. Sharafi and T. Elmekkawy applied in [11] a multi-objective PSO approach to optimize the size of the hybrid system depending on the ϵ-constraint technique that has been applied to reduce the system cost, load loss probability, and greenhouse gas emissions. Maleki and A. Askarzadeh presented in [12] four different heuristic algorithms, namely PSO, Tabu Search (TS), simulated annealing (SA), and harmony search (HS) to assess the performance of a hybrid SPV/wind/battery to meet the load required with minimum total annualized cost continuously, it is found that PSO has the best results. In comparing this model with SPV/wind/fuel cell (FC), it is found that the former is an economically better choice. The Monte Carlo simulation technique has been applied to resolve probabilistic three-phase power flow. Biomass has been added to some nodes in the IEEE-13 node test system to improve numerical applications. The results attained show a reduction in power losses and unbalanced factors. A novel hybrid method has been introduced using the shuffled frog leaping technique (SFL) and probabilistic three-phase power flow; the results show the best locations and sizes to inject biomass into a distribution system [13].

S. Singh and S. C. Kaushik presented an optimal sizing methodology for a stand-alone, grid-connected PV-biomass HES. ABC algorithm is used to specify the optimum HES configuration with the least LCO while minimizing the annualized cost of the system. The results showed that a grid-connected hybrid PV-biomass system is more cost-effective and reliable than a stand-alone one. A comparison between the results obtained from the applied algorithm and the HOMER software showed that the algorithm gave better results [14]. In [15], an artificial bee colony (ABC) technique has been introduced to perform the feasibility study of the PV/wind/biomass system; the results of the proposed algorithm have been verified compared with (PSO) algorithm and HOMER software results. In case of source failure, the applied model can supply smooth power flow. Upadhyay and Sharma investigated in [16] an optimal hybrid model using a genetic algorithm (GA), PSO, and biogeography-based optimization techniques (BBO) by considering three energy management strategies: cycle charging, peak shaving load, and load following. The cycle charging strategy gave more economical results than the other two methods.

In [17], the PSO-based algorithm was applied to optimally design a standalone PV/wind hybrid energy system to minimize the COE and maximize reliability. The results of the optimized hybrid system were compared with those of the utility grid regarding cost savings. The results showed that the PSO algorithm can reach the optimum solution with relative simplicity and computational proficiency. P. Anand et al. presented an optimal design to size solar / biomass/biogas / battery-based HES to provide a village in India with electricity. Various configurations of off-grid and grid-connected systems using grey wolf optimization (GWO) were applied. The study concluded that the best configuration was the grid-connected solar / biomass/biogas/battery system. In comparing the results obtained from the proposed model with HS and PSO algorithms, it is evident that the applied model has better results [18].

In [19], an optimal sizing of a standalone wind, PV/diesel generator/biomass, and battery bank HES has been presented to supply a remote area in India with electricity using different optimization approaches such as GA, PSO, butterfly PSO, and teaching learning-based optimization (TLBO) to minimize multi-objective function. The multi-objective function includes technical, economic, and social factors. Different configurations were examined, and it was found that TLBO performs better, followed by BFPSO, PSO, and GA. Zhichao et al. presented in [20] a standalone microgrid composed of wind/biomass/ diesel/battery has been presented. The steady-state and transient analysis of the wind turbine generator's wind power curtailment control (WPCC) has been investigated. A new parallel double-mode operation approach with a "fault detector" has been proposed. A case study of the proposed methods is tested and verified in a remote Canadian area.

Eissa, Mohamedeltayib Omer Salih, et al. [21] emphasized Libya's opportunity to capitalize on agricultural residues, noting that approximately 4.5 million tons of crop waste was produced in 2021, predominantly from potatoes, wheat, barley, and maize. This biomass possesses a calorific value of around 17.7 TJ and can significantly contribute to reducing greenhouse gas emissions while fostering energy sustainability and decreasing reliance on fossil fuels. However, to fully harness this potential, investing in infrastructure for waste collection and processing and implementing supportive policies for the biomass energy sector is crucial. To reduce the carbon footprint, Elmariami, Abdelbari, et al. concluded that wind energy is crucial for mitigating environmental degradation and addressing climate change, all while enhancing energy security in Libya. Establishing a 20 MW wind farm could diversify the energy portfolio and lessen dependence on oil and gas, preventing the emission of 7.6 million tons of greenhouse gases (GHGs). Most energy consumption (77.7%) and CO2 emissions (63.35%) arise during manufacturing. This analysis highlights the urgent need for strategic investments in renewable infrastructure in Libya [22].

Mrehel, Omar Giuma, and Abduladem Gerara Salama [23] examined the wind energy potential in southern Libya, focusing specifically on the regions of Sabha, Obari, Alqtroun, and Hun. They analyzed 10-minute average wind speed data at various heights and extrapolated these measurements to 100 meters using Windographer software. Their findings indicate a significant feasibility for wind energy development, with March exhibiting the highest wind potential and

September the lowest. Among the studied locations, Sabha emerged as the most promising site for wind energy production, underscoring the opportunity for wind energy to enhance Libya's sustainable energy portfolio. Nassar, Yasser F., et al. [24] utilized Life Cycle Assessment (LCA) to evaluate wind farm installations in Libya, considering all lifecycle stages from shipping to turbine disposal. They employed the System Advisor Model (SAM) and long-term climate data to assess wind energy viability. A key finding was the introduction of the Life Cycle Levelized Cost of Energy (LCLCOE), which includes environmental damage costs. The Gamesa turbine showed the best performance for a 100 MW wind farm, with a capital cost of $146,916,400. GHG emissions ranged from 32 to 70 GHG/kWh, with carbon payback periods of 4.5 to 12.3 months and energy payback periods of 13 to 22 months. The findings highlight the potential of wind energy in Libya as a sustainable alternative and stress the importance of strategic site selection and efficient turbine technologies for enhancing energy output and reducing environmental impacts. Proper planning can further support Libya's energy diversification and economic growth.

Badi, Ibrahim, et al. [25] developed a spatial model aimed at aiding decision-makers in identifying the most suitable locations for Solar Power Plants (SPPs) in the Misrata District of Western Libya. They employed Geographic Information Systems (GIS) with the hybrid SWARA-DEMATEL (SWA'TEL) multi-criteria decision-making approach to assess potential sites based on financial, social, and specialized criteria. The model classifies areas into five suitability levels, pinpointing 1,667 km^2 as highly suitable for SPP development. A sensitivity analysis confirmed the model's reliability and adaptability to various scenarios, establishing it as a valuable tool for advancing renewable energy infrastructure in Libya and applicable to similar regions. Nassar, Yasser F., et al. [26] investigated the sustainable utilization of local eco-friendly resources to address global energy demands and mitigate climate change, highlighting the benefits of hybrid renewable energy systems (HRES) compared to single-source systems. They specifically proposed a hybrid system for Brack City, Libya, which integrates a parabolic dish solar concentrator (PDSC) with a biomass digester to overcome challenges such as high temperatures that can diminish solar PV efficiency. The proposed system features a 36,560 m^3 biomass digester capable of producing 27 million m^3 of biogas annually, a 1,230 kW

Stirling generator, and a 6,006 m² PDSC. It is anticipated to contribute 5.67 million kWh to the grid each year, with a payback period of 20.04 years and a total capital cost of $12.37 million. The Levelized Cost of Energy (LCOE) is approximately $0.075/kWh, with an expected annual CO_2 emissions reduction by 7.8 kilotons. This innovative approach underscores the potential for reliable and sustainable energy solutions in Libya and comparable regions.

Nassar, Yasser F., et al. examined in [27] Libya's objective of achieving 30% renewable energy in its power mix by 2030, focusing on solar energy technologies. The study evaluated five Concentrated Solar Power (CSP) technologies—parabolic troughs, solar dishes, linear Fresnel reflectors, solar towers, and concentrated photovoltaic solar cells across 22 locations in Libya, utilizing the Levelized Cost of Energy (LCOE) as the primary evaluation metric. The research identifies the most suitable CSP technology for each site, considering the environmental costs associated with fossil fuel emissions. The findings illustrate the feasibility of CSP in Libya, supporting the country's renewable energy ambitions while promoting cleaner energy solutions and maintaining global competitiveness. Nassar, Yasser F., et al. [28] conducted a comprehensive study on the temperatures and topographies of Libya to assess the potential for wind and solar energy generation. Their research utilized various technological configurations to evaluate wind energy, concentrated solar power (CSP), and photovoltaic (PV) solar energy across twelve locations. The Levelized Cost of Energy (LCOE) analysis from January 2007 to June 2020 revealed that wind energy represents the most economically advantageous option, with an LCOE ranging from 1.5 to 5.9 ¢/kWh. In comparison, PV solar energy had LCOE values between 5.2 and 6.4 ¢/kWh, while CSP emerged as the priciest alternative, with costs reaching 8.0 ¢/kWh. The proposal for a 1000 MW renewable power plant can potentially decrease CO_2 emissions by 3.82 million tons, resulting in an annual savings of $286.5 million in carbon taxes.

In [29], Lagili, Hamza S. Abdalla, et al. evaluated Libya's wind and solar energy potential using data from 2022, specifically focusing on Az-Zawiyah. The study addressed challenges such as civil war and data scarcity. They compared five satellite datasets (CFSR, ERA5, ERA5-Land, MERRA-2, and TerraClimate) with actual measured data to assess resource accuracy. The findings revealed that CFSR and

ERA5-Land are reliable for wind evaluations, while all datasets are appropriate for solar assessments. The analysis spanned five coastal agricultural regions from 2000 to 2022 and estimated energy demand for typical farms. The results highlight the significant potential of renewable energy to satisfy agricultural energy needs, diminish greenhouse gas emissions, and support Libya's development, indicating a potential transformation in electricity generation and sustainability. Badi, Ibrahim, Ali Abdulshahed, and Emhemed Alghazel employed [30] a hybrid GREY-TOPSIS method to identify the optimal location for a solar farm in Libya, assessing six potential sites against twelve criteria. The GREY method found that average solar radiation and sunshine hours were the most critical factors, weighing 0.9. Misrata received the highest ranking (0.53), followed closely by Benghazi (0.47). This methodology offers a scalable framework to support sustainable development in urban regions.

Nassar, Yasser, et al. [31] created a solar and wind atlas for Libya, utilizing fifteen years of weather data from twenty-two cities. This atlas provides crucial insights into solar irradiance and wind speeds, drawing on data from the SolarGis database. It highlights Libya's significant renewable energy potential and is a valuable resource for policymakers, energy planners, and investors in their decision-making processes. The atlas supports the integration of renewable energy into the power grid, bolsters energy security, fosters local expertise, and encourages innovation and job creation, ultimately guiding Libya's transition towards sustainable energy and a greener future. Maka, Ali OM, Salem Salem, and Mubbashar Mehmood [32] investigated Libya's energy challenges and emphasized the potential of solar photovoltaic (PV) technology as a sustainable solution. They recognized that residential buildings are the largest energy consumers and reviewed the current energy systems and the usage of solar PV. Their study evaluated how solar PV can provide affordable energy solutions while exploring Libya's potential and the challenges and opportunities associated with solar energy development.

2.5.2 Research Gap

Libya's energy infrastructure relies heavily on fossil fuels, with limited integration of renewable energy resources despite its vast potential for solar and wind energy generation. The nation faces several critical challenges:

1. **Overreliance on Fossil Fuels:** Contributing to high greenhouse gas (GHG) emissions and unsustainable energy practices.
2. **Grid Instability:** The centralized grid struggles with reliability and fails to accommodate renewable energy's variability.
3. **Lack of Renewable Integration:** Previous studies in Libya have focused on theoretical assessments of renewable energy potential without detailed optimization models or hybrid systems analysis.
4. **Energy Management Gaps:** In the Libyan context, limited research exists on advanced control systems like Automatic Generation Control (AGC) for hybrid renewable energy systems.

Research Gap: While global literature has explored hybrid renewable systems and advanced control strategies, the application of these methods to Libya's energy system remains underexplored. Specifically:

1. **Limited Use of Multi-Criteria Decision Analysis (MCDA):** Prior studies have not systematically ranked and validated renewable energy sources for Libya using robust MCDA techniques in conjunction with simulation tools like HOMER Pro.
2. **Absence of Advanced Optimization in AGC:** Existing AGC methods used globally often fail to address the unique challenges of integrating solar, wind, and biomass in Libya's grid. Additionally, these methods lack adaptability to the variability of hybrid systems in real-world scenarios.
3. **Biomass as a Supplementary Resource:** Biomass is frequently overlooked as a viable option in Libya despite its potential to mitigate the intermittency of solar and wind energy.
4. **Inadequate Algorithms for Energy Dispatch:** Previous works have not adequately explored hybrid systems' emissions, costs, and power losses using advanced algorithms.

How the research gap advances knowledge:

1. **Comprehensive Renewable Energy Evaluation (Chapters 3 and 4):**
   - **HOMER Pro Integration:** The study evaluates the feasibility of multiple hybrid configurations for powering a convention center in Sabratha, balancing cost, emissions, and reliability. The use of HOMER Pro for

simulation ensures practical validation of MCDA results.

- **MCDM Techniques:** The application of VIKOR, COPRAS, and other methods provides a nuanced ranking of renewable energy options, which aligns with Libya's resource profile. These techniques systematically integrate environmental, economic, and technical criteria, providing actionable insights.

2. **Novel Optimization Techniques (Chapter 5):**
   - **ELED Method and Algorithms:** By introducing the ELED method and testing four advanced algorithms (MALO, SA, BAT, QPEICC), this research optimizes the scheduling of generating units to minimize costs, emissions, and power losses.
   - **Biomass Integration:** The study demonstrates biomass's critical role as a complementary energy source, achieving optimal performance at a 50% biomass ratio.
3. **Innovative AGC Solution (Chapter 6):**
   - **GA-Fuzzy Logic Sel-tuning PID Controller:** A groundbreaking approach to dynamically optimize PID parameters, this method outperforms traditional PID controllers and heuristic-based algorithms. It enhances frequency stability and load management in hybrid renewable systems.
   - **Libyan Context Focus:** By incorporating biomass, solar, and wind into AGC operations, the research tailors its solutions to Libya's renewable energy profile, addressing local challenges like intermittency and grid reliability.
4. **Validation Through Rigorous Simulation:**
   - Realistic scenarios were tested (e.g., sudden 80 MW load on wind plants), ensuring that the proposed methods are robust and practical for Libya's grid dynamics.
   - Results are benchmarked against conventional methods, highlighting the significant improvements achieved.

Contributions to Libya's Energy Context: This research bridges the gap between theoretical assessments and practical implementation by:

1. **Demonstrating Feasibility:** This study validates using hybrid renewable

systems for key infrastructure in Libya, paving the way for large-scale deployment.

2. **Promoting Sustainability:** Reduces reliance on fossil fuels and lowers emissions, aligning with global environmental goals.
3. **Enhancing Grid Stability:** This section introduces advanced AGC methodologies that ensure a reliable power supply despite the variability of renewables.
4. **Strategic Decision Support:** Provides policymakers with robust tools and validated methods for prioritizing renewable energy investments.

This research advances renewable energy integration, optimizes energy management, and addresses specific challenges in Libya's energy landscape, setting a strong foundation for transforming the country's energy sector toward a sustainable future.

2.5.3 Comparative Analysis between Hybrid Renewable Energy Systems (HRES) and Single-Source Systems

This analysis highlights the distinct performance metrics of hybrid solutions, emphasizing their significant advantages:

1. **Cost-Efficiency**
   - **HRES:** The integration of diverse renewable energy sources, such as solar, wind, and biomass, significantly enhances the overall reliability of energy systems while concurrently diminishing reliance on supplementary backup systems, including batteries and diesel generators. This multifaceted approach not only promotes greater system resilience but also contributes to a reduction in operational and maintenance expenditures throughout the lifecycle of the energy system.
   - **Single-Source Systems:** While simpler and less expensive upfront, they frequently necessitate integrating larger energy storage systems or backup solutions to address intermittency issues. This requirement can ultimately lead to increased long-term expenses.
2. **Energy Output**
   - **HRES:** Hybrid energy systems enhance the optimization of energy

generation by integrating complementary sources of power, such as wind turbines and solar photovoltaic (PV) systems. Wind turbines exhibit superior performance during nighttime and under cloudy weather conditions, times when the output of solar PV systems typically diminishes. This synergistic integration of diverse energy sources contributes to a more stable and elevated overall energy output, thereby improving the reliability and efficiency of renewable energy systems.

- **Single-Source Systems:** Energy output depends on resource limitations, such as solar panels relying on sunlight, which causes energy generation to be inconsistent.

3. **Carbon Emissions**
   - **HRES:** The inherent flexibility of renewable energy systems markedly diminishes dependence on fossil fuel-based backup sources, substantially reducing carbon emissions. For instance, integrating solar energy with biomass can facilitate a continuous power supply while ensuring a minimal environmental footprint. This synergistic approach exemplifies the potential of hybrid renewable systems to enhance energy reliability and sustainability while simultaneously addressing environmental concerns.
   - **Single-Source Systems:** The operational frameworks of solar and wind energy systems may necessitate increased emissions from supplementary non-renewable energy sources during downtime. This is particularly relevant in systems that rely solely on solar or wind resources, where the intermittency of energy generation can lead to a reliance on fossil fuel-based systems to maintain energy supply continuity.

Chapter 3

Generating Heat and Power from Biomass - An Overview, and Using HOMER Software to Investigate, Size, and Apply Renewable Energy Sources in a Convention Center in Sabratha

This chapter contains materials published in research papers [33] and [34].

3.1 Generating Heat and Power from Biomass – An Overview [33]:

3.1.1 Abstract

Countries and big power companies utilize renewable energy sources to promote development, expand electricity access, and meet their policy targets for reliable, secure, sustainable, and affordable energy. It isn't easy to specify which renewable energy technology is the most appropriate without having access to reliable information on the relative benefits of these energy sources. Regarding biomass as a green energy source to generate power, the type of biomass, the amount of energy required, and the local environment all influence the technique selection. Because biomass energy generation uses organic waste materials and emits fewer greenhouse gases than fossil fuels, it can support sustainable practices. To ensure the sustainable production and use of biomass for heat and power generation, it is imperative to consider the environmental and social implications, including but not limited to land usage, biodiversity, and community involvement. This chapter provides an overview of using biomass as a renewable energy source to generate heat and power. Different

technologies are introduced.

3.1.2 Introduction

The demand for biomass is increasing rapidly both within the Canadian provinces and globally, driven by decision-makers to support biomass energy or renewable energy sources. Global biomass energy consumption is anticipated to grow between 0.6 and 2.3% annually until 2030 [7]. In 2012, 19% of worldwide energy production was predicted to be renewable, and 9% of this energy was estimated to come from traditional biomass use (i.e., cooking and heating). Electricity generation from biomass is relatively low at about 1.8% of the total energy generation. Electricity generation from wind, in comparison, is slightly higher at approximately 2.9% of the global energy generation [7]. The driving forces to increase forest biomass power generation encompass reducing carbon emissions, foreign fossil fuel reliance, creating job opportunities, developing rural areas, and reducing energy costs. From an economic viewpoint, the driving force behind forest biomass energy is carbon emission reduction. Since it is considered renewable energy, forest biomass energy producers are qualified for government incentives to make it economically feasible [7].

3.1.3 Biomass Power Generation Technologies

Using biomass instead of fossil fuels to generate power has many advantages, including lowering greenhouse gas emissions, improving the security of supply, saving energy costs, reducing waste, and developing local economies. To what extent will it be beneficial? It relies on nature and the source of the biomass feedstock [35]. When analyzing the use of biomass to generate power, it is crucial to consider three components of the process:

- Biomass feedstocks: they have different forms and vary in their properties, affecting their power generation use.
- Biomass conversion: the biomass feedstocks in this process are converted to the energy form, which will be used for heat and power generation.
- Power generation technologies: biomass as a fuel input is currently used in various commercial power-generating technologies [35].

It is essential to know the energy content, moisture content, ash content, and homogeneity of biomass feedstock. These components significantly impact biomass feedstock cost per unit of energy, treatment, transportation, storage, and readiness for different conversion techniques. We can convert bioenergy into power using biochemical processes, such as anaerobic digestion, or thermal-chemical processes, such as combustion, gasification, and pyrolysis [35].

3.1.3.1 Biomass Combustion Technologies

Direct combustion technology is the most common method of generating power from biomass. It is commercially available at scales of more than 100 MW. More than 90% of the biomass energy generated around the globe is through combustion [36]. The availability and costs of feedstock play a significant role in project size and price. When a plant's size doubles, capital costs will rise by 62%, which is a 100% increase in capacity [37]. The combustion-based biomass plants have two main components:

- The biomass-fired boiler, with which steam is produced, and
- The steam turbine is where we generate electricity.

The boilers are available in different forms, the most common being stoker and fluidized bed. These two can either be fueled entirely by biomass or co-fired with a mixture of biomass and other solid fuels (e.g., coal) [37].

3.1.3.2 Boiler Types

- Stoker boilers: The fuel in Stoker boilers is burned on a grate. This generates hot flue gases, which are used to produce steam. A fixed or moving grate is used to remove the ash resulting from the combusted fuel. Stoker boilers are available in two types: underfeed and overfeed. The first provides the fuel and the air from under the grate, and the latter offers the fuel from above the grate and the air from below [36].
- Fluidized bed boilers: These are classified according to the following diagram; **Figure 3.1**:

The fluidization velocity in the circulating bed units is higher than in the bubbling bed. When the fuel used is biomass, the atmospheric-bubbling fluidized bed boilers (BFB) are used more than the pressurized fluidized bed boilers (CFB). Even when biomass has a high moisture content, fluidized bed boilers are more effective than stoker boilers [36]. The boilers produce steam, then inject it into steam turbines, which convert the heat into mechanical power generated by electricity [38].

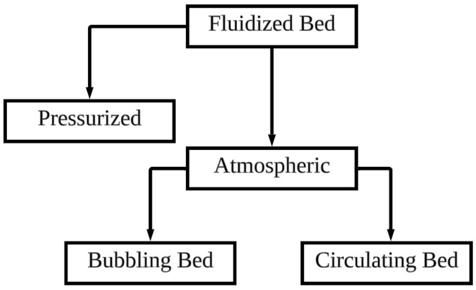


Figure 3.1: Fluidized bed gasifiers.

3.1.3.3 Combined Heat and Power (CHP)

Co-generation occurs when the electricity and heat are produced simultaneously from one energy source. The overall efficiency is higher in CHP systems than when the electricity and heat are produced separately in the industrial and commercial sectors; **Figure 3.2**. Biomass-fired CHP systems supply heat or steam in the industrial sector for space or water heating in buildings. The biomass CHP plant's feasibility is often affected by electricity price, biomass availability, and biomass feedstock cost [39].

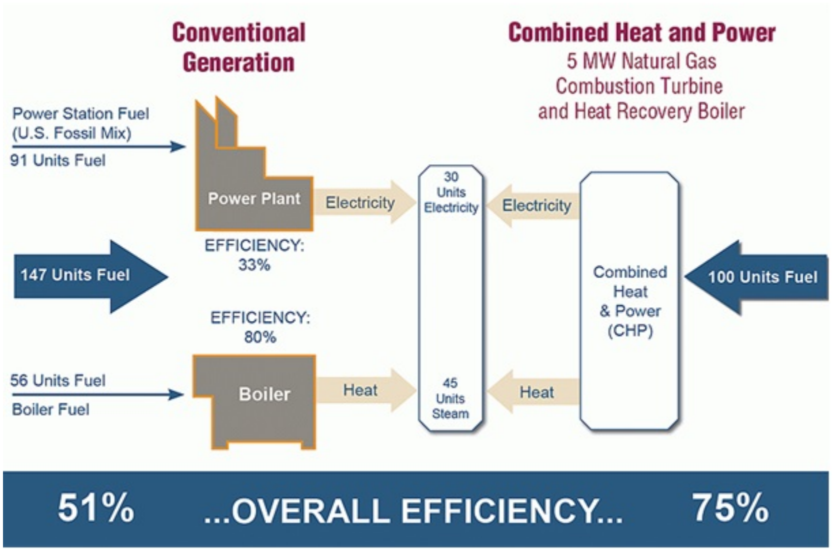


Figure 3.2: An example of efficiency gains from CHP [40].

There are many biomass sources available for co-generation. Still, the most important ones are the sugar cane and wood processing industries, where the feedstock is effortlessly available at low cost, and the heat needed for processing can be generated onsite [40]. The co-firing of biomass with solid fuels in large power plants is becoming common. About 55 GW of coal-fired capacity in North America and Europe is currently co-fired with biomass. About 45 GW of thermal power generation capacity in Europe is cofired, with biomass content ranging from 3% to 95% [41].

Biomass co-firing has the advantage that the power efficiency, on average, in co-firing plants is more significant than that of unmixed biomass combustion plants. Even though the incremental investment costs are low, they can raise the price of a co-fired power plant by one-third [42]. The three achievable technology set-ups for cofiring are:

- Direct co-firing, by which biomass and coal are fed into the boiler either with shared or separate burners;
- Indirect co-firing, by which the fuel gas produced from solid biomass is burned together with the coal; and
- Parallel co-firing, by which biomass is burned in a separate burner, and steam is added to the coal-fired power plant.

Although it is technically possible to co-fire up to 20% of capacity without any technical modifications, most co-firing plants currently use up to 10% biomass. The mixed fuel (co-fired mix) relies on the boiler's type [41]. Fluidized bed boilers substitute much more biomass than pulverized coal-fired and grate-fired boilers. Sophisticated biomass co-firing plants could be run 100% from biomass, specifically those seasonally provided with large biomass quantities. Nevertheless, co-firing more than 20% often requires a more advanced boiler design, process control, various combustion considerations, fuel blend control, and handling systems. This means greater control is needed over the mixed-feedstock combustion [42]. When biomass's moisture content is high (e.g., municipal solid waste), biomass is often co-fired with natural gas to stabilize the combustion; the natural gas ratio, in this case, is fundamentally low [41].

3.1.4 Anaerobic Digestion

Anaerobic digestion (AD) converts biomass feedstocks with high moisture content into biogas. AD is a naturally occurring process, and if it is well harnessed, it can provide a very efficient means of manipulating organic materials from different industrial processes, agricultural processes, and municipal waste streams into a usable fuel source [42]. AD is often operated continuously and needs a stable feedstock supply. The feedstock is frequently checked and pre-treated to minimize the probability of killing the natural digestion process and to maximize methane production. Multiple feedstock co-digestion usually attains the best balance of biogas yield and achieves process stability. AD has two main products: biogas and a residue digestate, which, after appropriate manipulation, is used as a bio-fertilizer [42].

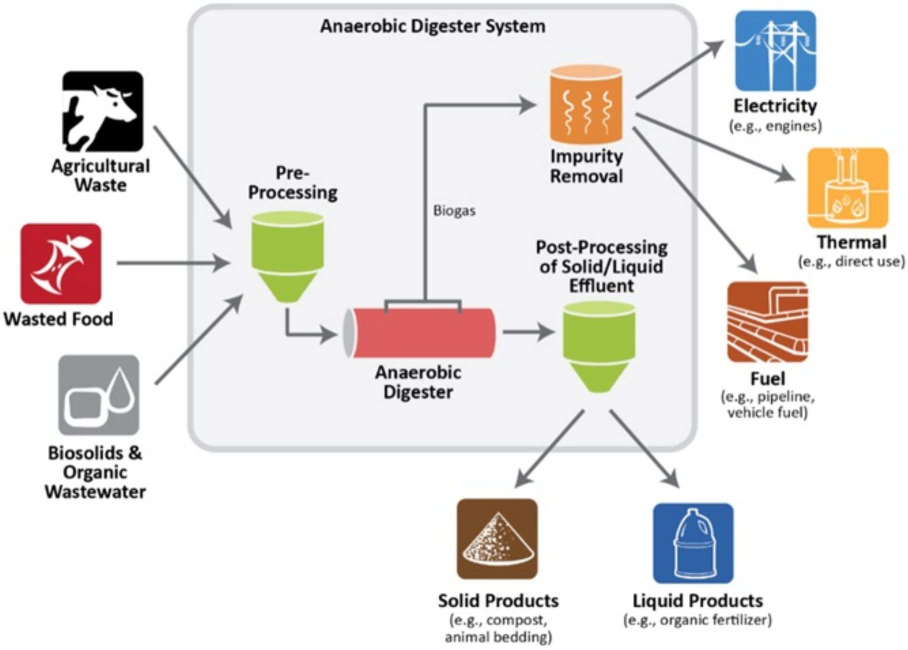


Figure 3.3: Anaerobic digestion system.

Biogas, in general, is a combination of methane (CH_4) and carbon dioxide (CO_2), in addition to some other slight elements, including hydrogen (H_2), hydrogen sulphide (H_2S), sulphur dioxide (SO_2), nitrogen(N_2) and ammonia (NH_3) Biogas is a fuel readily used in power units and combined heat and power units. After proper cleaning and upgrading, it can also be used in place of natural gas. Even though digesters and landfill gas are recognized technologies, their feedstock is limited. Wide-ranging plants fed by agricultural, industrial, organic, and municipal solid wastes (MSW) burn up to 9,000 tons of MSW/MW/year [42].

3.1.5 Biomass Gasification Technologies

Biomass can be converted into a producer gas using gasifier technologies. This gas can then be burned in simple or combined-cycle gas turbines. This is more efficient than biomass combustion when driving a steam turbine. From an economic viewpoint, complexity and costs must be reduced to improve performance and efficiency [43]. The main three types of gasification technology are:

- Fixed bed gasifiers.
- Fluidized bed gasifiers (circulating or bubbling).
- Entrained flow gasifiers.

Yet, there are a lot of configurations, and gasifiers are usually arranged based on four distinct characteristics:

- Oxidation agent: Air, oxygen, steam, or a combination of these gases.
- Heat for the process: Either direct or indirect, by the combustion process inside the reactor vessel or supplied to the reactor from an external source, respectively.
- The pressure level: Gasification occurs at atmospheric or higher pressures.
- Reactor type: The three main types of gasification technology mentioned above [43].

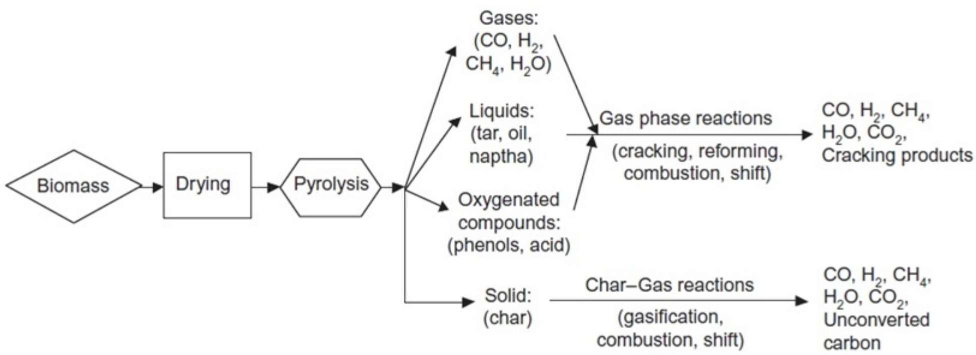


Figure 3.4: Reaction sequence and potential paths for gasification [5].

Gasification happens in two steps: pyrolysis, where biomass feedstocks are decomposed by heat. (This produces up to 90% volatile liquids and gases; the rest is char). Next is the gasification process, in which the volatile hydrocarbons and the char are exposed to a very high temperature to be gasified in the presence of a reactive agent like air, oxygen, steam, or a mixture of them to make H_2, CO, and some CO_2, methane, tar, and ash. The previous two steps are accomplished in various reactor vessel zones without additional equipment. A third step is sometimes needed, where contaminants like tars and other particulates are removed [43]. Gasifiers based on air are pretty cheap; they typically produce producer gas (a mixture of flammable gases, mainly CO and H_2, and non-flammable gases, principally N_2 and CO_2). The producer gas created has a high H_2 and low energy content ($5\ to\ 6\ MJ/m^3$ on a dry basis). Gasifiers based on O_2 or steam produce syngas with relatively high CO content and H_2 with a very high energy content ($9\ to\ 19\ MJ/m^3$), although at a higher cost than air-based ones [43].

The gasification process is an endothermic operation that necessitates significant heat. After producer gas is created, a fair number of contaminants will be produced, according to the power generation technology applied. Tars, for example, may clog engine valves, accumulate on turbine blades, decrease performance, and increase maintenance costs. Producer gas cleanup is often required, and then the producer gas may substitute natural gas in gas turbines; it can also produce liquid biofuels like ethanol, gasoline, and synthetic diesel [43]. One key characteristic of gasifiers besides the producer gas they produce is the size range to which they are suited. Fixed bed downdraft gasifiers about 1 MWth in size do not scale well because it is hard to maintain uniform reaction conditions [43]. On the other hand, fixed bed updraft gasifiers have fewer limitations on their scale, and entrained flow gasifiers can offer wide-range gasification solutions.

3.1.5.1 Fixed Bed Gasifiers

Fixed-bed gasifiers commonly have a grate to assist in gasifying the biomass and keep a stationary reaction bed. They are straightforward to design and operate and experience very little decay of the reactor body. Types of fixed bed designs:

- Updraft fixed bed gasifier.
- Downdraft fixed bed gasifier.
- Cross-draft fixed bed gasifiers [38].

For thermal applications, as much as 1 MWth, fixed bed gasifiers are the best solution. While downdraft gasifiers do not scale appropriately beyond 1 MWth, the updraft designs can scale up to 40 MWth. Biomass gasification technology is successfully deployed in different countries, and rice-husk gasification is widely applied. Piles of rice husks are fed into small biomass gasifiers to produce gas. In turn, the gas produced is used to supply internal combustion engines with fuel to generate electricity. The by-product of this operation is rice-husk ash that can be used in concrete. There are several equipment providers. For example, Husk Power Systems (HPS) has installed 60 mini-power plants, which supply more than 250 communities and about 25,000 households with power [43].

3.1.5.2 Fluidized Bed Gasifiers

There are two types of fluidized bed gasifiers: bubbling fluidized bed (BFB) and circulating fluidized bed (CFB), which are either atmospheric or pressurized. The gasification operation in these gasifiers happens in a bed of hot passive materials (often sand or alumina) hanging by oxygen-deprived gas moving upward. The bed of these passive materials increases in parallel with the increased flow until it becomes fluidized [38].

Table 3.1: Advantages and drawbacks of fluidized bed gasifiers

Advantages	***Disadvantages***	
Fluidized bed gasifiers	***BFB***	***CFB***
Creates a homogenous good, quality producer gas	They need complicated control	They need complicated control
They accept different feedstocks and particle sizes	They respond slowly to load changes	They react slowly to load changes
Excellent performance of heat transfer through bed materials contact	Complex and expensive	Complex and expensive
Big capacity of heat storage	More efficient heat exchange than CFB	Less efficient than BFB

Using the passive materials, fluidized bed reactors increase the biomass reaction rate, improving performance. Besides improving performance, fluidized bed gasifiers accept different feedstocks and produce gas with a high energy content. However, compared to fixed-bed reactors, they cost more and are more complex [38]. **Table 3.1** depicts the pros and cons of fluidized bed gasifiers.

3.1.5.3 Entrained Flow Gasifiers

Entrained flow gasifiers are favourable in plants with the integrated gasification combined cycle. Their reactors usually operate at about 1400 and between 20 – 70 bar pressure, in which powdered fuel is entrained into the gasifying medium. Entrained-flow gasifiers could be considered plug-flow reactors. Even though the gas reaches the reactor temperature swiftly upon entering, solids tend to heat up slower due to the larger thermal capacity and the nature of the plug flow [38].

3.1.5.4 Gas Clean-up

According to the feedstock and gasification operation, the gasification operation produces gas containing many contaminants. When the gas combusts in a boiler or an internal combustion engine, the contaminants are not often a big issue. On the other hand, when it fuels turbines to produce electricity at higher efficiency, some gas clean-up form will be needed to ensure that the gas diminishes contaminant concentrations to the minimum, see **Table 3.2** [44]. This approach is very costly, and every project's cost must be carefully analyzed because impurities and contaminant removal raise the capital and operating costs.

Table 3.2: Example of producer gas contaminants

Contaminants	***Examples***	***Potential problem***
Particles	Ash, char, fluid, bed material	Erosion in gasifier and prime mover
Alkali metals	Sodium, and potassium compounds	Hot corrosion
Nitrogen compounds	NH_3 and HCN	Local pollutant emissions
Tars	Refractive aromatics	Clogging of filters and other fouling
Sulfur, chlorine	H_2S and HC_1	Corrosion, emissions

Every technology has a different contaminant tolerance, so selecting the gasifiers, feedstocks, and technology in addition to the design can reduce gas clean-up requirements. Many technologies are currently available to clean up producer gas outflow. Cyclones can remove as much as 90% of larger particles at an acceptable cost. Still, high-temperature ceramic filters, sintered metal filters, or electrostatic precipitators are needed to remove smaller particles[44], [45].

Tars are a significant issue because they can build up on the turbine blades and contaminate turbine systems. One solution is cracking the tars by thermal or catalytic processes. Another solution is wet scrubbing of the gas, which removes as much as half of the tar, and up to 97% of the tar can be removed when used together with a venturi scrubber. The drawback of simple scrubbing systems is that the biogas settles down and builds an unwanted stream that must be discarded. However, the OLGA tar removal operation hinges upon multiple scrubbers and successfully recycles almost all the tar to the gasifier to be removed [44]. OLGA (Oil and Gas Washer) is a technique that removes tar from syngas.

3.1.6 Pyrolysis

Pyrolysis is a subcategory of the gasification process. It uses the same procedure as gasification but at a limited temperature, usually between 300 °C and 600°C. Traditional pyrolysis requires heating the original material in a reactor vessel isolated from air, usually between 300°C and 500°C. At those temperatures, the volatile matter is released from the biomass.

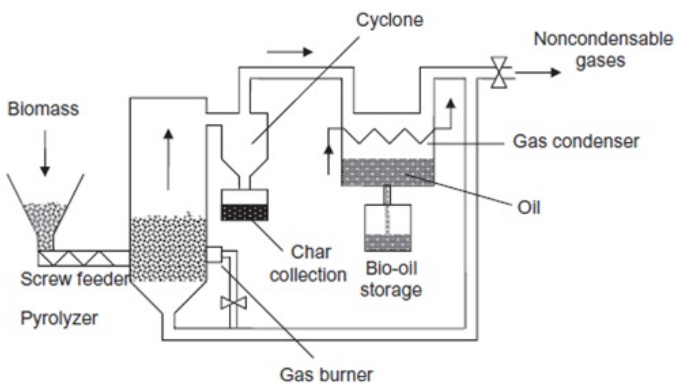


Figure 3.5: Simplified layout of a pyrolysis plant.

A liquid bio-oil, gaseous products, and a solid residue are created at this point. The residue is charcoal; its energy density is roughly twice that of the biomass feedstock, and it burns at very high temperatures [38]. The volatiles are collected using advanced pyrolysis techniques. The temperature must be chosen carefully to control the composition process. Even though the created liquid bio-oil has very similar properties to crude oil, it comes contaminated with acids and must be manipulated for fuel use. Electricity and heat could be generated by the charcoal and the oil produced using this technology [38].

3.1.7 Feedstock

From a chemical viewpoint, the biomass structure consists of high moisture content and a fibrous formation that contains lignin, carbohydrates, and ash. The botanical term used for biomass extracted from woody or fibrous materials is lingo-cellulose. It is a mixture of lignin, cellulose, and hemicellulose polymers in a multifarious matrix [38].

Table 3.3: The heat content of various biomass fuels (dry basis)

	Higher heating value MJ/kg	***Lower heating value MJ/kg***
Woody crops		
Black locust	19.5 - 19.9	18.5
Eucalyptus	19.0 - 19.6	18.0
Hybrid poplar	19.0 - 19.7	17.7
Douglas fir	19.5 - 21.4	NA
Poplar	18.8 - 22.4	NA
Maple wood	18.5 - 19.9	NA
Pine	19.2 - 22.4	NA
Willow	8.6 - 20.2	16.7 - 18.4
Forest Residues	NA	NA
Hardwood wood	18.6- 20.7	NA
Softwood wood	18.6 - 21.1	17.5 - 20.8

The biomass energy density relies on the chemical structure. **Table 3.3** depicts the energy density of different biomass feedstocks (on a dry basis). The table shows that hardwoods have higher energy densities. The quality of biomass feedstock relies on moisture and ash content, particle size, and density [38].

3.1.7.1 Moisture Content

Biomass moisture varies between 10% and 60%, and even more from some organic wastes. CFB and stocker boilers accept fuels with higher moisture content than gasifiers. In the case of anaerobic digestion, several options are available, including high solids-dry, high solids-wet, and low solids-wet configurations. In the low solids-wet case, manure slurry, for example, has a solids content of 15% or less. The drawback of a high moisture content is that it decreases the feedstock's energy value. It also raises transportation and fuel costs [28].To improve the feedstock energy density, reduce transportation costs, and improve combustion efficiency, drying is needed either by natural or accelerated means [28].

3.1.7.2 Ash Content and Slagging

One of the most significant issues with feedstocks is ash content. Ash content creates deposits inside the gasifier and combustion chamber. These deposits, called "slagging" and "fouling," can lessen performance and raise maintenance costs. Compared to wood, grass and field crop residues have higher ash amounts. The condensation of volatile compounds vaporized in the boiler formed fouling deposits in the convection parts. Slagging happens in the boiler parts that face direct flame irradiation. Slagging deposits contain a powdery layer accompanied by deposits of silicate and alkali compounds [41].

To minimize fouling and slagging, the combustion temperature must be kept low enough to avoid fusing the ash. An alternative option is to design high-temperature combustion. This helps form clinkers (hardened ash), which are easy to dispose of. Some biomass types need unique combustion systems to deal with the ash created. Rice husks, for example, need unique combustion systems because of the silica content of the husks [41].

3.1.7.3 Feedstock Size

It is essential to know the biomass size and density due to their influence on the rate of heating and drying during the process. The larger the particles, the slower the heat up; consequently, more char and less tar are produced [28]. In fixed-bed gasifiers, flow problems in the bunker section will be caused by fine-grained and fluffy feedstock, leading to an undesirable pressure drop in the reduction zone and a high proportion of dust particles in the gas. In downdraft gasifiers, the significant pressure drop can diminish the gas load. As a result, the temperature will be low, and the tar production will be higher. Dealing with equipment depends on the structure, size, density, composition of the fuel, and moisture content. Good design improves the efficiency of the combustion/gasification process [41].

Table 3.4: Biomass power generation technologies and feedstock requirements.

Biomass conversion technology	*Particle size (mm)*	*Moisture content (%)*	*Average capacity range (MW)*
Stoker grate boilers	6 - 50	10 - 50	4 - 300
Fluidized bed combustor	<50	<60	Up to 300
Co-firing: pulverized	<6	<25	Up to 1500
Co-firing: stoker, fluidized bed	<72	10 - 50	Up to 300
Updraft fixed bed gasifiers	6 - 100	<20	5 - 90
Downdraft moving bed gasifiers	<50	<15	25 - 100 kW
Circulating fluidized bed gasifiers	6 - 50	15 - 50	5 - 10
Anaerobic digesters	NA	65 - 99.9	NA

3.1.7.4 Overview of Biomass Power Generation Technologies and Biomass Feedstock Characteristics

Table 3.4 gives a general review of biomass technology and the need to know the feedstock's particle size and moisture content. When efficiency is required, moisture content and feedstock size are the strictest requirements for co-firing in coal-fired power plants [41].

3.1.8 Conclusion

Biomass is an organic material with carbon absorbed by plants through photosynthesis; it is applied to get bioenergy. The carbon in this biomass is released after combustion and goes back into the atmosphere when it is used to generate energy. Modern bioenergy is considered emission-free since it absorbs carbon in proportion to the biomass produced. Besides the environmental and energy security gained from other renewable energy sources, biomass can be scheduled to generate power and enhance the growth demand for other renewable energy sources. In CHP, biomass can significantly improve the cost of biomass power generation, specifically when the cost sources are low (e.g., agriculture and industry residues).

In conclusion, biomass energy has some pros and cons as follows:

Advantages:

- Abundant renewable source: Biomass can be found in various places, from agricultural fields and woodlands to yard waste, paper waste, food waste, and even animal dung. Unlike fossil fuels, the energy needed for biomass growth is supplied by the sun, a limitless and renewable source.
- Reliability: Biomass energy is 'dispatchable', meaning it can be controlled and adjusted to meet the demand, making it a dependable energy source.
- Less waste: Utilizing biomass to create power lessens the garbage that would otherwise wind up in landfills.

Drawbacks:

- Space: To minimize transportation expenses and distance, biomass plants must be close to the biomass source, which usually takes up a lot of land. Because of the size of these factories, utilizing space-efficient industrial conveyors, vibrating feeders, and other equipment is crucial to cost control.
- Environmental and health concerns: The environmental impact of biomass energy, such as deforestation and intensive land use, is a valid concern. However, these issues can be addressed through careful logging techniques, tree replanting, sustainable agriculture, and harvesting on marginal lands. Similarly, the health effects of burning biomass can be mitigated by removing methane from landfills and converting it into electricity, which reduces greenhouse gas emissions.
- Cost: Biomass is more expensive than other renewable energy sources like solar and wind. The poor energy density of biomass, up to 50% of it is water, is another factor driving up costs.

3.2 Using HOMER Software to Investigate, Size, and Apply Renewable Energy Sources in a Convention Center in Sabratha, Libya [34]:

3.2.1 Abstract

It's essential to note that a successful transition from fossil fuels to green energy necessitates a comprehensive and integrated approach involving collaboration between governments, industries, communities, and individuals. This transition may also address challenges such as intermittency in renewable energy sources and the need for infrastructure upgrades. As technology continues to advance and awareness grows, the goal of replacing fossil fuels with green energy becomes more inevitable. The concern about the dependence on fossil fuels and their environmental impact has been increasing recently. This led to more research in alternative energies to reduce the reliance on fossil fuels and to protect the environment. Two strategies can be applied to reduce dependence on fossil fuels. They are, firstly, reducing energy consumption by applying energy savings programs. And secondly, using renewable energy sources [46]. This chapter uses the HOMER Pro software to explore, analyze, and optimize the design of renewable energy systems, aiming to develop the most efficient model for a standalone hybrid power system. The application of this software allows for a comprehensive evaluation of various configurations, enhancing the integration of diverse energy sources to meet specific energy demands efficiently. Through systematic analysis, the optimal balance between cost, reliability, and sustainability is sought, contributing to the advancement of hybrid energy solutions. This system intends to supply power to a convention center in Sabratha, Libya.

3.2.2 Introduction

One of the most debated topics nowadays is global warming. Burning fossil fuels produces large amounts of greenhouse gas emissions; global warming is caused by increasing the quantity of these greenhouse gases in the atmosphere. Global levels of greenhouse gases have risen drastically since the Industrial Revolution dawned in the

1750s [47]. The most man-made carbon dioxide (CO_2) emissions come from burning fossil fuels [48]. Nitrogen oxides (NO_x) emissions are caused mainly by using synthetic fertilizers for agriculture, fossil fuels for combustion, and livestock manure management [49]. The conventional fuel for power generation comes from fossil fuels; there is an increasing concern nowadays about generating electricity from fossil fuels because of their emissions, higher prices, and exposition to depletion. Governments, scientific associations, and companies are sponsoring more research to decrease the reliance on fossil fuels [50]. There are two scenarios to apply: either by applying energy-saving programs or using more renewable energy sources to generate power.

Renewable energy sources have less environmental harm because they have either zero or very few emissions compared to fossil fuels. Wind, solar, biomass, geothermal, tides, and other clean energy sources have become better alternative clean energy sources to replace or reduce generating energy from conventional sources [51], [52]. However, all these renewable energy resources are not always available throughout the year and have high initial costs, making them less competitive. Many researchers have proposed hybrid models to overcome this challenge, relying on the weather and having an economical, reliable, and sustainable energy supply. A hybrid combination of two or more renewable sources improves the system's efficiency and performance. Hybrid renewable energy systems (HRES) consist of one renewable energy source combined with one conventional energy source or other renewable energy sources that work either in a standalone or grid-connected mode [51]. Stand-alone renewable energy systems must have enough storage capacity to manipulate power fluctuation from renewable energy sources [53]. Hybrid combinations of different renewable sources complement each other and supply higher energy efficiency. Hybrid energy systems (HES) are more common in remote and isolated areas. Moreover, they have become popular in distributed generation (DG).

Many HES have been installed in different countries over the last decade, resulting in systems development and competing with other conventional sources [54], [55]. Designing HES depends on the renewable energy sources available in the site where the hybrid system will be installed. To establish an economical and reliable HES, its design must be optimal from a sizing and operation strategy viewpoint [55]. In [56], [57], several studies were conducted to determine the optimum sizing and the appropriate power management to meet various load demands by the users. Many software packages are applied for HES [58], [59]. Hybrid optimization of multiple energy resources (HOMER) software has been extensively developed to select the optimal generation technologies and their sizes [60]. L. Olatomiwa et al. [61] have investigated the feasibility of different power generation configurations composed of solar panels, wind turbines, and diesel generators in various geopolitical locations in Nigeria using Homer software. They concluded that the solar/wind/diesel/battery HES configuration is optimum for fuel consumption and CO_2 reduction.

D. Chade et al. [62] studied the integration of wind turbines and a hydrogen energy storage system to enhance the diesel infrastructure on Grimsey Island, Iceland. They analyzed electrical consumption and wind resources using HOMER software for energy balance simulations. The findings indicate that this system could be a viable solution, with a payback period of under four years for the optimal configuration. R. Sen and S. C. Bhattacharyya [63] analyzed the optimal design and planning of an off-grid HES in a remote village in India. The study considered a combination of small-scale hydropower, solar panels, wind turbines, and bio-diesel generators. In comparing their proposed HES with conventional grid extension, they concluded that the HES is cost-effective, sustainable, techno-economically viable, and environmentally friendly.

HOMER software is widely used for most of the RES-based systems. Thus, based on what was mentioned above, this chapter uses HOMER software to study the feasibility assessment of the optimal HES in a convention center northwest of Sabratha, Libya.

3.2.3 Design of Hybrid Renewable Energy System

Hybrid power generation systems are often designed to solve the power supply problem in some rural areas. These systems minimize the annualized cost while satisfying the required power supply.

Technology selection and system sizing:

This design stage determines the system's configuration and specifies the generation technologies to build the hybrid system. For a hybrid energy system, it is essential to determine the type of renewable energy system to be included and the number and capacity of renewable energy units to be installed. It must also be determined whether the hybrid system is stand-alone or grid-connected. Diesel generators, fuel cells, or other backup units are often integrated into the system.

Table 3.5: Energy optimized parameters

Source	*Optimized parameter*
Wind	Wind power, cost minimization
Solar	Solar irradiation, cost minimization
Diesel generator	CO_2 emission reduction, cost minimization

The hybrid system selection relies on the availability of renewable resources. Based on these renewable resources, a feasibility study for various combinations uses several optimization techniques to get the optimum configuration. The number and size of the selected components must be optimized for an efficient, economical, and reliable system. Many factors and constraints influence the system sizing, including greenhouse emissions, economics, and reliability.

3.2.4 The System Modeling

The National Renewable Energy Laboratory (NREL) in the United States created the HOMER computer model to aid in designing micropower systems and to facilitate the comparison of power production technologies for various uses. HOMER models the physical behaviour of a power system and its life-cycle cost—that is, the entire cost of installing and maintaining the system over its lifespan. With HOMER, a modeller can evaluate various design alternatives based on their technical and financial advantages.

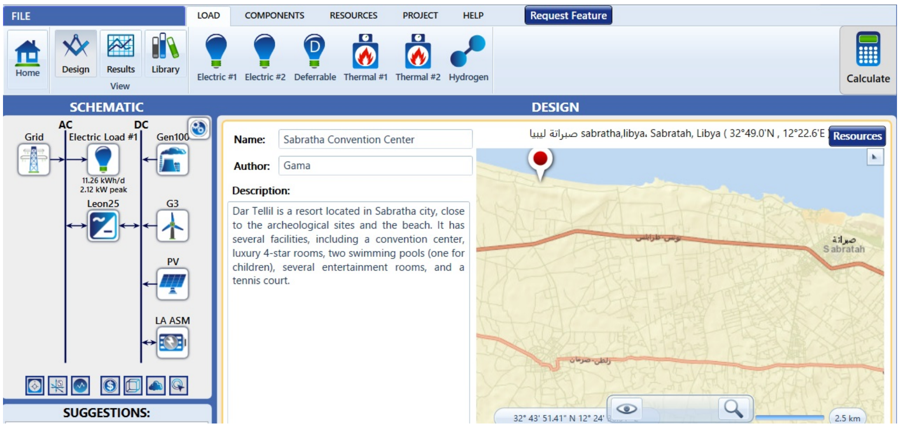


Figure 3.6: The proposed hybrid energy system.

Additionally, it helps to comprehend and measure the impact of input changes or ambiguity. The convention center under study in this chapter is located in northwest Sabratha, Libya; the center's altitude and longitude are 32°49.0'N and 12°22.6'E. The average temperature is °C25, and the humidity is 50%. It has Mediterranean weather. **Figure 3.6** shows the proposed hybrid energy system, a screenshot of the HOMER Pro software that includes the system components and the site location. The convention center is located in Dar Tellil resort, in Sabratha, close to the archaeological sites and the beach. The resort has several facilities, including luxury 4-star rooms, two swimming pools (one for children), several entertainment rooms, and a tennis court.

3.2.5 Resource Assessment

The load profile is taken from the General Electricity Company of Libya (GECOL) record. Hybrid Optimization of Multiple Energy Resources (HOMER) software is applied to estimate the most appropriate, feasible configuration of wind, solar, diesel generators and batteries. Since renewable energy sources are intermittent, backup facilities are often used to avoid power deficiency.

3.2.5.1 Wind energy source

The monthly average wind speed data was downloaded from HOMER Pro. Software, which in turn was downloaded from NASA Surface Meteorology and Solar Energy. The wind power in Watts is defined by the following equation [64]:

$$P = \frac{1}{2} \cdot \rho \cdot A \cdot C_p \cdot V^3 \cdot N_g \cdot N_b \tag{3.1}$$

where ρ is the air density in kg/m^3, A is the rotor-swept area in m^2, C_p is the coefficient performance, V is the wind speed velocity in (m/s), N_g is the generator's efficiency, and N_b is the gearbox bearing efficiency.
The power curve is an essential indicator for evaluating wind turbine performance. It is frequently used to track and assess wind turbine performance and shows the generated power versus wind speed. **Figure 3.7** depicts the power curve of a 100 kW wind turbine.

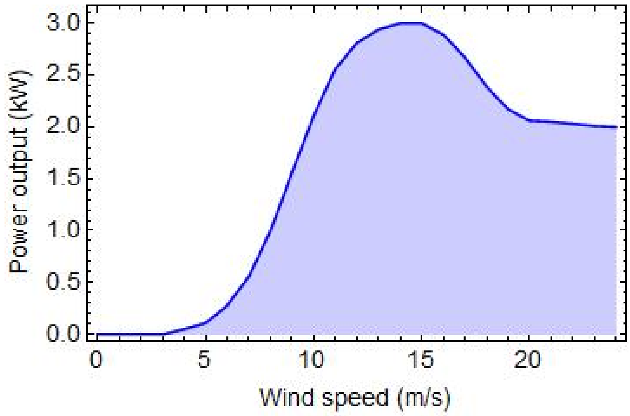


Figure 3.7: A 100 kW wind turbine power curve.

3.2.5.2 Solar energy source

The solar data for the convention center location is taken from HOMER Pro software, which was downloaded in return from NASA Surface Meteorology and Solar Energy. The PV-GIS web tool calculates the annual potential of any installed PV system using the following equation [65]:

$$E = 365 \times P_k \times rd_p \times R_{d,g} \tag{3.2}$$

where E is the annual potential for the power generated in kWh, P_k is the installed equipment peak power in kilowatts (kW), rd_p is the system performance ratio or derating factor, and $R_{d,g}$ is the average of daily global radiation in watthours (wh).

3.2.6 Analysis Criteria

After selecting the renewable sources and running HOMER Pro, the following design configurations have been established:

- Wind, battery, and inverter model.
- Wind, diesel generator, battery, and inverter model.
- Solar, battery, and inverter model.
- Solar, diesel generator, battery, and inverter model.
- Solar, wind, battery, and inverter model.
- Solar, wind, diesel generator, battery, and inverter model.

HOMER classifies these results according to NPC, COE, CEQ, and other constraints.

Figure 3.8 shows a copy of the optimization results. The optimization results are presented in prices ascending order.

Export... Export Details...

Optimization Results
Double click on a system to see its Simulation Details.

Architecture								Cost		
PV (kW)	PV-MPPT (kW)	G3	Gen100 (kW)	LA ASM (#)	Converter (kW)	Dispatch		NPC ($)	LCOE ($/kWh)	Operating cost ($/yr)
		2	100	50	100	LF		$249,654	$4.70	$4,228
		4		100	100	CC		$289,564	$5.45	$6,155
50.0	1.00	1		50	100	CC		$346,951	$6.53	$4,599
50.0	1.00		100	50	100	LF		$356,312	$6.71	$3,621
50.0	1.00	1	100	50	100	CC		$377,608	$7.11	$3,876

Figure 3.8: The HOMER optimization results.

3.2.6.1 Net present cost (NPC)

The total net present cost in Dollars ($), as shown in **Figure 3.8**, represents the present value of all the project costs during its lifetime, subtracted from the present value of all the revenue earned over its lifetime.

The costs considered here include capital costs, replacement costs, fuel costs, O&M costs, and emissions penalties. The total net present cost is calculated by HOMER as follows:

$$C_{NPC} = \frac{C_{yt}}{CRF(i_r, R_p)} \tag{3.3}$$

where C_{NPC} is the total net present cost in \$, $C_y t$ is the total annualized cost in \$/year, CRF are the capital recovery factors, i_r is the interest rate in %, and R_p is the project's lifetime in years.

3.2.6.2 Cost of Energy (COE)

The levelized cost of energy (COE) is defined by HOMER as the average cost per kWh of valuable electrical energy produced by the hybrid system. The cost of energy (COE) is calculated by HOMER as follows:

$$COE = \frac{C_{yt}}{E_p + E_d + E_{gs}} \tag{3.4}$$

where C_{yt} is the total annualized cost in \$/year, E_p is the primary load served in kWh/year, E_d is deferrable load served in kWh/year, and $E_g s$ are the total grid sales.

3.2.6.3 Carbon emission quantity (CEQ)

CEQ is calculated by HOMER as follows:

$$CEQ = F_{fc} \times CO_2(ef) \tag{3.5}$$

where F_{fc} is fossil fuel consumption, and $CO_2(ef)$ is the CO_2 emission factor.

3.2.7 Results and Discussions

HOMER software gives results based on the power resources and the load demand required for the project. The simulation results will be ranked based on the total NPC. The configuration with the lowest NPC will be considered the optimal configuration. **Figure 3.8** shows the feasible configurations ranked according to the NPC.

3.2.7.1 Optimization results and system analysis

According to the optimal results given by HOMER, the best feasible configuration is the model with two units of 3 kW wind turbines, one unit of 100 kW diesel generator, 50 strings of 1 kWh lead-acid batteries, and one unit of a 100-kW system converter.

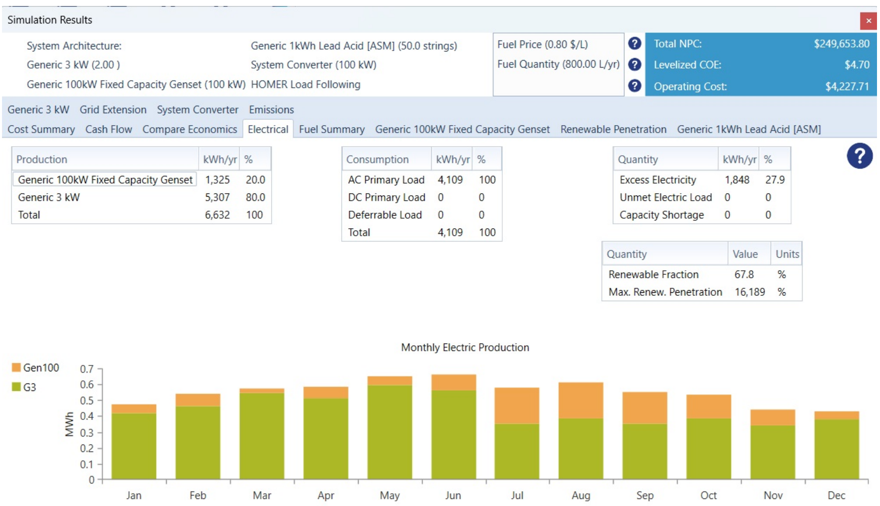


Figure 3.9: Electricity generated from the wind/ generator/ battery model.

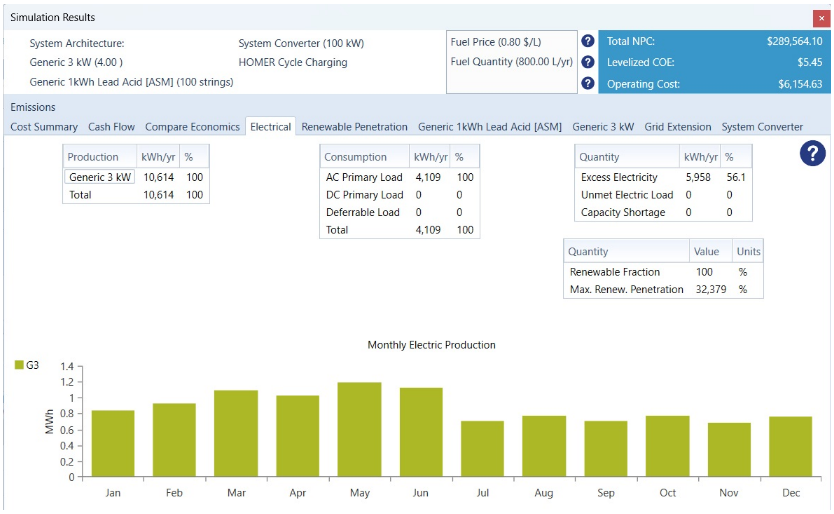


Figure 3.10: Electricity generated from the wind/battery model.

3.2.7.2 Electricity generation

According to HOMER, the most feasible model, as shown in **Figure 3.9**, was the wind/ diesel generator/ battery model. In this model, 80% of the energy produced came from wind turbines, which is about 5307 kWh/ year. The remaining 20% of the energy produced came from the diesel generator.

The second feasible model was the wind/ battery one. As shown in **Figure 3.10**, 100% of the 10.614 kWh/ year came from the wind source.

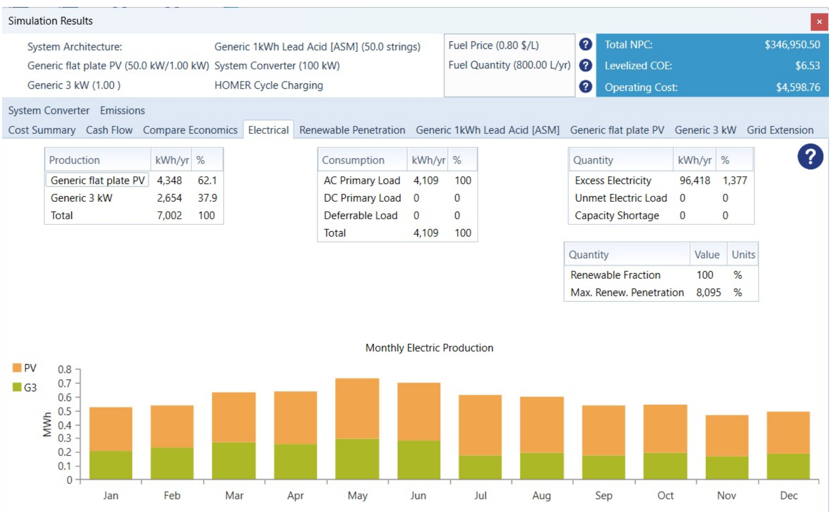


Figure 3.11: Electricity generated from the solar/ wind/ battery model.

Figure 3.12: Electricity generated from the solar/ generator/ battery model.

Figure 3.11 shows the third feasible model, which consists of solar, wind, and battery components. 62.1% of the generated energy came from solar panels, and 37.9 % came from wind generators. **Figure 3.12** shows the fourth feasible model with a solar/ diesel generator/ battery. 93% of the energy produced was from solar, about 4348 kWh/year. The remaining 325 kWh/year (6.95%) was from the diesel generator.

Eventually, the least feasible model is shown in **Figure 3.13**. This model encompasses solar/ wind/ diesel generator and battery components. 62.1% of the energy produced came from solar panels. The remaining 37.9% came from wind turbines. The diesel generator will not be used in this model.

Figure 3.13: Electricity generated from the solar/ wind/ generator/ battery model.

3.2.7.3 Emission reduction

Even though the wind/generator/battery model is the cheapest option, as shown in **Figure 3.9**, it has the worst emission value, as shown in **Table 3.6**. On the other hand, the solar/ wind/ generator battery model is the most expensive one. Still, it has zero emissions because the generator was not used in this case but was kept on stand-by for contingency cases. A trade-off must be made between these options to achieve a continuous power supply and low emissions value.

Table 3.6: Emissions value in kg/year

	CO_2 (kg/yr)	*CO (kg/yr)*	***UB* (kg/yr)**	***PM* (kg/yr)**	*SO_2 (kg/yr)*	*NO_x (kg/yr)*
W, G, B	1289	8.77	0.355	0.0351	3.16	0.701
W, B	0	0	0	0	0	0
S, W, B	0	0	0	0	0	0
S, G, B	334	2.27	0.092	0.091	0.819	0.182

where UB: Unburned hydrocarbons, PM: Particulate matter, (kg/yr): kilogram/year, W: Wind, G: Diesel generator, B: Battery, and S: Solar.

3.2.7.4 Cost benefits

Figures 3.8 to **3.13**, at the top right of each figure, show each model's total NPC, levelized COE, and operation cost. The wind/generator/battery model has the least total NPC. **Table 3.7**. shows the detailed prices of each model.

Table 3.7: Detailed prices of the optimum configurations.

The model	*Total NPC in ($)*	*Levelized COE in ($)*	*Operating cost in ($)*
W, G, B	249,653.80	4.7	4,227.71
W, B	289,564.10	5.45	6,154.63
S, W, B	346,950.5	6.53	4,598.76
S, G, B	356,311.50	6.71	3,621.07
S, W, G, B	377,607.80	7.11	3,876.05

Figures 3.14 and **3.15** show one-week time series renewable load-served data for three different models. The dark colour represents the total electrical load served, the green represents the renewable penetration, and the yellow represents the total

renewable power output.

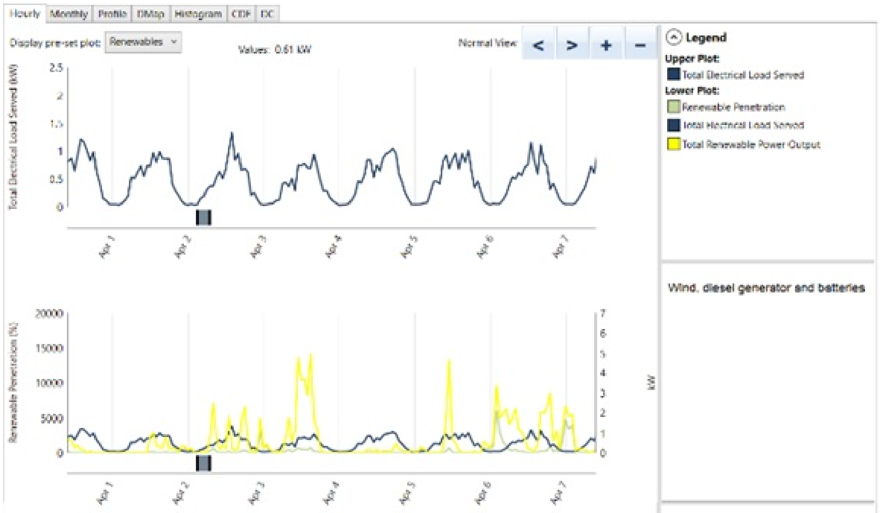


Figure 3.14: One-week time series renewable load served data for W /G/B model.

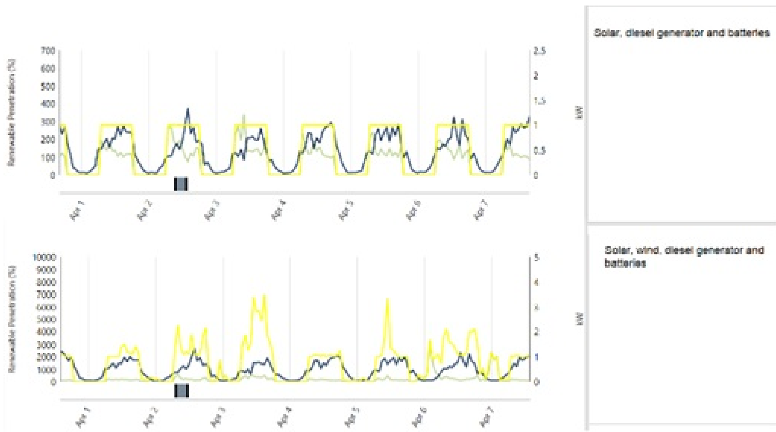


Figure 3.15: One-week time series renewable load served data for S/G/B and S/W/G/B models.

3.2.8 Conclusion

Electric power is one of the most essential things in our daily life. Generating electricity from conventional resources harms the environment. Replacing all or part of these conventional sources mitigates their effects by reducing greenhouse emissions. This chapter used HOMER Pro. software to apply renewable energy sources at a convention center in Sabratha, Libya. The results show that the electric power can be generated from clean energy sources. The simulation results were ranked according to their total NPC from the lowest to the highest price, where the lowest price was considered the optimal configuration.

Based on the results obtained from HOMER Pro. Software, the wind/ diesel generator/ battery model, the wind/ battery model, the solar/ wind/ battery model, the solar/ diesel generator/ battery model, and the solar/ wind/ diesel generator/ battery model are ranked first, second, third, fourth, and fifth, respectively. Care must be taken when considering the optimal configuration because the cheapest option may have the worst pollutant emissions. Trade-offs between the projected models must be made for a continuous power supply with less emissions.

Chapter 4

Hybrid Renewable Energy Resources Selection Based on Multi-Criteria Decision Methods for Optimal Performance

This chapter contains materials published in a research paper [66].

4.1 Abstract

Multi-criteria decision methods (MCDM) are investigative tools and techniques that help decision-makers assess and select the optimal alternatives based on multiple and mostly conflicting criteria. These techniques are explicitly helpful when dealing with complex decision issues where different factors need to be considered simultaneously. This chapter used different MCDM techniques to select the best alternative renewable energy sources in Msallata City, southeast of Tripoli, Libya. The selection was based on the commitment from the Libyan government's Ministry of Energy to lower its carbon footprint. The renewable energy sources considered here are solar, wind, and biomass. MCDA is widely used to solve various decision problems based on alternative evaluation. MCDA methods are applied in every field and can define problems, alternatives, and criteria. However, every MCDA technique can give different results. This chapter has tested four MCDA methods based on the renewable energy sector to find the best alternative. The results suggest that a combination of wind and solar is the most critical energy source; solar plants alone are the second most crucial energy source. The least essential energy source in this model is biomass alone. This work is validated using HOMER Pro Software. Many MCDA techniques are applied in almost all disciplines but may have different results. This

work proved that the best MCDA for dealing with renewables for the proposed selection is either The COmplex PRoportional ASsessment (COPRAS) or VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). COPRAS is an MCDA technique developed by Zavadskas, Kaklauskas, and Sarka in 1994; it is applied to maximize and minimize index values. VIKOR is an abbreviation of a Serbian term that means Multicriteria Optimization and Compromise Solution; it ranks and selects from various alternatives with conflicting criteria.

4.2 Introduction

The world's population has grown dramatically in the last 50 years; consequently, energy consumption and demand have also increased drastically. In 2010, the globe's energy consumption increased by 5.6%, considered the highest growth in 40 years [67]. The fact that fossil fuel sources are finite and their impact on the environment has urged governments and companies to upgrade from conventional fuel sources to renewable ones [68]. From 2023 to 2025, the average annual solar PV installation additions will reach 165 GW, about 60% of total renewable energy expansion. Moreover, the generation costs of utility-scale PV farms are anticipated to decrease in the next few years by 36%, making solar energy the cheapest option to upgrade the electric grid in most countries [68]. The cost of onshore wind declined by 15% in 2020; on the other hand, the annual offshore wind energy capacity additions are expected to double the 2020 level between 2023 and 2025 [6]. Renewable energy will cover approximately 99% of the global power demand in 2025. The electricity generated from renewables is expected to increase more than nine times in the EU and the UK and more than three times in the US. In China and India, renewables are expected to meet approximately 65% of the growth in electric demand [6].

The primary sources of energy in Libya are oil and gas. Still, there are also several thermal power plants in Libya, the most important of which are West of Tripoli (600 MW), East of Tripoli (1400 MW), Misratah (600 MW), and Tobruk (740 MW) [69]. According to the General Electricity Company of Libya (GECOL), 99.2% of the generated power in 2004 came from fossil fuels (72.7% from oil and 26.5% from gas, respectively) [70]. In 2017, GECOL announced that the generated power was 4900

MW, while the demand exceeded 6500 MW, with a 1600 MW deficit. Therefore, the electric grid experienced repetitive power outages in most Libyan regions. Based on the growing energy demand, GECOL estimated the maximum load to increase to 10,795 MW by 2020, 14,834 MW by 2030, and 21,669 MW by 2050, respectively. As a result, the CO_2 and GHG emissions released will increase [69]. With the growing energy demands, the renewable energy department at GECOL has proposed some solar and wind power projects in the last decade [71]. The Libyan government has committed to adding 30% of its total generation capacity by 2030 from renewables [72].

This chapter studies the option of applying wind, solar, and biomass energy in an area in Msallata, Libya, as part of GECOL's contribution to meeting the increasing load demand and lowering the carbon footprint resulting from the use of fossil fuels. In this chapter, various MCDA methods, namely Vise Kriterijumska Optimizacija Kompromisno Resenje (VIKOR), The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Fuzzy TOPSIS, and The COmplex PRoportional ASsessment (COPRAS) were applied to evaluate a hybrid energy system based on solar, wind and biomass energy sources. The criteria weights of the MCDA methods were generated using the analytic hierarchy method (AHP). The results obtained were compared with those of the HOMER Pro software. The novelty is to design several models to solve multicriteria decision problems for a hybrid energy system and compare optimization methods (HOMER Pro. Software) with multicriteria decision methods. Biomass feedstock will be used for the first time as a fuel in Libya, where about 99.2% of the fuel used to generate power comes from fossil fuels. There is not a lot of literature about applying renewable energy sources in Libya. References [73], [74] concluded that solar and wind energy are Libya's most important renewable energy sources and could play a significant role in covering most of the increased power demand and reducing the carbon footprint caused by applying conventional fuel. Ahmed MA Mohamed et al. [75] studied the financial and technical challenges of utilizing renewable energy resources in Libya. Based on the literature review and field visits, solar and wind energy are the primary renewable sources. Even though renewable energy technology in Libya is in its early stages, the study revealed the importance of developing the infrastructure of the renewable energy sector in Libya to cover the increased power load demand and to lower the consumption of oil and natural gas [75].

In this chapter, we assessed our study using the load profile of an area in Msallata City. Using HOMER Pro software, we determined each model's net present cost (NPC), the energy produced, the energy consumed, the emissions, and many other results that we will not discuss in this study. In the results and discussion chapter, we will discuss the energy produced, the energy consumed, and the cost-benefit of each energy source applied in this study. In future work, we will add waves and tides to the survey to know if they are as important as solar and wind.

4.3 Literature Review

This work presents a study on renewable energy sources and MCDA techniques. In references [70] and [71], the options available to apply some renewable energy sources to the Libyan power grid are studied. J. Veleba and Z. Buhawa [74] investigated initial, steady state, and optimization load flow analysis to the transmission lines of the Libyan power grid by adding large-scale wind farms. A. M. Mohamed et al. investigated in [75] the financial and technological difficulties facing applying renewable energy resources in Libya. They introduced some recommendations to enhance renewable energy. C. N. Wang et al. applied in [76] a hybrid Fuzzy AHP (FAHP) and TOPSIS to select wind power plants from seven different locations in Vietnam. J. Gao et al. [77] presented an MCDA technique for site selection of the CAES project based on probabilistic language term sets (PLTSs) and regret theory, applied the entropy weight method to weigh the criteria and concluded in a case study in China that Yungang Mine of Datong Coal Mine Group is the best CAES project site location. C. Li, C. Xu, and X. Li introduced in [78] a multicriteria decision-making framework for DPVPS site selection along the high-speed railways. They presented the power consumption capacity of high-speed railway TPSS and its impact on high-speed railway TPSS. A case with sensitivity analysis is used to verify the MCDA framework for DPVPS site selection along high-speed railways.

M. Abdel-Basset et al. proposed a new hybrid methodology for the selection of offshore wind power station location (OWPS), combining the AHP and Preference

Ranking Organization Method for Enrichment Evaluations (PROMETHEE)-II methods in the neutrosophic environment [79]. H. H. Aly proposed different accurate hybrid models in [80] to forecast the wind speed and power based on neuro Wavelet, time series, and Recurrent Kalman Filter to reduce overall system accuracy. In [81], a hybrid optimized model of Adaptive Neuro-Fuzzy Inference System (ANFIS), Recurrent Kalman Filter (RKF), and Neuro-Wavelet (WNN) was presented to forecast wind power based on data taken from a doubly fed induction generation model. S. H. Mousavi-Nasab and A. Sotoudeh-Anvari [82] compared the rank reversal problem in COPRAS, TOPSIS, and VIKOR methods. They introduced their importance in material selection and the usefulness of the rank reversal method when a criterion is removed from or added to a decision process. R. Joshi introduced in [83] a novel bi-parametric exponential information measure based on Intuitionistic Fuzzy Sets (IFSs) and presented a new MCDA algorithm based on TOPSIS and the proposed bi-parametric measure and applied the algorithm in detecting machine malfunctioning using a numerical example. A. M. Rosso-Cerón et al. presented in [84] a novel algorithm based on fuzzy multi-criteria decision-making methods (FMCDM) based on a mixed-integer linear model to impose solar and wind energy into the Colombian energy mix.

E. Özcan et al. [85] studied the maintenance scenarios of 14 high criticality level equipment in a large-scale hydroelectric power plant in Turkey. They applied AHP and TOPSIS techniques to obtain the criteria and determine the ranking of the equipment, respectively. They built an artificial neural network (ANN) model using 11 years of fault data for selected equipment groups and estimated the possible fault dates. R. Krishankumar et al. presented a blended approach to MCDA under the probabilistic hesitant fuzzy information (PHFI) features. Also, ranked the PHFI with the COPRAS method. The applied technique has been implemented through a case study of cloud vendor selection, and the results have been validated with the results of various existing techniques [86]. S. Soltaniyan et al. developed in [87] a combined version of MCDA and multi-agent modelling technique (MAMT) to attain the maximum possible profits of an intended renewable generation plan and to enhance the electricity market indices. They applied a multi-agent fuzzy Q-learning electricity market modelling approach combined with TOPSIS as a new technique to enhance renewable energy for the first time in the literature. The proposed technique is validated on the IEEE 30-bus test system. T. Soha and B. Hartmann [88] presented GIS-based site suitability to support site selection for the power-to-gas (PtG) technology. The results show centralized PtG systems are favoured over regular PtG installments in all biogas plant sites. B. Wang et al. applied the TOPSIS method to analyze the hydropower generation efficiency in Canada from a power generating potential viewpoint, profitability, environmental profits, and social responsibility, respectively [89].

F. Ribeiro, P. Ferreira, and M. Araújo [90] presented a long-term strategic MCDA technique composed of thirteen criteria to evaluate five hypothetical scenarios drawn for the Portuguese electricity generation system in 2020. H. Zhao and N. Li presented a novel hybrid framework to support the sustainable development of thermal power. They applied the fuzzy Delphi method to recognize 22 final criteria. Introduced a hybrid evaluation model that operates in the fuzzy environment based on the analytic network process (ANP) and TOPSIS. The proposed framework was validated with a case study from the China Huaneng Group Corporation [91]. H. S. Dhiman and D. Deb presented in [92] a fuzzy-based MCDA technique for three wind farm sites in Massachusetts. They evaluated four alternatives for four penalty costs by actual and predicted wind power that are normalized further. Applied Fuzzy TOPSIS and Fuzzy COPRAS as modified TOPSIS and COPRAS techniques to attain the ranking under a fuzzy environment. S. S. Hosseini Dehshiri and S. J. Hosseini Dehshiri [93] applied a combined technique of Geographic Information System (GIS) and MCDA to specify an area to build wind farms to produce hydrogen in Yazd province in Iran. S. Feyzi et al. introduced in [94] a new decision-making approach to determine the criteria for establishing a municipal solid waste incineration (MSWI) power plant to increase the sustainability in the north of Iran by applying the decision-making trial and evaluation laboratory (DEMATEL) combined with fuzzy analytic network process (FANP) technique and GIS. B. Zlaugotne et al. [95] applied five MCDA techniques to find Latvia's best renewable energy source. In PROMETHEE-GAIA, TOPSIS, and VIKOR, hydropower has the highest rank. On the other hand, the best alternative energy source between COPRAS and MULTIMOORA is solar PV.

C. N. Wang et al. applied in [76] data envelopment analysis (DEA), FAHP, and

TOPSIS to find the most feasible location to build a solar power plant in Vietnam. A. U. Rehman et al. applied MCDA to select the best wind power plant location in the Gulf region to invest in [96]. Y. Wu et al. [97] introduced a two-stage location decision-making structure to select a site in Hezhang County for distributed wind power coupled hydrogen storage (DWPCHS). They conducted empirical research about applying DWPCHS on this site. S. Zambrano-Asanza, J. Quiros-Tortos, and J. F. Franco presented a novel technique to specify optimal sites for solar power plants that are connected to the medium-voltage level in the Ecuadorian power grid, applied GIS-based MCDA and spatial overlay with electric load [98]. T. Ali et al. presented in [99] a novel hybrid MCDA approach applying an aggregated weighting and ranking method to promote PGTs based in Bangladesh. Of the six existing PGTs, gas was the best, and wind was the worst. Solar PGT was the most feasible option for all PGT options. In [100], a sophisticated hybrid deep learning clustered model is presented to forecast wind speed and power, applying different artificial intelligent systems for optimal performance. A. Rahmati and M. Sanaye-Pasand [101] presented a general protection scheme to alleviate the disadvantages of power transformer relays. This scheme presented a novel MCDA based on fuzzy logic. The developed power transformer protection (DPTP) relay reinforces the sensitivity and reliability of the power transformer protection. B. G. Urošević and B. Marinović presented a framework to rank small hydropower projects to decision-makers in Bosnia and Herzegovina based on various criteria. They applied the PROMETHEE technique to rank 24 small hydropower plants and used AHP to obtain the weights of the main criteria [102]. M. Ehteram, H. Karami, and S. Farzin applied the kidney algorithm technique to optimize the Karun reservoir operation in a hydropower plant project [103]. J. Waewsak, S. Ali, and Y. Gagnon applied in [104] a GIS-AHP technique to specify suitable locations in Thailand to build energy facilities running with green energy, namely with para rubber trees as a biomass resource.

4.4 Research Development

Four different MCDA techniques are introduced and tested to validate the proposed work to select the optimal energy source to supply power to a city with excellent solar irradiation and wind speed. The load profile data for Msallata City, where customers have different peaks at different times, has been collected from GECOL; see **Figure 4.1**. A load profile is a chart illustrating the electrical load variation versus time variation. It varies based on customer type (commercial, industrial, or residential), temperature, and holiday season. Commercial and industrial customers have higher load demands in the morning and afternoon, while residential customers may consume more power in the afternoon and evening.

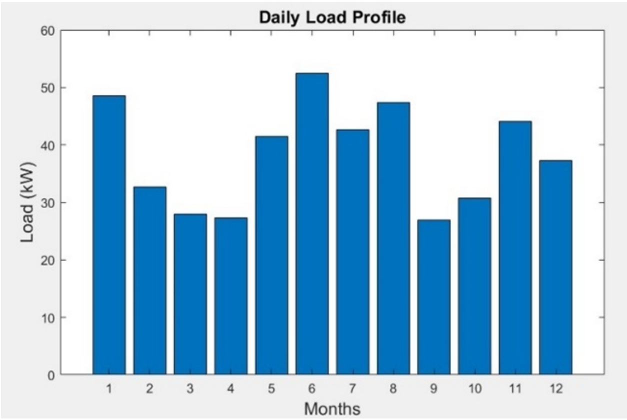


Figure 4.1: Load profile for an area in Msallata City.

The proposed models are evaluated and validated using accurate data and HOMER Pro. Software to calculate the overall cost of different techniques and the emissions emitted by applying various power sources. Based on the analysis, a hybrid wind and solar plant are the most critical energy sources, followed by a solar plant as the second most important. The third best alternative was the wind model based on three MCDA techniques; the fuzzy TOPSIS technique considers the wind energy model the fourth best alternative source. PV, wind, and biomass hybrid models are considered the fourth most crucial energy source in the three MCDA techniques; the fuzzy TOPSIS technique considers the wind energy model the best third alternative source. The biomass model has the most minor importance in this model.

4.4.1 Criteria Weighting

The criteria weights are calculated using the AHP weighting method. Thomas L. Saaty developed AHP in the 1970s to model some decision-making processes through pairwise comparisons and experts' judgments to obtain priority scales; it has been applied extensively since then and is currently applied in decision-making problems [105].

To validate the results of the AHP, the consistency ratio (CR), which will be discussed later in the results and discussion section, is calculated using the following formula:

$$CR = \frac{CI}{RI} \tag{4.1}$$

where the CI is calculated through this formula:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{4.2}$$

For more details, see [105] and [106].

Table 4.1: Criteria used to evaluate the attributes.

	Name	*Unit*
F1	Cost of Energy (COE)	\$/kWh
F2	Operating and Maintenance (O&M)	\$/year
F3	Total Fuel Consumption (t/yr)	Ton/year
F4	Production (pr)	kWh
F5	Lifetime (lt)	Years

Table 4.1 depicts the criteria applied to evaluate the attributes. Msallata city is currently supplied with power from the Libyan grid, which is generated from conventional fuel. HOMER Pro. Software is applied to assess the characteristics of the hybrid system.

Table 4.2: Alternative power sources.

	Name
A1	Wind + Batteries
A2	PV + Batteries
A3	Biomass
A4	Wind + Biomass + Batteries
A5	PV + Biomass + Batteries
A6	Wind + PV + Batteries
A7	Wind + PV + Biomass + Batteries

Table 4.2 shows the power sources suggested in this chapter. They are either one power source or a combination of two or more.

Table 4.3 shows the alternatives and attributes. This table contains the decision matrix data that will be normalized and applied in the four MCDA techniques in this chapter.

Table 4.3: Alternatives and attributes.

Alternatives	*Attributes*				
	COE	O&M	Ton/yr	pr	lt
A1	1.78	6000	0	319063	20
A2	1.12	1500	0	218313	17
A3	5.96	18900	0.411811	157500	25
A4	2.82	4500	0.021571	167782	22
A5	2.63	3500	0.022225	132300	20
A6	0.852	3000	0	186501	18
A7	2.41	2000	0.011112	128494	20

4.4.2 Multicriteria Decision Analysis Methods

Multi-criteria decision analysis MCDA is a methodology that deals with various conflicting criteria in decision-making problems in almost every discipline when different or conflicting criteria are considered at the same time to rank or make a decision (or objectives) need to be considered together to rank or choose between the alternatives being evaluated [107].

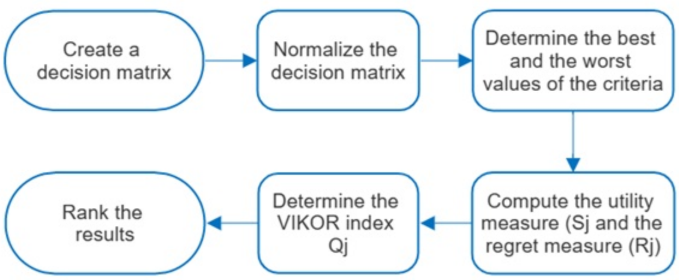


Figure 4.2: Steps for VIKOR technique.

4.4.2.1 VIKOR

The VIKOR method is an MCDA technique developed by Serafim Opricovic in his Ph.D. dissertation in 1979 to solve decision problems with conflicting or incommensurable criteria, assuming the decision is justifiable for conflict problems. The solution desired is to be closest to the ideal, and all alternatives are determined based on established criteria. VIKOR ranks alternatives and determines the solution named compromise closest to the perfect. **Figure 4.2** depicts the steps of the VIKOR technique; for more details, see [108].

VIKOR steps:

1. Create the decision matrix.

$$I = \begin{bmatrix} i_{11} & i_{12} & \dots & i_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ i_{m1} & i_{m2} & \dots & i_{mn} \end{bmatrix} \tag{4.3}$$

   where i_{11} to i_{1n} are the attributes and i_{11} to i_{m1} are the alternatives.

2. Determine the normalized decision matrix:

$$k_{ij} = \frac{I_i^j}{\sqrt{\sum_{i=1}^{m}(I_i^j)^2}} \tag{4.4}$$

   where $i = 1, 2, \dots, m; j = 1, 2 \dots, n$.

3. Determine utility measure U_i and regret measure R_i. When decision-makers cannot express their preference, they compromise their solution by a maximum group utility (represented by $minU_i$) of the majority and by a minimum individual regret (represented by $minR_i$) of the opponent U_i and R_i are boundary measures to formulate the rank.

   Utility measure for beneficial attribute:

$$U_i = \sum_{i=1}^{n} w_i \left[\frac{(k_{ij})_{max} - (k_{ij})}{(k_{ij})_{max} - (k_{ij})_{min}} \right] \tag{4.5}$$

   Utility measure for non-beneficial attribute:

$$U_i = \sum_{i=1}^{n} w_i \left[\frac{(k_{ij}) - (k_{ij})_{min}}{(k_{ij})_{max} - (k_{ij})_{min}} \right] \tag{4.6}$$

Regret measure for beneficial attribute:

$$R_i = Maximum\,of \left\{ w_i \left[\frac{(k_{ij})_{max} - (k_{ij})}{(k_{ij})_{max} - (k_{ij})_{min}} \right] \right\} \tag{4.7}$$

Regret measure for non-beneficial attribute:

$$R_i = Maximum\,of \left\{ w_i \left[\frac{(k_{ij}) - (k_{ij})_{min}}{(k_{ij})_{max} - (k_{ij})_{min}} \right] \right\} \tag{4.8}$$

4. Compute the Qi value:

$$Q_i = v \left[\frac{(U_i) - (U_i)_{min}}{(U_i)_{max} - (U_i)_{min}} \right] + (1 - v) \left[\frac{(R_i) - (R_i)_{min}}{(R_i)_{max} - (R_i)_{min}} \right] \tag{4.9}$$

where v can take any value between 0 and 1; in our case, it is considered 0.5.

5. Rank Q_i, the rank will be in descending order. The highest Q_i value represents the best alternative.

4.4.2.2 TOPSIS

Hwang and Yoon developed the TOPSIS technique in 1981 to find the closest alternatives to the ideal solution [98]. **Figure 4.3** depicts the steps of the TOPSIS technique; for more details, see [109].

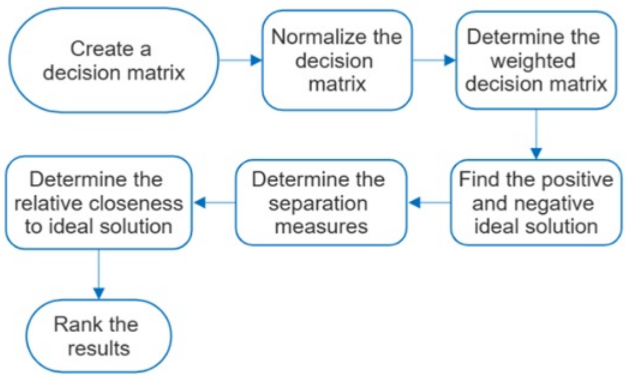


Figure 4.3: Steps for TOPSIS technique.

TOPSIS steps:

1. Determine the decision matrix:

$$X = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \tag{4.10}$$

2. Establish the normalized decision matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}} \tag{4.11}$$

where $i = 1, 2, \dots, m$; $j = 1, 2 \dots, n$.

3. Determine the weights (AHP used in this chapter)
4. Determine the weighted normalized decision matrix:

$$v_{ij} = w_j \times r_{ij} \tag{4.12}$$

5. Compute ideal best (v_j^+) and ideal worst (v_j^-). In non-beneficial attributes, the ideal best will be the most negligible value and the ideal worst will be the highest value. In the case of beneficial attributes, the highest value is considered ideal best, while the lowest value is considered ideal worst.

$$\{v_1^+, \dots, v_n^+\} = \left\{\{(\max_i v_{ij}|_j \in K), (\min_i v_{ij}|_j \in K')|, i = 1, 2, \dots, m\right\} \tag{4.13}$$

$$\{v_1^-, \dots, v_n^-\} = \left\{\{(\min_i v_{ij}|_j \in K), (\max_i v_{ij}|_j \in K')|, i = 1, 2, \dots, m\right\} \tag{4.14}$$

where K is the index set of benefit criteria and K′ is the index set of cost criteria.

6. Compute the separation measure for each row:

Positive ideal separation:

$$S_1^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_i^+)^2} \tag{4.15}$$

Negative ideal separation:

$$S_1^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_i^-)^2} \tag{4.16}$$

7. Determine the relative closeness to the ideal solution:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{4.17}$$

Rank the results: The higher value will get the first rank.

4.4.2.3 Fuzzy TOPSIS

Chen-Tung Chen developed the fuzzy TOPSIS method in 1997 in a journal article titled Extensions of the TOPSIS for Group Decision-Making under Fuzzy Environment. Chen extended TOPSIS with triangular fuzzy numbers and proposed a vertex technique to measure the distance between two triangular fuzzy numbers. **Figure 4.4** depicts the steps of the fuzzy TOPSIS technique and **table 4.4** shows the fuzzy weights for each criterion.; for more details, see [110].

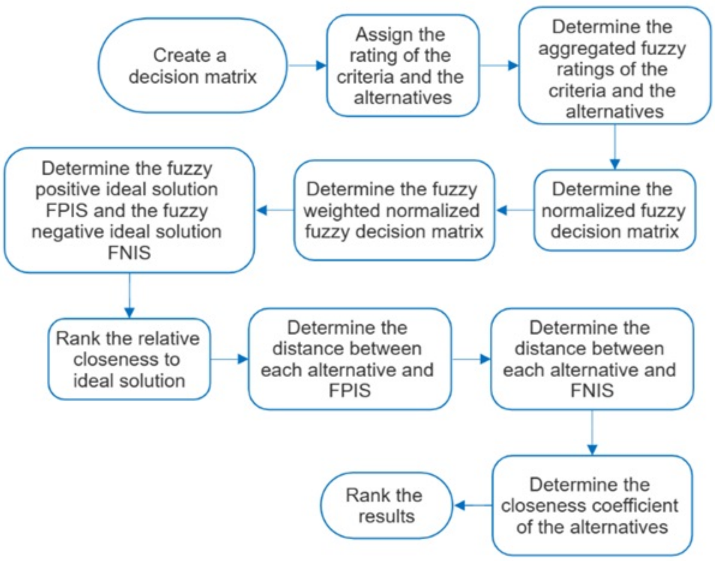


Figure 4.4: Steps for Fuzzy TOPSIS technique.

Chen presented a vertex technique to measure the distance between two triangular fuzzy numbers [110]. If $\tilde{x} = (a_1, b_1, c_1), \tilde{y} = (a_2, b_2, c_2)$ are two different triangular fuzzy numbers, then:

$$d(\tilde{x}, \tilde{y}) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \tag{4.18}$$

Fuzzy TOPSIS steps:

Table 4.4: The fuzzy weights for each criterion

Importance	*Symbol*	*Fuzzy weight*
Very low	VL	(0, 0.1, 0.3)
Low	L	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.7)
High	H	(0.5, 0.7, 0.9)
Very high	VH	(0.7, 0.9, 1)

The following steps are taken when fuzzy TOPSIS is applied [77]:

1. Collect the subjective evaluations of the decision maker on the weights based on the importance of each criterion. Say we have decision makers with m members; the fuzzy rating of the m^{th} group about alternative O_i and criterion B_i is represented as:

$$F_{ij}^{m} = (a_{ij}^{m}, b_{ij}^{m}, c_{ij}^{m}) \tag{4.19}$$

The weight of the criterion B_j is represented as:

$$\tilde{w}_{ij}^{m} = (w_{j1}^{m}, w_{j2}^{m}, w_{j3}^{m}) \tag{4.20}$$

2. Determine the aggregated fuzzy ratings for each alternative and the aggregated fuzzy weights for every criterion.

3. The aggregated fuzzy ratings $\tilde{F}_{ij} = (a_{ij}^{m}, b_{ij}^{m}, c_{ij}^{m})$ are determined as follows:

$$a_{ij} = \min_{m}\{a_{ij}^{m}\},\ b_{ij} = \frac{\sum_{m=1}^{m} b_{ij}^{m}}{m},\ c_{ij} = \max_{m}\{c_{ij}^{m}\} \tag{4.21}$$

The aggregated fuzzy weights $\tilde{w}_{ij} = (w_{j1}, w_{j2}, w_{j3})$ are calculated by formulas:

$$w_{j1} = \min_{m}\{w_{j1}^{m}\},\ w_{j2} = \frac{\sum_{m=1}^{m} w_{j2}^{m}}{m},\ w_{j3} = \max_{m}\{w_{j3}^{m}\} \tag{4.22}$$

4. Measure the normalized fuzzy decision matrix $\tilde{R} = [\tilde{r}_{ij}]$.

For benefit criteria:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^{+}}, \frac{b_{ij}}{c_j^{+}}, \frac{c_{ij}}{c_j^{+}}\right),\ c_j^{+} = \max_{i}\{c_{ij}\} \tag{4.23}$$

Or for non-benefit (cost) criteria:

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \; a_j^- = \min_i \{a_{ij}\} \tag{4.24}$$

5. Determine the weighted normalized fuzzy decision matrix:

$$\tilde{V} = (\tilde{v}_{ij}) \tag{4.25}$$

where $\tilde{v}_{ij} = \tilde{r}_{ij} \times w_j$

6. Determine the Fuzzy Positive Ideal Solution (FPIS) (A^+) and Fuzzy Negative Ideal Solution (FNIS) (A^-).

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \cdots, \tilde{v}_n^+) \tag{4.26}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \cdots, \tilde{v}_n^-) \tag{4.27}$$

7. Calculate the distance from each alternative to the FPIS (d_i^+) and to the FNIS (d_i^-).

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+) \tag{4.28}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{4.29}$$

8. Determine the closeness coefficient CC_i for every alternative.

For every alternative O_i, CC_i is calculated as follows:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{4.30}$$

9. Rank CC_i in descending order. The highest closeness coefficient will be considered the best alternative.

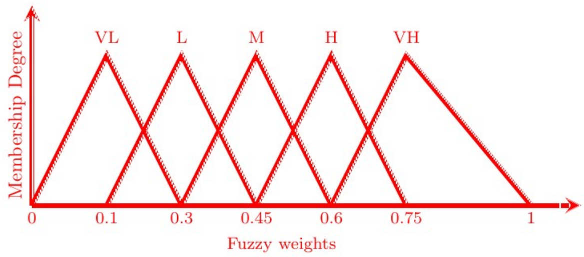


Figure 4.5: Aggregated fuzzy weights for each criterion.

4.4.2.4 COPRAS

Zavadskas, Kaklauskas, and Sarka developed the complex proportional assessment method in 1994 to evaluate the maximum and minimum index values and their effect on the attributes. **Figure 4.6** depicts the steps of the COPRAS technique; for more details, see [111].

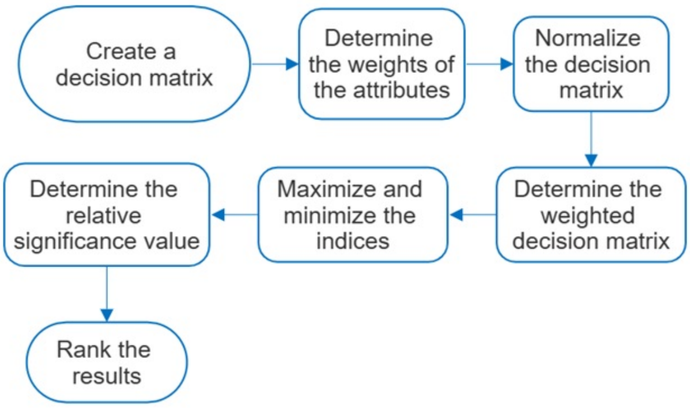


Figure 4.6: Steps for COPRAS technique.

COPRAS steps:

1. The decision matrix and the weights for the criteria are expressed as follows:

$$D = \begin{bmatrix} d_{11} & \dots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{m1} & \dots & d_{mn} \end{bmatrix} \tag{4.31}$$

$$w_j = [w_1, \cdots, w_n] \; and \; \sum_{j=1}^{n}(w_1, \cdots, w_n) = 1. \tag{4.32}$$

2. Normalize the decision matrix:

$$n_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{4.33}$$

3. Obtain the weighted normalized decision matrix:

$$N_{ij} = w_j \times n_{ij} \tag{4.34}$$

4. Compute the sum of the benefit criteria values:

$$B_i = \sum_{j=1}^{k} N_{ij} \tag{4.35}$$

5. Determine the sum of the cost criteria values:

$$C_i = \sum_{j=k+1}^{m} N_{ij} \tag{4.36}$$

6. Compute the relative significance of each alternative:

$$Q_i = B_i + \frac{\min(C_i) \times \sum_{i=1}^{n} C_i}{C_i \times \sum_{i=1}^{n} \left(\frac{\min(C_i)}{C_i} \right)} \tag{4.37}$$

7. Determine the utility degree (performance index) of each alternative:

$$UD_i = \frac{Q_i}{\max(Q_i)} \times 100\%. \tag{4.38}$$

4.5 Case Study

Even though Libya is prosperous in solar and wind power, about 99.2% of the electricity is from fossil fuels. The Libyan grid has recently experienced a lot of power outages due to the aging of the existing network, lack of developments, and increasing load demand. One solution to this issue is adding renewable energy sources to the grid. This chapter researches applying renewable energy sources in a city called Msallata, located southeast of Tripoli, Libya. According to GECOL, this city is known to have excellent wind speed. Four MCDA approaches, namely VIKOR, TOPSIS, Fuzzy TOPSIS, and COPRAS are applied to find the optimal renewable energy source to provide the city with electricity. HOMER Pro software using wind, solar, and biomass sources is applied to validate the results determined by MCDA techniques.

4.5.1 Resource Assessment

The load profile for Msallata City is taken from the GECOL record. HOMER Pro software is applied to estimate the criteria for the subject model. Because they are intermittent, solar panels and wind farms are usually connected with backup generators to avoid any power deficiency. The fuel source for the generator in our current model is biomass.

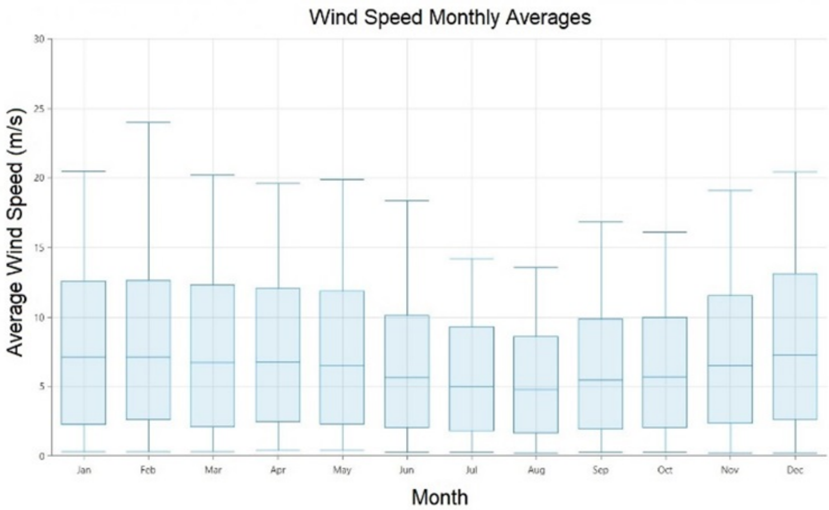


Figure 4.7: The monthly average wind speed for Msallata City determined by HOMER.

4.5.1.1 Wind Energy Source

The average wind speed in Libya ranges from 6 m/s to 7.5 m/s at 40 m height. This considerable wind energy source is distributed over an area of $1,750,000 km^2$ and can supply Libya and Europe with huge amounts of electrical power [71]. Homer Pro Software is applied to download this paper's monthly average wind speed data, **Figure 4.7**. HOMER Pro software downloads such data from NASA Surface Meteorology and Solar Energy.

Figure 4.8 depicts a 95-kW turbine power curve with a cut-in speed of 4 m/s, a cut-out speed of 25 m/s, and a rated power output between 10 and 15 m/s.

The wind power formula could be estimated using this equation [64]:

$$P = \frac{1}{2}\rho \cdot A_s \cdot C_p \cdot V^3 \cdot \epsilon_g \cdot \epsilon_b. \tag{4.39}$$

where ρ is the density of the air in kg/m^3

A_s is the swept area of the rotor in m^2,

C_p is the coefficient performance,

V is the velocity of the wind speed in (m/s),

ϵ_g is the efficiency of the generator

ϵ_b is the efficiency of the gearbox bearing.

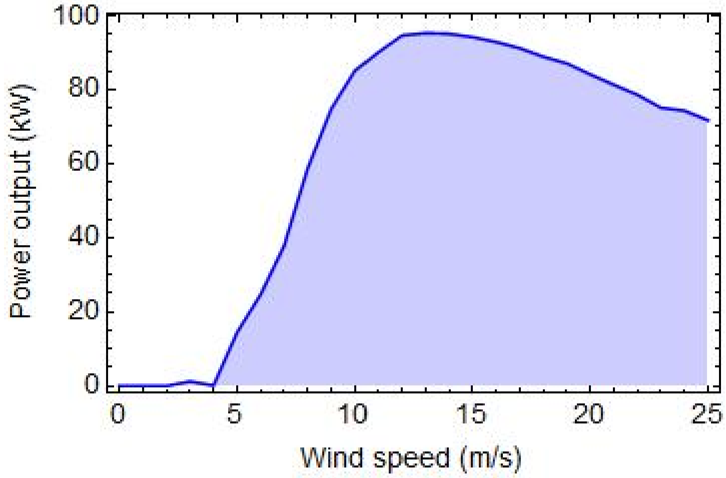


Figure 4.8: A 95 kW Wind turbine power curve.

Table 4.5: Monthly average wind speed in (m/s) in some Libyan cities from 1985 – 1995. [19]

Cities	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Avg*
Benina	4.3	4.8	5.7	6.2	5.9	6.0	5.8	5.3	5.1	5.0	4.8	4.4	5.3
Ejdabia	2.2	2.8	3.9	3.6	3.6	3.4	3.5	3.0	2.7	2.3	2.0	2.0	2.9
Sorman	3.4	2.8	3.0	3.4	3.3	3.2	3.0	2.7	2.8	2.7	2.6	2.8	3.0
Zuara	4.5	4.5	5.2	5.4	5.3	5.0	4.4	4.5	4.8	4.4	4.0	4.2	4.7
Sirt	5.1	5.3	5.5	5.6	5.3	4.9	4.3	4.3	4.7	4.7	4.6	4.9	4.9
Mesrata	5.2	5.3	6.1	5.7	5.4	5.0	4.2	4.1	4.6	4.5	4.8	5.3	5.0

Table 4.5 depicts the monthly average wind speed in (m/s) in some Libyan cities from 1985 to 1995, while **Figure 4.9** depicts the daily profile wind speed for Msallata city determined by HOMER.

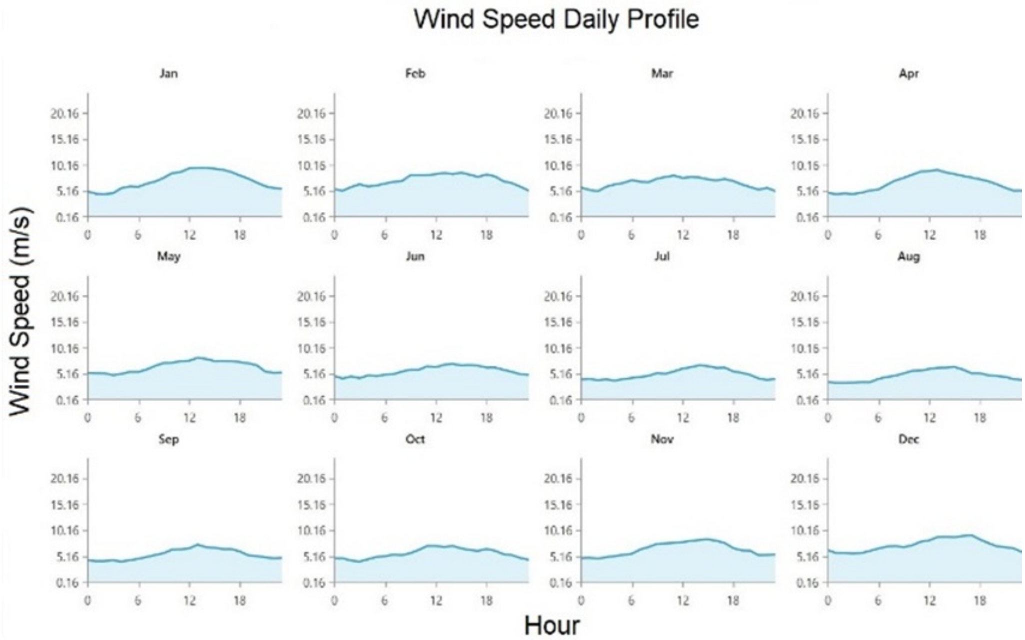


Figure 4.9: The daily profile average wind speed for Msallata City is determined by HOMER.

4.5.1.2 Solar Energy Source

The average solar radiation in Libya is about 7.5kWh/m^2/day, between 3000 and 3500 sunshine hours per year [72]. HOMER Pro Software is used to obtain the solar data for this chapter, which is then downloaded from NASA Surface Meteorology and Solar Energy.

The annual energy of any installed PV system could be estimated using the following equation [65]:

$$E_{an} = 365 \times P_{pk} \times rd_p \times R_{d,g} \tag{4.40}$$

where E_{an} is the annual energy for the power generated in kWh, P_{pk} is the peak power of the installed equipment in kilowatts (kW), rd_p is the system performance's rating or derating factor, and $R_{d,g}$ is the average of daily global radiation in watthours (Wh).

Tables 4.6 depict the daily average of total radiation in ($kWh.m^2$) for some Libyan cities from 1982 to 1988. **Figure 4.10** depicts the daily profile solar irradiation for Msallata city, determined by HOMER.

Table 4.6: Daily average of total radiation in ($kWh.m^2$) during 1982 – 1988 [19].

Cities	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Avg*
Tripoli	2.95	3.87	5	5.97	6.45	7.09	7.05	6.47	5.48	4.0	3.15	1.83	4.94
Gath	4.0	4.8	4.7	6.3	6.3	6.6	6.8	6.3	5.8	5.1	4.1	3.5	5.36
Jalo	3.66	4.54	5.37	6.56	6.74	7.16	7.17	6.74	5.74	4.83	3.86	3.44	5.48
Sabha	4.18	4.88	5.81	6.68	6.65	7.35	7.26	6.96	6.51	5.56	4.75	3.97	5.88
Shahat	2.3	2.72	3.93	5.45	6.05	6.73	6.72	6.14	4.67	3.59	2.69	1.97	4.41
Hon	3.54	4.2	5.1	6.19	6.61	7.06	7.09	6.69	5.91	4.72	3.8	3.19	5.34
Al-kofra	4.43	5.38	6.04	6.86	7.24	7.43	7.25	7.19	6.45	5.67	4.7	3.99	6.05
Al-Quryat	3.55	4.63	5.65	6.61	6.75	7.12	7.39	7.02	5.45	4.32	3.47	3.2	5.43
Al-Jagbob	3.8	4.7	5.59	6.71	7.1	7.67	7.66	7.1	6.22	5.13	4.0	3.51	5.77

4.5.1.3 Biomass

Using biomass to generate heat and power is increasing rapidly internationally, and it is driven by governments and decision-makers wanting to lower the carbon footprint caused by applying conventional fuels. Global biomass energy consumption is expected to increase by 2.3% annually until 2030 [34]. In this chapter, HOMER Pro Software applied biomass feedstock as a backup generator to supply power when there is not enough wind speed or solar irradiation to generate it.

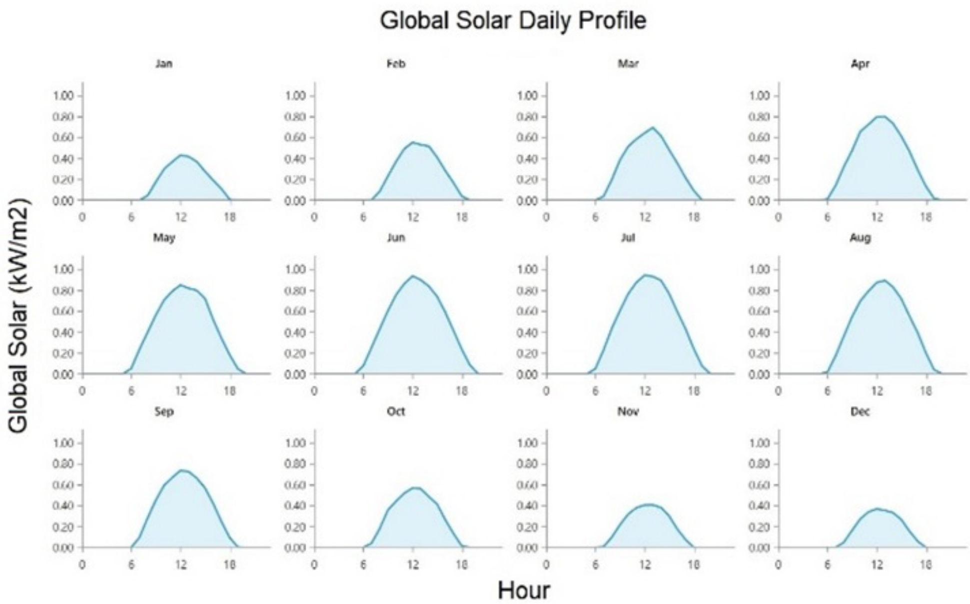


Figure 4.10: Daily profile average solar irradiation for Msallata City determined by HOMER.

HOMER Pro Software allows users to model generators to run most biomass feedstock types. The software enables users to model biomass gasification, biogas fuel, and biogas-fueled or cofired generators. Under the biomass resource menu, users can specify the biomass capacity and price. If the biomass feedstock is raw material, it needs to be converted to biogas using gasification; then, it can be burned in a biogas or cofired generator.

4.6 Results and Discussions

The AHP method is applied to determine the criteria weights; pairwise comparison is made by assessing the criterion's importance over the other criterion; the results are illustrated in **table 4.7**.

Table 4.7: Pairwise comparison matrix.

	COE ($/kWh)	***Production (kWh)***	***O&M ($/yr)***	***Lifetime (years)***	CO_2 ***emissions***
COE ($/kWh)	1	5	9	3	7
Production (kWh)	0.20	1	5	0.33	3
O&M ($/yr)	0.11	0.2	1	0.14	0.33
Lifetime	0.33	3	7	1	5
CO_2 emissions	0.14	0.33	3	0.2	1

In the pair comparison technique, the value 1 indicates that both criteria have equal importance; values 3, 5, 7, and 9 represent low, moderate, strong, and very strong importance, respectively. For opposed criteria, essential values are proportionally opposed. After determining the criteria weight (ω_{ij}), it is very important to verify that the summation of the weights equals 1 ($\omega_{ij} = 1$). About the consistency index, the consistency ratio should be less than or equal to 0.1 to assume that the matrix is reasonably consistent.

Table 4.8: Random Consistency Index.

N	3	4	5	6	7	8	9	10	11	12	13	14	15
RCI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

In the proposed model, the consistency ratio was 0.054153, less than 0.1, so we can consider the matrix reasonably consistent. **Table 4.8** depicts the random consistency index, where the numbers 1 and 2 are omitted because their RCI value equals zero. See

Saaty (1980), pp. 21 [46].

Table 4.9 shows each criterion and its importance, where beneficial is considered when maximum value is desired while non-beneficial for minimum value consideration.

Table 4.9: Criterions and their importance

Criteria	*Unit*	*Attributes*
Cost of Energy	$/kWh	Non-beneficial
O&M	$/years	Non-beneficial
CO_2 Emissions	Ton/year	Non-beneficial
Production	kWh	Beneficial
Lifetime	Years	Beneficial

Figure 4.11 depicts all criteria and their weights. The most important criteria are COE with 50.3% weight, a lifetime with 26%, production with 13.4%, and CO_2 emissions with 6.8%, respectively. The less critical criterion is operating and maintenance, which weighs 3.5%.

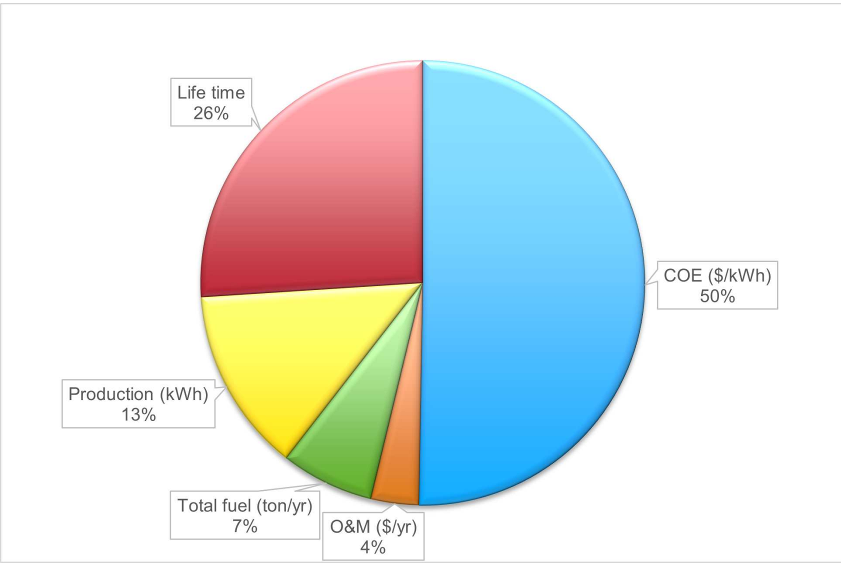


Figure 4.11: Pie chart of the weight of each criterion.

Table 4.10 depicts the rank of all power sources applied for Msallata City based on all techniques applied. The rank will be based on the number of power sources applied; in this case, it will be from 1 to 7 based on their importance, where 1 is the most important, and 7 is the least important.

Table 4.10: The rank of the power sources is based on each technology applied.

Power Source	***VIKOR***	***TOPSIS***	***Fuzzy TOPSIS***	***COPRAS***	***HOMER Pro.***
Wind + Batteries	3	3	4	3	3
PV + Batteries	2	2	2	2	2
Biomass + Batteries	7	7	7	7	7
Wind + Biomass + Batteries	5	6	5	5	5
PV + Biomass + Batteries	6	5	6	6	6
Wind + PV + Batteries	1	1	1	1	1
Wind + PV + Biomass + Batteries	4	4	3	4	4

The novelty of the proposed work is that it assesses the proposed site performance based on four different techniques to choose the best combination of renewables for minimizing the generation cost and CO_2 emissions. Based on the results, we can conclude that a combination of wind and solar energy sources is the most critical energy source because all the techniques ranked it first. Solar energy is second in the row according to all methods applied. Wind energy sources are third in the VIKOR, TOPSIS, and COPRAS methods, whereas Fuzzy TOPSIS puts them in fourth place.

The fuzzy TOPSIS technique ranks the combination of Solar, wind, and biomass as third. VIKOR, TOPSIS, and COPRAS techniques put the combination of solar, wind, and biomass in fourth place, whereas Fuzzy TOPSIS considers wind energy fourth in rank. Biomass is the less critical energy source in the area under study based on all applied techniques.

Cost-benefit Analysis: The main advantage of applying renewable energy is the absence of fossil fuel costs. Moreover, PV and wind energy plants have lower operation and maintenance costs than conventional fuel plants. The total net present cost (NPC) of the hybrid wind and solar model is $663,707.80, and the levelized cost of energy (COE) is $0.8515. The total NPC of the solar model is $874,808.90, and the levelized COE is $1.12. In the wind model, the total NPC was $1,388,200, and the Levelized COE was $1.78, while the total NPC of the hybrid wind, solar, and biomass model reached $1,883,473, and the Levelized COE was $2.41.

4.7 Conclusion and Justification of the Applied Methodologies

4.7.1 Conclusion

This work applied four different MCDA techniques to rank the power energy sources based on their importance. Although all MCDA techniques applied use different aggregation functions and normalization techniques, they try to get results close to the ideal solution. Validation was done using an optimization technique (HOMER Pro software). Based on the results, some renewable energy sources could be added to the Libyan grid to face the significant energy demand, improve the electric power service, and lower the carbon footprint by applying conventional energy sources. Biomass could be applied in combination with wind and solar energy sources.

Based on the results, all the techniques applied rank a hybrid energy system composed of wind and solar and a solar farm as the best and second-best alternatives, respectively. All the applied techniques considered a wind farm the third best alternative, except fuzzy TOPSIS, which considered wind energy alone the fourth option in its rank. All the methods agree that biomass alone is the least attractive option.

HOMER Pro software is applied to validate the results. Based on the results obtained from HOMER, VIKOR, and COPRAS, a hybrid energy system composed of wind and PV, PV energy system, Wind energy system, a hybrid energy system composed of wind, PV, and biomass, a hybrid energy system composed of wind and biomass, a hybrid energy system composed of PV and biomass, a biomass energy system, are ranked, first, second, third, fourth, fifth, sixth and seventh, respectively. Based on that comparison of selection and the constraints used in this research, we conclude that the best MCDAs to select a hybrid energy system, in our case, are VIKOR and COPRAS. Both gave reasonable results compared to a realistic scenario used from HOMER Pro software. The low importance of biomass alone as a feedstock to generate power in Libya is linked to the fact that Libya is prosperous in solar and wind power. Because solar and wind power are intermittent, biomass feedstock could be used as a backup generation fuel.

4.7.2 Justification of the Applied Methodologies

1. **Appropriateness of HOMER Pro Software**

   HOMER Pro is a well-established tool for optimizing and analyzing hybrid renewable energy systems. The following factors justify its selection for this study:

   - **Comprehensive Analysis:** It allows the simulation and optimization of various energy configurations by assessing technical, economic, and environmental metrics.
   - **Validation of Results:** HOMER Pro is used to validate the ranking and feasibility of energy alternatives generated by the MCDM techniques, ensuring consistency with real-world scenarios.
   - **Scenario Flexibility:** It effectively models complex hybrid systems under various constraints and scenarios, including wind, solar, and biomass.
   - **Relevance to Study Goals:** By integrating system-specific constraints, HOMER Pro provides a robust framework for comparing renewable energy options in the Libyan context, characterized by high solar and wind energy potential.

2. **Multi-Criteria Decision-Making (MCDM) Techniques**

   MCDM methods such as VIKOR, COPRAS, and fuzzy TOPSIS rank renewable energy options based on multiple criteria, including cost-efficiency, energy output, and environmental impact. Their appropriateness is rooted in the following:

   - **Addressing Multi-Dimensionality:** Renewable energy system evaluation involves diverse and often conflicting criteria. MCDM techniques provide a structured approach to balancing these factors.
   - **Contextual Relevance:** The techniques consider local energy availability, cost structures, and operational constraints, making them suitable for assessing renewable energy systems in Libya.
   - **Comparative Insights:** MCDM methods enable the ranking and prioritization of alternatives, allowing for informed decision-making on the most suitable energy systems.

- **Robustness and Consistency:** Using multiple MCDM methods ensure robustness by cross-validating the rankings, reducing bias inherent in single-method approaches.

3. **Findings Supporting Methodology Appropriateness**
   - **Agreement Across Methods:** Both VIKOR and COPRAS ranked a hybrid system of wind and PV as the best option, corroborating results from HOMER Pro. This alignment indicates that MCDM techniques and HOMER Pro effectively complement each other.
   - **Biomass as a Backup Option:** All techniques ranked biomass alone as the least viable option, consistent with Libya's natural wind and solar energy advantages. This demonstrates that the methodologies reflect the country's renewable energy potential accurately.
   - **Fuzzy TOPSIS Variation:** The slight deviation in fuzzy TOPSIS rankings highlights the importance of applying multiple techniques to capture diverse decision-making perspectives.

4. **Strengths of VIKOR and COPRAS for the Study**
   - **VIKOR:** Prioritizes alternatives based on a compromise solution, balancing trade-offs between conflicting criteria. This makes it suitable for addressing the diverse requirements of hybrid energy systems.
   - **COPRAS:** Emphasizes proportionality in decision-making, making it adept at ranking options with varying feasibility and efficiency.

Both techniques aligned well with HOMER Pro results, further validating their applicability in this study. The combination of HOMER Pro and MCDM techniques, specifically VIKOR and COPRAS, is highly appropriate for evaluating renewable energy systems in Libya. HOMER Pro ensures realistic and scenario-based validation, while MCDM techniques provide structured rankings based on multiple criteria. Together, these methodologies offer a robust framework for identifying optimal hybrid systems that leverage Libya's rich solar and wind resources, while acknowledging the limited role of biomass as a backup fuel.

Chapter 5

A Modified Ant Lion Optimization Technique for Economic Emission Dispatch Including Biomass

This chapter contains materials that are published in a research paper [112].

5.1 Abstract

Economic Load Dispatch (ELD) and Emission Dispatch (ED) are optimization approaches utilized in power systems to estimate the optimal allocation of power output among different generators. Both techniques are essential for the efficient and sustainable operation of power grids. The economic load and emission dispatch (ELED) method plays a crucial role in the operation of power systems. The main objective of ELED is to schedule the committed generating units to supply power at optimum operation and minimum fossil fuel emission. In this chapter, biomass energy is integrated gradually into an IEEE 30 bus test system comprising six generating units to reduce the conventional fuel ratio and maintain the total generated power up to seven hundred megawatts. Adding biomass as a fuel will drastically reduce the emissions from conventional fossil fuels.

The model consists of the fuel cost objective function, the emission-level target produced by conventional thermal generators, and the operational cost generated partially by biomass. The effectiveness of the suggested ELED model is tested on the conventional thermal generators system and the modified biomass-thermal power generation system using a modified ant lion optimization algorithm (MALO). The optimized ELED biomass-using MALO results are tested and validated using three

optimization techniques. These techniques are Simulated Annealing (SA), BAT, and Quadratic Programming, and Equal Increment Cost Criterion (QPEICC) algorithms. The results prove the effectiveness of the integrated biomass model based on the MALO algorithm by minimizing the emission value, the fuel cost, and the power loss.

5.2 Introduction

Economic load dispatch (ELD) is a critical task in power system operation. Its main objective is to schedule the committed generating units to supply power at optimum operation (minimum operating cost while satisfying all constraints) [113]. There is a growing concern about the emission level from the fossil fuels used to generate power. Fossil fuels produce particulate matter such as ash and gaseous pollutants like carbon monoxide (CO), carbon dioxide (CO_2), sulphur oxides (SO_x), and nitrogen oxides (NO_x). Governments and power companies have increasingly realized the importance of maintaining a cleaner environment. Due to this constraint, the maximum allowable emission level is as essential as production costs [114]. As a result, a new approach emerged, the economic emission dispatch (EED) method. EED is an optimization problem that results in the most minor emission level of operation of a power system [115]. Modern power generation systems have productive ways to reduce chemical emissions, such as applying improved fuel types with low emission content and improving the system efficiency by retrofitting new technologies to upgrade the existing power plant equipment, consequently reducing emissions [116], [117].

The generation of electricity from fossil fuels releases unwanted gases into the atmosphere. These pollutants affect humans and other life forms like animals, birds, and fish. It is also risky for vegetation, produces acid rain, reduces visibility, and causes global warming. Increasing concern over this issue forced the power utilities to reduce their emissions [118]. The goal is to produce electricity at the cheapest possible prices while maintaining the minimum pollution level. Many possible solutions have been introduced to reduce pollution, including installing post-combustion cleaning equipment, replacing old fuel burners with newer ones, using low emissions, and dispatching with emission concerns [119]. Integrating renewable energy into the primary grid is considered one of the most important topics these days. Their integration is reducing the CO_2 emissions. Renewables are nonlinear, fluctuating, and intermittent sources of energy. Different hybrid models are proposed in the literature to forecast the one hour ahead of different renewable energy sources [80], [81], [100]. Biomass is a good solution for increasing energy integration with less CO_2 emissions than fossil fuels.

5.3 Biomass as a Clean Fuel

According to Energy Fact Book 2016–2017, Biomass is considered a renewable energy resource only if the consumption rate does not exceed the rate of production [120]. A fundamental underlying assumption was that using wood biomass for heat and energy would diminish the reliance on fossil fuels and, consequently, diminish greenhouse gas emissions while supporting a green economy in rural areas [121]. From an environmental viewpoint, the life cycle of biomass as a renewable material has a neutral effect on CO_2 emission. In addition, it offers a possible closed mineral and nitrogen cycle. The environmental risk of the produced sulphur dioxide (SO_2) during fossil fuel combustion that leads to acid deposition is not a significant issue in biomass systems because it has low sulphur content (less than 0.2% compared to 0.5 to 7.5% for coal) [122]. Biomass emits approximately the same amount of carbon during conversion as is taken up during plant growth. As a result, the use of biomass does not contribute to a build-up of CO_2 in the atmosphere [123].

5.4 Literature Review

EED schedules the committed generator outputs with the anticipated load demand and optimizes cost and emission simultaneously while maintaining the operating constraints. A lot of techniques are applied to perform EED. Nanda et al. considered EED a multiple, conflicting objective problem and used goal-programming techniques to solve it [123]. Ahmed et al. presented a linear programming-based optimization procedure where the objectives were considered one at a time [124]. In [125], an evolutionary algorithm-based approach has been applied to evaluate the economic impacts of environmental dispatching and fuel. D. B. Das and C. Patvardhan introduced a multi-objective stochastic search technique for the EED [126].

Recently, several studies have been made to develop multi-objective evolutionary search strategies. S.P. Shalini and K. Lakshmi designed a nonlinear bi-objective optimization problem to minimize two conflicting objectives: fuel cost and emission from thermal power plants. The Lagrangian Relaxation (LR) method is used to solve it [113]. In [127], artificial bee colony (ABC) followed by weighted sum technique (ABCWS) is applied on a standard IEEE 30 bus test system, multi-objective particle swarm optimization [128], [129], multi-objective evolutionary algorithm (MOEA) [130], fuzzy clustering-based particle swarm optimization (FCPSO) [131]. A novel evolutionary algorithm for financially assessing an economic power system operation throughout a combined economic and emission dispatch problem (CEED) [132]. A new meta-heuristic search algorithm called Bat Algorithm (BA) is introduced to solve the Environmental/Economic power Dispatch (EED) problem in power systems considering the power limits, valve-point effects, and transmission loss [133]. M. J. Hadidian-Moghaddam et al. presented the Ant Lion Optimization technique (ALO) to determine the optimal location and size of distributed generation (DG); they applied this technique on 33 and 69-bus IEEE networks. Comparing the results with particle swarm optimization (PSO) and genetic algorithm (GA), techniques showed better performance [134].

In [135], ALO has been implemented with Loss Sensitivity Factors (LSFs) for optimal location and DG-based RES sizing in different distribution systems. Applying the proposed algorithm on two IEEE radial distribution systems diminished total power losses and improved net savings. H. Mohan et al. applied the ALO technique to solve practical hydrothermal power generation scheduling (HTPGS) problems with wind integration. The results of this algorithm were compared with other established NI algorithms for the wind-integrated hydrothermal scheduling problem, and the performance was found to be superior [136]. This chapter applies the MALO algorithm to solve an economic dispatch problem with losses and emissions by gradually injecting biomass into an IEEE 30 bus test system containing six thermal units to minimize fuel cost, emission, and power loss.

5.5 Mathematical Modeling

The evident approach is to figure out the optimal amounts of the generated powers for the system's thermal units by minimizing the emission level and cost of generation. The objective of the multi-objective EED problem is to calculate the output power of all generating units at minimum cost while maintaining the following constraints:
Objective function

$$Minimize \sum_{i=1}^{m} F_i(P_i) + \sum_{j=1}^{n} E_i(P_i) \tag{5.1}$$

where $F_i(P_i)$ is the cost of the fuel of the i^{th} plant in (MW), $E_i(P_i)$ is the emission cost. Usually, the fuel cost is represented with the following second-order polynomial:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{5.2}$$

where a_i, b_i and c_i are the fuel cost coefficients.

The emission function is represented with the following quadratic function:

$$E_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i \tag{5.3}$$

where α_i, β_i and γ_i are the emission cost coefficients.

Constraints:

Power balance constraints:

$$\sum_{i=0}^{n} P_i = P_D + P_L \tag{5.4}$$

Generating limits and constraints:

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{5.5}$$

Transmission loss constraints:

$$P_L = 1 - \sum_{i=0}^{n} \beta_{ij} P_i \tag{5.6}$$

In the proposed ELED, the biomass energy is integrated into the previous equations, and the Objective function is changed to be:

$$Minimize \sum_{i=1}^{m} F_i(P_i) + \sum_{j=1}^{n} E_i(P_i) \tag{5.7}$$

$$Maximize \sum_{i=1}^{m} P_{bm} \tag{5.8}$$

where P_{bm} is the integrated biomass power.

The power balance constraints have the biomass as follows:

$$\sum_{i=0}^{n} P_i = P_D - P_{bm} + P_L \tag{5.9}$$

The generating limit constraints are changed to be:

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{5.10}$$

$$P_{bm}^{min} \leq P_{bm} \leq P_{bm}^{max} \tag{5.11}$$

The transmission loss constraints have biomass power included, as shown in the following equation:

$$P_L = 1 - \sum_{i=0}^{n} \beta_{ij}(P_D - P_{bm} + P_L) \tag{5.12}$$

5.6 Simulation Results

Table 5.1: A Sample of 0 MW and 100 MW biomass power values integrated into the system.

BP	*CFP*	*Algorithm*	*FC*	*EV*	*Losses in MW*
0	700	MALO	3.60E+04	1374.58	18.82
		SA	3.69E+04	1298.67	19.43177
		BAT	3.69E+04	1294.231	19.2981
		QPEICC	3.69E+04	1298.708	19.4317
100	600	MALO	3.14E+04	1014.4	13.9038
		SA	3.21E+04	956.2378	14.2375
		BAT	3.21E+04	953.14	14.1434
		QPEICC	3.21E+04	956.2078	14.2373

where BP is the biomass portion in MW, CFP is the conventional fuel portion in MW, FC is the fuel cost in \$/hour, and EV is the emission value in kg/hour.

The model is evaluated using MATLAB software and is based on equations from **(5.1)** to **(5.12)**. Only the thermal plant is utilized, after which biomass is gradually integrated. To mitigate the random process of the MALO technique, numerous runs are conducted using different biomass values to attain the optimal performance and parameters of the proposed methods.

Table 5.2: A Sample of 200 MW and 300 MW biomass power values integrated into the system.

BP	*CFP*	*Algorithm*	*FC*	*EV*	*Losses in MW*
200	500	MALO	2.7 E+04	718.518	9.737
		SA	2.74E+04	677.0166	9.885231
		BAT	2.74E+04	675.13	9.8233
		QPEICC	2.74E+04	677.0342	9.8852
300	400	MALO	2.27E+04	500.238	6.3381
		SA	2.29E+04	500.2311	6.411022
		BAT	2.30E+04	500.231	6.3771
		QPEICC	2.30E+04	500.231	6.411

Tables 5.1 and **5.2** display partial results for the four applied algorithms, showcasing fuel costs, emission values, and power losses. These results are based on a six-unit system. Additionally, graphical representations of the simulation results for the tested model using MALO can be found in **Figures 5.1** to **5.3**.

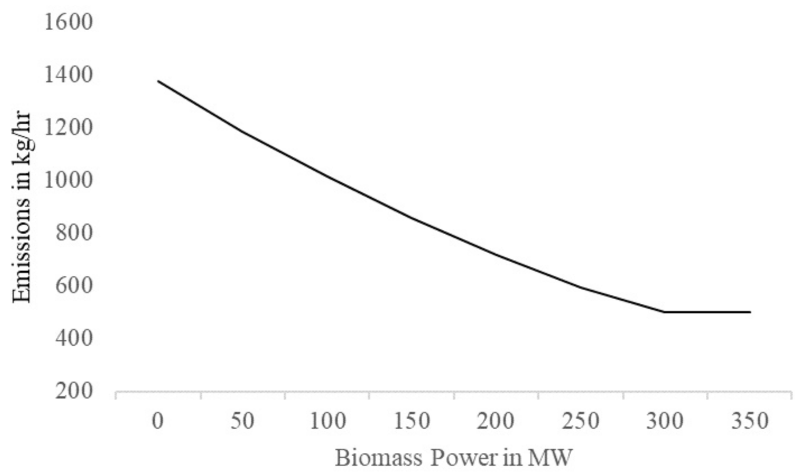


Figure 5.1: The relation between the biomass and the emission values.

Figure 5.1 depicts the relationship between biomass and emission values. The emission values decrease significantly until the biomass value reaches 300 MW.

However, beyond the 300 MW biomass threshold, the emission values do not decrease further.

Figure 5.2 shows the relation between the biomass value and the fuel cost. The graph shows a linear relationship between biomass value and fuel costs; the higher the biomass value, the lower the fuel costs. **Figure 5.3** shows the relation between the fuel costs and the emissions. The higher the biomass proportion, the lower the emissions from conventional fuels.

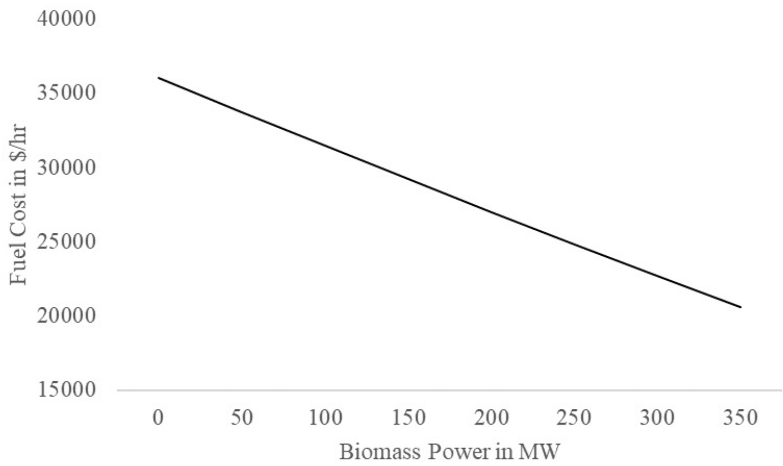


Figure 5.2: The relation between the biomass and the fuel cost values.

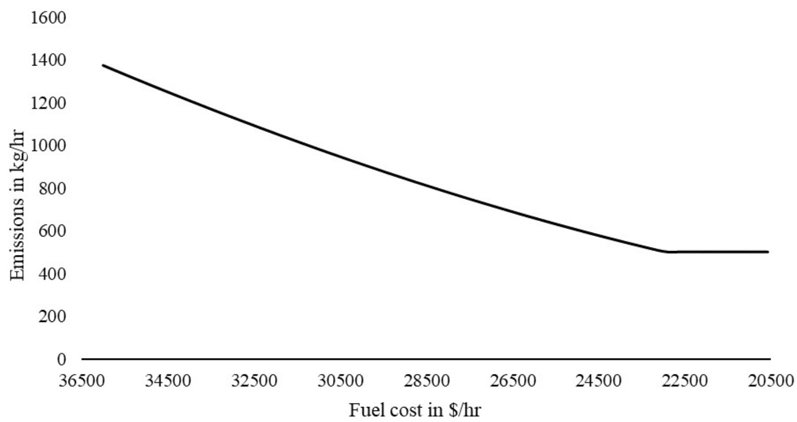


Figure 5.3: The relation between the fuel cost and emission values.

Tables 5.3 and **5.4** display the power generated in each unit using the four algorithms. The MATLAB program gradually increased the added biomass from 0 to 350 MW, with an increment of 1 MW for each iteration (n=0:1:350 MW), but **tables 5.3**

and **5.4** show some samples, precisely at 0, 100, 200, and 300 megawatts. **Table 5.5** displays the fuel types, emission coefficients, and power limits for the IEEE 30 Bus System with Six Generator Buses. **Table 5.6** shows B loss coefficients for the Six Generator Buses.

Table 5.3: A sample of 0 MW and 100 MW biomass power values integrated into the system using the four algorithms.

Biomass portion	**0 MW**				**100 MW**			
	MALO	**SA**	**BAT**	**QPEIC**	**MALO**	**SA**	**BAT**	**QPEIC**
P1 (MW)	24.97	28.29	29.38	28.29	21.19	23.86	24.75	23.86
P2 (MW)	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P3 (MW)	102.66	118.96	118.69	118.69	82.09	95.64	95.42	95.64
P4 (MW)	110.63	118.68	118.46	118.67	94.37	100.70	100.54	100.71
P5 (MW)	232.68	230.76	230.40	230.76	205.36	202.84	202.55	202.83
P6 (MW)	219.05	212.74	212.37	212.75	186.99	181.20	180.89	181.20

Table 5.4: A sample of 200 MW and 300 MW biomass power values integrated into the system using the four algorithms.

Biomass portion	**200 MW**				**300 MW**			
	MALO	**SA**	**BAT**	**QPEIC**	**MALO**	**SA**	**BAT**	**QPEIC**
P1 (MW)	17.41	19.49	17.41	19.49	13.50	14.81	15.31	14.81
P2 (MW)	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P3 (MW)	61.51	72.59	61.51	72.59	40.29	47.88	47.70	47.88
P4 (MW)	78.11	82.92	78.11	82.92	61.33	63.79	63.65	63.79
P5 (MW)	178.04	175.09	178.04	175.09	149.87	144.94	144.71	144.94
P6 (MW)	154.93	149.79	154.93	149.79	125.00	125.00	125.00	125.00

Table 5.5: Fuel, emission coefficients, and power limits for the IEEE 30 bus system

Unit	**a**	**b**	**c**	α	β	γ	P_{min}	P_{max}
1	0.15247	38.53973	756.79886	0.00419	0.32767	13.85932	10	125
2	0.10587	46.15916	451.32513	0.00419	0.32767	13.85932	10	150
3	0.02803	40.39655	1049.32513	0.00683	-0.54551	40.2669	40	250
4	0.03546	38.30553	1243.5311	0.00683	-0.54551	40.2667	35	210
5	0.02111	36.32782	1658.5696	0.00461	-0.51116	42.89553	130	325
6	0.01799	38.2704	13356.2704	0.00461	-0.51116	42.89553	125	315

In **Table 5.5**, the units for a, b, c, α, β, γ, and δ are (\$/hr), (\$/MWhr), (\$/$(MW)^2$hr), (kg/$(MW)^2$hr), (kg/MWhr), and (kg/hr), respectively. P_{min} and P_{max} are the minimum and the maximum power in megawatts.

Table 5.6: B Loss coefficients for the six generating units

0.00014	0.000017	0.000015	0.000019	0.000026	0.000022
0.000017	0.00006	0.000013	0.000016	0.000015	0.00002
0.000015	0.000013	0.000065	0.000017	0.000024	0.000019
0.000019	0.000016	0.000017	0.000071	0.00003	0.000025
0.000026	0.000015	0.000024	0.00003	0.000069	0.000032
0.000022	0.00002	0.000019	0.000025	0.000032	0.000085

5.7 Conclusion

This chapter introduced the ELED method. The main objective of ELED is to schedule the committed generating units to supply power at optimum operation and minimum emission based on alternative energy. In this chapter, biomass energy is used and injected into an IEEE 30 bus test system containing six thermal power plant generating units to reduce the emissions from conventional fossil fuels.

Biomass is integrated into the six-unit system, and the power loss, emissions, and fuel costs are calculated. Four different algorithms are used: MALO, SA, BAT, and QPEICC. The four algorithms give very close results with variations in fuel costs and power losses. The MALO algorithm shows the best performance regarding fuel costs and power losses. In general, the higher the biomass ratio in the system, the lower the fuel costs, the generated powers, the power losses, and the emissions. In this chapter, we found that the best value of biomass is 350 megawatts (50% of the fuel used to generate power); beyond that value, the system will give less performance.

Future work will focus on using more algorithms on IEEE 9, 14, 30, and 118 test systems to show how injecting biomass into the IEEE test system lowers emissions and fuel costs, injecting more renewables like PV, wind, and tidal, and studying how energy management will minimize CO_2 emissions and overall cost.

Chapter 6

Automatic Generation Control of Multi Area Hybrid Energy System Using A Proposed Novel Optimized PID Controller Based on Genetic Algorithm and Fuzzy Logic Systems

This chapter contains materials that are published in a research paper [137].

6.1 Abstract

Automatic Generation Control (AGC) is a crucial component of power systems that secures the balance between power generation and consumption and is maintained in real-time. The main objective of AGC is to regulate the power output of generators to meet the changing demand and maintain the system frequency within permissible limits. Human activities overwhelm our environment with CO_2 and other global warming issues. The current electricity landscape necessitates a superior, continuous power supply and addressing such environmental concerns. These issues can be resolved by incorporating renewable energy sources (RESs) into the utility grid. Thus, this chapter presents an optimized hybrid fuzzy logic self-tuning controller for automatic generation control (AGC) with various renewable sources. This controller regulates the frequency deviations of the power system and governs the change in the tie-line load of a multi-area hybrid energy system composed of wind, biomass, and photovoltaic energy sources. MATLAB Simulink software was applied to design and test the system. The PID controller has been tuned using four algorithms, namely, genetic algorithm (GA), pattern search (PS), simulated annealing (SA), and particle swarm optimization (PSO), and the results are compared with the

proposed novel optimized PID controller (GA-fuzzy logic self-tuning technique) to validate it. The results show the superiority of the proposed hybrid GA-fuzzy logic self-tuning algorithm over the other algorithms in bringing the power system back to its regular operation. The chapter also proposes an operation strategy to lower the utilization of biomass energy in the presence of other renewable energy sources.

6.2 Literature Review

Paper [33] presents an overview of applying biomass as an RES to generate heat and power. Different technologies are introduced. Paper [112] integrated biomass energy into an IEEE 30 bus test system composed of six generating units to minimize the conventional fuel ratio and greenhouse gases. In [138], H. H. H. Aly presented dynamic models of tidal current turbines applying a direct drive permanent magnet synchronous generator (DDPMSG) and doubly fed induction generator (DFIG). The stability analysis results found better performance of the tidal current turbines using a DDPMSG over the DFIG one and that applying PID controllers improves the stability analysis.

K. Jagatheesan et al. [139] presented a nature bio-inspired firefly (FFA)-tuned PID controller for AGC of a multi-area reheat thermal power system. The results derived were compared with GA and PSO-tuned PID controllers. From the results derived, the proposed technique gave the best results regarding the Integral of Time and Absolute Error (ITAE), settling time, undershoot, and overshoot. D. K. Gupta et al. [140] introduced a PID controller tuned using a nature bio-inspired FFA, Particle Swarm Optimization (PSO), and the Gravitational Search Algorithm (GSA) for AGC of multi-area hydro, gas, and thermal power systems. ITAE is considered as the objective function. The results derived from the proposed algorithm show the efficiency of applying it to obtain stable frequency and load responses. Rabindra R. K. Sahu, S. Panda, and S. Pradhan [141] presented a novel hybrid firefly algorithm and pattern search (HFA–PS)-tuned PID model for AGC of multi-area power systems considering the Generation Rate Constraint (GRC). ITAE has been considered to be the objective function. The results derived from the proposed model demonstrated superior outcomes compared to some modern heuristic optimization techniques such as the Bacteria Foraging Optimization Algorithm (BFOA), Genetic Algorithm (GA), and conventional Ziegler–Nichols (ZN)-based PI/PID controllers for the same interconnected power system. A. Ghosh et al. [142] proposed an optimized Ziegler–Nichols (ZN)-based tuned PID controller for AGC of a single-area thermal power system and a multi-area PV-integrated thermal power system.

A. K. Barisal and S. Mishra [143] presented a nature bio-inspired BFOA, PSO, and Improved-PSO-tuned PID controller for AGC of two-area diesel, hydro, thermal, and wind power systems. ITAE is considered as the objective function. The results derived from the proposed algorithm show its effectiveness in obtaining a stable frequency response and load response on the tie-line. Applying parallel DC/AC links enhanced the dynamic stability of the system and dropped the cost index. S. K. Bhagat et al. [144] introduced a hybrid PSO-GA controller with a tilt-integral-derivative (TIDN) filter controller for AGC control of a multi-area power system. H. Haes Alhelou, M. E. Hamedani Golshan, and M. Hajiakbari Fini [145] introduced a wind-driven optimization (WDO)-algorithm-tuned PID controller for the three-area power system LFC. C. Huang et al. [146] presented a natural bio-inspired Gravitational Search Algorithm (GSA)-based linear active disturbance rejection control (LADRC) approach for the LFC of the two-area power system. ITAE is considered as the objective function. The results derived from the proposed algorithm show the efficiency of applying it to obtain stable frequency and load responses. H. Changmai and M. Buragohain [147] presented a natural bio-inspired, GA-tuned, PID-controller-based linear quadratic regulator (LQR) for the LFC of the two-area power system. In [148], Y. L. Karnavas and E. Nivolianiti introduced a nature bio-inspired Harris Hawks Optimization (HHO) for LFC of an isolated multi-source power system. By comparing the proposed algorithm with the Whale Optimization Algorithm (WOA), Grey Wolf Optimizer (GWO), and PSO, it was found that the proposed algorithm exhibited superior performance in terms of power stability, settling time, overshoot, and undershoot.

R. Shankar, K. Chatterjee, and R. Bhushan studied, in [149], the LFC of a multi-source two-area power system with an energy storage system (redox flow battery) in a deregulated power environment. An opposition-based harmonic search (OHS) technique has been applied to tune the PID controller. Economic load dispatch has been integrated into the LFC. The redox flow battery is applied to absorb any transient or sudden load change. In [150], E. Çelik et al. presented a nature bio-inspired dragonfly search algorithm (DSA)-tuned PID controller for LFC of a single-area and two-area thermal power system. A (1 + PD)-PID cascade controller has been optimized via DSA using ITAE to obtain optimal results. N. R. Babu et al. [151] studied the impact of different solar insulation types on the LFC of two-area thermal power systems. Tilt integral minus derivative control (TI-DN) with filter has been applied as a supplementary controller with the crow search optimization (CSO) technique to optimize LFC. The paper found that the amalgamation of HVDC with AC tie-line amalgamates system dynamics. R. R. Kumar, A. K. Yadav, and M. Ramesh [152] presented a PID-based LQR controller for the LFC of a wind/solar-based renewable microgrid. The results reveal the proposed controller's dynamic and frequency response effectiveness.

M. Amaro Pinazo, R. Antara Arias, and J. Mirez Carrillo reviewed, in [153], the analysis and performance of four different control technologies for wind turbines based on electromagnetic and mechanical torques. V. Patel, D. Guha, and S. Purwar [154] presented a fractional-order adaptive sliding mode control (FO-ASMC) to improve the frequency regulation of power systems. The efficiency of the proposed control scheme has been tested under different load and wind disruptions. The results reveal this method's effectiveness in frequency response and system stability. P. Saxena, N. Singh, and A. K. Pandey studied, in [155], the frequency fault ride-through (FFRT) capability of solar-based microgrids and proposed an adaptive PI-based virtual damping (PIVD) controller to augment the dynamic performance. This controller de-loads solar power while tracking frequency errors; the de-load process produces virtual inertia reserve (VIR) to stabilize the grid in case of contingency, in place of batteries. The model has been validated via MATLAB, and the results derived showed that the suggested model is qualified to ride through severe fault scenarios with minimal frequency disruption.

W. Guo and J. Yang presented, in [156], a novel nonlinear mathematical model of hydro-turbine governing systems based on the nonlinear characteristics of penstock head loss. P. Dash, L. C. Saikia, and N. Sinha proposed, in [157], a Flower Pollination Algorithm (FPA)-tuned Proportional Integral-Proportional Derivative (PI-PD) cascade controller for AGC of a four-thermal power system. R. El-Sehiemy et al. presented, in [158], an Artificial Rabbits Algorithm (ARA)-optimized PID controller for LFC of multi-area power systems. ITAE has been considered to be the objective function. The results derived from the proposed model demonstrated superior outcomes compared to some modern heuristic optimization techniques such as PSO, differential evolution (DE), JAYA optimizer, and self-adaptive multi-population elitist (SAMPE) JAYA.

Ekinci, Serdar, et al. presented in [159] a hybrid power system that integrates a reheated thermal power plant with a photovoltaic (PV) system, addressing the dynamic challenges through Automatic Generation Control (AGC). A Proportional-Integral (PI) controller, optimized using the RIME algorithm, effectively manages frequency oscillations and tie-line power variations. This study represents the first application of the RIME optimization method in AGC processes. Utilizing an enhanced Integral of Time Absolute Error (ITAE) as the objective function, the research assesses the performance of the RIME-tuned PI controller across various scenarios. It benchmarks its effectiveness against established optimization techniques such as the Binary Whale Optimization Algorithm (BWOA), Sailfish Optimization Algorithm (SOA), Slime Mould Algorithm (SMA), Firefly Algorithm (FA), and Genetic Algorithm (GA). The results consistently indicate that the RIME algorithm surpasses these methods, proving more effective in curtailing frequency oscillations and stabilizing tie-line power. This illustrates RIME's potential as a robust tool for enhancing AGC performance, thereby contributing to greater stability and reliability in power systems.

Alarifi, Abdulaziz, et al. [160] introduced an innovative automated control scheduling method to enhance renewable energy systems within smart cities. They tackled the power generation and distribution discrepancies by dynamically adjusting the system according to forecasted energy needs. The incorporation of Q-learning significantly improves the automation and accuracy of power predictions. Experimental results demonstrate the effectiveness of this approach in boosting operational efficiency and reducing imbalances. This research is crucial in optimizing renewable energy management, promoting sustainability, and ensuring a reliable power supply to address future urban energy challenges.

In their research, Ritu et al. highlighted in [161] advancements and opportunities in Automatic Generation Control (AGC), concentrating on various control strategies designed to address load perturbations and power generation deficits. They reviewed methods that tackle system non-linearities, including Gain Droop Behavior (GDB), Gain Repeatability Control (GRC), and Disturbance Behavior (DB). The study identified critical gaps, particularly in developing resilient controllers that leverage deep learning and machine learning for Load Frequency Control (LFC) in microgrids facing cyber-attacks. Additionally, the research emphasizes the importance of demand response-based frequency regulation in hybrid systems integrated with renewable energy, which remains an underexplored area. Advanced techniques are also examined, such as fractional-order controllers, fuzzy logic-assisted methods, cascaded controllers, the integration of electric vehicles, demand response strategies, and mechanisms aimed at enhancing resilience. This study summarizes recent developments in AGC within systems that combine conventional and renewable energy sources while outlining future research directions to improve frequency stability in modern power grids.

Ashfaq, Tayyab, et al. emphasize in [162] strategies aimed at reducing power system fluctuations stemming from variations in load demand. They focus on secondary control, tie-line power exchange, and optimization techniques. These methods effectively diminish frequency deviations and alleviate stress on controllers, thereby enhancing overall system stability and efficiency. The adaptive-PID controller, which dynamically adjusts its parameters, demonstrates superior performance compared to traditional approaches like the Ziegler–Nichols method and particle swarm optimization algorithms, providing a more effective alternative to conventional trial-and-error strategies. Furthermore, the study proposes incorporating additional meta-heuristic methods, such as gradient descent, to improve the performance of Automatic Generation Control (AGC) systems. These findings offer valuable insights for bolstering power system stability and efficiency, thereby supporting the development of a sustainable energy sector.

Ming et al. [163] assessed various automatic generation control (AGC) strategies in power systems that integrate renewable energy sources. The study begins with an overview of AGC systems, underscoring the significant impact of renewable energy incorporation on AGC control models. It delves into key advancements in AGC strategies, including PID, MPC, ANN, fuzzy logic, deep reinforcement learning, optimal control, and adaptive control methods, evaluating their effectiveness in frequency regulation. A thorough literature review highlights intelligent optimization algorithms tailored for renewable energy-powered systems. The study identifies challenges faced by grids with high renewable energy penetration and proposes solutions to ensure frequency stability. This work is a valuable resource for advancing research on AGC in renewable energy-integrated systems, contributing to the goal of reliable and stable power system operations in the context of increasing renewable energy adoption. Ullah, Kaleem, et al. [164] proposed real-time dynamic dispatch strategies for AGC systems, integrating wind power and electric vehicle areas (EVAs) to enhance secondary power dispatch. The study models power generation units, including thermal power plants (THPPs), gas turbines, and wind power plants (WPPs), alongside EVAs to analyze their contributions to active power regulation.

The aforementioned studies underscore significant advancements in power systems and the integration of renewable energy; however, they share common limitations, such as a lack of experimental validation, insufficient exploration of real-world implementation challenges, and limited consideration of economic and stakeholder factors. Future research outlined in [159] should prioritize experimental validation, address nonlinearities, and explore the integration of RIME into various power configurations to enhance its applicability. Expanding real-world testing, hybridizing systems with conventional energy sources, and conducting economic and urban integration analyses in [160] are crucial for strengthening adoption within smart cities.

Furthermore, incorporating empirical validations, practical constraints, and socio-economic assessments into [161] would enhance the real-world relevance of proposed AGC strategies. In [162], validation through simulations or case studies, exploration of modern hybrid systems, and cost-effectiveness analyses are essential for practical application. Addressing scalability, economic feasibility, and cybersecurity gaps is critical in [164] for advancing reliable and sustainable power systems.

By effectively addressing the gaps identified in these studies, the GA-Fuzzy Logic self-tuning PID controller emerges as a scalable, adaptable, and reliable solution for enhancing the stability and efficiency of power systems that integrate renewable energy sources. This innovation is pivotal in improving such systems' overall performance and sustainability, effectively tackling the challenges posed by renewable energy generation's dynamic and intermittent nature.

Automatic Generation Control (AGC) is critical in maintaining frequency stability and tie-line power exchange in power systems, especially in hybrid systems combining renewable energy sources (RES) with conventional power generation. Below is a critical analysis of prevalent AGC methodologies, their strengths, limitations, and suitability for hybrid systems:

1. **Proportional-Integral-Derivative (PID) Control Strengths:**
    - Simplicity and ease of implementation.
    - The system is extensively recognized and commonly implemented in established frameworks.
    - Effective in steady-state error reduction.

    Limitations:
    - Insufficient for systems with high renewable energy source penetration due to slow response to variability and disturbances.
    - Manual tuning is required, which can be time-consuming and may not yield optimal results for complex systems.

    Suitability for Hybrid Systems
    - The system has limited scalability and is not well-suited to adapt to changes in renewable energy outputs.
    - Performance can be enhanced through advanced tuning mechanisms like fuzzy logic or optimization algorithms.
2. **Model Predictive Control (MPC):**

    Strengths:
    - Predicts future states using dynamic system models.
    - Handles constraints effectively, making it well-suited for multi-variable systems.
    - Achieving high precision in control actions is crucial, particularly for hybrid systems that utilize storage and renewable energy sources (RES).

    Limitations:
    - The task is computationally intensive and requires significant processing

power.

- It relies heavily on accurate system modelling, which may not always be feasible for hybrid systems with complex dynamics.

Suitability for Hybrid Systems

- Highly effective for systems where constraints and predictability matter, such as microgrids or hybrid setups with battery storage.

3. **Fuzzy Logic Control:**

Strengths:

- Effectively manages non-linearities and uncertainties without the need for precise models.
- Highly adaptable to changes in renewable energy output.

Limitations:

- The effectiveness of performance relies on the quality of the rule base, which in turn necessitates expert knowledge.
- There may be a need for enhanced optimization capabilities by integrating other techniques.

Suitability for Hybrid Systems

- This system is well-suited for environments with high renewable energy source (RES) penetration because it effectively manages variability.
- The effectiveness can be improved when used in conjunction with optimization algorithms.

4. **Artificial Neural Networks (ANN):**

Strengths:

- Learns about system dynamics and adapts to changing conditions over time.
- Suitable for non-linear and complex systems.

Limitations:

- It requires extensive training data and computational resources.
- There is a risk of overfitting, leading to decreased model interpretability.

Suitability for Hybrid Systems

- Highly adaptable to hybrid systems, but it may require hybridization with other methods, such as model predictive control (MPC) or fuzzy logic, for increased robustness.

5. **Optimization-Based Controllers (e.g., Genetic Algorithms, Particle Swarm Optimization): Strengths:**
    - Effective in parameter tuning for complex systems.
    - Identifies global optima in non-linear and multi-objective scenarios.

    Limitations:
    - There is a significant computational overhead, particularly in applications that require real-time processing.
    - May experience difficulties with convergence in large-scale systems.

    Suitability for Hybrid Systems
    - Best utilized additional controllers (e.g., PID, fuzzy logic) to improve performance in hybrid systems.

This chapter presents an innovative PID controller that has been finely tuned through heuristic-based optimization techniques to improve a multi-area hybrid renewable energy system, specifically in the context of Libya's energy landscape. Building on subsection (1.2), which identifies existing research gaps and relevant contributions in this field, the proposed controller aims to enhance the control system's efficiency by optimizing settling time and minimizing overshoot and undershoot.

6.3 Introduction

The main objective of the electric power control technique is to generate power and deliver it to the grid economically while preserving the voltage and frequency within their permissible limits. Fluctuation in real power commonly affects the system frequency, while reactive power impacts the voltage magnitude. Hence, real and reactive power are controlled separately. Load frequency control (LFC) technology controls real power and frequency and is the foundation of many modern concepts for controlling large systems.

When a sudden load occurs in the system, the turbine speed decreases before the governor can calibrate the input of that system to the new load. As the turbine speed decreases, the error signal becomes smaller and smaller, and the governor flyball's position becomes closer to the constant speed point, yet there will be an offset in the speed. An integrator is usually added to overcome the offset and restore the speed to its nominal value [165]. As the load changes perpetually, the generation is regulated automatically to restore the speed; accordingly, the frequency is set to the nominal value. This mechanism is known as the AGC. The role of AGC in power grids is to distribute the loads among the stations and the generators to attain optimal generation and to control the scheduled interchanges of tie-line power while maintaining a steady frequency. Various studies have been conducted on LFC and AGC, which address various modern control systems for the power system's successful generation [165].

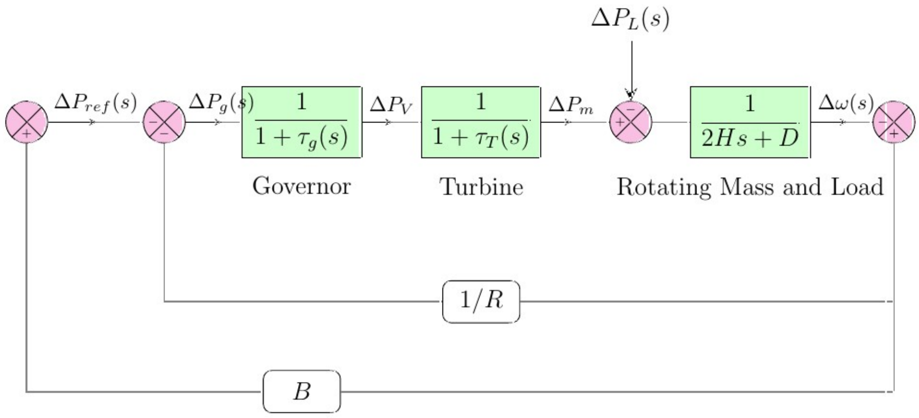


Figure 6.1: AGC of an isolated power system network, redrawn from [165].

Figure 6.1 shows the AGC of an isolated power system, where H is the per unit inertia constant, its unit is seconds, and its value ranges between zero and one second based on the size and the type of the machine. The D is the damping coefficient. R is the droop voltage magnitude; governors typically have a 5 to 6 percent speed regulation from zero to full load. B is the frequency bias factor. $\Delta\omega(s)$ is the frequency-sensitive load change. $\Delta P_L(s)$ is the non-frequency sensitive load change. ΔP_m is the change in mechanical power output. ΔP_V is the change in steam valve position. ΔP_{ref} is the reference set power. ΔP_g is the speed governor comparator, τ_g is a simple time constant, and τ_T is the prime mover's time constant between 0.2 and 2.0 s.

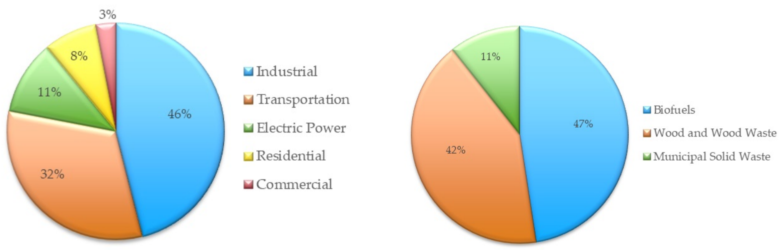
$$B = \frac{1}{R} + D \tag{6.1}$$

$$\Delta P_V(s) = \frac{1}{1+\tau_g} \Delta P_g(s) \tag{6.2}$$

$$H = \frac{Kinetic\ energy\ in\ MJ\ at\ rated\ speed}{Machine\ rating\ in\ MVA} = \frac{W_K}{S_B} \tag{6.3}$$

$$G_T(s) = \frac{\Delta P_m(s)}{\Delta P_V(s)} = \frac{1}{1+\tau_T s} \tag{6.4}$$

The energy sources applied in AGC and LFC studies were not limited to conventional energy sources but also included RES. Even though biomass is considered an RES, minimal research has been conducted on its application as an energy source in power plants. In the United States, until the middle of the 1800s, biomass was the primary source of the nation's annual energy consumption. By 2022, the United States' primary energy consumption was about five percent from biomass [166].



(a) US biomass energy consumption.

(b) Biomass types

Figure 6.2: The US biomass energy consumption by sector in 2022, and biomass types.

Figure 6.2 (a) depicts the US biomass energy consumption in the year 2022, where the consumption was 2266 trillion British thermal units (TBtu)—1565 TBtu, 539 TBtu, 413 TBtu, and 147 TBtu from the industrial, transportation, residential, electric power, and commercial sector, respectively. **Figure 6.2 (b)** depicts the energy consumed from biomass in the US, which accounts for 5% of the total energy consumption [166].

This work proposes and optimizes a multi-area hybrid renewable energy system composed of three renewable energy sources: wind, biomass, and solar, as depicted in **Figure 6.3**. The proposed work is validated by using software programs that can simulate it. MATLAB R2017b software is a powerful tool that allows users to predict a system's behaviour. It can be used to evaluate a new design, diagnose problems with an existing design, and test a system under various conditions. A mathematical model of the system is needed to run a simulation, which can be expressed as a block diagram, code, schematic, or even state diagram. As Peck (2004, p. 4) puts it:

> *When a researcher builds a simulation model, they have created a world in which they have access to all of the laws and components of that world, and the relationships among those components. Not only do researchers have access to these things, but they can also manipulate them. To the extent that researchers can match their simulated world to the real world, they should be able to read things off the simulated world that will tell them something about the real world.*

MATLAB Simulink R2017b is applied to design and optimize the subjected model. GA, PS, SA, PSO, and the novel GA-fuzzy logic self-tuning techniques tune the PID controller's parameters by minimizing ITAE and the net present cost (NPC). The novelty here is integrating biomass into AGC and developing the GA-fuzzy algorithm. System performance is examined by considering the frequency and load disturbance in all three areas. The effectiveness of the novel GA-fuzzy logic self-tuning technique was proved by comparing its performance with the other four optimization techniques. The paper also presents an operating strategy to utilize wind, solar, and biomass energy sources.

6.4 System Description (PID Controller and the Proposed Hybrid Energy System)

This work presents the novel GA-fuzzy logic self-tuning and some heuristic-based optimization techniques for AGC of multi-area hybrid energy systems. Regarding the heuristic-based optimization techniques, four different optimization techniques, namely, GA, PS, SA, and PSO techniques, are applied. These algorithms, in addition to the novel GA-fuzzy logic self-tuning algorithm, are applied to tune the PID controller's parameters, diminish the fluctuation in the frequency, and control the power flow in the plants and the tie-line.

The PID controller is one of the most used controllers in many disciplines. Its output could be represented by **equation (6.5)**.

$$y(t) = K_p x(t) + K_i \int x(t)dt + K_d \frac{d(x)t}{dt} \tag{6.5}$$

where $x(t)$, $y(t)$, K_p, K_i, and K_d correspond the input, the output, the proportional gain, the integral gain, and the derivative gain, respectively. K_p improves the transient response, rise time, and settling time, K_i improves the steady state response, and K_d improves the transient response by predicting errors that may happen in the future.

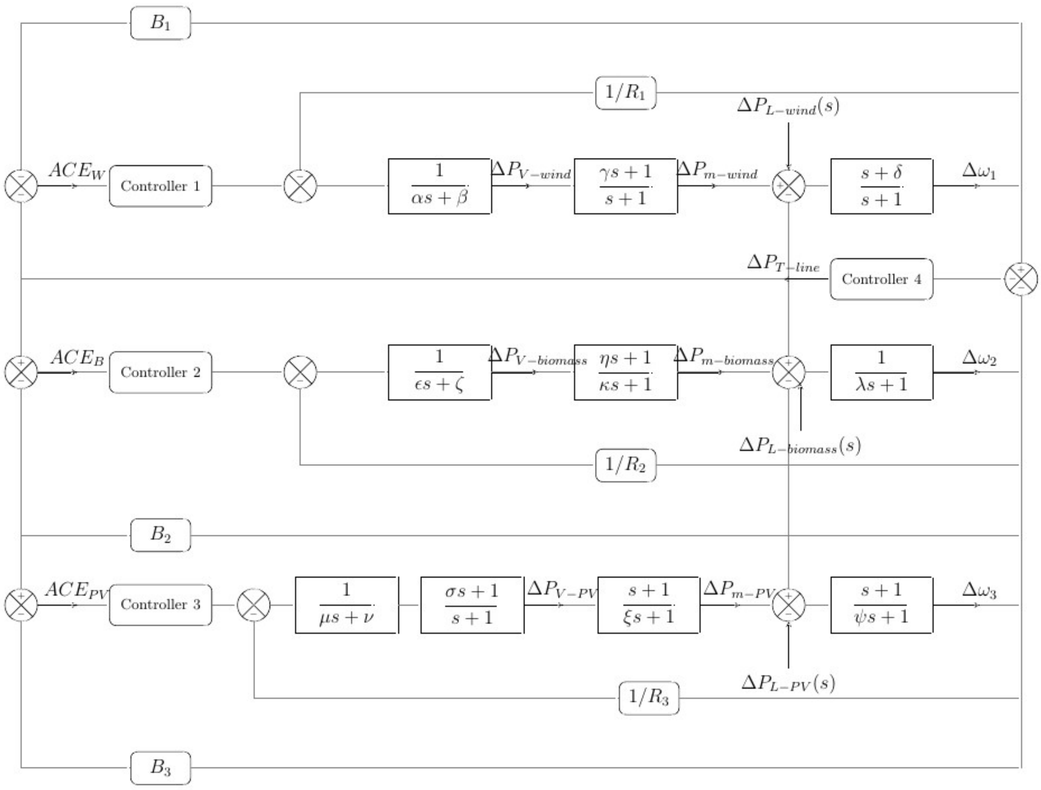


Figure 6.3: AGC of the proposed multi-area renewable energy system.

The objective functions in this work are ITAE and NPC (see **equations (6.6)** and **(6.16)**). The goal is to tune the PID parameters by minimizing the objective function.

$$ITAE = \int_0^{t_s} t \cdot |x(t)| \cdot dt \tag{6.6}$$

where t_s is simulation time. Tuning the controller's parameters is crucial for optimal operation.

Research papers consider many performance indices, such as the integral of absolute error (IAE), integral of squared error (ISE), integral of time-weighted squared error (ITSE), and ITAE. However, ITAE was proven to give satisfactory optimization results concerning LFC and AGC regarding settling time, undershoot, and overshoot. Therefore, we consider ITAE an objective function in our current work.

$$ITAE = \int_0^{t_s} (|\Delta F_W| + |\Delta F_B| + |\Delta F_{PV}| + |\Delta P_{tl}|) \cdot t \cdot dt \tag{6.7}$$

where ΔF_W, ΔF_B, and ΔF_{PV} represent the variation in the frequency in the wind power plant, the biomass power plant, and the photovoltaic power plant, respectively, moreover ΔP_{tl} represents the variation in tie-line power. The proposed optimization technique minimizes the objective function for finding the PID controller's parameters.

The constraints were as follows:

$$K_{p_{min}} \leq K_p \leq K_{p_{max}}$$

$$K_{i_{min}} \leq K_i \leq K_{i_{max}}$$

$$K_{d_{min}} \leq K_d \leq K_{d_{max}}$$

where $K_{p_{min}}$, $K_{p_{max}}$, $K_{i_{min}}$, $K_{i_{max}}$, $K_{d_{min}}$, and $K_{d_{max}}$ are the minimum proportional gain, the maximum proportional gain, the minimum integral gain, the maximum integral gain, the minimum derivative gain, and the maximum derivative gain, respectively.

From equation (**6.5**), we have:

$$Y_1 = K_{p1} \times ACE_W + K_{i1} \times \int ACE_W + K_{d1} \times \frac{dACE_W}{dt} \tag{6.8}$$

$$Y_2 = K_{p2} \times ACE_B + K_{i2} \times \int ACE_B + K_{d2} \times \frac{dACE_B}{dt} \tag{6.9}$$

$$Y_3 = K_{p3} \times ACE_{PV} + K_{i3} \times \int ACE_{PV} + K_{d3} \times \frac{dACE_{PV}}{dt} \tag{6.10}$$

where ACE is the area control error, which is the difference between each plant's electric power into the grid via generation or purchases and the electric power taken out as load, losses, or sales.

$$ACE_W = B_1 \Delta F_W + \Delta P_{tl}$$

$$ACE_B = B_2 \Delta F_B + \Delta P_{tl}$$

$$ACE_{PV} = B_3 \Delta F_{PV} + \Delta P_{tl}$$

where ACE_W, ACE_B, and ACE_{PV} are the area control error for the wind, the biomass, and the solar plants, respectively. **Figure 6.3** and ACE equations show that ACE relies on the frequency and the tie-line power, where ACE is the input. Appendix A shows the parameters for the proposed AGC of the model depicted in **Figure 6.3**.

6.5 Why introducing the novel GA-Fuzzy Logic self-tuning PID controller

The following gaps in current research justify the need for the novel GA-Fuzzy Logic self-tuning PID controller:

1. **Scalability Challenges:** Existing control strategies, including traditional Proportional-Integral-Derivative (PID) controllers and optimization-based methods as of [163], frequently encounter challenges in scaling effectively within systems characterized by high levels of renewable energy penetration. Such systems exhibit rapidly increasing complexity resulting from the diverse and intermittent characteristics inherent to renewable energy sources (RES). A Genetic Algorithm-Fuzzy Logic self-tuning PID controller has been proposed to address these limitations. This advanced control mechanism dynamically adjusts its control parameters, adapting to the evolving intricacies of system size and complexity while maintaining performance efficacy. This approach enhances the adaptability of control systems in the context of renewable energy integration and significantly mitigates the performance degradation often associated with traditional methods.
2. **Adaptability to Variable Renewable Outputs:** Many conventional Automatic Generation Control (AGC) methods exhibit limited adaptability when confronted with the unpredictability and variability inherent in renewable energy outputs. This inadequacy can result in operational inefficiencies and potential frequency instability, particularly during abrupt shifts in generation or load. The proposed control strategy integrates fuzzy logic to facilitate real-time adaptability alongside genetic algorithms (GA) for optimal parameter tuning. This synergistic approach enhances the controller's capability to effectively respond to fluctuating inputs, thereby improving the stability and efficiency of

the power system in the context of increasing renewable energy integration.

3. **Inadequate Handling of Hybrid Power Systems:** Hybrid systems that integrate thermal, renewable, and energy storage components frequently encounter significant control challenges stemming from their distinct dynamic behaviours. Conventional control solutions often optimize performance with a singular focus on specific system types, neglecting the interplay between diverse components. The Genetic Algorithm-Fuzzy Logic (GA-Fuzzy Logic) self-tuning PID controller presents a comprehensive approach to effectively managing the varying dynamics inherent in hybrid systems. This methodology ensures enhanced stability and balanced operational performance across the integrated components, thereby addressing the complexities associated with these multifaceted energy systems.
4. **Lack of Comprehensive Stability Across Scenarios:** Contemporary control methodologies demonstrate proficiency in particular scenarios; however, they often encounter challenges when subjected to fluctuating load conditions, elevated renewable energy source (RES) penetration, or disturbances within the grid. The innovative controller presented herein endeavours to mitigate these limitations by synergistically incorporating the rule-based reasoning inherent in fuzzy logic with the global optimization capabilities afforded by genetic algorithms (GA). This integration enhances system stability across various operational conditions, improving responsiveness and reliability in dynamic environments.
5. **Limited Focus on Future Grid Requirements:** Emerging electrical grids characterized by minimal system inertia, increased penetration of Renewable Energy Sources (RES), and the implementation of microgrid structures necessitate the development of advanced control systems capable of functioning effectively within decentralized and distributed operational environments. The proposed controller presents a significant advancement in this domain, offering improved flexibility and robustness. This makes it particularly well-suited for the complexities and demands of modern and future grid architectures.

By effectively addressing existing gaps in current methodologies, the GA-Fuzzy Logic self-tuning PID controller presents itself as a scalable, adaptable, and reliable solution for improving the stability and efficiency of power systems that integrate renewable energy sources. This advancement is crucial for enhancing such systems' overall performance and sustainability in response to the dynamic nature of renewable energy generation.

6.6 Fuzzy Logic Control

Lotfi Asker Zadeh introduced the fuzzy logic approach in 1965 [167]. It comprises three steps: fuzzification, rule-based inference engine, and defuzzification, as depicted in **Figure 6.4**. It can be applied to nearly every discipline, including models whose mathematical modelling is not well defined, and it has been applied widely in LFC and AGC.

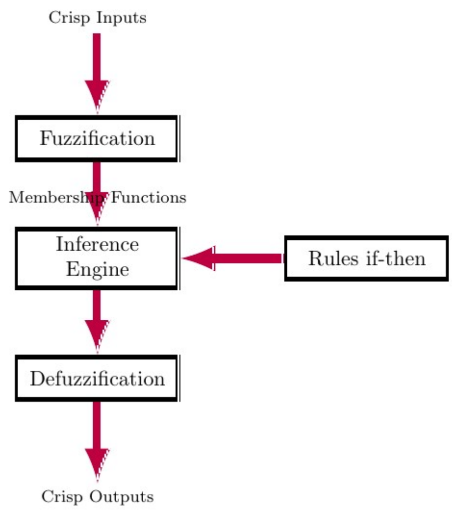


Figure 6.4: A Block diagram of a fuzzy logic control system.

M. A. R. Shafei, D. K. Ibrahim, and M. Bahaa presented, in [168], a PSO-tuned fuzzy logic controller for the LFC of a two-area power system. The performance of the proposed controller has been validated by comparing its results with those of a recently published PID-P controller, where it achieved less settling time and less undershooting and overshooting values. In [169], T. Hussein and A. Shamekh proposed a gain-scheduling PI fuzzy logic two-level LFC for a two-area power system. This technique eliminates steady-state error and results in good transient response. The results derived from applying the criterion of integral square error (ISE) using MATLAB Simulink show the proficiency of the proposed technique. B. Khokhar, S. Dahiya, and K. P. S. Parmar proposed, in [170], a novel hybrid fuzzy proportional derivative–tilt integral derivative (FPD-TID) controller for the load frequency control (LFC) analysis of a standalone microgrid. The developed controller has been optimized using a robust chaotic crow search algorithm (CCSA).

A. Ghafouri, J. Milimonfared, and G. B. Gharehpetian applied in [171] fuzzy-adaptive frequency control to study the effect of microgrids and wind penetration on LFC. The improved hierarchical coordinated control technique has been applied to the IEEE 39-bus system, including microgrids and wind farms. The results validated the developed method's effectiveness in improving the power quality and frequency response.K. Ben Meziane, R. Naoual, and I. Boumhidi presented, in [172], the interval type-2, fuzzy-logic-based, tuned PID controller for AGC of a two-area hydro, gas, and thermal power system with an Advanced Thyristor Controlled Series Capacitor (ATCSC). ITAE is considered as the objective function. The results derived from the proposed algorithm show the efficiency of applying it to obtain stable frequency and load responses. Compared to other controllers, the presented technique demonstrates an excellent damping response. A. Bloul, A. Sharaf, and M. El-Hawary [173] introduced a low-cost, flexible AC transmission system (FACTS)-based, flexible fuzzy-logic-controller-tuned arm filter and Green Plug compensation scheme for single-phase nonlinear loads to improve power quality, correct power factor, diminish switching transients, and reduce harmonics.

In Boolean algebra, we only have two states: either true (1) or false (0)—something working 100% or not working at all (0). This can be applied to limited applications, including switches. In real life, many applications do not follow the Boolean algebra rules; numbers like 0.1, 0.15, and 0.2 have some value, whereas they are rounded to zero in Boolean algebra. The speed of objects is not just halted or full speed; there are grades in between, such as the slowest, slower, slow, fast, faster, and the fastest. This is not limited to speed applications but is applied to many cases. In our study, the turbine does not have just two states, open or closed, but can be 5%, 10%, . . . , and 95% open. Based on that, Boolean algebra does not always suit all applications where we must include all the previous turbine states. To include those scenarios, we applied fuzzy logic, which allowed us to deal with all states between zero and one. **Table 6.1** illustrates a basic example of distinguishing between Boolean algebra and fuzzy logic.

Table 6.1: Comparison between Boolean algebra and fuzzy logic

%% ***Turbine operation in Boolean algebra***	%% ***Turbine operation in fuzzy logic***

If (valve==0)
{
// Turbine is Off
}
Else
{
Turbine is On
}
	If ((valve >==0) && (valve <0.25))
	{
	// Turbine is quarter opened
	}
	Else if ((valve >==0.25) && (valve <0.5))
	{
	//Turbine is half-opened
	}
	Else if ((valve >==0.5) && (valve <0.75))
	{
	//Turbine is three-quarters opened
	}
	Else if ((valve >==0.75) && (valve <1.0))
	{
	//Turbine is fully opened
	}

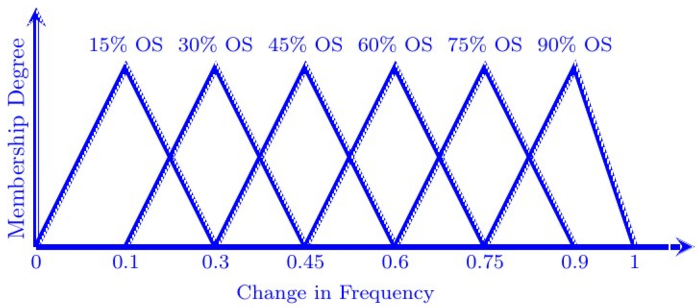


Figure 6.5: The model Input (Change in Frequency).

The frequency is the system's input in all three plants, and the turbine valve is the output. To form the membership functions in the novel GA-fuzzy logic self-tuning approach, we need to specify the range of the inputs and the outputs, where the input in our model is the frequency in Hz, and the output is the turbine valve position. **Figures 6.5** and **6.6** depict the range of the frequency fluctuation and the turbine valve position of the proposed model, respectively. In **figures 6.5** and **6.6**, OS is overshoot, 0% means there is no overshoot in the response, O is open, 0% means the valve is closed, whereas 100% means the valve is fully open.

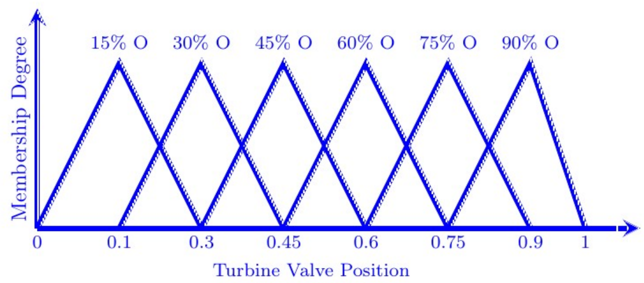


Figure 6.6: The model Output (Turbine Valve Position).

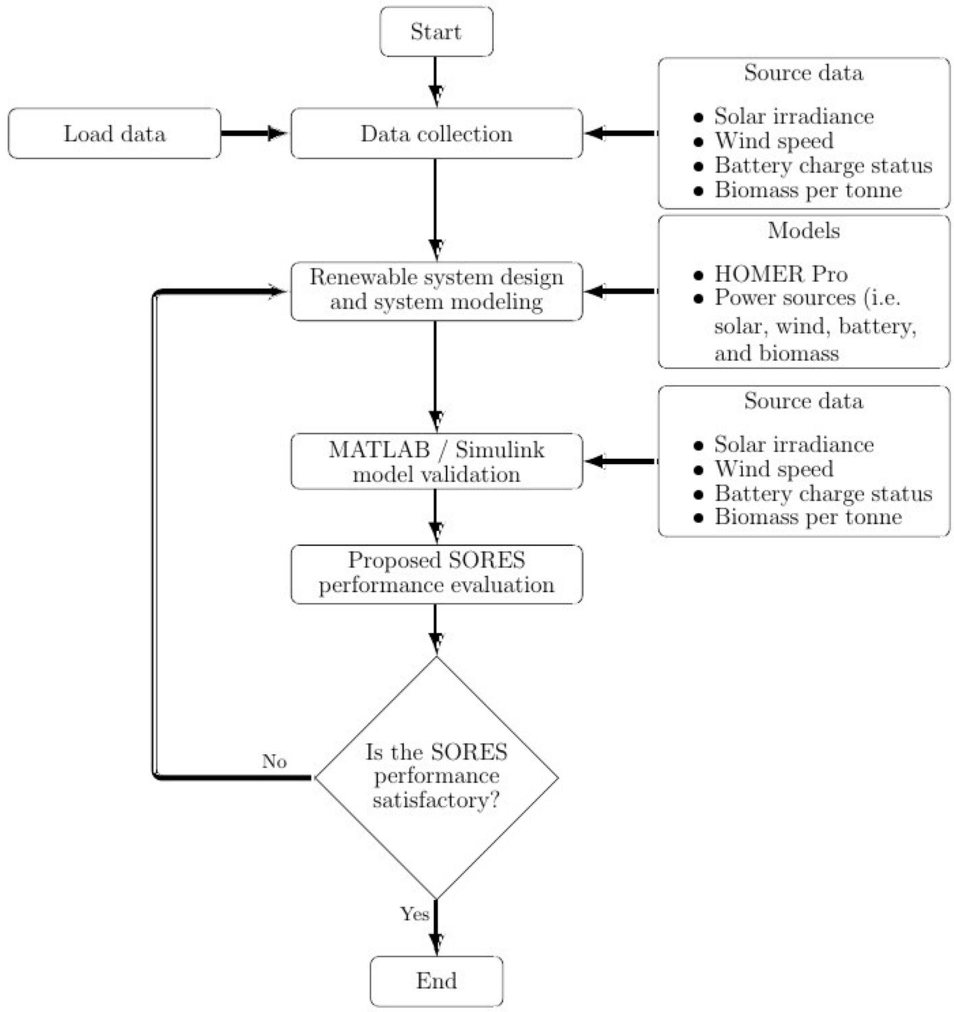


Figure 6.7: Strategy of operation of the RES (SORES).

6.7 System Configuration

A strategy for the operation of the RES (SORES) has been proposed (**Figure 6.7**); this hybrid system comprises a wind energy system, a photovoltaic (PV) system, a biomass gasifier system, and a battery storage system. The wind turbine and solar panels produce DC, so an inverter is required to convert DC into AC.

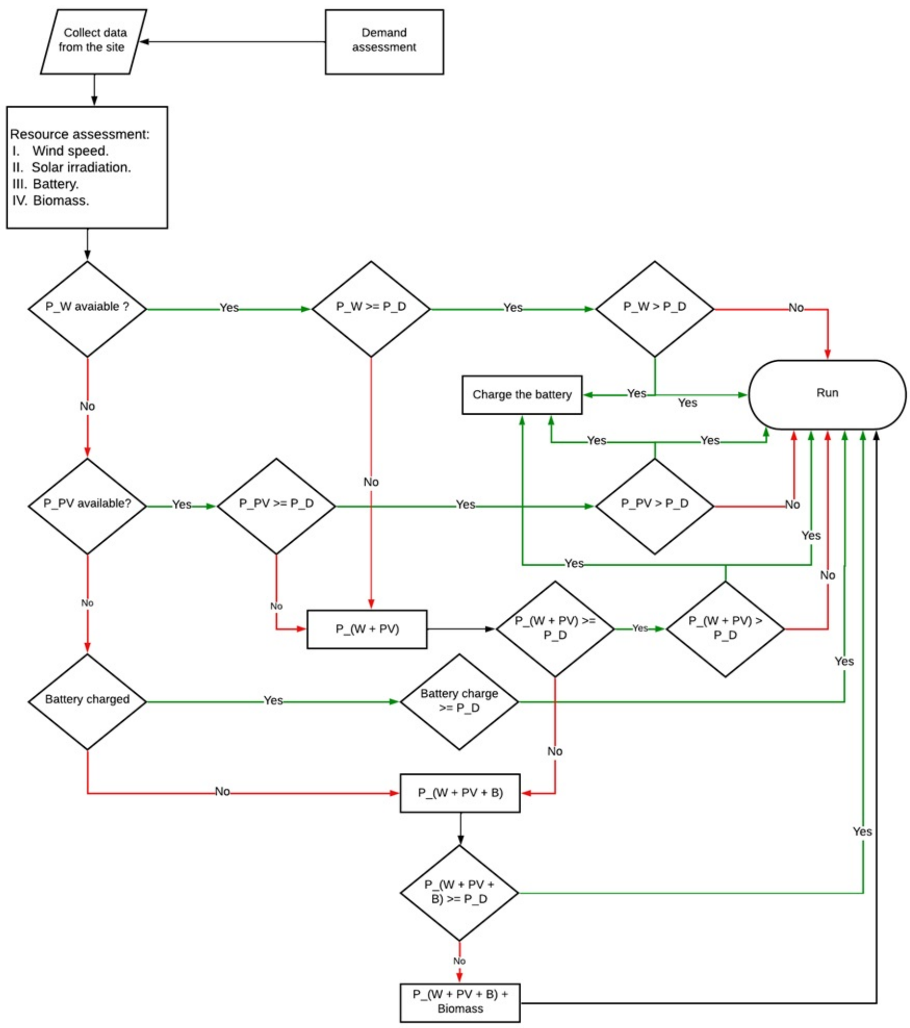


Figure 6.8: The schematic flowchart of the proposed strategy of operation (SOP).

The biomass gasifier produces AC, coupled directly to the AC bus. A battery bank storage system will be included in the HES to store surplus energy when generation exceeds demand and supply power when there is deficit energy. The control system will arrange to meet the sudden demand in the following sequence: When there are enough wind gusts to meet the demand, the wind source will cover the sudden demand.

Solar sources will cover sudden demand when there is enough solar irradiation to meet the demand. If both wind and solar sources can meet the demand, they can be utilized to provide the load needed. When both wind and solar energy sources cannot meet the demand, biomass energy will be applied to meet the demand. Using this control strategy, we minimize the use of biomass energy to generate power. **Figure 6.8** shows the schematic flowchart of the proposed operation strategy.

6.8 Mathematical Modeling of the Components

It is very important to model the system mathematically to size it properly. The system needs to be optimized under different operating conditions.

6.8.1 Mathematical Modeling of the Wind Energy System

The electrical power output of a wind energy system at any instant (t) in kW can be calculated using the following equation:

$$P_W = \begin{cases} 0, & V_{ci} > V(t). \\ \frac{\frac{1}{2} \cdot N_W \cdot C_P \cdot \rho_a \cdot A_W \cdot \eta_g \cdot (V(t))^3}{1000}, & V_{ci} \leq V(t). \\ P_r, & V_r \geq V(t) \\ 0, & V_{co} < V(t) \end{cases} \tag{6.11}$$

where N_W is the number of wind turbines in service, C_P is the power coefficient of the designated wind turbine model, ρ_a is the air density (roughly 1.2 kg/m^3), AW is the swept area of the wind turbine rotor, η_g is the generator efficiency of the wind power system (roughly 90%), P_r is the wind turbine rated power, $V(t)$ is the wind speed in (m/s). and V_{ci}, V_{co}, and V_r are cut-in, cut-out, and rated speeds, respectively.

6.8.2 Mathematical Modeling of the Photovoltaic System

The power output of the solar photovoltaic can be obtained using the following equation:

$$P_{PV}(t) = C_{PV} \times D_{PV} \times \frac{Q_{PV}(t)}{Q_{PV,STC}} \tag{6.12}$$

where C_{PV} denotes the rated capacity of the photovoltaic system under standard test conditions (STC) and panel efficiency of 14%, D_{PV} is a derating factor of the PV array that is used to consider reduced output under real-world conditions like dust, shadow, etc. (80%), $Q_{PV}(t)$ represents solar irradiance incident on PV array in kW/m^2, and $Q_{PV,STC}$ is the solar radiation at STC ($1kW/m^2$).

6.8.3 Mathematical Modeling of the Biomass Gasifier System

The hourly power output obtained from the biomass gasifier system $P_{Bm}(t)$ in kW can be computed using the following equation:

$$P_{Bm}(t) = \frac{Q_{Bm} \times CV_{Bm} \times \eta_{Bm} \times 1000}{365 \times 860 \times H_D} \tag{6.13}$$

where Q_{Bm} is the annual available amount of biomass in (ton/yr), CV_{Bm}, is biomass calorific value in $kcal/kg$, η_{Bm} is the biomass to electricity overall conversion efficiency of the biomass gasifier (20%), and H_D represents the biomass gasifier systems's operating hours per day.

6.8.4 Mathematical modelling of the battery bank storage system

Battery banks are often installed in the wind and PV models. They save energy when they produce surplus energy and supply the network with energy when the system has a deficit. During charging, the battery bank capacity at time (t) can be expressed using the following equation:

$$U_{Bt}(t) = U_{Bt}(t-1) + [(U_{s-AC}(t) \times \eta_{rec} \times \eta_{chg}) + (U_{s-DC}(t) \times \eta_{chg})] \tag{6.14}$$

where $U_{Bt}(t-1)$ is the energy that is stored in the battery bank in (kWh); $U_{s-AC}(t)$ is the energy surplus from the AC source, the biomass gasifier in this case; $U_{s-DC}(t)$ is the energy surplus from the DC source, the PV array, and the wind energy based system after serving the load; η_{rec} is the rectifier efficiency (90%), and η_{chg} is the battery bank charging efficiency (90%).

While discharging, the battery bank capacity at time (t) can be calculated from the following equation:

$$U_{Bt}(t) = U_{Bt}(t-1) + \left[\frac{U_{nl}(t)}{\eta_{inv} \times \eta_{dchg}}\right] \tag{6.15}$$

where $U_{nl}(t)$ is the load net deficit, which RES does not serve; η_{inv} is the inverter efficiency (95%); and η_{dchg} is the battery discharging efficiency (100%).

6.9 Problem Formulation

The problem formulation contains the objective functions and the constraints. The main objective function is to minimize ITAE and the NPC of the hybrid system. The total NPC of the hybrid system represents the present value of all the project costs during its lifetime minus the present value of all the revenue earned over its lifetime. The costs considered here include capital costs, replacement costs, fuel costs, O&M costs, and emissions penalties. The revenues include the biomass gasifier, diesel generator, and salvage values of batteries. If the system is grid-connected, the costs of purchasing electricity from the grid will be added to all project costs, and selling power to the grid will be added to revenue costs.

The total net present cost is calculated using HOMER as follows:

$$C_{NPC} = \frac{C_{yt}}{CRF(i_r, R_P)} \tag{6.16}$$

where C_{NPC} is the total net present cost in USD, C_{yt} is the total annualized cost in USD/year, CRF is the capital recovery factor, i_r is the interest rate in %, and R_p is the project's lifetime in years.

CRF transforms the system components' present value into equal increments of annual payments over the project lifetime and is computed as follows:

$$CRF(i_r, R_P) = \frac{i_r(1+i_r)^{n_{pl}}}{i_r(1+i_r)^{n_{pl}} - 1} \tag{6.17}$$

where i_r is the yearly real interest rate, and n_{pl} is the project lifetime. The yearly real interest rate is the discount rate used to switch between one-time and annualized costs, while the nominal interest rate is a bank loan.

6.9.1 Constraints

The HES can be optimized using the following constraints:

6.9.1.1 Power Reliability Constraints

Equation (6.18) depicts the annual capacity shortage fraction (F_{CS}):

$$F_{CS} = \frac{E_{CS}}{E_D} \tag{6.18}$$

where F_{CS} is the capacity storage fraction, E_{CS} is the total capacity shortage in (kWh/yr), and E_D is the total electrical demand in (kWh/yr).

6.9.1.2 Battery Bank Storage Limits

In any instance (t), the battery bank storage falls into the following constraint:

$$E_{Bt_{min}} \leq E_{Bt}(t) \leq E_{Bt_{max}} \tag{6.19}$$

where $E_{Bt_{min}}$ and $E_{Bt_{max}}$ are the battery bank storage's minimum and maximum capacity, respectively. The following equations represent $E_{Bt_{min}}$ and $E_{Bt_{max}}$:

$$E_{Bt_{min}} = \frac{N_{Bt} \cdot V_{Bt} \cdot S_{Bt}}{1000} \times SC_{min} \tag{6.20}$$

$$E_{Bt_{max}} = \frac{N_{Bt} \cdot V_{Bt} \cdot S_{Bt}}{1000} \times SC_{max} \tag{6.21}$$

where N_{Bt}, V_{Bt}, S_{Bt}, SC_{min}, and SC_{max} are the number of batteries, the battery voltage in (V), the battery capacity in Ampere Hour (AH), the minimum state of charge, and the maximum state of charge, respectively.

6.9.1.3 Lower and Upper Bounds

The wind, solar, and battery bank storage systems are subject to the following constraints:

$$0 \leq P_{PV}(t) \leq say\ (100)\ where\ P_{PV} = Integer \tag{6.22}$$

$$0 \leq P_{WT}(t) \leq say\ (100)\ where\ P_{WT} = Integer \tag{6.23}$$

$$0 \leq P_{Bt}(t) \leq say\ (100)\ where\ P_{Bt} = Integer \tag{6.24}$$

6.9.1.4 Excess Electricity

When the total electricity generation exceeds demand and batteries reach their maximum storage capacity, we are in the excess electricity stage. **Equations (6.25)**, **(6.26)**, and **(6.27)** estimate excess electricity in (kWh/yr):

$$P_{EH} = \begin{cases} P_G(t) - P_D(t), & P_G(t) > P_D(t),\ and\ E_{Bt}(t) = E_{Bt_{max}} \\ 0, & Otherwise \end{cases} \tag{6.25}$$

$$P_G(t) = P_{Bm}(t) + \eta_{inv} \times [P_W(t) + P_{PV}(t)] \tag{6.26}$$

$$E_{EY} = \sum_{t=1}^{8760} P_{EH}(t) \tag{6.27}$$

where $P_{EH}(t)$, $P_G(t)$, $P_D(t)$ and E_{EY} represent the hourly excess power in (kW), the total hourly generation from all applied resources in (kW), the hourly power demand in (kW) and the annualized excess electricity in kWh/yr.

6.9.2 Optimization

Meta-heuristic optimization techniques have become very popular recently. The very well-known ones are Ant Colony Optimization (ACO) [174], GA [175], and PSO [176].

6.9.2.1 Meta-heuristics Classes

Meta-heuristics can be divided into two main classes:

6.9.2.1.1 Single Solution Based: In Simulated Annealing (SA) [177], the search process starts with one candidate solution and then improves over iterations.

6.9.2.1.2 Population Based: They execute the optimization using a set of solutions (population). The search process starts with a random initial population (multiple solutions), which is enhanced over the course of iterations. Swarm Intelligence (SI) is one of the most popular branches of the population-based meta-heuristics. The most popular SI techniques are ACO, Artificial Bee Colony (ABC) [178], and PSO.

6.9.2.2 Meta-heuristics Categories

Meta-heuristics can also be categorized into three main classes:

6.9.2.3 Evolutionary Algorithms (EA):

These algorithms are often inspired by natural concepts of evolution, such as GA and differential evolution (DE) [179].

6.9.2.3.1 Physics Based: They mimic physical rules, such as Gravitational Local Search (GLSA) [180], Charged System Search (CSS) [181], Central Force Optimization (CFO) [182], and the Black Hole (BH) algorithm [183].

6.9.2.3.2 SI Algorithms: They often mimic the social behaviour of swarms, herds, and flocks in nature. Some of the algorithms are PSO, ACO, the ABC and the Bat-inspired Algorithm (BA) [184], and Grey Wolf Optimization (GWO) [185]. According to the No Free Lunch (NFL) theorem, no meta-heuristic can solve all optimization problems. Some algorithms may show promising results on a set of issues, but the same optimization technique may perform poorly on different problems.

This work uses the Hybrid Optimization Model for Electric Renewables (HOMER) Pro Version 3.16.2 software to determine the NPC and the LCOE, and the GA-fuzzy logic self-tuning technique is applied to optimize the ITAE in our AGC model.

6.9.2.4 Algorithms Applied for AGC:

Many heuristic optimization algorithms range from straightforward "trial and error" methods to intricate algorithms like evolutionary algorithms. Both the implementation and use of the techniques are simple. The problem's mathematical formulation is flexible. GA, PS, SA, PSO, and GA-fuzzy logic self-tuning techniques are applied to our model; **Figure 6.9** illustrates the flowchart of our novel hybrid GA-fuzzy logic self-tuning technique.

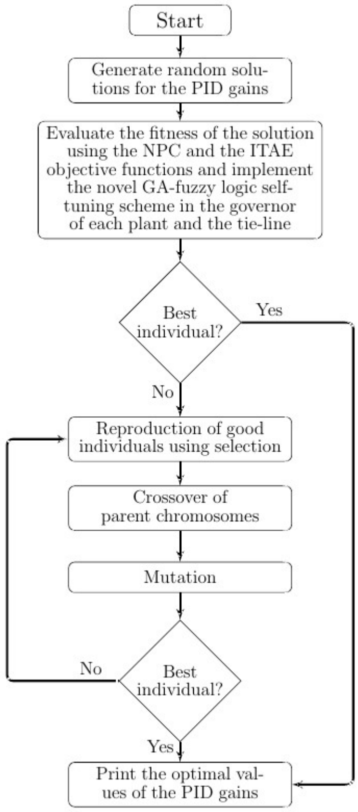


Figure 6.9: The flowchart of the GA-Fuzzy Logic Self-Tuning algorithm.

GA-Fuzzy Logic Self-Tuning Algorithm procedure:

1. Set the values of ω and P_{tl}.
2. Obtain the values of ω and P_{tl}, then calculate $\Delta\omega$ and ΔP_{tl}.
3. Once the values of $\Delta\omega$ and ΔP_{tl} are determined, decide the control action to be made.
4. Send the control actions to all three plants and calculate ITAE using the GA-fuzzy algorithm.
5. Use a fixed-length chromosome to represent the problem variable domain. Select the size of the chromosomal population N, the crossover probability P_c, and the mutation probability P_m.
6. Establish a fitness function to gauge each chromosome's effectiveness within the

issue domain. The fitness function establishes the basis for choosing which chromosomes to mate with during reproduction.

7. Generate a starting population of size N chromosomes randomly $(x_1, x_2, \cdots, \ldots, x_N)$.
8. Determine the fitness value of every single chromosome: $f_{x1}, \cdots, f_{xn}$.
9. Choose a pair of chromosomes from the existing population to mate with. Parent chromosomes are chosen based on fitness-related probability. Fitter chromosomes are more likely to be selected for mating than less suitable ones.
10. Apply the crossover and mutation genetic operators to produce a pair of offspring chromosomes.
11. Insert the progeny chromosomes into the newly formed population.
12. Step 9 should be repeated until the size of the new chromosomal population equals that of the original population, N.
13. Use the new (offspring) chromosomal population in place of the original (parent) population.
14. Repeat from step 8 until the termination creation is fulfilled. Examine whether the solution that satisfies the equality constraint is feasible.

6.10 Testing and Simulation Conditions of GA-Fuzzy Logic Method

The testing and simulation conditions discussed in the results and discussion section below were carefully chosen to reflect realistic operational scenarios, ensure comprehensive evaluation, and validate the proposed GA-fuzzy logic PID controller's performance under diverse and challenging conditions. The rationale for these specific choices is explained as follows:

1. **Sudden 80 MW Load on the Wind Plant**
   - The wind power plant's 80 MW step load was chosen to simulate a realistic sudden load increase in medium-scale renewable energy systems. This value reflects typical demand fluctuations in renewable energy grids, ensuring the system's response to abrupt changes is tested under practical conditions. A larger step, such as 100 MW, was avoided to maintain

alignment with the operational capacity limits of the modelled plant, ensuring stability during testing.

2. **Sudden 30 MW Load on the Biomass Plant**
   - The 30 MW load increment for the biomass plant reflects its role as a supplementary energy source. Due to its slower ramp-up capability compared to wind or solar systems, biomass is often utilized to manage smaller, incremental loads. This load aligns with operational scenarios in hybrid systems where biomass bridges energy gaps caused by the intermittency of wind and solar power.
3. **Sudden Demand Drop in the Photovoltaic Plant**
   - A sudden -40 MW load drop was implemented to mimic scenarios such as cloud cover reducing solar power generation. This test evaluates the system's ability to maintain stability during rapid decreases in generation, a common challenge in photovoltaic systems.

By designing tests and simulation conditions grounded in realistic operational scenarios, the study ensures that its findings are practical and applicable and address the specific challenges of hybrid renewable systems in real-world power grids.

6.11 Results and Discussion

The literature indicates that every optimization technique relies on a fitness function to adjust the PID parameters. Our study utilizes the objective function ITAE (**equation (6.7)**) as the fitness function. It incorporates the frequency changes across all three plants and the frequency variation in tie-line power. In the context of multi-area AGC, the ITAE criterion significantly enhances the system's dynamic performance and response control by optimizing the gains of the PID controller, as demonstrated in the figures below. A multi-area power plant transfer function could be designed similarly to a single-area power plant with the addition of tie-line power flow; see **Figure 6.3**. When no extra load demand occurs on the system, the system frequency will be stable, and all three plants will work parallel at the nominal frequency of 60 Hz. This work tests the system by adding wind, biomass, and solar power plant loads. In this work, the frequency in Hz is measured in the three plants, and the mechanical power flow in MW in all three plants is measured as well, in addition to measuring the tie-line power flow in MW. In the case of any sudden load occurring in any of the three power plants, the system frequency will fluctuate, and the power plant will augment its power generation to meet the increased load demand.

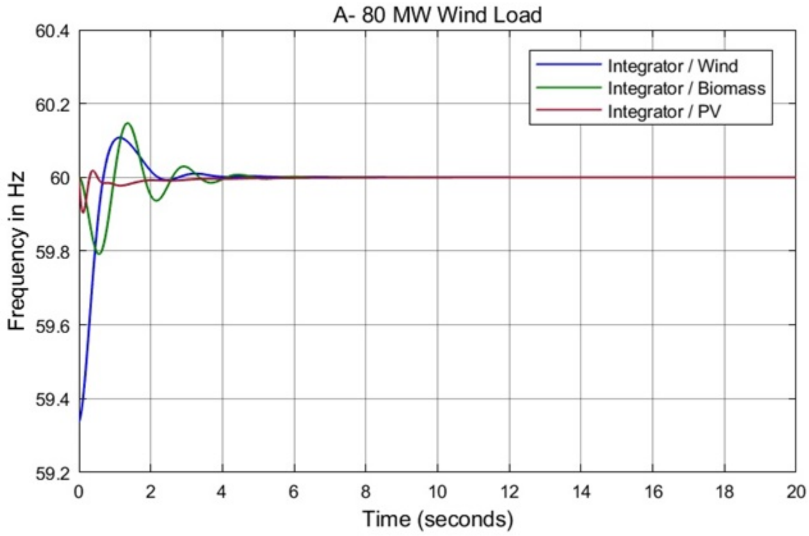


Figure 6.10: Integrator -frequency response - 80 MW wind load.

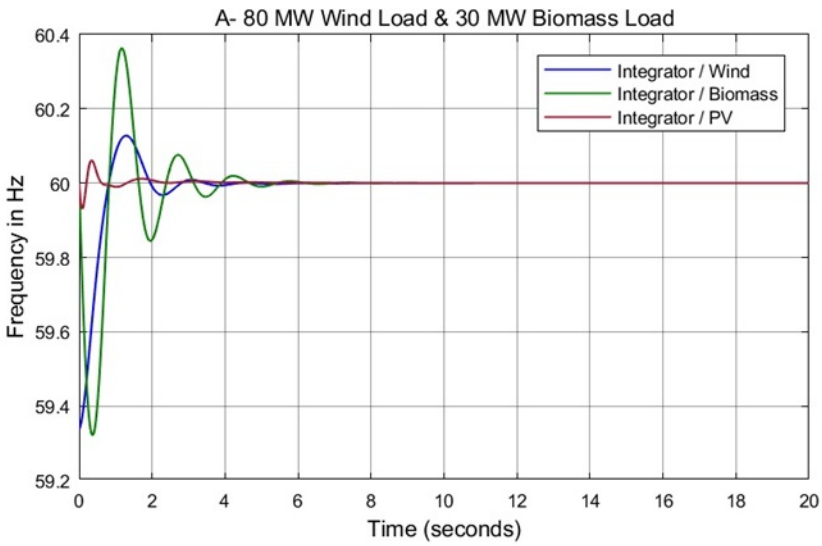


Figure 6.11: Integrator - frequency response - 80 MW wind load & 30 MW biomass load.

If the system is not designed professionally, all three power plants will increase their generation to meet the demand, and the tie-line will provide the power; consequently, the frequency may vary between 59 Hz and 61 Hz, or worse. In practice, when an unexpected demand occurs in a specific plant, that power plant must absorb that demand; the other plants must not sense it, and the tie-line power should have 0 MW power flow.

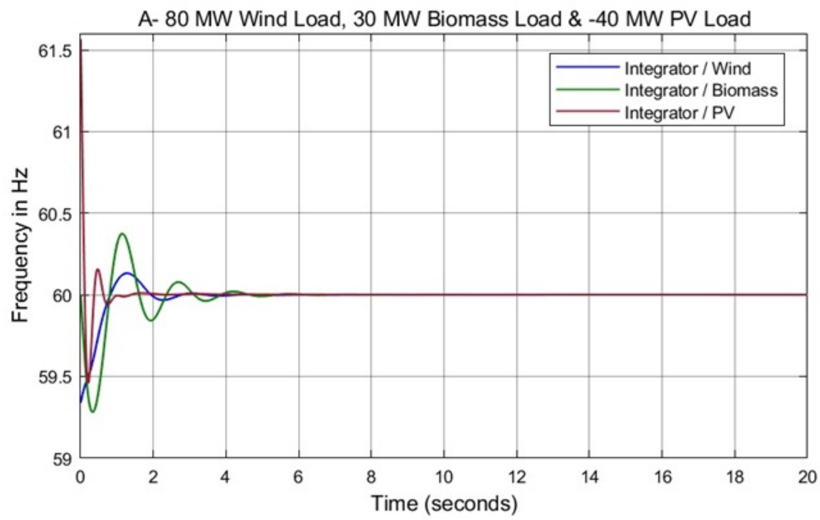


Figure 6.12: Integrator - frequency response - 80 MW wind load, 30 MW biomass load & -40 MW photovoltaic load.

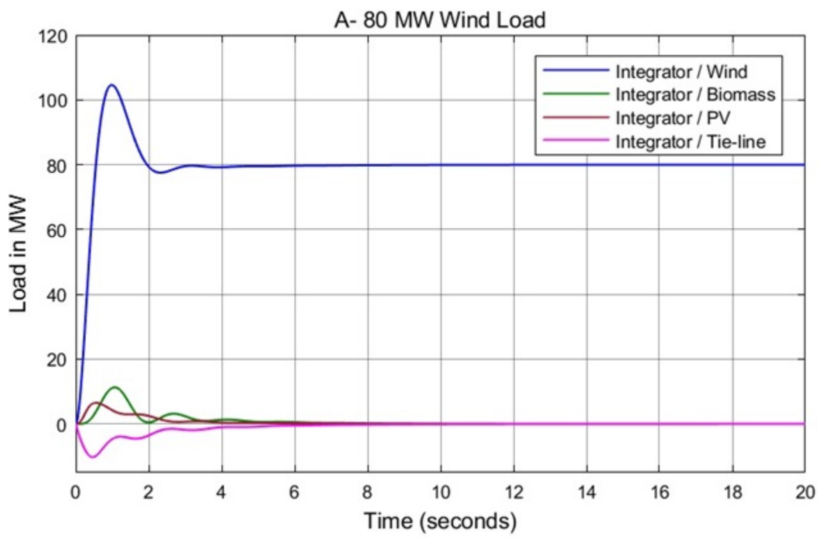


Figure 6.13: Integrator - load response - 80 MW wind load.

To overcome such scenarios, an integrator is added to the model. As can be seen in **Figures 6.10** and **6.13**, when an increment load of 80 MW is added to the wind power plant, the whole load is supplied from that source; the biomass power plant, the photovoltaic power plant, and the tie-line supply 0 MW of load and the frequency is kept steady at 60 Hz.

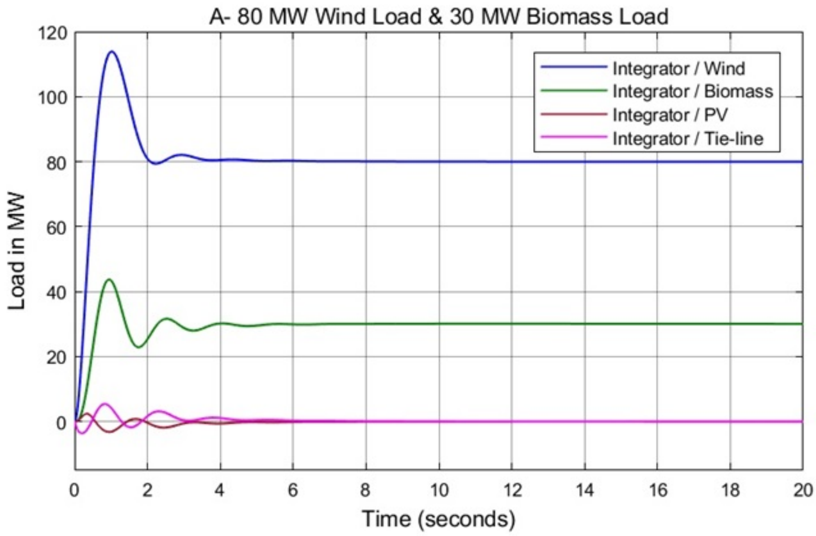


Figure 6.14: Integrator - load response - 80 MW wind load & 30 MW Biomass Load.

When adding another increment load of 30 MW to the biomass power plant in addition to the existing 80 MW load on the wind power plant, the demand is covered by the designated power plants, the photovoltaic power plant, and the tie-line supplied 0MW of load and the frequency is kept steady at 60Hz, see **Figures 6.11** and **6.14**.

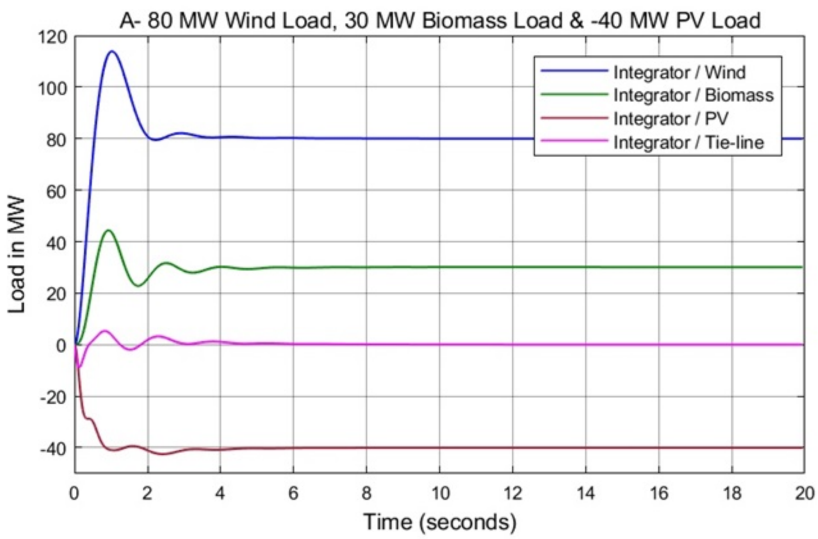


Figure 6.15: Integrator - load response - 80 MW wind load, 30 MW biomass load & -40 MW photovoltaic load

To test the system's functionality, a sudden load decrease of -40 MW is applied to the photovoltaic power plant in addition to the existing 80 MW load on the wind power plant and the 30 MW on the biomass power plant.

The designated power plants cover the demand, the tie-line supplies 0 MW of load, and the frequency is kept steady at 60Hz; see **Figures 6.12** and **6.15**. The desired results are obtained when the integrator is added but with a longer settling time, overshoot, and undershoot, as seen in **Figures 6.10** to **6.15**.

To get better results, the frequency should be steady in minimal time, with less settling time and less overshooting and undershooting; the PID controller should be added in place of the integrator. The PID's parameters could be tuned manually to get good results, but many optimization techniques may promptly give better results. In the proposed model, GA, PS, SA, and PSO are applied to tune the parameters, and then the novel GA-fuzzy logic self-tuning technique is used.

Table 6.2: The PID parameters use different algorithms.

	Parameters	*GA*	*PS*	*SA*	*PSO*	*GA-Fuzzy*
Controller I	P	21.5457	20	19.99679	20	30
	I	17.30914	20	13.25205	15.43407	24.08826
	D	3.633331	14.93847	3.751003	3.970836	4.72576
Controller II	P	21.71193	20	6.856002	18.72205	15.95172
	I	29.9966	20	19.9941	17.68945	30
	D	0.029296	0.228512	0.005082	0	0
Controller III	P	27.93593	20	6.517656	20	29.99936
	I	22.96649	20	19.99775	20	27.68385
	D	3.053391	20	1.268777	8.207062	17.06332
Controller IV	P	21.17271	10.18554	19.71834	17.08208	26.20549
	I	5.398859	0.268551	5.126602	4.375707	5.24566
	D	14.78407	0.251951	12.20899	16.78958	27.84191

Table 6.2 shows the parameters of the P, I, and D; these parameters are obtained by MATLAB software. As is well known, power loads are variable; they fluctuate continuously at every moment. On the contrary, PID controllers have shortcomings in their parameters as they cannot be tuned online to accommodate load changes. As a result, PID controllers cannot deliver the appropriate response for every load fluctuation. This means that some concessions must be taken to test the PID controller's performance in all scenarios with various settings.

In control theory, the overshoot occurs when a signal exceeds its stability target, while undershoot is the opposite. When we applied the integrator, the frequency response went up to 61.5 Hz and down to 59.3 Hz, and it took about 4 seconds until it became stable at 60 Hz. When the frequency is recovered to 60 Hz, the load demand will be covered by the designated generation plants. 1.2 Hz fluctuation is unacceptable from an engineering point of view, and other steps must be taken to improve the frequency and the power output. In the following section, the PID controller is applied instead of the integrator, and the results are compared.

Table 6.3: Comparison values of rise time between the applied algorithms.

	Rise Time					
	Integrator	**GA**	**PS**	**SA**	**PSO**	**GA-Fuzzy**
ΔF_W	0.6383	5.94×10^{-4}	1.64×10^{-4}	2.57×10^{-4}	6.32×10^{-4}	3.75×10^{0}
ΔF_B	1.21×10^{-5}	4.97×10^{-7}	0.0069	6.56×10^{-7}	4.94×10^{-8}	4.14×10^{-2}
ΔF_{PV}	0.0801	5.21×10^{-4}	1.37×10^{-4}	2.44×10^{-4}	5.69×10^{-4}	8.37×10^{-6}
ΔP_{T-line}	2.80×10^{-5}	1.40×10^{-3}	1.91×10^{-4}	1.90×10^{-3}	9.71×10^{-4}	2.00×10^{-3}
ACE_W	0.3718	3.91×10^{-4}	8.59×10^{-5}	4.14×10^{-4}	3.43×10^{-4}	5.48×10^{-5}
ACE_B	3.39×10^{-1}	1.63×10^{-2}	1.65×10^{-2}	3.58×10^{-2}	1.89×10^{-2}	2.50×10^{-3}
ACE_{PV}	0.768	1.11×10^{-0}	1.11×10^{-0}	1.12×10^{-0}	1.11×10^{-0}	3.01×10^{-1}

By using the PID controller and adjusting its P, I, and D gain parameters according to **Table 6.2**, the system becomes stable faster with less overshoot and undershoot, as can be seen in **Tables 6.3** to **6.6** and **Figures 6.16** to **6.21**.

Table 6.4: Comparison values of settling time between the applied algorithms.

	Settling Time					
	Integrator	**GA**	**PS**	**SA**	**PSO**	**GA-Fuzzy**
ΔF_W	2.6067	0.5813	0.7642	0.7443	0.7738	6.3051
ΔF_B	4.389	1.6777	2.4703	1.165	2.3389	3.0165
ΔF_{PV}	0.7863	0.0863	0.0429	0.0937	0.0951	5.5882
ΔP_{T-line}	7.45	5.1307	0.1585	8.9649	4.2436	10.846
ACE_W	3.1814	2.1047	2.0722	2.048	2.1251	6.2576
ACE_B	4.906	0.2603	0.1037	0.489	0.2915	0.0056
ACE_{PV}	2.8787	2.0544	2.0973	2.1189	2.015	3.5384

Because all the algorithms give very similar responses except for the novel GA-fuzzy logic self-tuning algorithm, we are content with demonstrating the frequency and the mechanical load responses when the PID parameters are tuned with the GA algorithm to limit the pages. **Figures 6.16** to **6.18** depict the frequency response when the PID parameters are tuned with the GA algorithm.

Table 6.5: Comparison values of peak overshoot between the applied algorithms.

	Peak Overshoot					
	Integrator	**GA**	**PS**	**SA**	**PSO**	**GA-Fuzzy**
ΔF_W	9.29×10^{-6}	1.35×10^{-7}	2.30×10^{-5}	6.04×10^{-7}	0	
ΔF_B	0.0142	1.22×10^{-4}	3.81×10^{-4}	0.0152	8.65×10^{-6}	0
ΔF_{PV}	0.0341	0.0222	0.0589	0.0357	0.0042	0
ΔP_{T-line}	2.16×10^{3}	1.19×10^{6}	6.79×10^{6}	1.93×10^{6}	1.04×10^{4}	1.05×10^{1}
ACE_W	35.2413	3.57×10^{1}	3.78×10^{1}	35.9763	3.85×10^{-1}	0
ACE_B	53.2843	3.07×10^{1}	3.06×10^{1}	51.2822	1.18×10^{0}	0
ACE_{PV}	0	9.36×10^{-2}	0	0.0048	3.94×10^{0}	0

Table 6.6: Comparison values of peak undershoot between the applied algorithms.

	Peak Undershoot					
	Integrator	**GA**	**PS**	**SA**	**PSO**	**GA-Fuzzy**
ΔF_W	0	2.54×10^{4}	0	0	0	9.29×10^{-6}
ΔF_B	0	0	0	0	0	0.0142
ΔF_{PV}	0	0	0	0	0	0.0341
ΔP_{T-line}	7.71×10^{3}	1.90×10^{5}	7.53×10^{6}	5.2×10^{6}	4.41×10^{4}	2.16×10^{1}
ACE_W	0	0	0	0	0	0.0241
ACE_B	6.2888	2.2179	2.3081	4.0984	1.0004	0.2843
ACE_{PV}	3.7812	1.542	1.9664	5.8355	0	0

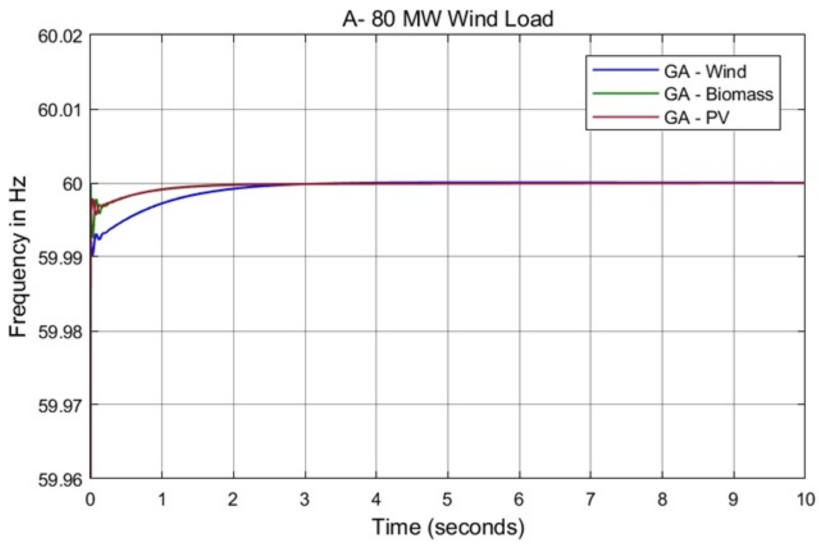


Figure 6.16: GA - frequency response - 80 MW wind load.

As shown in **Figure 6.16**, when the wind power plant experienced a sudden load of

80 MW, it experienced some fluctuation of the frequency between 59.98 Hz and 60.01 Hz. It took about 2.5 seconds until the system became stable. When a sudden 30 MW load occurred in the biomass power plant (**Figure 6.17**) and a decrement -40 MW load in the photovoltaic power plant (**Figure 6.18**), the frequency experienced more fluctuation between 59.96 Hz and 60.02 Hz, and it took about 3 seconds until the system became stable.

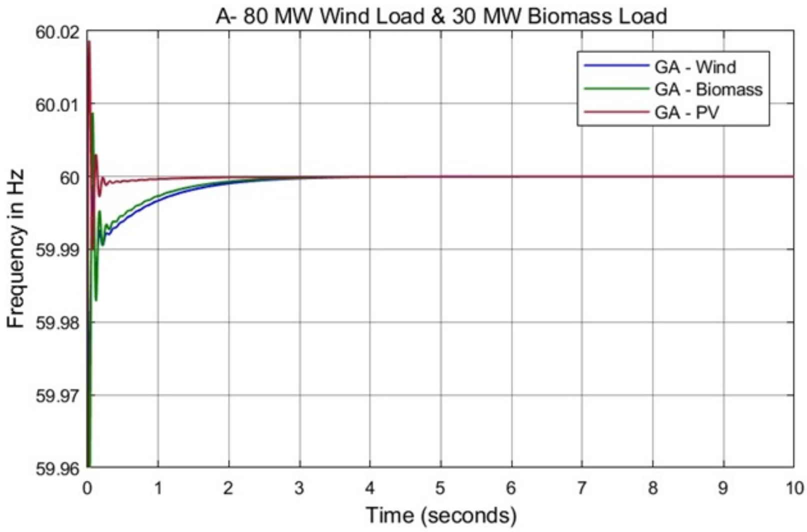


Figure 6.17: GA - frequency response - 80 MW wind load & 30 MW biomass load.

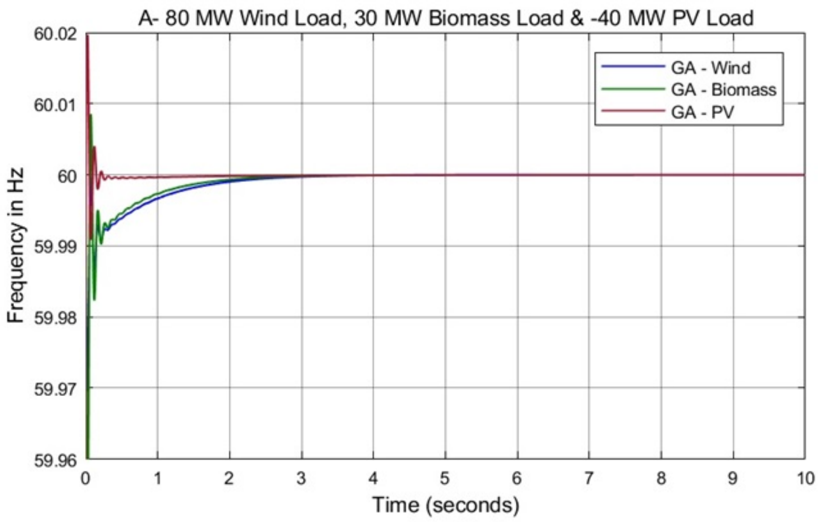


Figure 6.18: GA - frequency response - 80 MW wind load, 30 MW biomass load & -40 MW photovoltaic load.

Figures 6.19 to **6.21** depict the mechanical load response when the PID parameters are tuned with the GA algorithm, as shown in **Figure 6.19**, when the wind power plant experienced a sudden load of 80 MW, and because the frequency was not fixed at 60 Hz, the biomass power plant provided about 105 MW of power to meet the sudden load demand and took about 3 seconds to supply 80 MW of load at 60 Hz frequency.

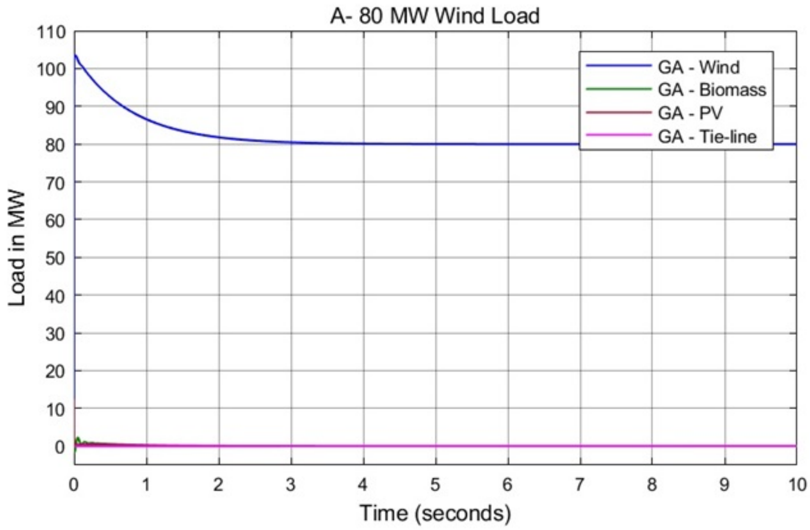


Figure 6.19: GA - load response - 80 MW wind load.

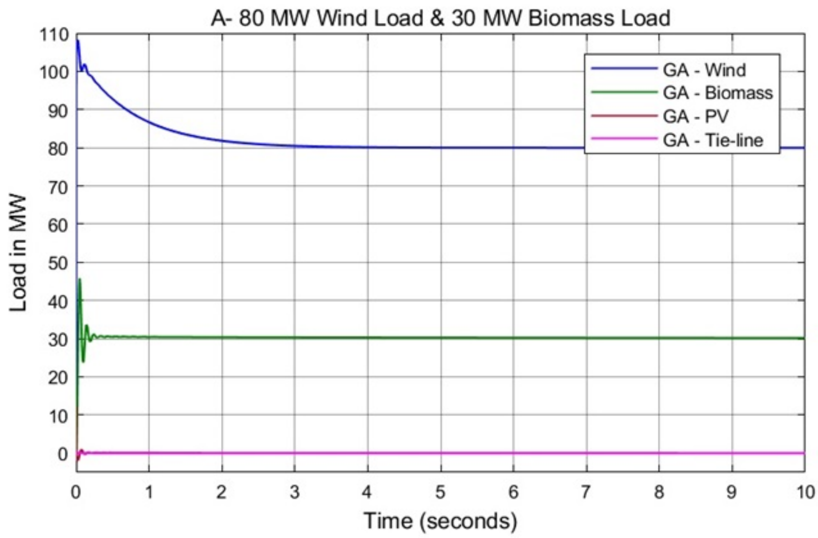


Figure 6.20: GA - load response - 80 MW wind load & 30 MW biomass load.

Adding an increment of 30 MW sudden load (**Figure 6.20**) and a decrement of -40 MW sudden load (**Figure 6.21**) to the biomass power plant and the photovoltaic power plant, respectively, made the system experience some fluctuation for about 3 seconds. Because of the instability in the frequency, the biomass power plant and the photovoltaic power plant provided more than the requested load for about 3 seconds.

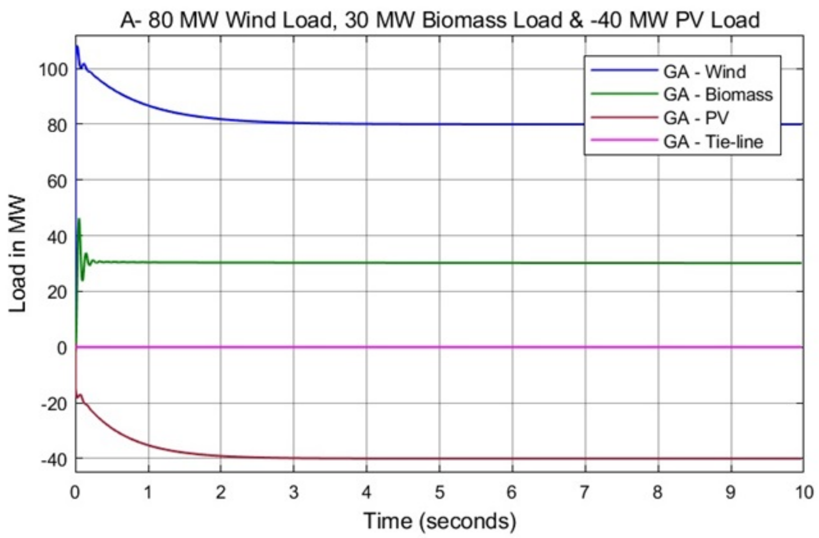


Figure 6.21: GA - load response - 80 MW wind load, 30 MW biomass load & -40 MW photovoltaic load.

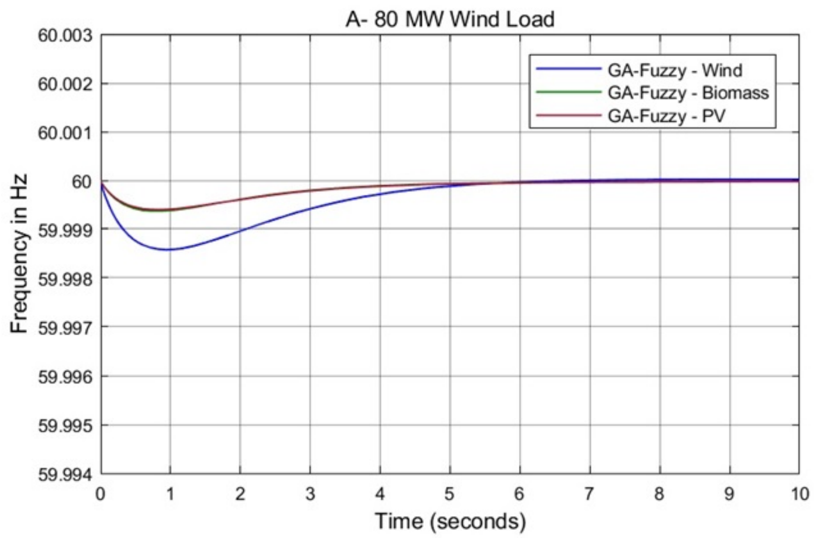


Figure 6.22: GA-Fuzzy Self-Tuning - frequency response - 80 MW wind load.

When the frequency became stable at 60 Hz, all three power plants provided the load needed. PID controllers provide compromised responses for all scenarios. Nevertheless, they may not offer the best solution for every condition. On the other hand, applying the GA-fuzzy logic self-tuning approach, when the rules for each circumstance are established separately, GA-fuzzy logic self-tuning control may offer the optimum response for each case. The best response might be obtained by applying the novel GA-fuzzy logic self-tuning control compared to other methods.

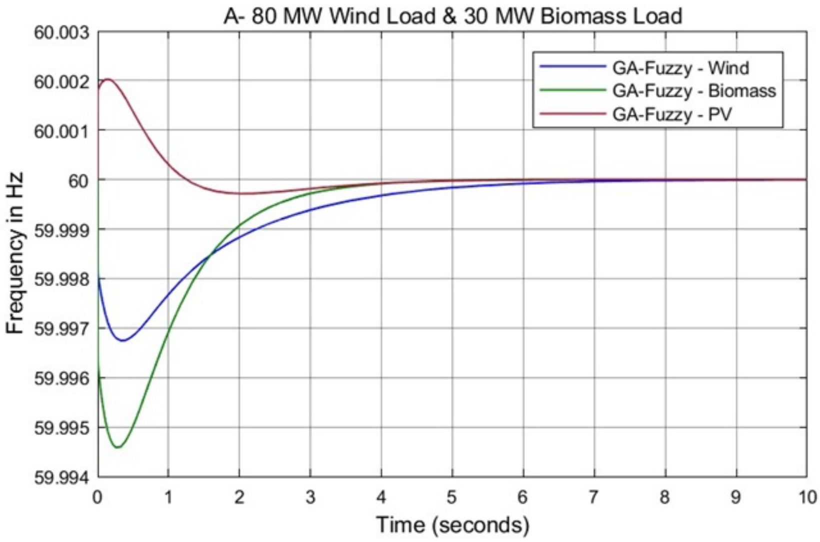


Figure 6.23: GA-Fuzzy Self-Tuning - frequency response - 80 MW wind load & 30 MW biomass load.

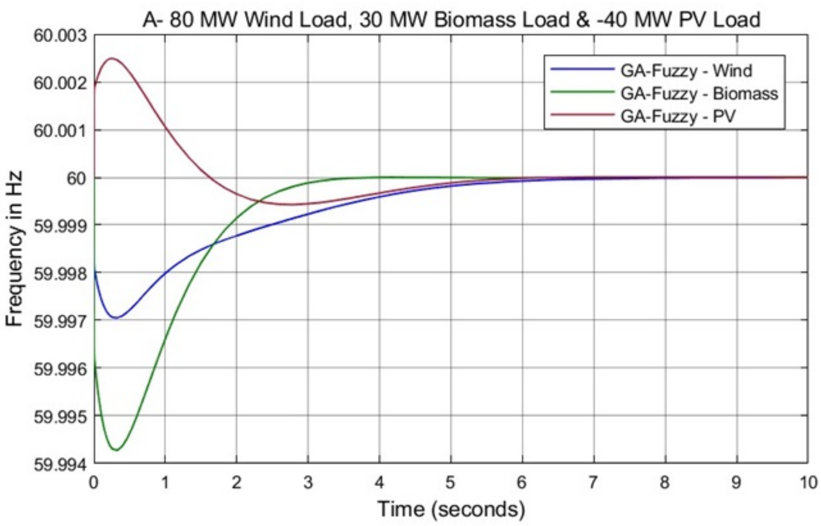


Figure 6.24: GA-Fuzzy Self-Tuning - frequency response -80 MW wind load, 30 MW biomass load & -40 MW photovoltaic load.

Figures 6.22 to **6.24** depict the frequency response when the PID parameters are tuned with the novel GA-fuzzy logic self-tuning algorithm, as shown in **Figure 6.22** when the wind power plant experienced a sudden load of 80 MW, it experienced a very slight change in the frequency between 59.9985 Hz and 60 Hz, which is about 0.0015 Hz difference.

Adding an increment of 30 MW sudden load (**Figure 6.23**) and a decrement of -40 MW sudden load (**Figure 6.24**) to the biomass power plant and the photovoltaic power plant, respectively, made the system again experience very slight change in the frequency between 59.9942 Hz and 60.0025Hz, which is about 0.0083 Hz difference. **Figures 6.25** to **6.27** depict the mechanical load response when the PID parameters are tuned with the novel GA-fuzzy logic self-tuning algorithm, as can be seen in **Figures 6.25** to **6.27**, the system promptly acted on the power demand, which the designated power plants immediately covered.

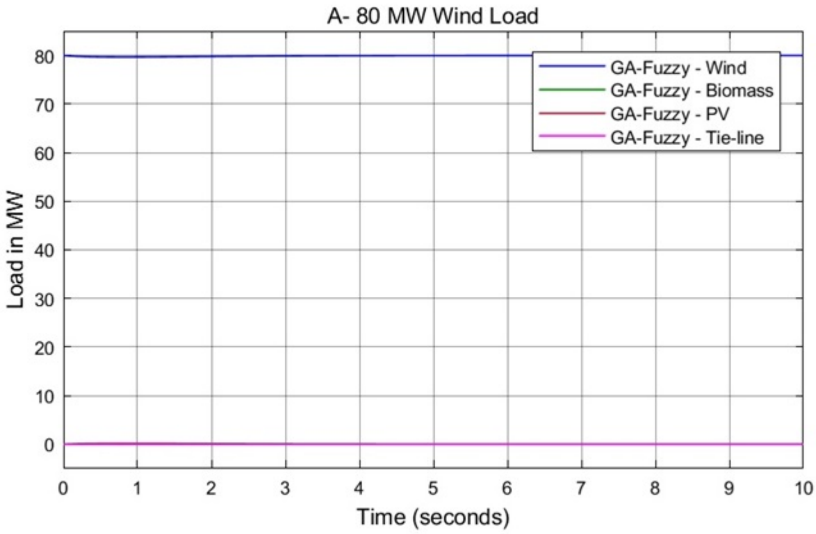


Figure 6.25: GA-Fuzzy Self-Tuning - load response - 80 MW wind load.

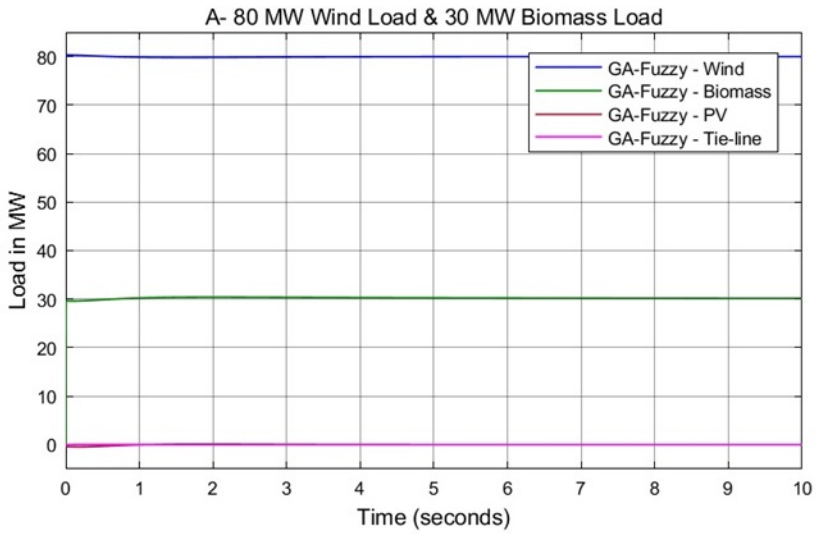


Figure 6.26: GA-Fuzzy Self-Tuning - load response - 80 MW wind load & 30 MW biomass load.

In comparing the results derived from the proposed novel GA-fuzzy logic self-tuning model with some modern heuristic optimization techniques, it is found that this model demonstrates superior frequency response, overshoot, undershoot, and settling time. The proposed GA-fuzzy logic self-tuning algorithm is an effective technique, as the search area is reduced, and the system performance is improved. After the model is checked for being able to meet the sudden demand, it will be programmed to work according to the schematic flowchart of the proposed strategy of operation shown in **Figure 6.8**.

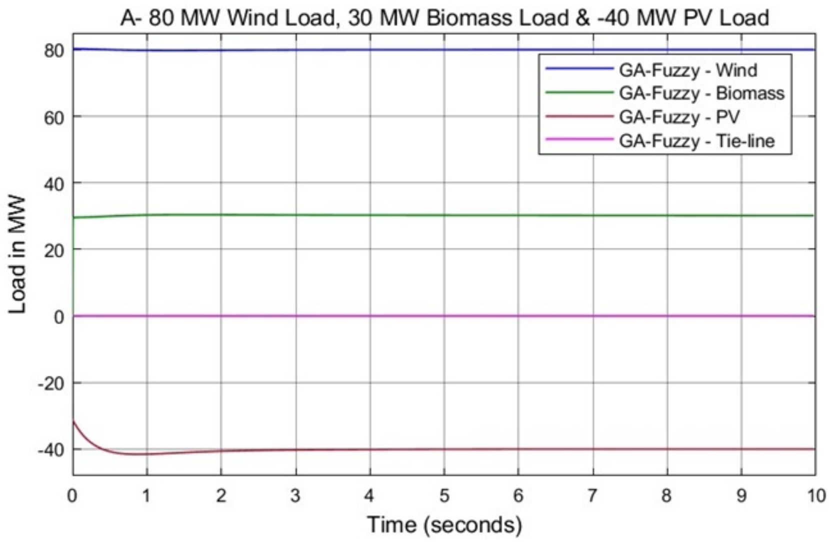


Figure 6.27: GA-Fuzzy Self-Tuning - load response - 80 MW wind load, 30 MW biomass load & -40 MW photovoltaic load.

Even though biomass is considered renewable energy, it emits CO_2 into the atmosphere, so the program is written to lower utilizing it. When there is enough wind speed or solar irradiation to meet the load demand, the wind or solar energy sources will cover the sudden demand. Because wind and solar energies are intermittent, they cannot always cover the demand. So, when there are not enough wind gusts or solar irradiation to meet the demand, the biomass power plant will cover it.

6.12 Comparison with Existing Literature and Justification for the GA-Fuzzy Logic PID Controller

The novel GA-Fuzzy logic PID controller presented in this thesis advances the state of the art in Automatic Generation Control (AGC) systems. Below is a detailed comparison with existing literature and an explanation of why this approach is significant.

Comparison with Literature

1. **Traditional PID Controllers:**
   - **Existing Work:** Conventional PID controllers are widely used in AGC systems due to their simplicity and reliability. However, these controllers often face challenges adapting to diverse and dynamic operational conditions, leading to suboptimal performance in overshoot, undershoot, and settling time.
   - **Thesis Contribution:** The GA-Fuzzy logic PID controller addresses these limitations by dynamically adjusting PID parameters, enabling superior performance across varying scenarios.
2. **Heuristic-Based Optimization Techniques**
   - **Existing Work:** Methods like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) have been employed to optimize PID controller parameters. These techniques improve performance but often struggle with local optima, require significant computation, and are less responsive to sudden changes in system dynamics..
   - **Thesis Contribution:** The integration of GA and fuzzy logic in this thesis combines the global search capability of GA with the adaptability of fuzzy logic, offering a more efficient and responsive optimization framework. Compared to standalone GA or PSO, the proposed method reduces computation time and enhances tuning accuracy..
3. **Fuzzy Logic Controllers**
   - **Existing Work:** Fuzzy logic controllers excel in handling uncertainty and nonlinearities but may lack precision in parameter tuning without additional optimization mechanisms.
   - **Thesis Contribution:** By incorporating fuzzy logic into the GA framework, the thesis leverages the strengths of both approaches, achieving precise and adaptive tuning of PID parameters..

4. **Hybrid Renewable Energy AGC Systems**
   - **Existing Work:** Most studies focus on integrating wind, solar, and traditional energy sources into AGC systems using standard or heuristic-optimized controllers. Biomass energy is rarely included in these models.
   - **Thesis Contribution:** This work uniquely incorporates biomass alongside wind and solar energy into AGC operations, demonstrating the feasibility of balancing multiple renewable sources. The proposed GA-Fuzzy Logic Self-Tuning PID Controller effectively manages the unique dynamics introduced by biomass energy.

Why GA-Fuzzy Logic Self-Tuning PID Controller?

1. **Dynamic Adaptability:**
   - The GA-Fuzzy logic approach dynamically adjusts PID parameters in response to system changes, ensuring robust performance under varying load conditions. Traditional PID controllers lack this adaptability, often requiring manual retuning.
2. **Improved System Response:**
   - Results from the thesis show significant improvements in settling time, overshoot, and undershoot compared to traditional PID controllers and heuristic-based optimization methods (GA, PSO, SA).
   - For example, under a sudden 80 MW load on a wind plant, the proposed method quickly stabilizes the system, maintaining frequency and load balance more effectively than existing methods.
3. **Robustness to Nonlinearities:**
   - Renewable energy sources introduce nonlinearities and intermittencies into AGC systems. The fuzzy logic component manages these complexities, making the system more resilient to wind, solar, and biomass energy supply fluctuations.
4. **Efficient Search and Tuning:**
   - The GA component efficiently searches for optimal parameters, while fuzzy logic refines the solution space, minimizing computational overhead and ensuring precise tuning.

5. **Comprehensive Validation:**
    - The proposed controller was validated under diverse operational scenarios, including load changes and demand drops across multiple renewable energy sources. These tests demonstrated its robustness and reliability, outperforming methods cited in the literature.

6.13 Conclusion and Future Work

6.13.1 Conclusion

In this work, the PID controller's parameters are tuned using different heuristic-based optimization techniques and the proposed novel GA-fuzzy logic self-tuning technique to control the frequency and the mechanical load of a multi-area renewable energy system. The proposed method has effectively minimized the search area and improved the system's accuracy, as seen in **Figures 6.22** to **6.27**.

The novelty of this work is adding biomass energy to the study of the AGC and the proposed hybrid GA-fuzzy self-tuning technique. The program was written to lower the use of biomass in the presence of wind and solar energy sources. The system is tested by adding a sudden 80 MW load to the wind power plant and checking the frequency and the mechanical load responses. Then, added another 30 MW sudden load to the biomass power plant and checked the frequency and mechanical load responses. After checking the system with increased sudden demands, a sudden decline in the demand was applied to the photovoltaic power plant.

Good results are obtained when the integrator is applied as a controller. Heuristic-based optimization techniques, namely GA, PS, SA, and PSO, gave better settling time, overshoot, and undershoot results. From the literature, it is found that PID controllers are limited by parameter tuning and cannot modify all their parameters at once for every situation. As a result, the PID controller offers a system response that is either compromised or sufficient. It falls short of providing the optimal reaction for all operational settings. The novel GA-fuzzy logic self-tuning algorithm has been applied to tune the PID parameters to overcome such disadvantages and obtain optimum results. **Figures 6.22** to **6.27** show that the novel

GA-fuzzy logic self-tuning algorithm provided optimum settling time, overshoot, and undershoot results.

By comparing the novel GA-fuzzy logic self-tuning algorithm with the other heuristic-based optimization techniques applied, we conclude that the proposed model offers the optimum response for all operational conditions. Applying renewable energy sources in place of conventional energy sources helps meet the 2050 commitment of lowering the carbon footprint or zero carbon emissions. A strategy of operation is introduced to specify which energy source would be applied at any instance.

Overall, the GA-Fuzzy logic PID controller represents a significant advancement over existing AGC strategies in the literature. Integrating the strengths of GA and fuzzy logic offers a robust, adaptable, and efficient solution for managing frequency and load in multi-area renewable energy systems. This contribution is particularly relevant for systems incorporating diverse energy sources, including underutilized biomass, enhancing the potential for sustainable and resilient energy management.

6.13.2 Future Work

In summary, no singular Automatic Generation Control (AGC) methodology adequately addresses the multifaceted challenges presented by hybrid power systems. Instead, hybrid or integrated approaches, such as Genetic Algorithm-Fuzzy Logic (GA-Fuzzy Logic) controllers or Artificial Neural Network (ANN)-enhanced Model Predictive Control (MPC), leverage the advantages of various methodologies to enhance scalability, adaptability, and overall system stability. Future research endeavours should prioritize developing robust, computationally efficient, and adaptive AGC strategies specifically tailored to accommodate the distinctive dynamics of hybrid power systems characterized by high renewable energy penetration.

As an extension of the proposed work, the following steps will be considered:

- A novel hybrid multi-objective optimization technique will be developed to incorporate additional constraints. The plan includes creating an application for management and optimization purposes to reduce energy costs and carbon footprints while improving system performance. Future efforts will also consider load seasonality and geographic variations, which could significantly enhance wind speed accuracy and solar irradiance predictions.

- Most analyses and validations typically focus on historical data related to meteorological conditions, wind speed, and solar irradiance tied to specific geographical locations. Future work will involve utilizing real-time data from nearby stations. This approach could lead to a more sophisticated strategy for designing a dynamic energy management platform that compares real-world and forecasted data.

Chapter 7

Conclusion and Future Work

7.1 Conclusion and Future Work

7.1.1 Conclusion

This thesis makes several pioneering contributions to the field of renewable energy, specifically focusing on integrating and optimizing hybrid renewable energy systems in Libya and similar regions. The main achievements of the research are summarized below, highlighting the unique contributions made to both the academic field and the practical implementation of renewable energy technologies.

1. **Feasibility and Optimization of Hybrid Renewable Energy Systems for Sabratha, Libya (Chapter 3)**
   By applying HOMER Pro software, this research demonstrates the technical and economic feasibility of generating clean energy for a convention center in Sabratha, Libya. The study identifies and ranks five distinct hybrid configurations based on Net Present Cost (NPC), providing valuable insights into Libya's most cost-effective and sustainable solutions for powering high-demand buildings. This chapter contributes to understanding the trade-offs between cost-effectiveness, emissions reduction, and the reliability of renewable energy systems in a Libyan context, highlighting the importance of balancing these factors when selecting an optimal configuration. The findings emphasize the potential for wind and solar energy to power large infrastructure projects, even in regions with intermittent power supply.
2. **Decision-Making Frameworks for Renewable Energy Integration (Chapter 4)**

Chapter 4 offers a robust, multi-dimensional approach to renewable energy integration by applying four Multi-Criteria Decision Analysis (MCDA) techniques. This analysis confirms that hybrid wind and solar systems are the most effective solution for Libya's growing energy needs, ensuring that power is available while minimizing emissions. The chapter also identifies the most effective MCDA methods (VIKOR and COPRAS), demonstrating their applicability in practical energy planning scenarios. These findings contribute significantly to the field of energy policy by providing a flexible, data-driven framework for energy planners, particularly in developing regions with abundant renewable resources, such as Libya. Incorporating biomass as a supplementary resource addresses the intermittency of solar and wind power, further enhancing the grid's resilience.

3. **Optimization of Energy Scheduling with Biomass Integration (Chapter 5)**
   The ELED method, introduced in Chapter 5, optimizes the scheduling of generating units to minimize emissions and operational costs, demonstrating how biomass can complement renewable energy sources like wind and solar in an IEEE 30-bus test system. This chapter provides a groundbreaking approach to energy management, mainly through the Modified AntLion Optimization algorithm (MALO), which outperforms others in reducing fuel costs and power losses. This work contributes to optimizing power generation in systems with mixed energy sources, providing new strategies for integrating biomass into existing grids to enhance efficiency and minimize environmental impact. The study's findings are pivotal for further developing smart grid technologies and efficient energy management systems in areas with diverse energy resources.
4. **Innovative Control System for Multi-Area Renewable Energy Systems (Chapter 6)**
   A significant contribution of this thesis is the introduction of a novel GA-fuzzy logic self-tuning technique for optimizing PID controller parameters in multi-area renewable energy systems. This innovative method improves the stability and response of the system under varying load conditions and power fluctuations, outperforming traditional control strategies. By dynamically adjusting PID parameters, the system can handle diverse operational scenarios

more effectively, ensuring optimal frequency and mechanical load management. This work provides an important advancement in control theory and renewable energy integration, addressing the limitations of conventional PID controllers and making the system more adaptable to real-world challenges.

7.1.2 Validation of the Work

The thesis employed rigorous validation approaches to ensure its findings' reliability and practical relevance across various chapters. Below is an account of how the work was validated:

7.1.2.1 Validation in Chapter 3: Renewable Energy Configurations

1. **HOMER Pro Simulations:**
   - The renewable energy configurations for powering a convention center in Sabratha, Libya, were simulated using HOMER Pro, a widely recognized software for energy system modelling.
   - Results included rankings based on total Net Present Cost (NPC) and emissions, providing a detailed trade-off analysis between cost-effectiveness and environmental sustainability.
   - HOMER Pro's optimization and sensitivity analysis capabilities validated each configuration's technical and economic feasibility under various scenarios, ensuring robust decision-making.

7.1.2.2 Validation in Chapter 4: Multi-Criteria Decision-Making (MCDM) Techniques

1. **Cross-validation with HOMER Pro:**
   - The results from four MCDM techniques (VIKOR, COPRAS, TOPSIS, and SAW) were compared against HOMER Pro's simulation outcomes.
   - This cross-validation ensured that the theoretical rankings generated by MCDM methods were consistent with practical, real-world scenarios modelled in HOMER Pro.
2. **Consistency Across Techniques:**

- Although the methods varied in mathematical formulation, VIKOR and COPRAS strongly aligned with HOMER Pro's practical results, further validating their effectiveness in renewable energy decision-making.

7.1.2.3 Validation in Chapter 5: Emission and Load Economic Dispatch (ELED)

1. **IEEE 30-Bus System Testing:**
   - The ELED method was tested on the IEEE 30-bus power system, a standard testbed in power systems research.
   - This ensured the method's applicability to real-world grid scenarios involving multiple generating units.
2. **Algorithmic Benchmarking:**
   - Four algorithms—MALO, SA, BAT, and QPEICC—were applied to optimize fuel costs, power losses, and emissions. The superior performance of MALO, in terms of reduced costs and losses, validated its practical efficiency.
3. **Sensitivity Analysis:**
   - Biomass integration was tested at varying levels, with results indicating an optimal ratio of 350 MW (50% of total fuel used) for minimizing emissions and costs while maintaining system performance.

7.1.2.4 Validation in Chapter 6: GA-Fuzzy Logic for AGC

1. **Comparative Performance Testing:**
   - The novel GA-fuzzy logic self-tuning technique was benchmarked against traditional PID controllers and heuristic optimization methods such as GA, PS, SA, and PSO.
   - Metrics, including settling time, overshoot, and undershoot, demonstrated the superior adaptability and accuracy of the proposed approach.
2. **Scenario Testing:**
   - The system was validated under varying operational conditions, including sudden 80 MW and 30 MW load changes on wind and biomass plants and a demand drop at a photovoltaic plant.

   - The GA-fuzzy logic technique effectively managed these disturbances, maintaining stability and performance.
3. **Experimental Validation:**
   - The method's effectiveness in tuning PID parameters dynamically was validated through multiple test scenarios, demonstrating its robustness across diverse renewable energy environments.

7.1.2.5 Overall Validation Approach

1. **Software Simulations:**
   - HOMER Pro and MATLAB simulations were critical tools for validating renewable energy configurations' technical and economic feasibility and optimization techniques.
2. **Comparative Analysis:**
   - Benchmarking against established methods (e.g., traditional PID, heuristic algorithms) provided clear evidence of the advantages of the proposed methods.
3. **Scenario-Based Testing:**
   - Testing under diverse and challenging operational conditions ensured the solutions were optimal, adaptable, and reliable.
4. **Sensitivity Analysis:**
   - Examining performance across varying conditions, such as biomass integration levels and sudden load changes, added robustness to the validation process.

By employing these comprehensive validation strategies, the thesis ensured its findings were scientifically sound, practically relevant, and aligned with the real-world challenges of integrating renewable energy systems.

7.1.3 Future Work

This thesis significantly advances renewable energy research by offering practical and innovative solutions to the challenges of integrating hybrid energy systems, particularly in regions with high renewable energy potential. It provides a solid foundation for future studies in energy system optimization, renewable resource management, and smart grid technologies. Future research can build upon this work by:

1. **Expanding Optimization Algorithms**
   The algorithms presented in this thesis could be enhanced to integrate additional renewable energy sources such as tidal and geothermal energy. Incorporating these resources would broaden the applicability of the optimization models, offering more comprehensive solutions for diverse geographical contexts.
2. **Scalability for National Grid Integration**
   Future studies should explore the scalability of hybrid systems for integration into national grids. This would involve addressing technical challenges like frequency regulation, load balancing, and grid stability, ensuring reliable operation at larger scales.
3. **Development of a Hybrid Multi-Objective Optimization Framework**
   A proposed direction includes designing a novel hybrid multi-objective optimization technique to optimize the integration of biomass, wind, and solar energy sources. This approach would account for additional constraints such as battery degradation, greenhouse gas emission ratios, and real-time energy demand. Key features of this optimization framework include:
   - Reducing energy costs and carbon footprints.
   - Minimizing battery area requirements.
   - Ensuring consistent energy supply during periods of low solar irradiation or wind speeds.
4. **Real-Time Energy Management Application:**
   An advanced application could be developed to manage and optimize energy systems dynamically. The application would adjust energy generation and consumption by utilizing real-time weather forecasts and predictive analytics, enhancing overall system performance and adaptability.
5. **Integration of Smart Grid Technologies:**
   A smart grid network design could efficiently manage electricity distribution by processing real-time signals through advanced decision-making tools such as

machine learning and predictive analytics. A data acquisition system would collect and analyze live data, enabling operators to forecast optimal renewable energy sources to meet fluctuating load demands.

6. **Incorporating Geographic and Seasonal Variations**
   Future research could incorporate geographic and seasonal variations in energy modelling. Utilizing real-time meteorological data from nearby stations, alongside historical data, could improve the accuracy of wind speed and solar irradiance predictions. This would enable the creation of a dynamic energy management platform capable of adapting to changing conditions and enhancing prediction reliability.
7. **Policy Implications for Developing Regions**
   This research lays a foundation for policymaking, especially in Libya and other developing regions. By leveraging the proposed methods, policymakers can formulate strategies to integrate renewable energy systems into their economies, fostering sustainable growth and environmental conservation.

In conclusion, this thesis advances the academic field by introducing innovative modelling techniques, decision-making tools, and optimization strategies for renewable energy systems. These contributions address existing challenges and pave the way for achieving some Libyan and global sustainable energy goals. By adopting the outlined future directions, researchers and practitioners can further enhance renewable energy integration, creating a cleaner and more resilient energy future.

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Appendix A: AGC Model Parameters

The parameters for the proposed AGC of the model that are depicted in **figure 6.3** are as follows:

The data for the wind power plant: $B_1 = 18$, $R_1 = 2.5$, $\alpha = 0.041$, $\beta = 0.2$, $\gamma = 0.75$, and $\delta = 1.3$

The data for the biomass power plant: $B_2 = 18$, $R_2 = 2.5$, $\in= 0.08$, $\zeta = 0.7$, $\eta = 10.06$, $k = 10.2$, and $\lambda = 0.3$

The data for the photovoltaic power plant: $B_3 = 18$, $R_3 = 2.5$, $\mu = 0.05$, $\nu = 0.02$, $\sigma = 0.6$, $\xi = 0.23$, and $\psi = 0.2$.

Appendix B: Specific Contributions and Challenges Related to MDCM and AGC

Multi-Criteria Decision-Making (MDCM) Outcomes and Contributions

- **Innovative Use of MDCM Techniques:** This research employs four distinct MDCM methods (VIKOR, COPRAS, TOPSIS, and SAW) to evaluate and rank renewable energy systems for grid integration in Libya. These methods provide robust decision-making frameworks incorporating multiple criteria, such as cost, emissions, and resource availability.
- **Validation through HOMER Pro:** By validating the MDCM results with HOMER Pro simulations, the research bridges the gap between theoretical evaluation techniques and practical modelling tools. This integration ensures that the MDCM rankings align with real-world feasibility.
- **Key Findings:** Across all methods, a hybrid wind and solar energy system emerges as the optimal solution, followed by a solar farm. Biomass is consistently ranked lowest in isolation but is highlighted as a practical backup resource to mitigate the intermittency of wind and solar power.
- **Policy Implications:** The work underscores the importance of diversified energy portfolios and provides a comprehensive framework for energy planners to prioritize sustainable energy sources based on local resource potential and policy objectives.
- **Challenges in MDCM:** A key challenge was reconciling discrepancies between different MDCM techniques due to variations in their mathematical formulations. To address this, the study emphasized methods like VIKOR and COPRAS, which produced results closely aligned with HOMER Pro's practical modelling scenarios.

Automatic Generation Control (AGC) Outcomes and Contributions

- **GA-Fuzzy Logic Self-Tuning Technique:** Chapter 6 introduces a novel self-tuning approach combining Genetic Algorithms (GA) with fuzzy logic to optimize PID controllers in multi-area renewable energy systems. This innovation significantly enhances AGC performance by dynamically adjusting PID parameters in response to changing operational conditions.
- **Enhanced System Stability and Response:** The proposed method delivers superior performance in terms of settling time, overshoot, and undershoot compared to traditional PID controllers and heuristic methods (e.g., GA, PSO, and SA). This improvement is critical for maintaining frequency and mechanical load stability in renewable-dominated grids.
- **Incorporation of Biomass in AGC Operations:** Integrating biomass alongside wind and solar resources demonstrates the potential for hybrid renewable systems to ensure grid stability under variable conditions. Scenarios tested include sudden load changes and demand drops, with the system effectively handling these disturbances.
- **Challenges in AGC Development:**
  - **Complexity in Tuning:** One of the significant challenges was ensuring that the GA-fuzzy logic method performed reliably across diverse operational scenarios without excessive computational overhead. This was addressed by minimizing the search area and focusing on practical constraints.
  - **System Adaptability:** The inherent variability of renewable energy sources posed difficulties in maintaining system adaptability. The proposed method successfully addressed this issue by incorporating predictive and adaptive capabilities into the control framework.

Key Outcomes Related to the Work

1. **MCDM:**
   - Demonstrated the practical application of decision-making frameworks to rank renewable energy systems for grid integration.
   - Validated the rankings through realistic simulations, aligning theoretical evaluations with practical feasibility.
   - Highlighted the complementary role of biomass in hybrid systems, ensuring reliability in intermittent energy landscapes.

2. **AGC:**
    - Delivered a significant advancement in AGC for renewable energy systems through a novel GA-fuzzy logic optimization technique.
    - Improved grid stability and response under variable renewable energy conditions.
    - Demonstrated the feasibility of integrating biomass into AGC operations to enhance hybrid system performance.

Broader Challenges and Future Directions: The challenges encountered in MDCM and AGC highlight the complexity of integrating diverse renewable energy sources into power systems. Future work could address these challenges by:

- Expanding the MCDM framework to include additional criteria such as social acceptance and regulatory barriers.
- Enhancing AGC techniques by incorporating advanced machine learning algorithms for real-time adaptability.
- Testing the proposed methods on larger, more complex grid systems to assess scalability and robustness.

By tackling these challenges, the research contributes to the global pursuit of sustainable and reliable renewable energy systems, directly supporting advancements in energy management, policy development, and grid optimization.

Appendix C: Sensitivity Analysis for System Design Robustness

A sensitivity analysis is crucial to assess the robustness of renewable energy system designs under varying economic and environmental scenarios. Chapters 3 through 6 of this study provide a comprehensive exploration of system configurations and optimization techniques, offering a foundation for evaluating the impact of fluctuating conditions on performance metrics such as cost, emissions, and system stability.

Economic Sensitivity

Chapter 3 used HOMER Pro software to identify the optimal configurations for powering a convention center in Sabratha, Libya. The analysis ranked systems based on total Net Present Cost (NPC), but trade-offs were highlighted between cost-effectiveness and pollutant emissions. A sensitivity analysis could extend this work by incorporating variables like fuel price volatility, capital cost fluctuations, and government subsidies. For instance, changes in diesel prices or incentives for renewable installations might alter the economic viability of configurations like the wind/diesel generator/battery model or the solar/wind/diesel generator system.

Environmental Sensitivity

Chapter 4 demonstrates the integration of MCDA techniques to rank renewable energy options, emphasizing hybrid systems that leverage Libya's solar and wind potential. Sensitivity analysis could examine the impact of changing environmental conditions, such as variations in solar irradiance, wind speeds, or biomass availability. These factors directly influence the feasibility and ranking of hybrid systems and could help determine their resilience under less favourable climatic conditions.

Technological Sensitivity

In Chapter 5, the ELED method was applied to integrate biomass energy into a thermal power plant system, optimizing emissions and costs. Sensitivity analysis could address the influence of technological advancements or degradation rates in renewable energy systems, such as improving biomass combustion efficiency or PV panel performance over time. This would help identify the thresholds at which biomass integration remains beneficial and economically viable.

Control System Adaptability

Chapter 6 introduces the GA-fuzzy logic self-tuning technique for optimizing PID controllers in a hybrid energy system. Sensitivity analysis could evaluate the controller's adaptability to increased renewable penetration, unexpected demand spikes, or prolonged low-resource conditions (e.g., cloudy or windless periods). Testing these variations would ensure the controller maintains system stability and minimizes overshoot or undershoot across diverse operational conditions.

Future Directions

Future sensitivity analyses could combine these factors, creating a multi-dimensional evaluation of system robustness. This approach ensures designs can withstand the dynamic and unpredictable nature of energy markets and environmental changes while optimizing cost, emissions, and reliability. Integrating real-world data and AI-driven forecasting methods can enhance predictive accuracy, guiding policymakers and stakeholders in making resilient and sustainable energy choices.

Appendix D: Implications for Energy Policy and System Design in Developing Regions

The findings across Chapters 3 to 6 underscore the potential of renewable energy systems to address the unique challenges of energy access, sustainability, and economic development in regions like Libya and similar developing countries. These insights have significant implications for energy policy and system design in these contexts, as follows:

1. **Prioritizing Hybrid Renewable Energy Systems**
   The study consistently highlights the superiority of hybrid renewable energy configurations, particularly those combining wind and solar power, regarding cost-effectiveness, reliability, and emissions reduction. These findings support policies encouraging investments in hybrid systems over single-source renewable solutions. In developing regions, where resource intermittency and grid instability are critical challenges, hybrid systems offer a robust solution to ensure continuous power supply while leveraging locally abundant renewable resources.
2. **Balancing Cost and Emissions**
   While cost minimization is a key objective in developing countries, this study emphasizes the importance of factoring environmental impact into decision-making. For instance, the optimal low-cost configurations identified in Chapter 3 often produce higher emissions. Policymakers should, therefore, implement incentive mechanisms, such as carbon credits or emissions caps, to encourage the adoption of cleaner systems, even if they involve slightly higher upfront costs. These measures can ensure long-term sustainability without compromising affordability.
3. **Strategic Role of Biomass Energy**

Although biomass alone ranks less attractive, its value as a supplementary source to mitigate the intermittency of wind and solar power is notable. This insight calls for policies promoting biomass as a backup energy source, particularly in rural or off-grid areas with low grid reliability. Developing regions with agricultural waste or forest resources can use biomass to enhance energy security while reducing reliance on diesel generators.

4. **Tailored Grid Modernization for Developing Regions**

   Chapter 5's application of the ELED method demonstrates that integrating renewable energy sources into traditional thermal systems can optimize emissions and operational costs. Developing regions should focus on incremental grid modernization strategies, integrating renewable sources like biomass, solar, and wind into existing infrastructure. This approach balances technological advancements with these regions' financial and technical constraints, making energy transition efforts more achievable.

5. **Leveraging Advanced Control and Optimization Techniques**

   The novel GA-fuzzy logic self-tuning PID controller discussed in Chapter 6 offers an advanced solution for managing system stability in multi-area renewable energy grids. This demonstrates the importance of investing in control technologies that dynamically adapt to load fluctuations and resource variability for developing countries. Policymakers and energy planners should consider capacity-building initiatives to train engineers and operators in deploying and maintaining such advanced systems.

6. **Emphasis on Multi-Criteria Decision Analysis (MCDA) for Policy Formulation**

   The application of MCDA techniques in Chapter 4 illustrates their utility in making balanced decisions for energy system planning. These methods provide a structured framework for evaluating cost, reliability, and environmental impact trade-offs. Policymakers in developing regions can adopt MCDA methodologies to prioritize energy projects that align with national goals for sustainable development, economic growth, and energy independence.

7. **Sensitivity to Local Contexts**

   The findings highlight the critical role of local resource availability in determining optimal system configurations. For example, Libya's abundant solar and wind resources make these options highly viable, while biomass plays a supplementary role. Policymakers should, therefore, ensure that renewable energy strategies are context-specific, leveraging geographic and resource advantages to maximize impact.

8. **Long-Term Vision and Capacity Building**

   The study's future-oriented suggestions, such as integrating additional renewables like tidal energy or scaling the GA-fuzzy logic controller to larger grids, highlight the need for a long-term vision in energy planning. Developing regions should prioritize research and development, pilot projects, and international collaborations to accelerate innovation and adoption of advanced renewable energy technologies.

By implementing this study's findings, developing regions can design energy systems that are cost-effective, environmentally sustainable, and adaptable to future demands. Policymakers should focus on creating an enabling environment through regulatory support, financial incentives, and capacity-building programs to drive the transition toward clean and reliable energy systems. This approach aligns with global sustainability goals while addressing developing nations' unique energy challenges.

Appendix E: Practical Implementation of Findings in Libyan Cities with High Wind and Solar Energy Potential

The study offers actionable insights to harness Libya's abundant renewable energy resources, especially in cities with high wind and solar energy potential like Sabratha, Tripoli, Benghazi, and Misrata. The findings can be practically implemented as follows:

1. **Developing Hybrid Renewable Energy Systems**
   - **Priority Projects:** Deploy hybrid systems combining wind and solar energy with battery storage, as HOMER Pro software identified as the top-ranked configuration. These systems can be installed to power public facilities, schools, hospitals, and convention centers in coastal cities like Sabratha, where wind and solar resources are abundant.
   - **Implementation Strategy:**
     - **Pilot Projects:** Start with small-scale installations to demonstrate cost-effectiveness and reliability.
     - **Scaling Up:** Gradually expand to larger systems powering residential and industrial areas.
   - **Incentive Programs:** Encourage private-sector participation by providing subsidies or tax breaks for hybrid system installations.
2. **Integrating Biomass as a Backup Source**
   - While biomass alone is less viable, it can serve as a backup energy source to address the intermittency of wind and solar power, especially during low-resource periods.
   - **Biomass Utilization Models:**
     - Leverage agricultural residues and municipal waste from cities like Benghazi and Tripoli for biomass production.
     - Implement combined heat and power (CHP) systems in rural areas

where biomass feedstock is readily available.

- **Training Programs:** Educate local stakeholders on biomass technology to maximize its efficiency and sustainability.

3. **Expanding Renewable Energy into the National Grid**
    - **Grid Upgrades:** Invest in grid modernization to integrate renewable sources seamlessly into the national power system.
    - **Zonal Integration:** For the first phase of grid integration, focus on regions with high renewable energy potential to maximize impact and cost-effectiveness.
    - **Reliability Measures:** Use findings from Chapter 6 to incorporate GA-fuzzy logic self-tuning PID controllers for balancing loads and maintaining frequency stability under varying demand conditions.
4. **Prioritizing Emissions Reduction**
    - Recognize trade-offs between cost and environmental impact, as highlighted in Chapter 3. Prioritize configurations that minimize emissions, even if they are not the cheapest.
    - **Policy Actions:**
        - Implement carbon pricing mechanisms to discourage reliance on high-emission options like diesel generators.
        - Mandate cleaner configurations for all new public and private projects in high-potential cities.
5. **Utilizing Advanced Decision-Making Tools**
    - **MCDA Integration in Policy Planning:** VIKOR and COPRAS can guide decision-makers in selecting renewable energy projects that balance cost, reliability, and sustainability.
    - **Community Involvement:** Involve local communities in decision-making to align renewable energy projects with local needs and priorities.
6. **Capacity Building and Knowledge Transfer**
    - Train engineers and technicians in designing, operating, and maintaining advanced systems, such as those integrating GA-fuzzy logic controllers.
    - Collaborate with international renewable energy organizations to bring expertise and funding to Libya.

- Establish academic programs focused on renewable energy technologies at some big universities in Libya, including Tripoli, Benghazi, Misrata and Sebha universities.

7. **Encouraging Private Sector and International Investment**
    - Develop public-private partnerships (PPPs) to attract investment in renewable energy projects.
    - Provide assurances to international investors by introducing stable energy policies and legal frameworks that promote renewable energy development.
8. **Promoting Energy Access in Underserved Areas**
    - Expand renewable energy deployment to off-grid rural and desert regions, where conventional grid extension is costly and impractical.
    - Use smaller-scale hybrid systems (wind, solar, and biomass) to power isolated communities, enhancing energy access and quality of life.
9. **Future Research and Continuous Improvement**
    - Test the GA-fuzzy logic self-tuning technique on larger systems and more complex scenarios to refine its application for Libya's evolving grid.
    - Explore integrating additional renewable sources like tidal and geothermal energy to diversify the energy mix.
    - Conduct sensitivity analyses under various economic and environmental scenarios to ensure robustness and adaptability.

These practical steps, grounded in this study's findings, provide a roadmap for transforming Libya's energy landscape. By leveraging its renewable energy potential, Libya can address its growing energy demand, reduce reliance on fossil fuels, and contribute to global carbon reduction goals while fostering sustainable economic development.

Appendix F: Policy Recommendations for Local Governments and Stakeholders to Facilitate Hybrid Renewable Energy Integration

To support the implementation of hybrid renewable energy systems in Libya, local governments and stakeholders can adopt the following policy measures and strategies:

1. **Establish a Renewable Energy Development Framework**
   - **National Renewable Energy Policy:** Develop and adopt a comprehensive renewable energy policy outlining targets for hybrid energy integration over the next 15–20 years.
   - **Legal and Regulatory Frameworks:** Establish clear guidelines for permitting, grid connection, and land use to encourage investments in wind, solar, and biomass energy projects.
2. **Introduce Financial Incentives**
   - **Subsidies and Tax Breaks:**
     - Provide subsidies for installing hybrid renewable systems, particularly in areas with high solar and wind potential like Msallata, Derna, Sabratha and Tripoli.
     - Offer tax breaks or exemptions on renewable energy equipment and materials to reduce upfront costs for developers.
   - **Carbon Pricing:** Implement carbon taxes or trading schemes to make fossil fuel-based energy less competitive than clean energy alternatives.
3. **Prioritize Hybrid Systems in Public Sector Projects**
   - **Public Facility Integration:** Mandate hybrid energy systems (e.g., solar-wind-battery models) for powering government buildings, hospitals, and schools to set an example for private-sector adoption.
   - **Rural Electrification:** Leverage hybrid systems to expand energy access in remote and underserved areas, reducing reliance on costly diesel generators.

4. **Modernize and Expand the Energy Grid**
    - **Grid Modernization:** Upgrade infrastructure to handle intermittent renewable sources by integrating smart grid technologies and energy storage systems.
    - **Decentralized Energy Models:** Promote microgrids powered by hybrid systems for localized energy supply in areas with high solar and wind resources.
    - **Energy Storage Investments:** Encourage the deployment of battery systems to enhance the reliability of hybrid systems.
5. **Foster Public-Private Partnerships (PPPs)**
    - **Collaborative Models:** Partner with private developers and international organizations to finance and implement large-scale hybrid renewable projects.
    - **Public Sector Support:** Streamline bureaucratic processes and offer guarantees to reduce investment risks for private stakeholders.
6. **Enhance Stakeholder Capacity and Awareness**
    - **Training Programs:** Train local engineers and technicians in the design, implementation, and maintenance of hybrid systems, focusing on emerging technologies like GA-fuzzy controllers.
    - **Public Awareness Campaigns:** Educate communities about hybrid renewable energy systems' economic and environmental benefits to increase public support.
7. **Support Research and Innovation**
    - **Funding for Innovation:** Allocate government funds for research on optimizing hybrid systems, such as incorporating tidal energy or advanced algorithms like the GA-fuzzy logic self-tuning technique.
    - **Academic Partnerships:** Encourage collaboration between universities, research institutions, and industry players to develop region-specific renewable energy solutions.
8. **Address Environmental and Economic Trade-offs**
    - **Balanced Decision-Making:** Use MCDA techniques, like VIKOR and COPRAS, in government planning to evaluate trade-offs between cost,

emissions, and reliability.

- **Biomass as Backup:** Promote biomass as a supplementary energy source in hybrid systems to enhance reliability, especially in low wind or solar output periods.

9. **Enforce Renewable Energy Mandates**
   - **Energy Mix Goals:** Set minimum targets for renewable energy's share in the national energy mix, emphasizing hybrid systems.
   - **Emission Standards:** Implement strict regulations to limit emissions from energy systems and incentivize low-emission configurations.

10. **Monitor and Evaluate Progress**
    - **Performance Metrics:** Establish benchmarks for hybrid energy projects, such as emissions reductions, cost savings, and grid reliability improvements.
    - **Feedback Loops:** Continuously evaluate implemented policies and adapt based on technological advancements and changing economic conditions.

By adopting these policy changes and recommendations, Libya can facilitate the integration of hybrid renewable energy systems, leveraging its vast solar and wind potential while addressing growing energy demands, reducing carbon emissions, and enhancing energy security. These actions align with global sustainability goals and position Libya as a regional leader in clean energy development.