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Optimization and control of solar-wind islanded hybrid microgrid by using heuristic and deterministic optimization algorithms and fuzzy logic controller

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ABSTRACT

The increasing interest in renewable energy-based power systems globally is driven by their abundance and environmentally friendly attributes. Islanded hybrid microgrid systems (IHMS) are a relatively new development in this field and involve the integration of two or more sustainable sources, such as wind turbines, solar photovoltaic (PV) systems, and other forms of renewable energy such as the ocean, wave, and geothermal energy. In order to ensure an uninterrupted power supply for the growing community and industrial sector of Perhentian Island, Malaysia, alternative power sources must be properly synchronized and managed through an energy management system. To this end, the main contribution of this study is the comprehensive analysis of various optimization methods in terms of net present cost (NPC) and convergence rate. The results of the analysis indicate that HOMER proved to be relatively faster in terms of convergence rate, with the NPC recorded as 387,185$ and the Levelized Cost of Energy (LCOE) recorded as 0.64$/kWh, which are the least among the other techniques evaluated. The hybrid energy system was designed to acquire the optimal quantity and size of power-generating modules, including PV systems, wind turbines, batteries, and diesel generators, while also meeting the load requirements. The optimization problem incorporated the LCOE and NPC into the cost function. Various optimization techniques were developed and tested. In addition, an advanced control method, which includes the use of Proportional–integral–derivative (PID) control and Fuzzy Logic Controller (FLC) with automated tuning, was applied to manage voltage and frequency. The control strategy was implemented in MATLAB Simulink, along with a full model of the islanded hybrid microgrid system. The simulation results demonstrate the effectiveness of the proposed FLC in maintaining the voltage and frequency within the acceptable range during various operating conditions. In conclusion, this manuscript provides a comprehensive study on the optimization and control of a solar-wind islanded hybrid microgrid. The proposed approach can be used as a valuable tool for the design and operation of solar-wind islanded hybrid microgrids in remote and islanded communities.

1. Introduction

One of the main reasons for voltage and frequency fluctuation is the absence of congruence between the source and the load demand, prompting instability in the active and reactive power. Therefore, the solution would be to enhance the flexibility of the power source or load modules. However, care must be taken so that the levelized cost of energy (LCOE), net present cost (NPC) do not become too high. This is hence an optimization problem that needs to be solved (Mohamed et al.,

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Nomenclature

Abbreviation	Elaboration
LCOE	Levelized Cost Of Energy
NPC	Net Present Cost
SHEMSs	Smart Home Energy Management Systems
PV	Photovoltaic
WT	Wind Turbine
CHP	Combined Heat And Power
POA	Pelican Optimization Algorithm
EM	Energy Management
IDR	Incentive- based Demand Response
MG	Microgrid
DRP	Demand Response Programme
MGO	MG Operator
ISMCDO	Integral Sliding Mode Control System
ISMC	Integral Sliding Mode Controllers
DOBC	Disturbance Observer-Based Controllers Using MATLAB/ Simulink
DGs	Distributed Generators
ESSs	Energy Storage Systems
FDI	Fake Data Injection
DoS	Denial-of-Service
DG	Diesel Generator
ECMS	Energy Consumption Minimisation Strategy
LP	Linear Programming
GA	Genetic Algorithm
PSA	Pattern Search Algorithm
FLC	Fuzzy Logic Controller
HVDC	High Voltage Direct Current
P_{demand}	Load Demands
P_{losses}	Total Power Losses
$P_{storage}$	Storage Power Needs
SOC	State of Charge
HRES	Hybrid Renewable Energy System
ILP	Integer Linear Programming
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
ACO	Ant Colony Algorithm
GWO	Grey Wolf Optimization
MPPT	Maximum Power Point Tracking
PnO	Perturb and Observe
IC	Incremental conductance

2017; Shezan and Lai, 2017).

The urgency for the use of renewable resources over conventional power sources has increased rapidly due to the first growth of human civilization and advancement of the technologies (Ishraque et al., 2022a; Kumar et al., 2023; Olabi et al., 2023).

With the rising and fluctuating energy need brought on by the COVID-19 pandemic, renewable energy-based Smart Home Energy Management Systems (SHEMSs) are essential in the residential sector to improve the effectiveness, sustainability, financial advantages, as well as energy conservation for a distribution process (Ishraque et al., 2022b; Ishraque et al., 2021; Varaprasad et al., 2022).

In this work, three renewable microgrid designs for Iran's Shiraz climate were used in conjunction with a multi-objective particle swarm optimisation technique. The following microgrid topologies were taken into consideration: photovoltaic (PV), wind turbine (WT), and combined heat and power (CHP) systems. The assumption was made that the microgrid was connected to the gas and electrical grids and that any excess power produced was sold to the grid. As the optimisation goal functions, the chance of a power supply failure and the cost of energy per unit were taken into consideration. The obtained findings showed that, because of the climate's poor wind energy availability, relying only on WT might considerably increase dependency on the power grid (Parvin et al., 2023).

This study suggests a novel Pelican Optimization Algorithm (POA) application for ideal Energy Management (EM) in Microgrid (MG), considering the Demand Response programme (DRP). Multi-objective optimisation is developed to increase the benefit to the MG operator (MGO) and lower operating costs overall, including the price of fuel for traditional generators and the price of power transactions. A hybrid demand response plan (DRP) based on incentive-based demand response (IDR) is suggested to assure MG dependability and achieve the best possible operation of the MG. Applying the Hybrid method to encourage customers to limit their use during peak hours will increase reliability (Alamir et al., 2023).

To achieve a power balance and regulate frequency in an MG system, this research suggests an integral sliding mode control system (ISMCDO) that includes a disturbance observer. The outcomes of this approach are contrasted with those of integral sliding mode controllers (ISMC) and disturbance observer-based controllers using MATLAB/Simulink (DOBC). Additionally, their performance indices are contrasted, and the findings show that the ISMCDO method is superior to other approaches. As a result, by using the ISMCDO controller, the secondary controller performances in the MG system may be enhanced, ensuring stability, flexibility, rapid reaction, and load balance maintenance even in the event of unexpected changes in loads and weather conditions (Ibraheem et al., 2023).

For islanded MG systems with distributed generators (DGs) and energy storage systems (ESSs), which are vulnerable to hybrid fake data injection (FDI) and denial-of-service (DoS) assaults, this article suggests a cyber-resilient control strategy. To account for limited FDI assaults on secondary controllers while accepting certain DoS attacks on communication lines, the suggested approach is built on the adaptive technique. The Lyapunov stability theory and the dwell time approach are used to demonstrate the error systems' stability. Under a hybrid cyber-attack, the suggested control can preserve frequency restoration, equitable power sharing, and energy balancing among DGs and ESSs. A 13-bus MG system with 3 ESSs and 3 DGs implements the suggested cyber-resilient control method (Wang et al., 2023).

The evaluations of several energy regulation plans for smart home equipment and related difficulties are offered in this respect. By evaluating multiple instances from the literature, several energy scheduling controller strategies are also examined and contrasted inside the COVID-19 framework (Kumar et al., 2022). It has also been discussed how to use and gain from SHEMS that are based on renewable resources. It has been shown that SHEMS which is based on renewable energy and uses enhanced multipurpose meta-heuristic optimisation methods with machine learning is more adapted to handle the pandemic's fluctuating household energy demand (Ayub et al., 2022). With the help of a wind energy conversion system (WECS) integrated modified 11-bus test system and a modified IEEE 39-bus test system, the efficacy of the designed controller is confirmed.

The obtained results demonstrate that the developed controller can effectively minimise inter-area oscillations in a WECS-concatenated power system and provide stability (Sengupta and Das, 2022).

With an emphasis on affordability, storage capability, lifespan, and emission, the continuous optimization targets and limitations of the battery storage capacity are examined. Additionally, this study offers a thorough analysis and identification of the numerous controller and enhancement approaches and algorithms concerning the framework, executions, major results, advantages, research gaps, as well as current

Table 1
The comparative literature review based on different optimization techniques and Fuzzy logic controllers for the Islanded Microgrid.

Authors	Year	Title	Key findings
Ahmed et al.	2020	Optimization of a hybrid microgrid using a genetic algorithm	The genetic algorithm effectively optimized the operation and control of a hybrid microgrid, resulting in improved efficiency and stability.
Li et al.	2020	Control of a hybrid microgrid using a fuzzy logic controller	The fuzzy logic controller effectively mitigated voltage and frequency fluctuations, improving the stability of the hybrid microgrid.
Zhang et al.	2019	Optimization of a hybrid microgrid using a particle swarm optimization algorithm	The particle swarm optimization algorithm effectively determined the optimal values for power-generating modules' size and number, resulting in improved efficiency of the hybrid microgrid.
Wang et al.	2019	Control of a hybrid microgrid using an ant colony optimization algorithm	Ant colony optimization algorithm effectively determined the optimal control parameters for the microgrid's energy management system, resulting in improved efficiency and stability.
Chen et al.	2019	Integration of renewable energy sources into a hybrid microgrid	Proper energy storage management and advanced control strategies are crucial for effectively utilizing renewable energy sources and improving the overall efficiency of a hybrid microgrid.

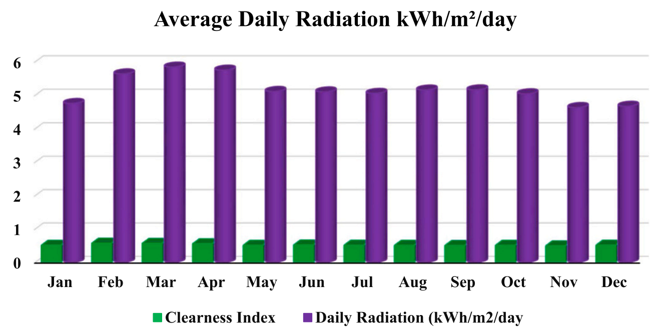

Fig. 1. : Monthly Average Daily Radiation at Pulau Perhentian.

problems and difficulties (Azeem et al., 2021; Muppidi et al., 2022).

The use of fuel and carbon secretion of the diesel generator (DG) in Mode-II is reduced using the energy consumption minimisation strategy (ECMS), which is based on linear programming (LP), genetic algorithm (GA), and pattern search algorithm (PSA). During Mode-III, DG is not required, and state machine control and fuzzy logic controller (FLC) techniques are used to optimise the energy flow between DERs (SMCS). The ESS level, fuel consumption cost, and quantity are employed as the EMS's execution criterion (Kaysal et al., 2022; Rana et al., 2022).

Various energy models with and without renewable sources are examined and emphasised in this study, along with the incorporation of complex ideas for example microgrids, smart grids, distributed generation, high voltage direct current (HVDC) linkages, and the energy system following liberalisation. Additionally, several investigated control systems have been considered and contrasted, including conventional, adaptive, optimum, resilient, machine learning, centralised as well as decentralised approaches (Peddakapu et al., 2022).

The suggested system control was based on keeping under the observation of the battery's level of energy and applied loads as effectively as feasible utilising renewable energy sources. The three proposed microgrid stability techniques are demonstrated by the estimated results

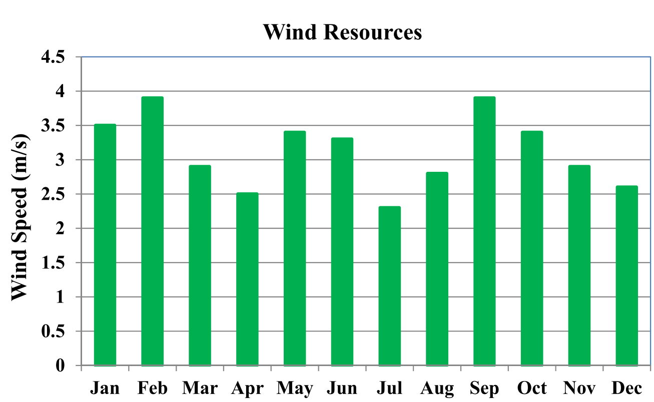

Fig. 2. Average Wind Speed at Pulau Perhentian.

using MATLAB Simulink (PID, artificial neural network, and fuzzy logic). The comparative findings demonstrated the practicality and efficacy of the fuzzy logic controller-based suggested approach for energy management in a microgrid (Al Sumarmad et al., 2022).

The comparative literature review based on the research findings using different optimization techniques and control strategies has been articulated in Table 1.

The research gaps and drawbacks of the above-mentioned literature survey lie in three different sections as mentioned below:

- Lack of integration of cost analysis and system stability analysis for the Islanded microgrid with the applications and advancement.
- Lack of co-relation between optimization and control for the microgrid design and operations for the remote and decentralized areas.
- Lack of synchronization while battery energy storage and diesel are connecting with the main grid to act as a back of renewable resources.
- The optimization techniques have a long convergence rate as well as complex interaction procedures with inaccurate non-optimized results.
- The model's predictive and adaptive controllers can not regulate the voltage and frequency at the same time.

The main contribution of this manuscript comprises two different segments:

- In the first segment of the manuscript, a comparative analysis of various optimization methods in terms of their Net Present Cost (NPC) and their convergence rate was conducted. NPC is a measure of the total cost of a project over its lifetime, taking into account both the initial costs and the costs of operation and maintenance. The convergence rate, on the other hand, refers to the speed at which an optimization algorithm reaches a solution. Different optimization methods such as linear programming, genetic algorithm, particle swarm optimization, and simulated annealing, and evaluate their performance in terms of NPC and convergence rate were compared. The goal of this analysis is to identify the method that offers the best trade-off between NPC and convergence rate. Through this analysis, we aim to provide insights into the relative strengths and weaknesses of the different optimization methods and to guide practitioners in the selection of an appropriate optimization method for a given problem.

- In the second segment of the manuscript, Fuzzy Logic Controller (FLC) and PID controller for the optimized and designed the system to mitigate voltage and frequency fluctuations were implemented. The FLC and PID controllers are widely used in power systems for the control of voltage and frequency. We present the design and implementation of FLC and PID controllers for the optimized system and evaluate their performance in terms of voltage and frequency stabilization. The focus of this segment is on the ability of the controllers

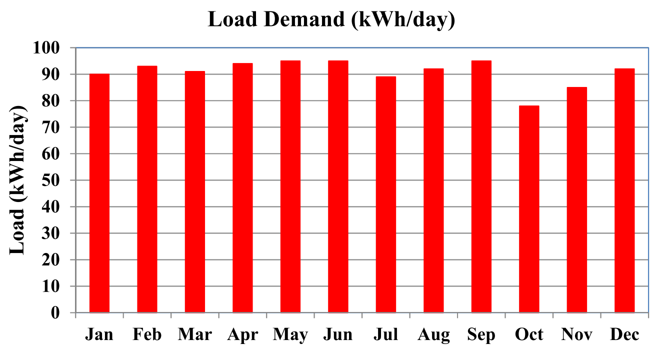

Fig. 3. Load Demand of a Small Community on Pulau Perhentian.

to effectively mitigate voltage and frequency fluctuations and to provide stable and reliable operation of the power system. The performance of FLC and PID controllers in terms of their ability to stabilize the voltage and frequency, and to provide a stable and reliable operation of the power system were also compared. The goal of this analysis is to provide insights into the relative strengths and weaknesses of the FLC and PID controllers and guide practitioners in the selection of an appropriate controller for a given power system.

2. Case Study - Pulau Perhentian Island, Malaysia

The subsequent research work will be done based on a case study for an island on the east coast of Malaysia, Pulau Perhentian. The climate for Pulau Perhentian is tropical, with a heavy monsoon season between November and February. For this island, the meteorological data including solar radiation and average wind speed has been collected from the Malaysian Meteorological Department (Khare et al., 2016). These are shown in Fig. 1 to Fig. 2. Also, the load demand is estimated to be approximately 100 kWh per day, with a peak load of 8.9 kW. The load demand is estimated based on the number of electrical appliances (e.g. fan, air-conditioner, television) for a small community of 90 people. The monthly load demand is shown in Fig. 3 (Bhandari et al., 2016).

3. Cost function

The objective of the optimization problem is to minimize the net present cost (NPC) of the power generating system. The NPC can be represented as a function of the size and number of modules. The optimization problem is subject to a set of constraints that represent the limitations of the power-generating system. The optimization problem of determining the ideal values for the size and number of power-generating modules can be formulated as a linear programming problem.

$$\min_{a,b,c,d,e,f\in N^0}\begin{pmatrix} w_1\left(a\bullet LCOE_{PV,5}+b\bullet LCOE_{PV,18}+c\bullet LCOE_{PV,30}+d\bullet LCOE_{WT}+e\bullet LCOE_{DG}+f\bullet LCOE_{BT}\right) \\ w_2\left(a\bullet NPC_{PV,5}+b\bullet NPC_{PV,18}+c\bullet NPC_{PV,30}+d\bullet NPC_{WT}+e\bullet NPC_{DG}+f\bullet NPC_{BT}\right)\end{pmatrix} \quad (1)$$

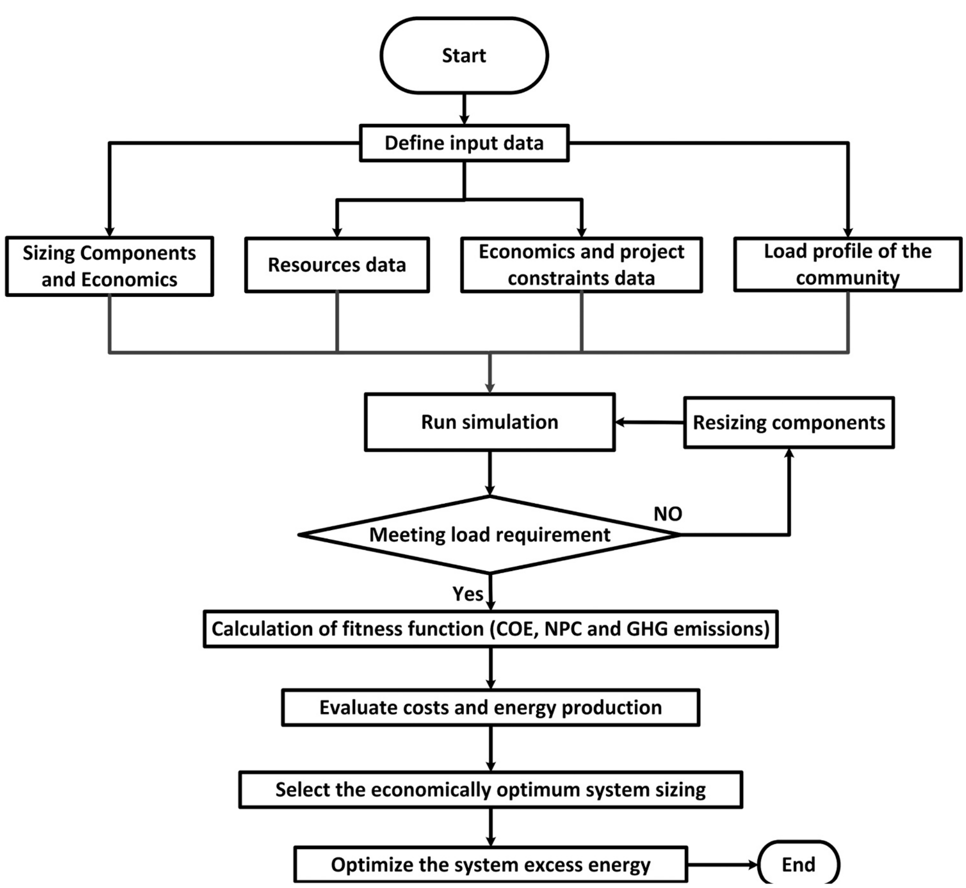

Fig. 4. Flowchart of HOMER Algorithm.

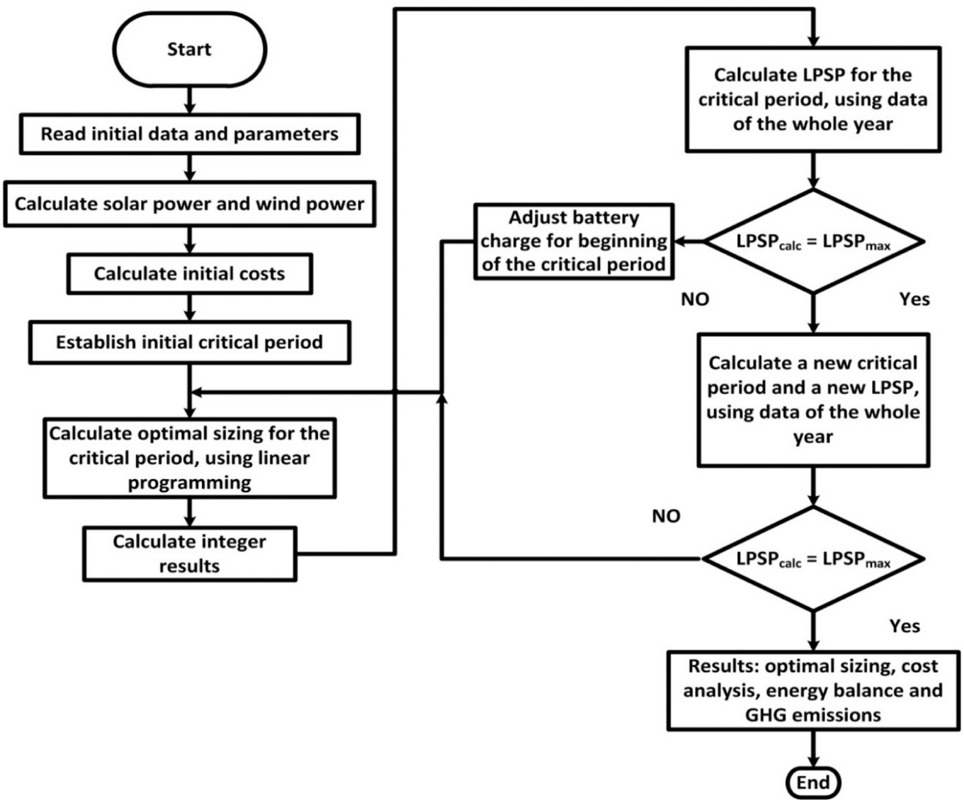

Fig. 5. Flowchart of Integer Linear Programming.

subject to:

- The power generated restriction requires that the power produced by each source, $P_{gen(i)}$, is equal to or less than the source's maximum capacity.

$$P_{gen(i)} \leq P_{gen,\max(i)} \tag{2}$$

- Power generation from all energy sources must be sufficient to meet all load demands (P_{demand}), total power losses (P_{losses}), storage power needs ($P_{storage}$), state of charge (SOC).

$$\sum_i P_{gen(i)} \geq P_{demand} + P_{losses} + P_{storage} \tag{3}$$

- The state of charge (SOC) of a storage system can be described by the following equations for charging and discharging:

Charging equation: dSOC/dt = P_charge/E_total (SOC is the state of charge of the storage system, dSOC/dt is the rate of change of the SOC, P_charge is the power needed to charge the storage system, and E_total is the total energy capacity of the storage system).

Discharging equation: dSOC/dt = -P_discharge/E_total (P_discharge is the power needed to discharge the storage system).

Constraints: 0 < = SOC < = 1 (SOC must be between 0 and 1).

The above equations represent the change in SOC of the storage system during charging and discharging. The charging equation shows that the rate of change of SOC is positive when the storage system is charging and is proportional to the charging power and the total energy capacity of the storage system. The discharging equation shows that the rate of change of SOC is negative when the storage system is discharging and is proportional to the discharging power and the total energy capacity of the storage system. The constraints ensure that the SOC always remains between 0 and 1.

In Eq. (1), $a, b, c, d, e, f \in \mathbb{N}^0$ refers to the numbers (integer including 0) of the 5 kW PV model, 18 kW PV model, 30 kW PV model, wind turbine, DG, and battery unit respectively, whereas w_1, w_2 are used to present the significance of the individual measure (Li et al., 2019).

4. Optimization Techniques

To resolve the optimization issue in Eq. (1), several optimization algorithms have been implemented. A commercially available software, HOMER, which is suitable for hybrid renewable energy system (HRES) optimization is used to provide the benchmark results. Next, several deterministic and stochastic optimization algorithms (ILP, PSO, GA, ACO, GWO) are run, and the results are compared to those obtained using HOMER (Srivastava and Giri, 2016). More importantly, the performances of each algorithm are also compared based on the convergence rate, as well as accuracy in the existence of uncertainties of solar radiation, wind velocity, and load demand. In the class of deterministic algorithms, Integer Linear Programming (ILP) has been chosen (Mellouk et al., 2019). It is also worth mentioning that HOMER is based on deterministic methods. On the other hand, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Algorithm (ACO), and Grey Wolf Optimization (GWO) stochastic algorithms are considered. The details of each of these algorithms are discussed in the following subsections (Singh et al., 2018).

5. Deterministic

5.1. HOMER

The method used in HOMER is a brute-force method, whereby all possible combinations of $a, b, c, d, e, f \in \mathbb{N}^0$ have been investigated, and the outputs of LCOE and NPC are obtained via simulation. In the end, all

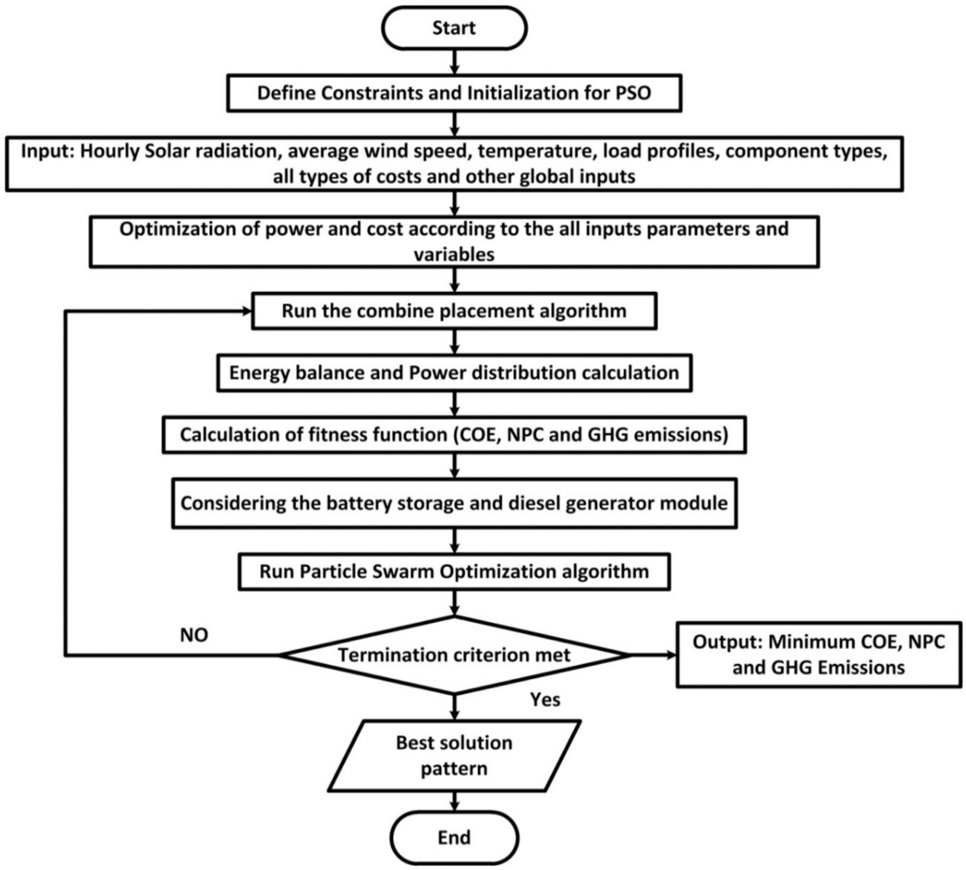

Fig. 6. Flowchart of the PSO Algorithm.

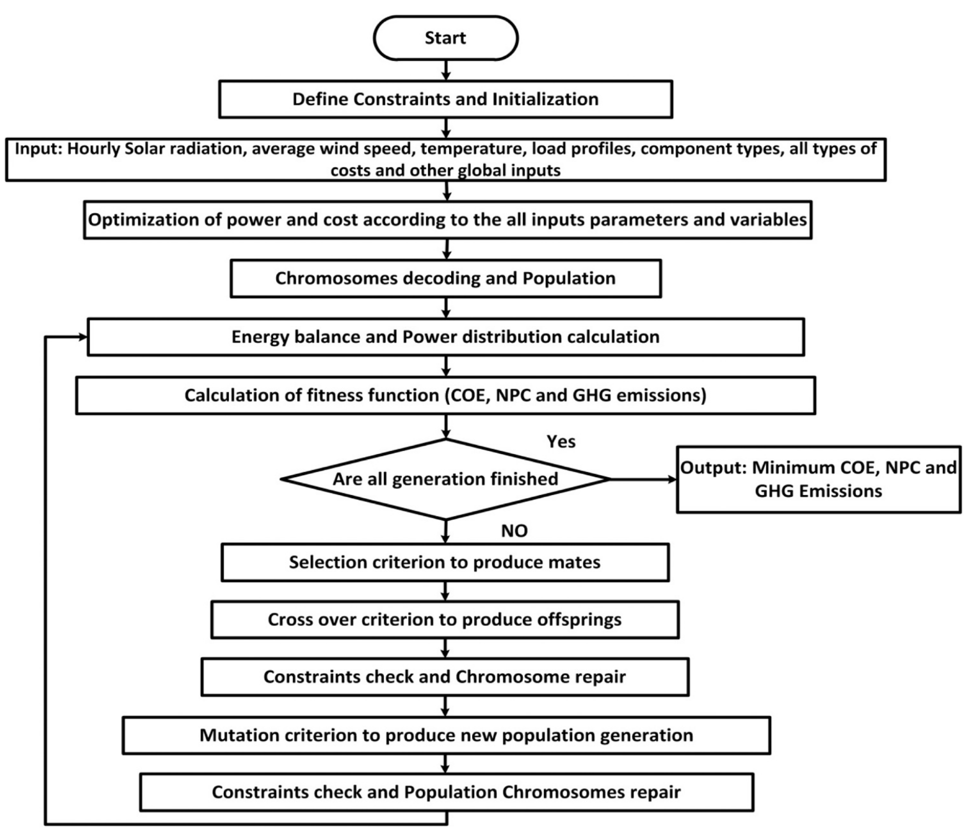

Fig. 7. Flowchart of the GA.

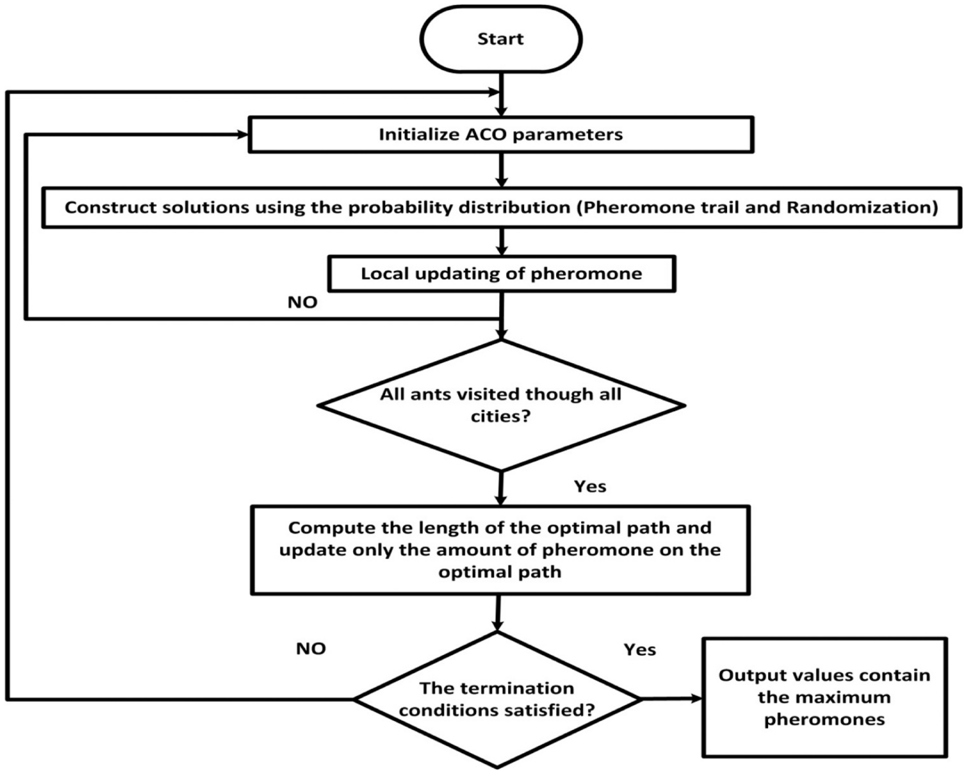

Fig. 8. Flowchart of the ACO Algorithm.

the results which satisfy the constraints are listed, and the optimal choice is selected manually. The flowchart of the HOMER algorithm is presented in Fig. 4 (Singh and Baredar, 2017).

5.2. Integer linear programming

The formulation of the optimization problem as integer linear programming (ILP) requires the estimation of the annual energy that should be provided by each renewable energy resource as well as its cost. Fig. 5 shows the detailed flowchart of ILP for solar wind islanded Microgrid system (Ming et al., 2018).

6. Heuristic

6.1. Particle swarm optimization

The PSO algorithm is composed of the following three steps:

- Determine each particle's fitness.
- Revise individual and global best finesses and positions.
- Revise each particle's position and velocity.

Each particle retains the highest fitness value it ever attained while the algorithm was running. Iterations are used to calculate and update the particle with the highest fitness relative to other particles (Mohamed et al., 2017). Up until a certain stopping criterion is satisfied, such as the number of iterations or the predetermined goal fitness value, the process is repeated. The following equation is used to update each particle's position in the swarm:

$$x^i_{k+1} = x^i_k + v^i_k \tag{4}$$

where at iteration k, x represents the particle position and v its velocity. Calculating the velocity is done as follows:

$$v^i_{k+1} = K \times \left[v^i_k + c_1 r_1 \left(p^i_k - x^i_k\right) + c_2 r_2 \left(p^g_k - x^i_k\right)\right] \tag{5}$$

where,

$$K = \frac{2}{2 - \phi - \sqrt{\phi^2 - 4\phi}} \tag{6}$$

$$\phi = c_1 - c_2 > 4 \tag{7}$$

p^i is the best position of individual particles and p^g is the best global position, c_1 and c_2 are cognitive and social factors, whereas r_1 and r_2 are random numbers between 0 and 1, v^i_k is known as inertia, It causes the particle to shift in an identical direction with the same speed, $c_1 r_1 \left(p^i_k - x^i_k\right)$ is known as the cognitive component, forcing the particle to revert to an earlier place where it had a high individual fitness, $c_2 r_2 \left(p^g_k - x^i_k\right)$ is known as the social parameter, owing the particle to follow the lead of its best neighbour and return to the best region the swarm has so far discovered. If $c_1 \gg c_2$, therefore, each particle is considerably more drawn to its ideal place, in contrast to the opposite, if $c_2 \gg c_1$, then, particles are drawn to the world's best place more. The flowchart of the PSO algorithm is shown in Fig. 6 (Zekry and Saad, 2019).

It is worth noting that for the PSO, the battery storage and diesel generator module have been newly added, which is a novelty compared to the existing research that is found in the literature (Arabi-Nowdeh et al., 2021; Yang et al., 2020).

6.2. Genetic algorithm

Natural selection serves as the basis for the heuristic optimization technique known as a genetic algorithm. Good genes from good parents are passed on to their offspring, whereas bad genes are discarded. Mutations of the genes allow possible escape from a local minimum. The flowchart of the GA algorithm is depicted in Fig. 7 (Singh and Bansal, 2018).

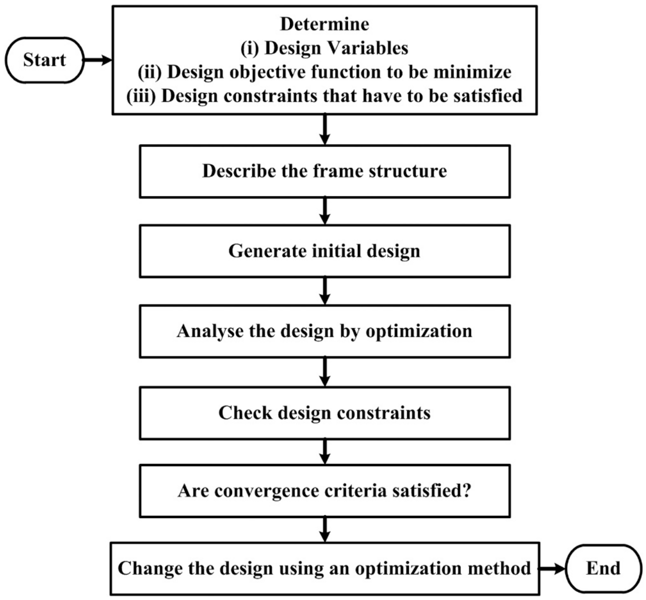

Fig. 9. Flowchart of the GWO Algorithm.

Table 2
Number of Components after Optimization.

Method	PV, 5 kW	PV, 18 kW	PV, 30 kW	WT, 10 kW	DG, 10 kW	Battery
HOMER	1	1	1	1	1	3
ILP	1	2	2	3	1	4
PSO	1	2	2	2	2	3
GA	0	3	2	2	1	2
ACO	1	2	2	2	0	3
GWO	3	2	2	3	0	4

6.3. Ant Colony Optimization

Finding good pathways through graphs is a computer problem that can be solved using the probabilistic ant colony optimization (ACO) algorithm. The ACO was inspired by real ants' capacity to determine the quickest route between their colony and a food supply. The fundamental concept of the ACO is to employ pheromone, a chemical produced by real ants, as a means for communication and an oblique type of memory for previously discovered solutions. Due to the ACO's effectiveness, it has been used to solve numerous combinatorial optimization issues. Fig. 8 shows the detailed flowchart of ACO for solar-wind islanded microgrid system (Amrollahi and Bathaee, 2017).

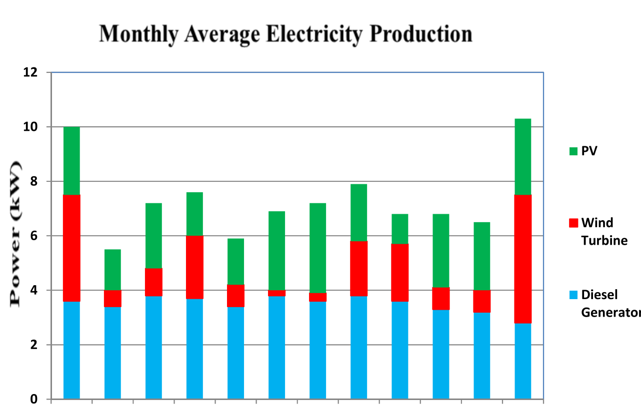

Fig. 10. Power Output from Different Sources for Pulau Perhentian, optimization by HOMER.

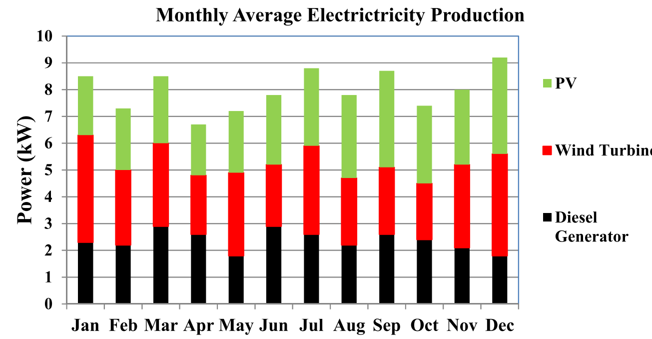

Fig. 11. Power Output from Different Sources for Pulau Perhentian, optimization by ILP.

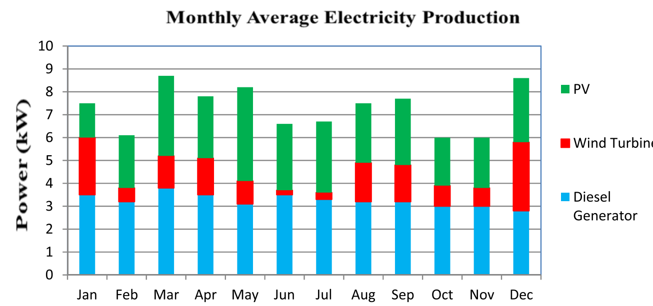

Fig. 12. Power Output from Different Sources for Pulau Perhentian, optimization by PSO.

6.4. Grey wolf algorithm

The leadership structure and method of hunting used by grey wolves in nature serve as inspiration for the GWO. Fig. 9 shows the detailed flowchart of GWO for the solar-wind islanded hybrid Microgrid system (Yahiaoui et al., 2016).

7. Results and comparisons

All the aforementioned algorithms have been implemented to calculate the optimal number of energy-generating modules, meeting the required load demand while still being economically viable. The optimal sizing results for different optimization techniques have been represented in Table 2 (Hussain et al., 2017). According to the comparative analysis it is observed and reported that HOMER and PSO produce less excess energy by choosing the least items from Table 2 as the optimal sizes for PV, wind turbine (WT), DG and battery modules. ACO and GWO have the batteries but do not have diesel generator backup as the dedicated load has been fulfilled by renewable resources and battery storage.

The monthly average electricity production from different sources

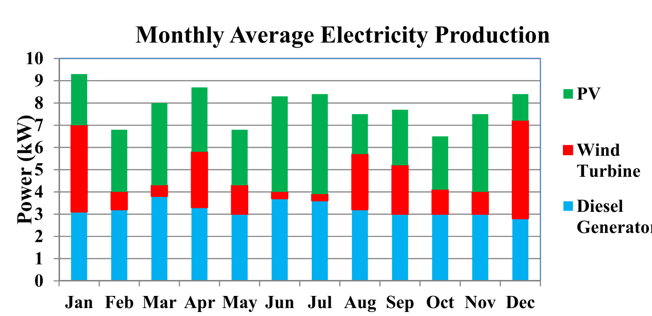

Fig. 13. Power Output from Different Sources for Pulau Perhentian, optimization by GA.

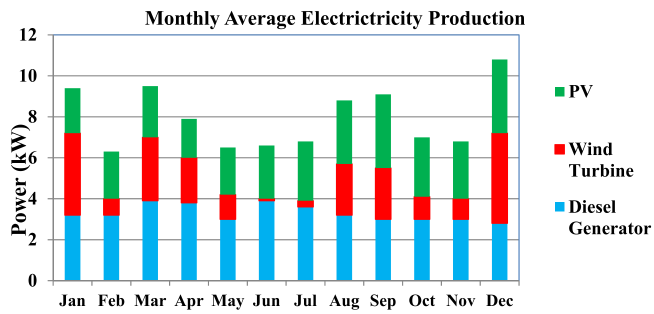

Fig. 14. Power Output from Different Sources for Pulau Perhentian, optimization by ACO.

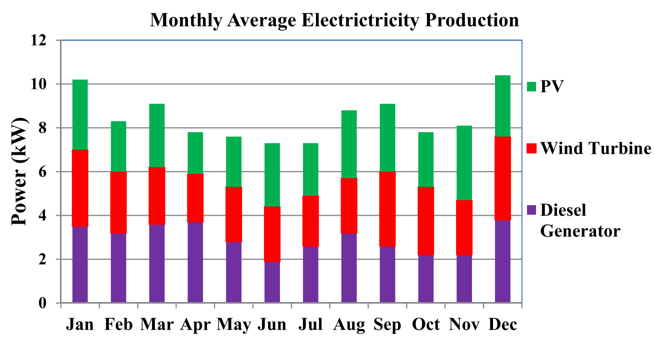

Fig. 15. Power Output from Different Sources for Pulau Perhentian, optimization by GWO.

Table 3
Comparison of Optimization Algorithms for Islanded Microgrid at Pulau Perhentian.

Optimization Technique	Convergence Rate	NPC/USD	COE/USD
HOMER	Relatively Fast	387,185	0.64/kWh
PSO	Faster	388,789	0.665/kWh
ILP	Slow	390,865	0.706/kWh
GA	Slow	391,456	0.716/kWh
ACO	Relatively slow	392,990	0.745/kWh
GWO	Relatively slow	390,189	0.692/kWh

for various optimization approaches is shown in Fig. 10–15. The electrical production curves show the variations in power production from month to month span according to the available renewable resources.

A comparison of the results from the various optimization algorithms is given in Table 3. From Table 3, the particle swarm algorithm (PSO) achieves the best result for both NPC and COE. Also, its convergence rate is fast, and it can handle uncertainties in solar radiation, wind speed, and load demand. According to the basic procedure of each algorithm the convergence rate, NPC and COE can be discussed briefly to justify the reason behind the optimization process that has been conducted and generates those numbers mentioned in Table 3. HOMER is the Blackbox and master of all simulation and optimization tools that have been used so far for the modern-day hybrid microgrid optimal sizing and techno-economic analysis. HOMER follows both deterministic and heuristic optimization strategies to generate optimal sizing and techno-economic results. That is why the convergence is relatively fast in HOMER and the NPC and COE are also the lowest in the list due to the predefined optimization objectives. According to the comparative analysis in-between PSO and other optimization algorithms, as follows ILP, GA, ACO and GWO, PSO performs better in terms of better convergence rate, lowest NPC and COE. PSO performs better than other algorithms due to the simple optimization technique, less complexity able to handle the uncertainty issues of the meteorological conditions. ILP, GA, ACO and

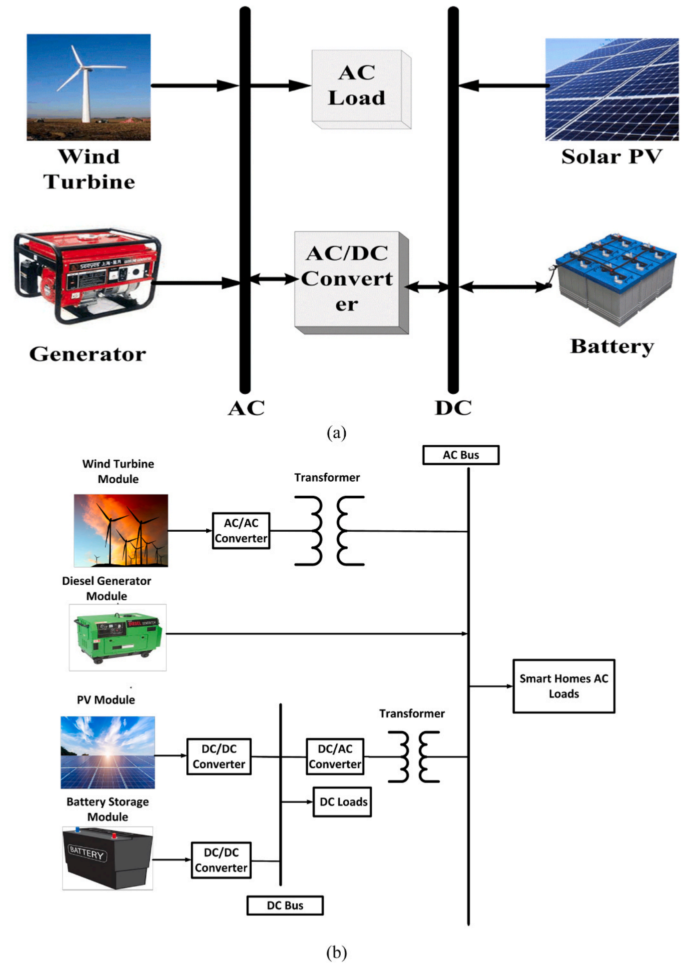

Fig. 16. : (a) A block diagram of an islanded Microgrid system for Pulau Perhentian, Malaysia without and (b) with a transformer.

GWO offers relatively slower speed in convergence than HOMER optimizer and PSO. Along with relatively slower speed, the techniques have higher NPC demand and relatively higher energy costs than HOMER and PSO as can be seen from the table.

8. Control techniques for mitigation of voltage and frequency fluctuation

8.1. Fuzzy logic control

Unlike conventional or digital logic, which only accepts discrete values of 1 or 0, a fuzzy control system analogy inputs values in terms of logical variables that take on analog values from 0 to 1. This is known as fuzzy logic (true or false, respectively).

The authors in [35] describe an unique fuzzy logic controller for HRES with several forms of storage. Consumer-related problems are resolved by the suggested plan. The issue is resolved by concentrating on satisfying the demand side's supply while retaining the lithium-ion battery's efficiency and dependability.

Using data from the solar power module, wind power module, and load, an extensive assessment of a fuzzy control scheme and validation of its efficacy is carried out [36]. Two switches make up the system. Since the wind speed is constant, the fuzzy logic controller regulates the duty cycle of one of the converter's switches that corresponds to the PV input. The maximum power point tracking algorithm provides the inputs to the fuzzy logic controller (MPPT). The purpose of the fuzzy logic controller is to regulate the duty cycle (d) for solar energy and the

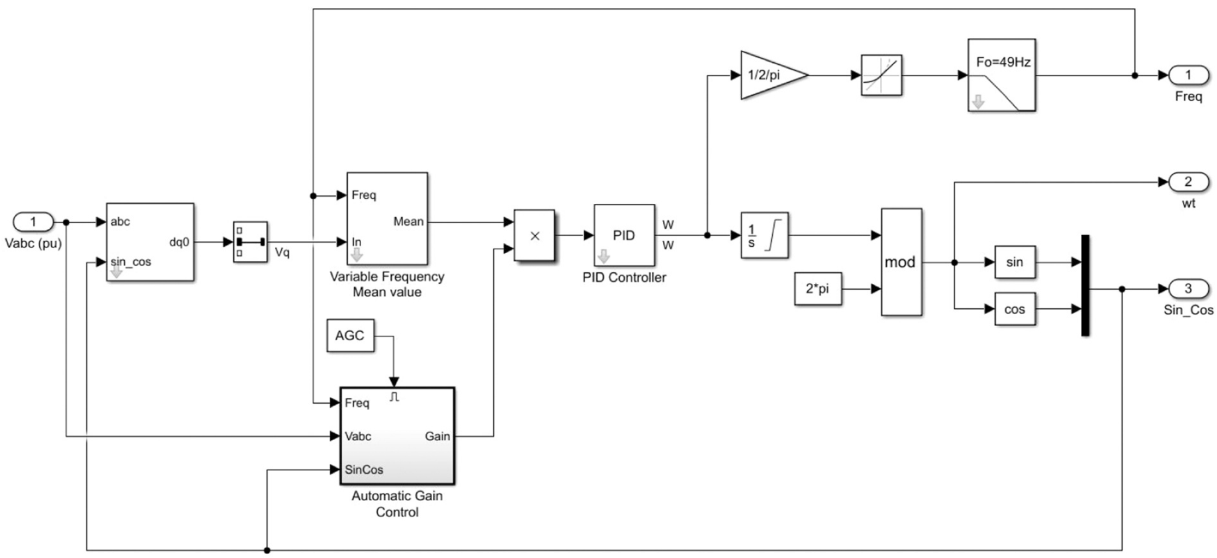

Fig. 17. : Simulink model of PID controller with automatic gain tuning.

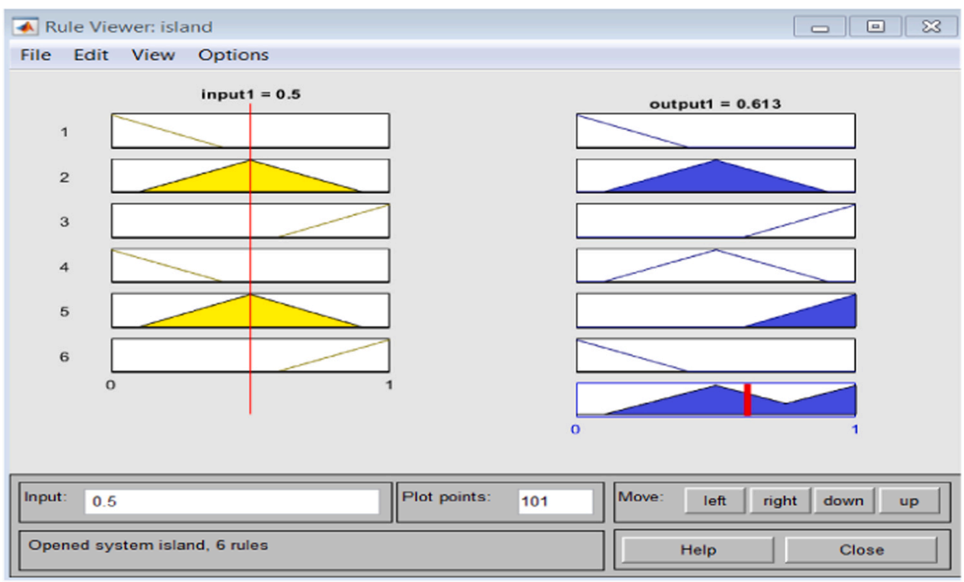

Fig. 18. Rule viewer for the designed FLC.

proportional-integral controller for WTs, respectively, to sequentially regularize the ideal rotor velocity and the pulse-width modulation in the boost converter [37].

This approach is unaffected by changes in system parameters and does not necessitate a particular intricate mathematical model or linearization about an operational point. In a fuzzy logic controller for a wind turbine subsystem, the pitch angle of the turbine is tuned following the values of the recorded wind velocity. The output impedance of the photovoltaic cell for the solar subsystem is equal to the measured impedance on load. To improve performance, both controllers are used [38].

8.2. Implementation of PID control with FLC and automatic gain tuning

This section describes the implementation of a PID control with automatic gain tuning (Vu et al., 2017), which provides good performance in mitigating voltage and frequency fluctuation.

Firstly, a single-line power system diagram of the islanded microgrid system is shown in Fig. 16 as (a) without transformer and (b) with transformer. It consists of several important modules such as a PV module, wind turbine, battery storage, converter module, DG, charge controller, voltage regulator, and frequency controller. The PID control with automatic gain tuning is shown in Fig. 17 (Abhinav et al., 2018).

The results of using PID control with automatic tuning are shown in the next few figures. Fig. 18 shows the rules viewer from the membership function for the FLC. Fig. 19 and Fig. 20 show the membership functions of the input and output modules for the designed FLC. Fig. 21 depicts the frequency response of the microgrid before tuning is applied. Fig. 22 shows the frequency of the IHMS after FLC and PID tuning for Pulau Perhentian, Malaysia where, it can be observed that, after tuning the response obtained significant improvement.

There are regular deviations in distribution and demand that can make frequency go somewhat above or under 50 Hz, which can be overseen yet there are additionally enormous unsettling influences in the framework, for example, a huge power production plant stumbling off, which can seriously influence the stock interest equilibrium and lose the frequency of the framework. Sudden changes in load and equally quick changes in renewable power generation can cause frequency

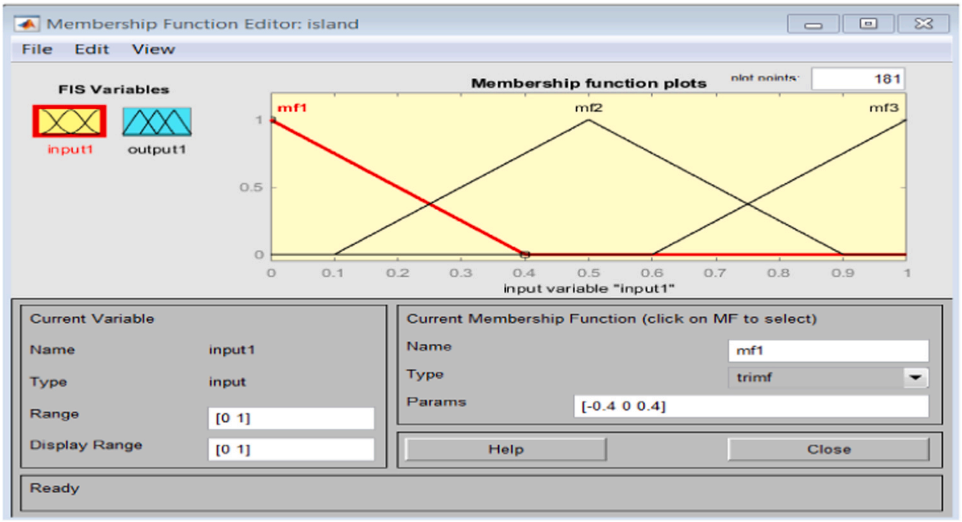

Fig. 19. Membership functions according to the input parameter for FLC.

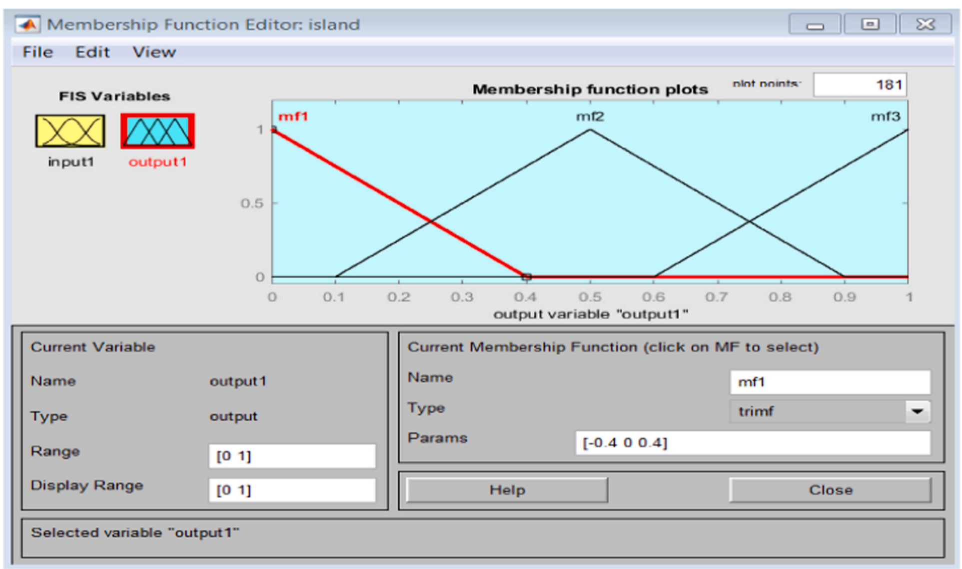

Fig. 20. Membership functions according to the output parameter for FLC.

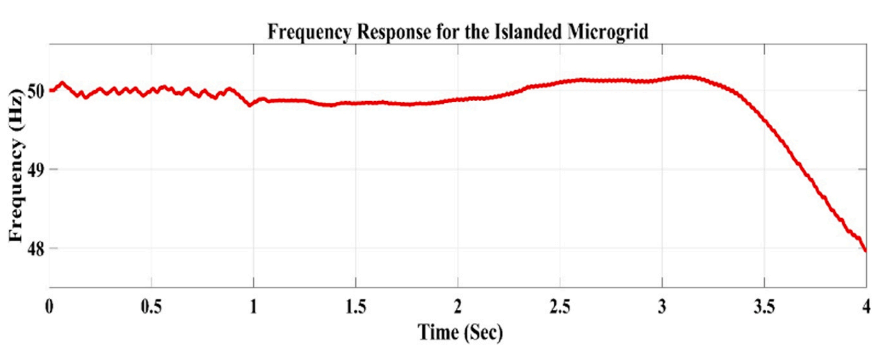

Fig. 21. : Frequency responses of the IHMS for Pulau Perhentian, Malaysia without tuning.

deviations. Due to these reasons, the frequency is falling to 49.5 Hz and sometimes goes up to 50.5 Hz. The diesel generator backup often helps the system frequency to keep it within 50 Hz. Intelligent active power control to tackle any sudden and large load-power generation imbalances. Bigger energy storage system to create generation flexibility and load following ability. FLC has been implemented with the PID controller to control the active power flow and sudden changes in the active load to keep the frequency within 50 Hz. It can be seen that the frequency is held quite close to 50 Hz. Fig. 23–27 shows the voltage in the load, PV module, wind turbine, battery, and diesel generator

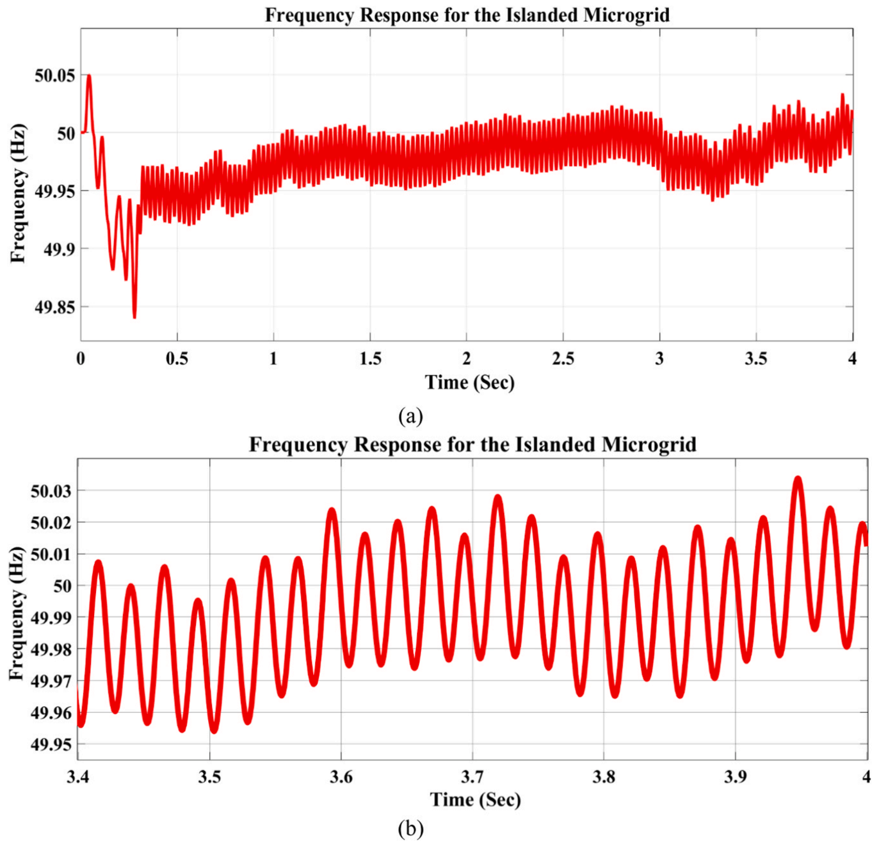

Fig. 22. **:** Frequency responses with FLC and PID tuned, (a) From 0–4 s (b) From 3.4–4 s of the IHMS for Pulau Perhentian, Malaysia.

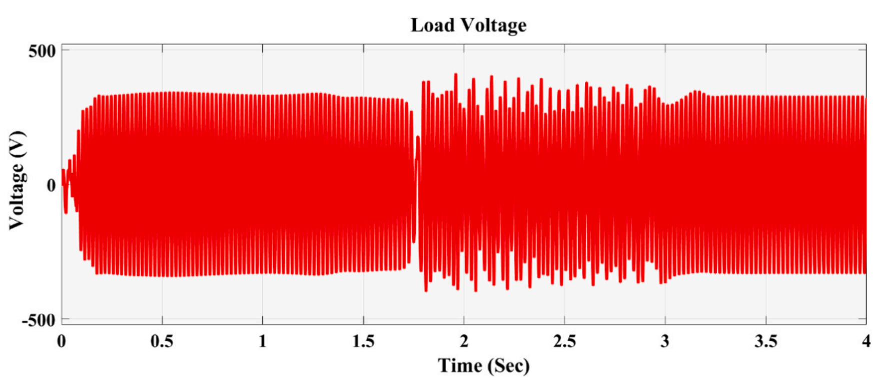

Fig. 23. **:** Load voltage response of the IHMS for Pulau Perhentian, Malaysia.

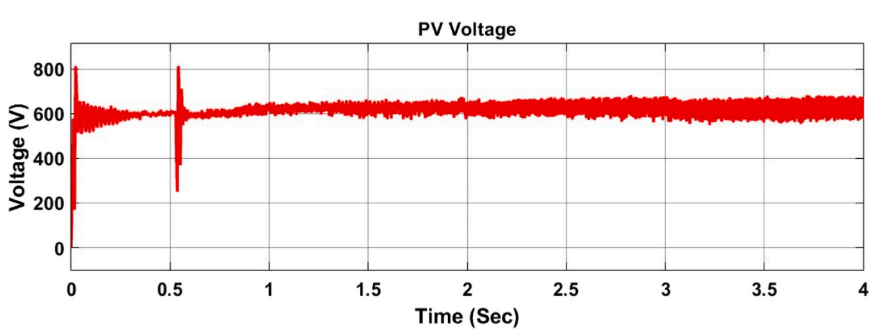

Fig. 24. **:** Voltage response of the IHMS for Pulau Perhentian, Malaysia from the PV module.

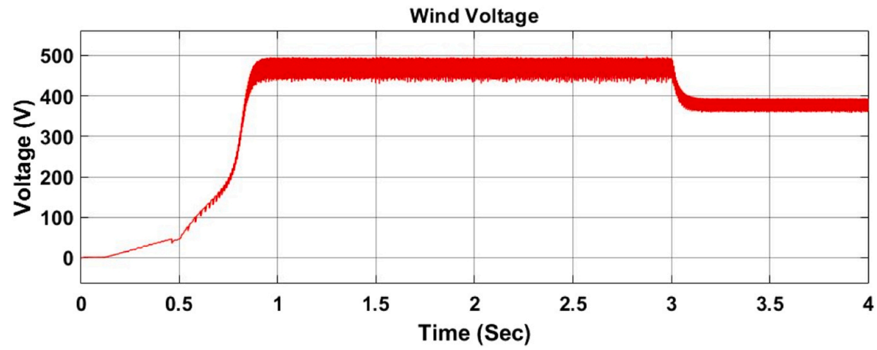

Fig. 25. : Voltage response of the IHMS for Pulau Perhentian, Malaysia from the wind turbine module.

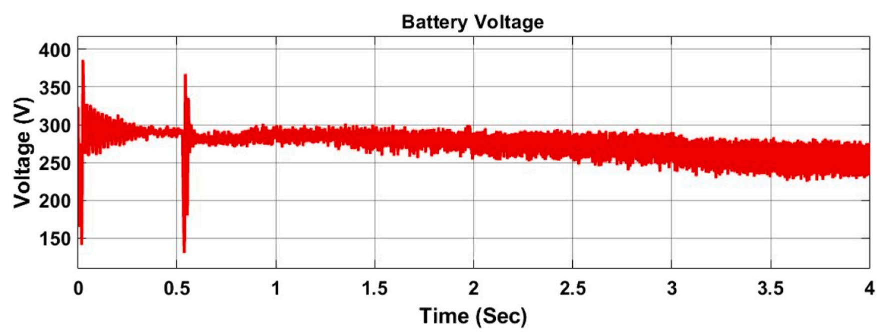

Fig. 26. : Battery voltage response of the IHMS for Pulau Perhentian, Malaysia from the battery module.

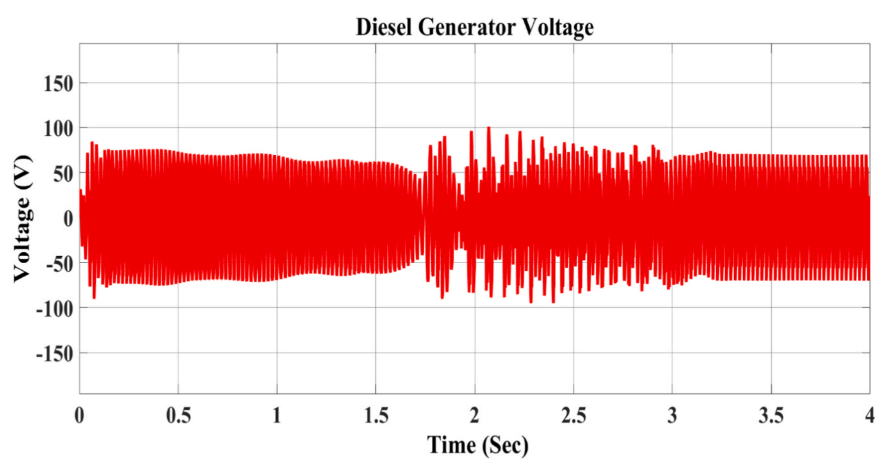

Fig. 27. : Diesel generator voltage response of the IHMS for Pulau Perhentian, Malaysia from the diesel generator.

respectively. From 0–0.5 s, there are some dynamic responses from the power electronic devices, and these have been stabilized after 0.5 s. The load voltage lies between − 400–400 V due to the sudden or periodic variations in load and renewable power generation affecting the bi-directional current flows between the loads and power sources. The PV voltage started rising to 600 V then after 0.5 s stabilized and stayed at 500–600 V as the PV generation to the load connected to 600 V. The wind voltage is changing so rapidly from 0 to 500–400 V in 4 s due to the sudden and periodic changes in the average wind speed and the load demand from the wind terminal. The FLC has been implemented with the PID controller to make the winding voltage stabilize in between 3 and 4 s. The battery voltage lies between 300 and 250 V and from 0.5 to 2.5 s remain at 300 V and then 2.5–4 s falls to 250 V and stabilized as the load terminal connected with the battery storage programmed at 250 V.

Fig. 28 shows the power responses for the various components in the microgrid. The power responses have their corresponding magnitudes within the expected ranges. Fig. 29 shows the PV output voltage without MPPT (Maximum Power Point Tracking) applied to the PV unit. Then a PSO (Particle Swarm Optimization) based MPPT is applied for tracking the maximum power point tracking purpose and thus improving the voltage performance of the PV unit as shown in Fig. 30. PSO has been adopted as the other conventional techniques of MPPT like Perturb and Observe (PnO), Incremental conductance (IC) have their own disadvantages. The PnO needs larger number of iterations, has lower convergence speed and accuracy. The IC on the other hand cannot track the change of voltage with the fast change in the solar radiation pattern. The MATLAB code used for PSO has been provided in the appendix section of this manuscript.

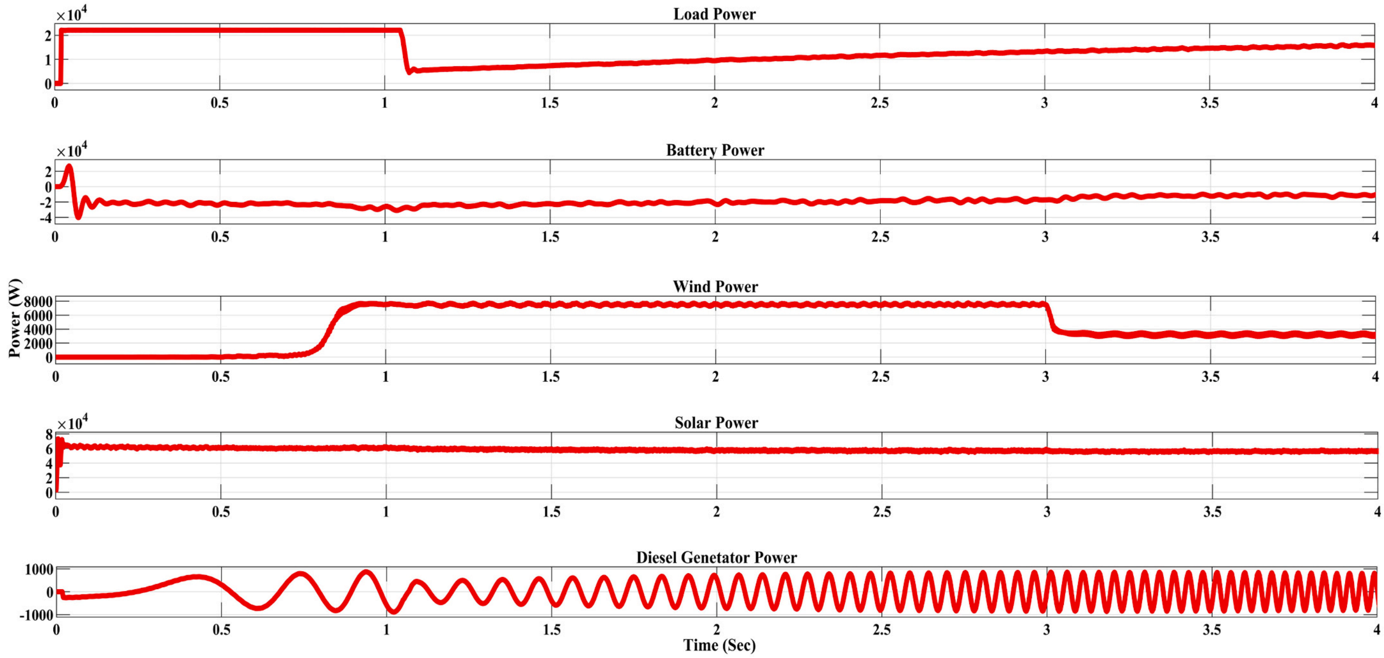

Fig. 28. : Power responses for various IHMS components.

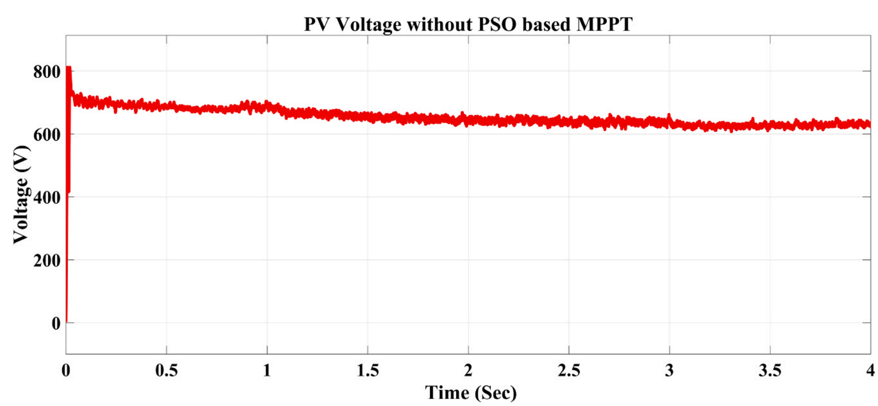

Fig. 29. : Solar PV voltage without PSO based MPPT.

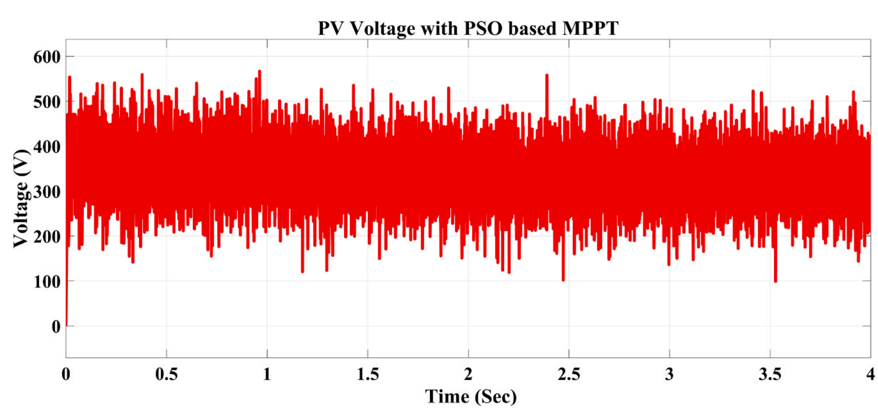

Fig. 30. : Solar PV voltage with PSO based MPPT.

9. Conclusion

In this paper, several deterministic and stochastic optimization approaches are applied to obtain the optimal number of different energy generating modules, which is the most economically attractive to be able to fulfil the load demand for a small community in Pulau Perhentian, Malaysia, considering the meteorological pattern of the area.

From the results and comparisons, it can be concluded that the

HOMER gives the best result for LCOE and NPC, and it has a good convergence rate and can handle uncertainties. Homer works on a deterministic algorithm which is called 'Homer Optimizer'. The components and controllers initially chosen for the design purpose are cheap themselves and the Homer optimizer itself is capable of finding the cheaper option from the available options using the optimizer.

In this paper, the issues of voltage and frequency fluctuations in islanded hybrid Microgrid systems are investigated, with the main reason being identified as the lack of energy generated to meet the load demand. The hierarchical procedure has been proposed to mitigate the above voltage and frequency fluctuation issues mentioned below:

Firstly, the hybrid energy system was optimized such that the optimal numbers and sizes of power generating modules (including PV, wind turbine, battery, and diesel generator) are obtained, while also having the ability to handle the load requirement. The optimization problem also considers the levelized cost of energy (LCOE) and net present cost, by incorporating these into the cost function. Several optimization algorithms were implemented and compared. The results show that the HOMER outperforms all the others, with the lower COE and NPC, and achieving the convergence rapidly.

Secondly, an advanced control approach is used to control the voltage and frequency. The PID control and FLC with automatic tuning are coded in MATLAB Simulink, along with a complete model of an islanded hybrid microgrid system. Simulation results show that by using the above control technique, the voltage and frequency are regulated well within the acceptable range.

CRediT authorship contribution statement

Sk. A. Shezan: Conceptualization, Methodology, Software, Data analysis, Writing – original draft, Validation, Visualization. **Md. Fatin Ishraque:** Conceptualization, Methodology, Software, Writing – original draft, Investigation, Resources, Formal analysis**. Mohammed Zeehan Saleheen**: Methodology, Software, Writing – original draft, Investigation, Resources, Formal analysis. **GM Shafiullah:** Conceptualization, Supervision, Formal analysis, Resources, Writing – review & editing. **Ramakrishna NSS:** Software, Writing – original draft, Investigation, Resources, Formal analysis**. Liton Chandra Paul:** Software, Writing – original draft, Investigation, Resources, Formal analysis**. SM Muyeen:** Conceptualization, Supervision, Formal analysis, Resources, Writing – review & editing. **Polamarasetty P Kumar:** Software, Writing – original draft, Investigation, Resources, Formal analysis**.**

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix

```
function D = PSO(V, I)%% Parameters of PSO.
Ni= 50;.
Np= 1;.
w= 0.9;.
c1 = 2;.
c2 = 2;.
D_min= 0.01;.
D_Max= 0.99;.
%% Initialization.
D=zeros;.
empty_Duty.Position = zeros;.
empty_Duty.Velocity = zeros;.
empty_Duty.Power = zeros;.
empty_Duty.Best.Position = zeros;.
empty_Duty.Best.Power = zeros;.
Duty = repmat(empty_Duty, Np, 1);.
GlobalBest.Power= 0;.
GlobalBest.Position= 0;.
for i = 1:Np.
Duty(i). Position = unifrnd(D_min,D_Max,1);.
Duty(i). Velocity = zeros;.
Duty(i). Power = V(i)*I(i);.
Duty(i). Best.Position = Duty(i). Position;.
Duty(i). Best.Power = Duty(i). Power;.
end.
BestPowers = zeros(Ni,1);.
%% Main loop of PSO.
for j = 1:Ni.
for i = 1:Np.
Duty(i). Velocity = w*Duty(i). Velocity.
+c1 *rand* (Duty(i). Best.Position - Duty(i). Position).
```

```
+c2 *rand* (GlobalBest.Position - Duty(i). Position);.
Duty(i). Position = Duty(i). Position + Duty(i). Velocity;.
Duty(i). Power = V(i)*I(i);.
if Duty(i). Power > Duty(i). Best.Power.
Duty(i). Best.Position = Duty(i). Position;.
Duty(i). Best.Power = Duty(i). Power;.
if Duty(i). Best.Power > GlobalBest.Power;.
GlobalBest.Position = Duty(i). Position;.
GlobalBest.Power=Duty(i). Best.Power;.
end.
end.
D(i)=Duty(i). Position;.
end.
end.
D;.
```

Component specification

The components specification utilized in the hybrid system design are given in the following section (from Tables 4 to 8).

Table 4
Significant parameters of battery.

Parameters	Value
Fuel cost	1 $/liter
Net cost	200 $/kW
Lifetime	900000 min (15,000 h)
Least load quotient	30%
Substitution cost	150 $/kW
O&M cost	4.6$/kW

Table 5
Significant parameters of battery.

Parameters	Value
Substitution Cost	80 $/kW
Rectifier efficiency	89%
Lifetime	10 years
Principal Cost	100 $/kW
Efficiency	95%
Rectifier aptitude	90%

Table 6
Significant parameters of converter module.

Parameters	Value
Inverter efficiency	90%
Substitution cost	50 $/kW
Rectifier efficiency	85%
Lifetime	20 years
Principal cost	210 $/kW

Table 7
Significant parameters of wind turbine module.

Parameters	Value
Cut off speed	15 m/s
O&M cost	20 $/kW
Lifetime	15 Years
Net cost	2000 $/kW
Rated speed	8 m/s
wind speed	3 m/s
Substitution cost	1500 $/kW

Table 8
Significant parameters of solar PV module.

Parameters	Value
O&M cost	20 $/kW
substitution cost	200 $/kW
Lifetime	20 Years
Tracking system	N/A
Derating factor	80%
Net cost	250 $/kW

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Corrigendum

Corrigendum to "Optimization and control of solar-wind islanded hybrid microgrid by using heuristic and deterministic optimization algorithms and fuzzy logic controller" [Energy Rep. 10 (2023) 3272–3288]

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