OPTIMUM GENERATED POWER FOR A HYBRID DG/PV/BATTERY RADIAL NETWORK USING META-HEURISTIC OPTIMIZATION ALGORITHMS

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Thesis title	Optimum Generated Power for a Hybrid DG/PV/Battery Radial Network Using Meta-Heuristic Optimization Algorithms
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ABSTRACT

This study presents four optimization algorithms used to optimize an existing DG/PV/Battery hybrid generating system on an isolated island to minimize the network losses and help in achieving optimal power generation at minimal costs, in addition to studying replacing the DG with a Wind Turbine. The efficacy of the four employed meta-heuristic optimization algorithms in this study (Firefly Algorithm, Particle Swarm Optimization, Surrogate Optimization, and Genetic Algorithm) was evaluated comparatively, considering factors, i.e., Coefficient of Determination (R^2), Cost of Energy (COE), and Loss of Power Supply Probability (LPSP). This research employed the forward Backward Sweep Method (FBSM) to compute the power flow calculations of the network. After analyzing the results obtained from the four algorithms, it was determined that integrating an extra 200 kW DG at bus 2 proved to be a successful approach for optimizing the system. This strategy led to the maximization of generated power while minimizing network losses and costs. The optimization outcomes indicate that employing DG allocation through the Firefly Algorithm surpasses the performance of the other three algorithms. It notably reduces the load on the primary DG and batteries by 30.48% and 19.24%, respectively. Wind speed fluctuations during the rainy season and the whole year noticeably vary in Indonesia, which affects the generated power and the capability of the system to satisfy the required load. This research presents an optimization

of an existing DG/PV/Battery and a proposed Wind/PV/Battery systems for a standalone network located on Tomia Island, Southeast Sulawesi, Indonesia.

ACKNOWLEDGEMENT

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Mohamed Elsayed Shiybahelhamd Abdelwareth,
20 June 2024,
Bangkok, Thailand.

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LIST OF ABBREVIATIONS

PSO	The Particle Swarm Optimization
GA	The Genetic Algorithm
COE	Cost of Energy ($/kWh)
DG	Diesel Generator
LPSP	Loss of Power Supply Probability
FA	The Firefly Algorithm
W	Watt
PV	Photovoltaic cell
LPSP	Loss of Power Supply Probability
R^2	Coefficient of determination
CO_2	Carbon dioxide
H_o	The daily insulation that can be reached and sensed on a horizontal surface.
FC	Fuel Cost
O&M	Operational and Maintenance
N_m	Solar cell numbers that had been set in Tomia.
$P_{pv}(t)$	The generated instantaneous power at time *t* in watt
A_m	The surface area (*m^2*) of a single PV panel.
η_g	PV panel efficiency
L	The latitude in degrees (°).
$G_{till}(t)$	The actual value of the hourly global solar irradiance is calculated on a tilted surface.
Is	The solar constant.
ω_s	Sunset hour angle parameter.
C_f	The actual price of a 1*L* of fuel

I_{on}	The values of the solar intensity at the normal incidence outside the atmosphere of the planet (Btu/hr-sqft).
β_O	The attraction occurs at a distance r = 0 among the fireflies.
ω	The true solar time.
β_r	Firefly Attractiveness parameter.
x_i	The firefly's Movement due to the attraction effect occurred among any two fireflies.
I_i	The light intensity of Firefly i
r_{ij},	the distance between two fireflies i and j
pi	PSO's particle best position.
gi	PSO's best position among all particles.
R_k	Resistance at bus k
X_k	Reactance at bus k
$rand()$	PSO's random main parameter
c_1, c_2	PSO's position and velocity parameters.
Q_k	Reactive power at bus k
$Q_{loss(k,k+1)}$	Reactive power losses in the line between bus k and $k+1$
P_{DG}	Diesel Generator (DG) generated power in watts.
P_{Batt}	Battery generated power in watts.
$P_{loss(k,k+1)}$	Active Power Losses in the line between bus k and $k+1$
P_k	Active power at bus k
P_{load}	The load power.
$P_{Add.DG}$	Additional DG generated power in watts.

Chapter 1
Introduction

1.1 Research Background

The significance of embracing renewable energy as a dependable and sustainable electricity source is undeniable, particularly given the current world challenges linked with conventional fossil fuel generation methods [1]. For over the past decades, employing the renewable energy as a reliable source of electricity has garnered global attention due to the global warming of our planet and its inhabitants as a direct response to several scientific warnings regarding the planet's future [2].

Hybrid generation systems, which combine multiple renewable resources like solar, wind, and hydroelectric power, offer a reliable solution to help in mitigating the impacts of the climate change dilemma [3-5] and also positively impact in minimizing the carbon dioxide emissions levels in the atmosphere. Consequently, substantial investments and research funding panels and committees from government and private sectors worldwide have been channeled into the importance of developing sustainable tools and equipment that can convert renewable energy resources to electricity, to supplant the existing conventional generation ways. Many nations are now focusing on the utilization of various renewable resources in order to fulfill the country's electricity requirements and contribute to the global objective of fostering clean power. Ongoing research endeavors aim to devise innovative approaches for getting the maximum benefits using developed optimizing systems and techniques. In line with this endeavor, many electricity-generating companies are progressively integrating renewable energy resources into their networks. Artificial intelligence (AI) has emerged as a reliable and versatile tool extensively employed to deliver optimal solutions. Electrical engineering researchers have utilized various AI and developed optimization algorithms to devise techniques that can effectively be optimizing the electrical systems [6-8].

Many meta-heuristic algorithms have proven to be effective in optimizing power systems , with a specific emphasis on minimizing costs and losses by strategically allocating Distributed Generation [9-11]. These algorithms are also utilized to determine the optimal size and location of DG units [12-17]; an exemplary study by L.F. Grisales-

Norena [18] highlights the utilization of Genetic Algorithms (GA) and fuzzy-based approaches to determine the optimal operation and bus location of batteries and capacitor banks. The study also includes a comparative analysis of both approaches. In another study, Nahar A. and Johnson A. conducted a successful analysis using five different meta-heuristic algorithms that led to optimizing the proposed Hybrid Network located in Saudi Arabia. The network comprises a wind turbine, a Photovoltaic (PV) system, and a biomass generator, and the study aimed to optimize their operation and integration [19]. For instance, an Improved sun flower optimization algorithm was utilized to optimize a distribution network considering the minimum losses and costs through capacitor allocation [20], Capacity ratio calculation method was presented in [21] to optimize a standalone hybrid Wind/PV system, Energy management strategies and their integrations in power systems were presented in [19, 22], provided in-depth investigations into selecting energy management systems (EMS) for microgrids and its integrations based on the energy efficiency, robustness, and storage and generation using different optimization approaches [23-30]. In the context of renewable energy-based distribution generation units, Adel A. Abou El-Ela [31] conducted an economic and environmental study on the IEEE 33-bus system and a 141-bus large-scale system using equilibrium optimization techniques.

The four optimization algorithms selected for this study are the Firefly Algorithm (FA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Surrogate Optimization. These algorithms were able to be adapted and fit with our case study's constraints and limits and worked efficiently. We tested many other algorithms, but they were not suitable. Some algorithms only provided limits without constraints, while others managed equality and inequality constraints inconsistently.

The Author's publications presented optimization techniques to optimize the power network in Tomia Island. For instance, FA was used in [32] to optimize the existing system (DG/PV/Battery) by separately minimizing the costs and losses, and in [33] FA and GA were utilized to minimize only the costs in the same existing system (DG/PV/Battery); the two aforementioned articles optimized the system without performing optimization analyses to generate the optimum power from each source and also without considering related performance indicators. In [34] GA and PSO were applied to optimize a proposed system (Wind-Turbine/PV/Battery) incorporating a wind turbine instead of the existing DG, considering wind speed fluctuations. And in [35] FA and Surrogate optimization were implemented to optimize the (Wind-Turbine/PV/Battery) also. In a proposed optimization techniques were implemented to optimize the (DG/PV/Battery/Add.DG) considering a multiobjective function approach to optimize the system considering the minimum losses and costs.

In this research, we are discussing the optimization techniques to optimize a real case study in Tomia Island, Southeast Sulawesi, Indonesia by searching for the optimum operation scenarios considering minimizing the network losses and costs using Optimization algorithms.

Our case study is located on an isolated island called Tomia, which is an Island that belongs to Wakatobi National Park in the south-east of Sulawesi, Indonesia, as seen in Figure 1.1. Wakatobi is a national park and a regency with a total population of 94,846 people and is listed as a tentative world heritage site by UNESCO [36]. Tomia Island is positioned at coordinates approximately 5.7628° S latitude and 123.9503° E longitude. It is one of the four major islands in the Wakatobi Archipelago, alongside Wangi-Wangi, Kaledupa, and Binongko. Tomia is surrounded by the Banda Sea, which provides rich marine biodiversity and vibrant coral reefs, making it a popular destination for diving and snorkeling. To the northwest, it borders Wangi-Wangi Island, and to the southwest, it is near Binongko Island.

The island's economy is primarily based on fishing, agriculture, and tourism due to its pristine coral reefs and diving spots. According to recent census data, Tomia Island has a population of approximately 15,000 residents who live in small coastal villages. The local community is known for its cultural heritage, including traditional weaving and dance.

The electricity network in Tomia is a medium voltage network of 20kV/380v, consisting of 21 buses and four PV farms with batteries (PLTS) located in different places, as seen in Figure 1.2; the main DG in this research is in bus number one (bus 1), and normally works full load operation during the night. That's why utilizing PV farms in Tomia Island was a necessary solution in order to decrease the burden on the DG, provide electricity to the whole island throughout the day, and decrease the DG running time, which will help in reducing the CO_2 emissions in Tomia.

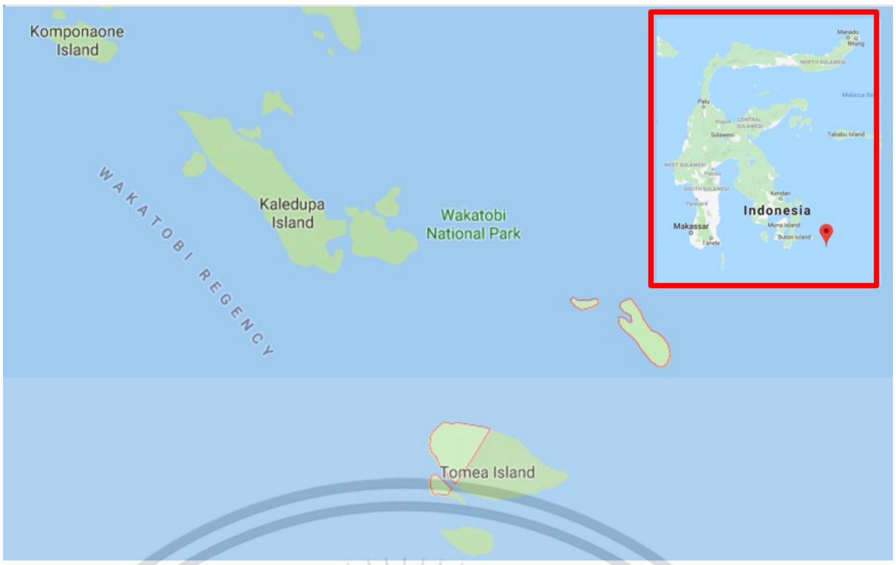


Figure 1.1 *The location of Tomia Island.*

(Source:- Google (2024) Tomia Island. Available at: https://maps.app.goo.gl/8ixcgNS88WU24kHc8 (Accessed: 19 June 2024)).

PLTS which means (solar power plant) is the other description of the Photovoltaic Generation System (PVGS) that was added to the existing network located in four locations: the first one in Kulati with an output solar power 140 kWp, the second in Dete with 112 kWp, the third in Kahaianga with 308 kWp and the last one in Lamanggau with 224 kWp, Real photos of the PV farms in Figure 1.3.

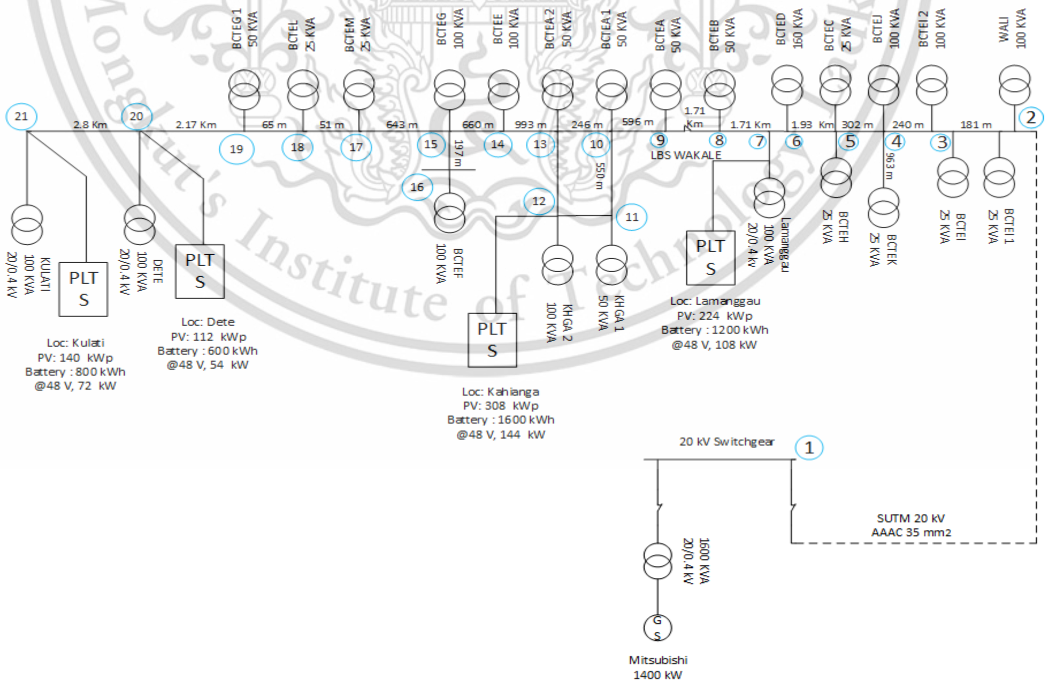


Figure 1.2 *Single Line Diagram of the case study in Tomia Island, DG case.*

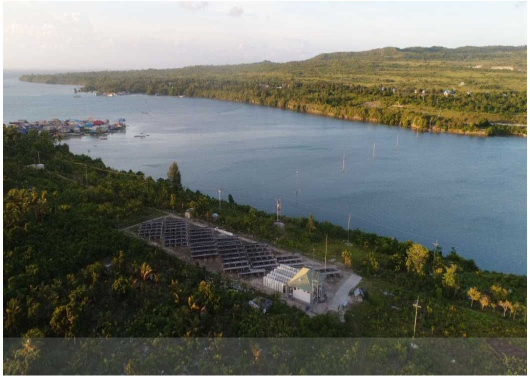
	
PLTS Lamamgau.	PLTS Kahaianga.
	
PLTS Dete.	PLTS Kulati.

Figure 1.3 *PV farms in the four locations on Tomia Island*

The solar radiation data provided for the Tomia location represents the daily measured solar radiation on-site. To derive hourly solar radiation values, we utilized the Liu and Jordan statistical method [37]. With the calculated hourly solar radiation, we then determined the hourly generated power from the PV farms. Integrating the hourly generated power from each energy source with the selected Optimization Algorithms to optimize the system and choose the optimum operation with the minimum costs during the day. Figure 1.4 shows the operating system of the existing case study during the day and night times.

Power flow calculations were conducted using the Forward-Backward Sweep Method (FBSM), which was chosen for its suitability in calculating losses for radial networks compared to the Newton-Raphson method. Many researchers prefer to use FBSM, which is renowned for its straightforwardness, fast computation, and dependable results. We are optimizing the existing system, which contains DG, PV, and Batteries, besides proposing another operating scenario by substituting the existing DG with a 950 kW Wind turbine to generate electricity with 100% clean energy, in addition to considering the wind speed vacillation and its effect in satisfying the required load.

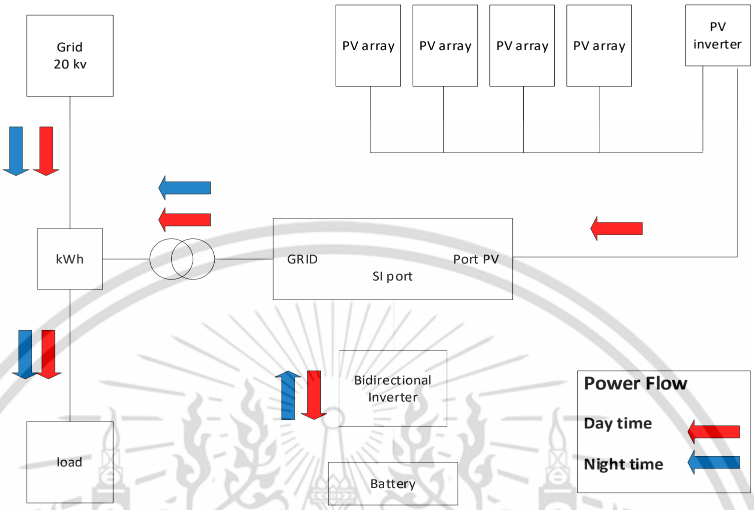


Figure 1.4 The operation system of our case study

This research used FA, PSO, GA, and Surrogate optimization Algorithms to optimize both operating scenarios. The algorithms employed in this study aimed to determine the optimal output power generated and delivered by each source, considering minimizing overall costs. Additionally, each algorithm was coupled with the Forward-Backward Sweep Method (FBSM) in order to calculate the optimal size of the Distributed Generation that would result in minimum losses within the system. Those algorithms have already run efficiently and have optimized the system to date.

1.2 Thesis Objectives

This research focuses on optimizing the hybrid radial network on Tomia Island, situated within Wakatobi National Park in southeastern Sulawesi, Indonesia. Wakatobi encompasses four islands: Wangi-Wangi, Binongko, Tomia (the subject of this case study), and Kaledupa, with a total population of 94,846 people. Notably, Wakatobi is recognized as a UNESCO provisional world heritage site.

The primary objective is to enhance the performance of the existing electricity infrastructure on Tomia Island, taking into account the unique challenges posed by its isolated location. Tomia Island faced connectivity challenges with the national grid in the region, leading to the establishment of the existing radial network. Initially, a Distributed Generation system consisting of a 1.4 Mwatt Diesel Generator (DG) served as the main energy source, operating for limited hours each night. However, this setup proved insufficient to meet the island's power demand.

Given Indonesia's current tropical climate, the energy that can be generated from the sun emerged as a viable source for a consistent electricity supply. Subsequently, four Photovoltaic (PV) stations were integrated into the radial network, forming a hybrid system that ensures round-the-clock electricity availability.

The electrical network under investigation is a 20 kV radial system consisting of 21 buses. Each bus is equipped with a 20 kV/400 V distribution transformer to deliver power to the load. The primary power source is a 1400 kW DG, complemented by four PV farms and battery systems located at Kahianga (308 kWp), Lamangau (224 kWp), Kulati (140 kWp), and Dete (112 kWp).

The Forward-Backward Sweep Method (FBSM) is employed for power flow calculations, determining active and reactive powers, and conducting sensitivity analyses for optimal DG location and size. Additionally, optimization algorithms are utilized to optimize output power from each source hourly, enabling system optimization and meeting the island's power demand throughout the day.

This research delves into comparing the effectiveness of various optimization techniques, including Fractional Algorithms (FA), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Surrogate Optimization, in providing optimization solutions for radial power networks considering minimizing costs and losses.

1.3 Main Contributions

The author's main contributions were discussed and published in various conferences and in the Sustainability journal by meeting the graduation requirements. Firefly Algorithms (FA) and Genetic Algorithms (GA) were employed to minimize costs within the existing system (DG/PV/Battery). However, these articles focused solely on cost optimization in some of the author’s published articles, without conducting analyses to optimize power generation from each source or considering relevant performance indicators. In addition, the four optimization algorithms for a proposed system (Wind turbine/PV/battery) included a wind turbine as a replacement for the existing DG. In this thesis study, we performed and explained the outcomes for all the optimization scenarios and runnings for the existing and proposed wind turbine systems, presenting a more comprehensive optimization approach.

The significant contributions of this research are outlined as follows:

1. Presenting optimization scenarios using Firefly Algorithms (FA), Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Surrogate algorithms. These scenarios succeeded in optimizing the proposed DG allocation integration scenario (DG/PV/Battery/Add.DG) within the Tomia Island network. This methodology is scalable and applicable to radial systems.
2. A multi-objective function optimization method is employed to optimize the system, considering minimizing system losses and costs while applying the Pareto optimality approach. This approach ensures a balanced optimization strategy that takes into account multiple objectives simultaneously.
3. The research generates optimal power output from each source using FA, GA, PSO, and surrogate algorithms. Performance indicators such as Loss of Power Supply (LPSP) and the coefficient of determination (R^2) are considered. These indicators provide valuable insights into the optimized system's performance, reliability, and overall effectiveness.
4. Presenting a solution to generate clean energy from renewable resources in Tomia Island by replacing the existing DG with a proposed Wind Turbine and studying the best and optimum operations by utilizing the implemented optimization methods in this study.

Overall, the contributions of this research extend beyond cost minimization to include a holistic optimization approach that addresses performance indicators and ensures the reliability and efficiency of the electricity network on Tomia Island.

1.4 Thesis Outline

The organization of this thesis is managed as follows:

Chapter 1 consists of the research background, Location of the case study, thesis objectives, main contributions, and the thesis outline breakdown.

Chapter 2 presents Tomia's Radial Network, SLD of the exit and proposed systems, Power flow calculations, and the implemented Methodologies.

Chapter 3 presents The Four Implemented Optimization Algorithms (FA, GA, PSO, and Surrogates), the parameters and the optimization implementations to generate the optimum solution of each algorithm, and the pseudo-code of each algorithm.

Chapter 4 presents the optimization outcomes, the optimum generated powers, losses, and costs of the four algorithms to the existing DG/PV/Battery, and the optimization outcomes of the proposed Wind/PV/Battery systems. The proposed method is then explicated and followed by the experimental results, discussion, and summary.

Chapter 5 is the conclusions and recommendations.

Chapter 2
Tomia's Power Flow Calculations and The Implemented Methodologies.

2.1 Introduction

This chapter shows the implemented methodologies employed to reach the optimal outcomes using the four aforementioned algorithms. Each one follows unique operational procedures tailored to its specific characteristics.

The primary goal is to enhance the efficient exploitaion of the availability of solar radiation, thereby reducing the workload of the existing Distributed Generation (DG) system. This strategy aims to allocate the DG to cover approximately 30-35% of the total power demand. We seek to achieve a more equitable and sustainable energy distribution within the system through optimized solar energy utilization, thereby improving overall efficiency.

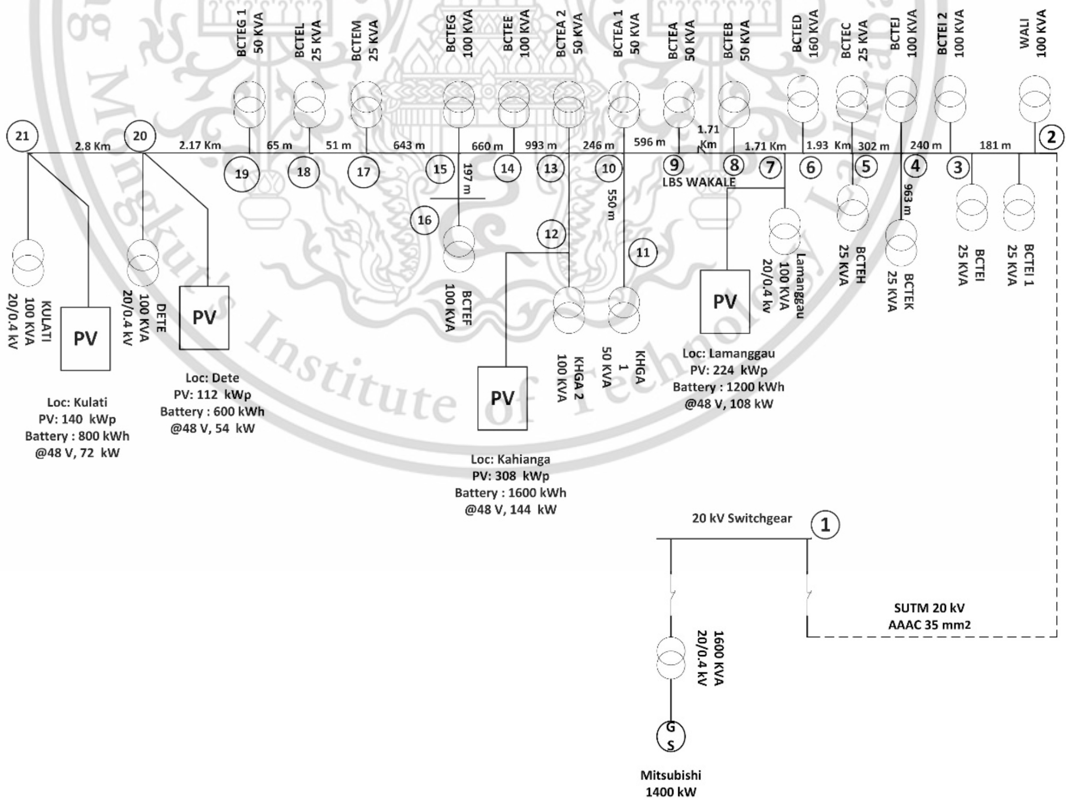


Figure 2.1 *Tomia's radial network SLD.*

This strategy aims not only to reduce overall costs but also to minimize CO_2 emissions on Tomia Island, making a significant contribution to the efforts of maintaining purity and helping decrease the contamination levels in Wakatobi National Park. The main objective of this study is to minimize the system's operational cost while simultaneously reducing network losses. The cable types and inter-bus distances employed in Tomia's electricity network are outlined, as depicted in Figure 2.1. An All-Aluminum-Alloy-Conductor (AAAC) cable type with a cross-sectional area of 35 mm2 is employed in this network. The values of the AC resistance and inductive resistance are 1.05 ohm/km and 0.295 ohm/km, respectively, which are utilized to determine the *R* and *X* values for all lines between each two buses. These parameters play a crucial role in accurately assessing power flow and losses within the network. The primary Distributed Generation is linked to the slack bus, influencing power flow calculations significantly. Utilizing the distances between bus pairs, we derive the actual resistance (*R*) and reactance (*X*) values, crucial for power flow and loss computations. In addition, Figure 2.2 shows the proposed system SLD by replacing the DG with a wind turbine.

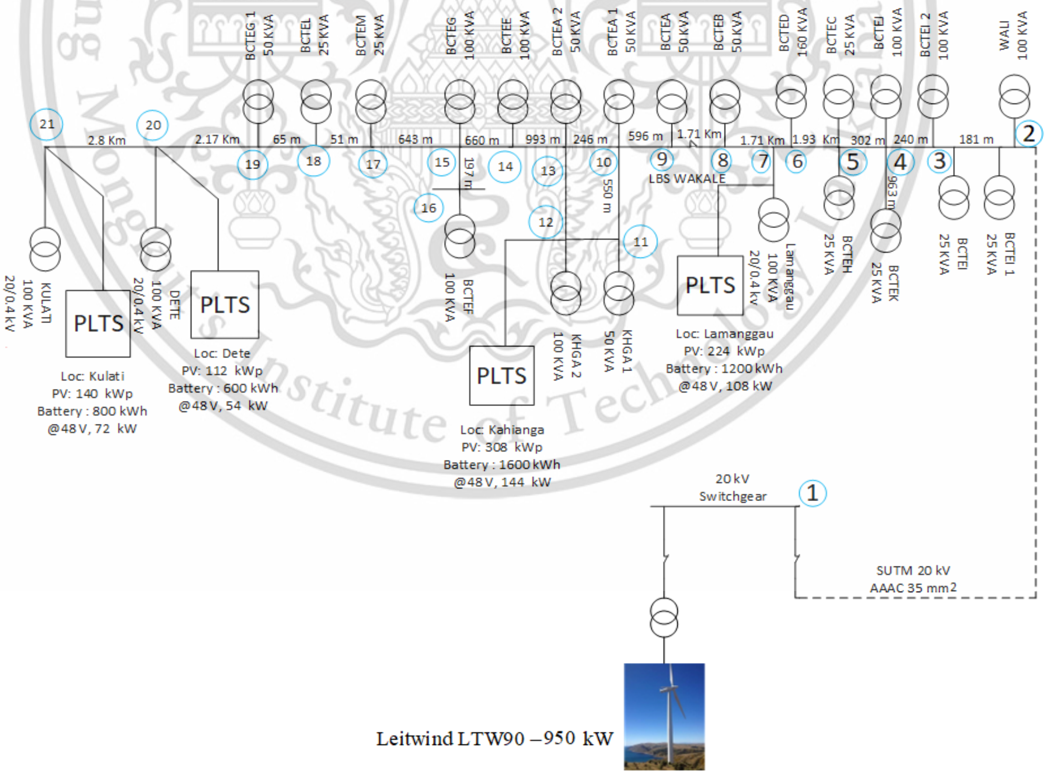


Figure 2.2 *The proposed operating scenario using a 950-kW wind turbine.*

2.2 Solar Radiation Analyses

The amount of power generated from exploiting the sun's radiation is computed using the following instantaneous power formula [9, 32, 38].

$$P_{pv}(t) = \eta_g * N_m * A_m * G_{til}(t) \quad (1)$$

The value of the instantaneous power generated in watts is denoted by $\boldsymbol{P_{pv}(t)}$. The number of solar cells set in Tomia PV farms is represented by $\boldsymbol{N_m}$, while $\boldsymbol{\eta_g}$ signifies the efficiency of the PV panels. The surface area in square meters of a single PV panel is denoted by $\boldsymbol{A_m}$, and $\boldsymbol{G_{til}(t)}$ represents the actual value of the calculated hourly global solar irradiance using the Liu and Jordan method on a tilted surface. Liu and Jordan's method is widely used by many researchers and is a reliable approach for determining solar radiation calculations per hour from the provided daily solar radiation values. It provides an accurate estimation of solar irradiance, taking into account factors such as tilt and location, which are crucial for optimizing PV system performance. Estimating the extraterrestrial daily insulation is one of the main and essential parameters. To achieve this, we employ the next formula, which can calculate the value of Ho, that represents the extraterrestrial daily insulation sensed and can be measured on a horizontal surface:

$$H_o = I_{on} * (\cos L * \cos\delta * \cos\omega s * \sin L * \sin\delta) * 24/\pi \quad (2)$$

The value of the sunset hour angle is represented by the parameter $\boldsymbol{\omega s}$, which is a crucial parameter in calculating the value of the sensed solar irradiance, where $\boldsymbol{\delta}$ represents the value of the solar declination (°). And finally, $\boldsymbol{\omega s}$ can be calculated using:

$$\cos\omega_s = -\tan L * \tan\delta. \quad (3)$$

While $\boldsymbol{L}$ is the value of the latitude in degrees (°), the $\boldsymbol{I_{on}}$ that its unit is (*Btu/hr-sqft*) represents the amount of solar intensity that is sensed at normal incidence that could be measured outside the planet's atmosphere. The next formula is used for calculating I_{on}:

$$I_{on} = r * I_{sc} \tag{4}$$

The parameter r signifies the value of the solar radiation intensity ratio, while I_{sc} denotes the solar constant, a fundamental physical parameter indicating the amount of solar radiation that can be received per unit area, estimating that this area is located beyond the planet's atmosphere, and also at the planet's mean distance from the Sun. The calculation of rd is performed as follows:

$$r_d = (\pi*(\cos\omega-\cos\omega_s)) / (24*(\sin\omega_s - (\omega_s*\cos\omega_s))) \tag{5}$$

Which ω represents the true solar time and equals:

$$\omega = (hour\text{-}12hour) * (15^o/hour) \tag{6}$$

kd is dimensionless, which is the ratio of the average intensity of the diffuse radiation to the extraterrestrial radiation intensity value, the monthly average daily diffuse radiation received on a horizontal surface D' equals, kd normally varies between (0.125 and 0.179), and the hourly-average solar radiation Idh can be calculated using:

$$D' = k_d * Ho \tag{7}$$

$$I_{dh} = G_{til}\,(t) = r_d * D' \tag{8}$$

2.3 Diesel Generator (DG)

Distributed Generation is pivotal in electricity systems; our distributed generator, in this case study, comprises a diesel engine coupled and connected with an electric generator. Particularly in isolated standalone systems, DG serves as a reliable and efficient option for converting fuel into electrical power. The cost of the consumed fuel can be determined using the following *FC (fuel cost)*, which is a quadratic and also non-linear formula [39]:

$$FC\ (fuel\ cost) = C_f\, \Sigma^{N}_{t=1}\ (aP_{DG(j)}{}^2 + bP_{DG(j)} + c) \quad (9)$$

The fuel cost coefficients are represented by ***a***, ***b***, and ***c***. $\boldsymbol{P_{DG(j)}}$ denotes the DG is the generated power at the ***jth*** interval, and $\boldsymbol{C_f}$ signifies the price of one liter (*1L*) of fuel. The utilized parameters and components are outlined in Table 2.1.

2.4 The modeling of the batteries

Battery banks complement PV panels in scenarios where the electricity system functions without DG. In instances where the generating power exceeds the requested load, at that moment, the battery banks initiate charging. The following formula is employed to compute the energy stored in the battery bank [40]:

$$E_{batt}(t) = E_{batt}(t-1) * (1-\delta) * [\,(E_{pv}(t) + E_{DG}) - (E_{load}(t)/\eta_{inv})]\ * \eta_{batt} \quad (10)$$

$$P_{batt}(t) = \begin{cases} P_{batt}(t-1) * (1-\delta) - P_g(t) * \eta_{batt};\, P_g(t) < 0 \\ P_{batt}(t-1) * (1-\delta) - P_g(t); \qquad ;P_g(t) < 0 \end{cases} \quad (11)$$

While $\boldsymbol{E_{batt}(t-1)}$ and $\boldsymbol{E_{batt}(t)}$ are the battery charge values that have been obtained at times $\boldsymbol{(t-1)}$ and $\boldsymbol{t}$, respectively, $\boldsymbol{\eta_{batt}}$ is the battery's charge efficiency, $\boldsymbol{\delta}$ is the hourly self-charge rate, $\boldsymbol{\eta_{inv}}$ is the inverter efficiency, $\boldsymbol{P_g(t)}$ is the value of the measured the over stored energy or can also be described in some references as the battery lack energy, and $\boldsymbol{E_{load}(t)}$ is the load demand.

2.5 The Calculations of the Wind Power

A wind turbine is a device designed to convert wind energy into electricity; this process can be accomplished by harnessing the wind's kinetic energy [3, 5, 6, 23, 25, 34, 38, 41, 42]. The mass flow rate, represented by $\dot{\boldsymbol{m}}$, of the air within the stream tube, remains constant throughout.

Table 2.1: Utilized parameters and components.

Apparatuses	Parameters	Values	Units
PV	Initial cost	600	$/kW
	O&M cost	0.01	$/kW
	Lifetime	25	Years
	CO_2 Emission	0.023	Kg/kWh
DG	Initial cost	1050	$/kW
	O&M cost	0.038	$/kW
	CO_2 Emissions	0.89	Kg/kWh
	Lifetime	240,000	Hours
Converter	Initial cost	520	$/kW
	Lifetime	25	Years
Battery	initial cost	285	$/kW
	Lifetime	5	Years
	CO_2 Emissions	0.027	Kg/kWh
	Efficiency	85	%
Others	The Project Lifetime	20	Years
	Interest rate	10	%

The wind velocity is denoted by $\boldsymbol{v}$, while $\boldsymbol{vb}$ represents the wind velocity that passes through the rotor blades' plane, and vd is the value of the downwind speed. The power that can be extracted by the blades, $\boldsymbol{Pb}$, is usually determined and defined as the the difference of the kinetic energy between the measured upwind and measured downwind air flows [24, 28, 30]:

$$Pb = 0.5 * \dot{m} * (v^2 - v^2{}_d) \tag{12}$$

The equation indicates that the wind power equals the upstream wind power multiplied by a factor. This factor represents the actual fraction of the wind's energy captured by the rotor blades, known as the rotor efficiency, typically denoted as $\boldsymbol{C_p}$.

$$Rotor\ efficiency = C_p = 0.5 * (1+\lambda) * (1+\lambda^2) \tag{13}$$

Therefore, P_r, which is the rated wind power that can be delivered or generated by the rotor, is shown and can be calculated using:

$$Pr = 0.5*\rho*Cp*Aw*(Vr)^3 \quad (14)$$

2.6 Power Flow calculations using FBSM.

The Forward-Backward Sweep Method (FBSM) is a method that can be employed to conduct and do power flow computations [18, 43-45], especially for radial systems [29]. This method is designed to handle the differential-algebraic system; Resistance (*R*) and Reactance (*X*) values are needed for each line to calculate losses, as mentioned earlier. Power flow within a radial system can be determined using a simplified set of floating equations [6], enabling the computation of voltage and current magnitudes, as well as active and reactive powers, using the following formulas [33].

$$P_{k+1}=P_k - P_{loss,k} - Pl_{k+1} \quad (15)$$

$$Q_{k+1}=Q_k - Q_{loss,k} - Ql_{k+1} \quad (16)$$

P_k and Q_k represent the active and the reactive power values going out from bus k towards bus $k+1$, P_{k+1}. Furthermore, Pl_{k+1} and Ql_{k+1} represent the real values of the load power at bus $k+1$ and the reactive load power at bus $k+1$, respectively, and $Q_{k+1}$are represent the active and reactive power values at bus $k+1$, respectively. The power loss between bus k and bus $k+1$was calculated using [45, 46].

$$P_{loss(k,k+1)} = R_k * (P_k^2 + Q_k^2) / V_k^2 \quad (17)$$

$$Q_{loss(k,k+1)} = X_k * (P_k^2 + Q_k^2) / V_k^2 \quad (18)$$

Determining total losses involves aggregating all losses across the network's lines. The Forward Backward Sweep Method (FBSM) operates in two distinct modes: Backward Sweep, accompanied by the Forward Sweep scenarios.

In the Backward Sweep mode, current magnitudes or power values are computed at each bus while maintaining alignment with voltage values. This process starts from the last bus and proceeds towards the first, with the slack bus serving as the initial reference point. Throughout backward propagation, voltage is held constant to derive the requisite values. Notably, power values are retroactively transmitted along the feeder via the reverse path.

Conversely, the Forward Sweep mode calculates the voltage drops at each node while incorporating updates on current and power flow. This process commences from the first bus and progresses towards the last. Given that the feeder is radial rather than circular, forward and backward propagations are merged to achieve optimal power flow outcomes. During forward propagation, power remains constant at each feeder section based on values obtained from the backward process. The Backward Sweep process computes current magnitudes or power values at each bus in correspondence with voltage values, advancing from the last bus to the first (the slack bus), with power values updated during backward propagation

2.7 Minimizing the network losses.

The most prevalent techniques for mitigating network losses include Capacitor Placement, Feeder Reconfiguration, and DG Allocation [47-51]. Capacitor Placement, suitable for high-voltage networks, enhances network stability and facilitates power factor correction. Strategic deployment of capacitors across the network minimizes overall losses. Feeder Reconfiguration, recommended for low-voltage networks, involves implementing load transfer switching scenarios to minimize losses. By reconfiguring feeders, the network operates more efficiently, resulting in reduced losses. DG Allocation, particularly effective for medium-voltage networks, strategically places Distributed Generation sources within the network. This method, considering power loss analysis criteria, aims to alleviate burdens and power demands while providing voltage support. These methodologies are pivotal in optimizing network performance, enhancing energy efficiency, and curbing overall losses in electrical distribution systems.

2.8 Loss of Power Supply Probability (LPSP).

The Loss of Power Supply Probability (LPSP) metric serves as a critical performance indicator for assessing system reliability. It aids in identifying scenarios where the generated power can not meet the demanded load. LPSP values typically range between ***0*** and ***1***, with ***LPSP = 0*** indicating full coverage of the load profile and ***LPSP = 1*** indicating an inability to meet the required load.

LPSP is instrumental in evaluating the reliability of hybrid systems and also assuring their performance. A desirable LPSP value should not surpass 5%, indicating a high level of reliability in supplying power to meet demand. The LPSP equation is expressed as follows [52-54]:

$$LPSP = \Sigma^{T}_{t=1} (E_l(t) - E_g(t)) / \Sigma^{T}_{t=1} E_l(t) \tag{19}$$

While E_g is the value of the generated power in kWh, and E_l is the value of the required load in kWh.

Chapter 3
The Four Implemented Optimization Algorithms

Meta-heuristic algorithms are favored and widely used over deterministic ones for their ability to optimize complex constraints and address problems that contain multi-objective functions. Renowned adaptability and flexibility, these algorithms explore large search spaces and can avoid local minima, also called local optima, by using stochastic search strategies. In the forthcoming sections, we will dive into the methodologies and operational principles of the four chosen optimization algorithms.

3.1 Firefly Algorithm (FA)

The Firefly Algorithm (FA), conceived by Xin-She Yang, was a moment of inspiration from the collective behavior and the communication styles of the fireflies [55, 56]. It stands out as a meta-heuristic technique renowned for its efficient resolution of optimization problems. Modeled after the movement patterns and the communication channels that observed in firefly swarms as they seek out nearby food sources, which represent the optimal solution [57-63]. In FA, fireflies utilize their flashing light as a means of communication. When a firefly locates food (i.e., the optimal solution), it intensifies its brightness, thereby attracting other fireflies, irrespective of gender, as fireflies are unisex. The algorithm hinges on three pivotal parameters: Attractiveness (β_r), Movement, and Distance between fireflies. Attractiveness (β_r) denotes the allure between fireflies and signifies the impact of each firefly's luminosity. The brightness of a firefly correlates with its proximity to the optimal solution. This attractiveness parameter is determined by the formula:

$$\beta_r = \beta_o * exp\,(-\gamma * r_{ij}^{m}\,)\,,\ with\ m \geq 1 \tag{20}$$

The absorption coefficient value, denoted by γ, signifies the extent of light absorption, ranging between 0 and 1. β_o denotes the value of the attraction occurring at a distance $r = 0$ among the fireflies, while parameter r represents the distance between the brighter firefly and any other firefly.

In the swarm, any two fireflies ***i*** and ***j*** are separated by a distance r_{ij}, commonly known as the Cartesian distance; this distance can be measured using:

$$r_{ij} = || x_i - x_j || = Sqrt\ (\Sigma^d_{k=1}\ (x_{i,k} - x_{j,k}\ )\text{^}2\ ) \qquad (21)$$

x_i and x_j represent two locations of any two fireflies located inside the swarm, d represents the dimensions, $x_{i,k}$ is the ith firefly spatial coordinates, and $x_{j,k}$ represents the ***jth*** firefly spatial location [64, 65]. The Movement x_i due to the attraction that happened and sensed among any two fireflies can be calculated using:

$$x_i = x_i + \beta_o * exp\ (-\gamma * r_{ij}^2) * (x_j - x_i) + \alpha * (rand-0.5) \qquad (22)$$

As depicted in the preceding formula, the firefly movement equation consists of three fundamental components. Firstly, x_i represents the current location of the firefly when the distance r is zero. The second component quantifies the level of attractiveness between the other fireflies in the swarm and the brighter one. The third component introduces the firefly movement randomization factor, especially if a firefly has not yet reached the optimal solution or achieved more excellent brightness. Here, it denotes a random number within the range of $[0,1]$. The randomization parameter α is an essential input for the algorithm, which also varies between $[0,1]$. Additionally, β_o, initially set to 1.0, denotes the initial level of attractiveness.

Algorithm 1 The FA pseudo-code implemented in this research.

Begin

1. Establish the Network constraints.
2. Identify the system's boundaries.
3. Define **F(x)**, which represents the Objective Function/Cost Function.
4. Determining the population size and initializing the initial population of fireflies x_i ($i = 1,2, \ldots n$).
5. Identifying the Light Intensity (*Ii*) at the location of x_i, Light absorption.
6. Identifying the randomization parameters.
7. while (t < The Maximum Iteration)

   for ***i*** = *1: n* for all n fireflies for j = *1: n* for all n fireflies

if (Ij > Ii)

Firefly “*i*” will move towards the firefly “*j*” in the d dimension.

end if

Attractiveness amount changes within distance r based on **($-\gamma * r$)**.

Evaluating the new solution and updating the new light intensity.

end for ***j***.

end for ***i***

Finding the current best value and then selecting the optimum solution

Posting and selecting the optimum generated power per hour for each power source.

end while

8. Results optimized and visualizations designed.

End process

3.2 Genetic Algorithm (GA)

Genetic Algorithm (GA), firstly developed and introduced to the world by John Holland in 1975, is a nature-inspired optimization method rooted in genetic principles [66-68]. GA employs three primary genetic operators: Natural Selection, Mutation, and Crossover, mirroring biological processes. Natural Selection involves selecting genes that are well-suited for survival and reproduction while removing less suitable ones. GA utilizes and uses the previous solutions that best fit the problem, fostering stochastic information for the exchange structure purposes to seek the optimal solution [18, 69-71]. Various gene selection methods are employed in Selection Methods, including Roulette Wheel Selection, Stochastic Remainder with or without Replacement, Deterministic Selection, n-Member Tournament, and Part Sum Selection. Roulette Wheel Selection is the most commonly used, assigning selection probabilities based on fitness, with fitter individuals having higher selection probabilities. Crossover combines two or more parent solutions for the generation of a new offspring by selecting random characters from parent solutions and exchanging them at a randomly chosen position (crossover point) to create a new solution. Common crossover methods include single-point, multiple-point, uniform crossovers, and variable-by-variable. Mutation introduces genetic diversity by altering individual genes in newly created offspring, ensuring that new individuals are distinct from their parents and each other. Mutation may replace alleles with new values or adjust existing values in small increments. GA iteratively evaluates and enhances candidate solutions through genetic operators, aiming to discover the best solution to a given optimization problem.

Algorithm 2 The GA pseudo-code that utilized in this research.

Begin

1. Establish the Network constraints.
2. Identify the system's boundaries.
3. Define **F(x)**, which represents the Objective Function/Cost Function.
4. Setting the value of the initial population number Ppop, and then generating the initial population populations, setting α to present the population size, δ as iterations number, β as elitism rate, γ for mutation rate, and the crossover probability.
5. while the generation < the maximum generation

    Fitness population evaluation

    for $i = 1: \delta$

    Elitism selection and selecting the best individuals

    end for i

    for i from elites to α as population size

    for j from 1 to crossover number

    select two randomly solutions and generate the best solution by -one-point crossover, then save.

    end for j

    end for i

    for k from 1 to crossover number

    mutate all the bits of the best solutions considering the rate of mutation

    rate γ.

    if the solution is unfeasible

    update it with a feasible one and repair the current solution.

    end if

    updating the current solution.

    end for k

---

update ***Ppop*** the current population

end while

6. Returning the optimal solution as the generated power per hour for each power source.
7. Results optimized and visualizations designed.

End process

3.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a widely utilized and efficient algorithm for solving optimization problems. Introduced in 1995 by Eberhart and Kennedy, the Particle Swarm Optimization (PSO) algorithm drew inspiration from the collective behaviors observed in swarms, birds, and fish during their search for optimal food sources and regions [72]. PSO models the interaction among individuals within a population to search for the optimal solution iteratively.

In PSO, the population comprises individuals known as particles; each particle can be a solution [9, 73, 74]. The algorithm optimizes the system toward the solution by adjusting the particles's locations and re-evaluating the condition by updating the particles' velocities following the best-known solution within the swarm. The fundamental concept involves collaboration among particles to explore and exploit the search space efficiently. The performance of the algorithm relies on various parameters, including the particles' number, inertia weight, and maximum velocity. These parameters dictate how particles navigate the search space, influencing the convergence speed and solution quality.

PSO is a versatile and effective optimization technique recognized for its capability to tackle complex optimization problems and explore solution spaces efficiently by emulating the collective behavior of natural swarms. The calculation of position and velocity is determined by:

$$xi\ (t) = xi,1\ (t), \ldots\ldots, xi,d\ (t), \ldots\ldots, xi,D\ (t) \tag{23}$$

$$vi\ (t) = vi,1\ (t), \ldots\ldots, vi,d\ (t), \ldots\ldots, vi,D\ (t) \tag{24}$$

This velocity adjustment and the particle's location can be calculated using:

$$xi,d\ (t+1) = xi,d\ (t) + vi,d\ (t+1) \tag{25}$$

$$vi,d\ (t+1) = w * vi,d\ (t) + c_1 * rand\ ()\ (pi,d\ (t) - xi,d\ (t)) + c_2 * Rand\ ()\ (gi,d\ (t) - xi,d\ (t)) \tag{26}$$

Where ***Rand ()*** and ***rand ()*** are random parameters, usually those two random parameters vary from [*0,1*], and w represents the inertia weight value; c_1 and c_2 denote position and velocity parameters, respectively, and their values are calculated based on the previous particles experiences [9, 73, 74]. In addition, these two learning factors, c_1, and c_2 are indicating the impact of a particle's personal best position (***pi***) and the best position among all particles (***gi***), respectively. The cognitive parameter, c_1, signifies the particle's past experiences, while c_2 reflects the influence of historical particle experiences within the swarm. A higher value of c_2 compared to c_1 suggests that the particle is more attracted to the best position (***gi***) among the population rather than its own best position (***pi***), and conversely, if c_1 surpasses c_2. These factors are mathematically defined to determine the degree of influence of pi and ***gi*** on the optimization process.

Algorithm 3 The PSO pseudo-code used in this research.

Begin

1. Establish the Network constraints.
2. Identify the system's boundaries.
3. Define **F(x)**, which represents the Objective Function/Cost Function.
4. Initiate the position, personal best (pbest), and global best (gbest) of particles with uniform distribution.
5. Setting algorithm parameters *N*, ***xi***, ***xu***, c_1, c_2, *imax*, and ***f***
6. Initializing velocities ***vi***, and the best particles positions ***x**** and ***g****
7. Randomly select ***r1*** and ***r2*** values.
8. for ***t*** = *1*: maximum generation

   for ***i*** = *1*: population size

   select two random numbers of ***r1***, ***r2***, and *vo*

   if ***pi(t)*** < *pbest (i,t)*

   update the particle's velocity *vi*

end if
if ***pi(t)*** < *gbest (i,t)*
update the new position ***xi***.
end if
update ***x**** and ***g****
end for ***i***
i = ***i*** + *1*;
end for ***t***

9. Providing the best solution as the optimal generated power per hour for each power source.
10. Results optimized and visualizations designed.

End process

3.4 Surrogate Optimization

Surrogate optimization represents a meta-model-based approach to optimization that resides within the domain of evolutionary computational techniques [75]. Over the last two decades, researchers have employed surrogate optimization to address both single and multi-objective optimization challenges, encompassing constrained fitness functions.

The Evolution control strategy serves as a foundational management model within surrogate optimization. This strategy involves fitness evaluations, local searches, mutations, and crossovers, all contributing to the filtering of fit and unfit populations and the identification of non-optimal or irrelevant solutions [76, 77]. The Re-evolution process oversees population clustering and categorizes populations into fuzzy clusters or crisp categories. Following this pre-selection phase, the top individuals are selected for re-evolution, impacting the average approximate error and ultimately determining the quality of the model. Surrogate quality assessment typically relies on rank correlation and continuous partial correlation methods.

Algorithm 4 The pseudo-code of the surrogate optimization algorithm used in this research.

Begin

1. Establish the Network constraints.

2. Identify the system's boundaries.
3. Initiate the experimental buildings and settings up, considering constant function values.
4. Define **F(x)**, which represents the Objective Function/Cost Function.
5. Intiate the optimization procedures, iterating until finding the initail feasible point
6. Assessing the parameters and their associated values, based on the surface respoce criterias.
7. Generate the candidate points, and then calculate them.
8. Delete the sampled points and generate new ones until unsampled points are found.
9. Choose the optimal candidate point and utilize it for conducting the simulation.
10. Continue iterating until achieving the minimum value of the objective function.
11. Return the most optimal point identified as the generated power per hour for each power source.
12. Results optimized and visualizations designed.

End process

Chapter 4
Results and Outcomes Using the Four Optimization Algorithms

In this chapter, we will discuss the outcomes of employing the four aforementioned optimization algorithms to explain the techniques used in each scenario, considering maximizing the output power generated by the source while at the same time minimizing the network losses and overall costs. A detailed discussion is provided on each algorithm's outcomes, differences are explained in each scenario, evaluations are shown, and advantages are summarised. There are two operating scenarios implemented in this research; the first scenario is optimizing the existing DG/PV/Battery standalone hybrid system; in the second scenario, we explored the feasibility and impact of eliminating the current Diesel Generator (DG) and studied the impact of substituting it with a suitable wind turbine, with a proper size and power ratings which can meet the load demand on Tomia Island.

Indonesia experiences two distinct seasons: dry and rainy. Wind speeds in Southeast Asia fluctuate as a result of these seasonal variations. Throughout the dry season, which lasts for 5 or 6 months in Indonesia, generally starts from the end of April or the beginning of MAY to the end of September or the beginning of October, wind velocities exhibit more excellent stability and strength compared to the wet season. As a result, we propose two operational runnings of the wind turbine. The first run entails year-round turbine operation, capitalizing on the average wind speed of 5.186 m/s, and the second run during the 5-month dry season.

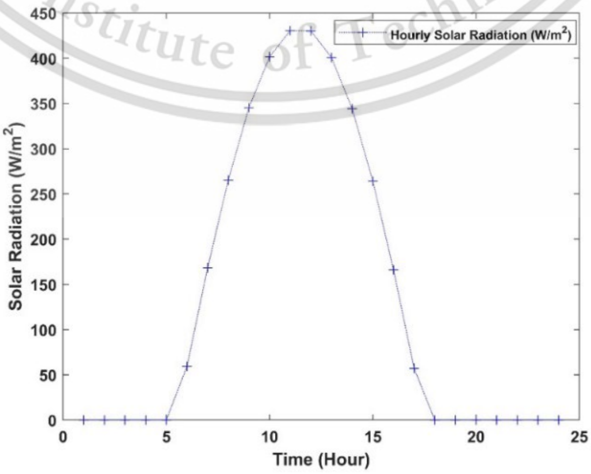


Figure 4.1 *One day's average hourly solar radiation using the Liu and Jordan method.*

It's crucial to acknowledge that each algorithm utilizes a distinct methodology for search and optimization. Therefore, careful deliberation is necessary when choosing the proper algorithm and adjusting the limits and the algorithm's constraints and parameters. Figures 4.1 and 4.2 depict the hourly solar radiation outcomes following the implementation of the Liu and Jordan statistical style.

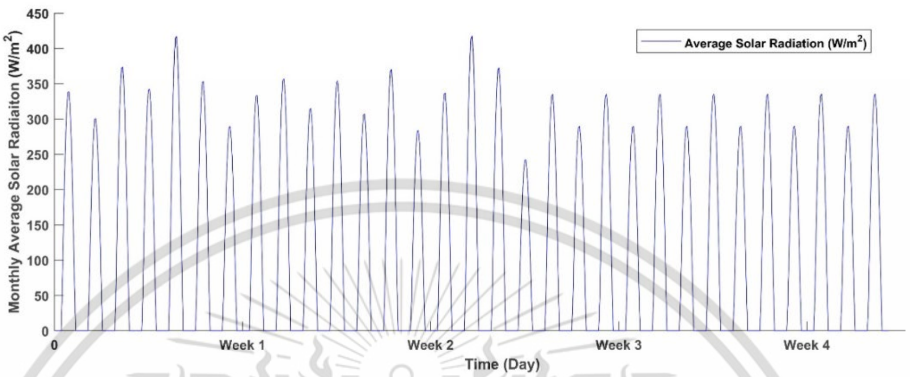


Figure 4.2 *One month's average hourly solar radiation using the Liu and Jordan method.*

Wind speed fluctuation is a critical issue in generating electricity from wind turbines; the windspeed in southeast Asia is considered low compared with other continents. That is why selecting a proper location is vital and will have a direct impact on the changes in the wind speed during both runnings, especially during the dry season, which should be considered in the calculations and optimization runs; figures 4.3 and 4.4 display the wind speed graphs utilized in this study, obtained from the publicly available Power NASA. Based on the website, the data were measured at a height of 50 meters (m/s) using the WS50M-MERRA-2 dataset for the years 2019, 2020, and 2021. The measurements were taken at one of the highest locations on Tomia Island, and the coordinates were -5.7539 Latitude and 123.9478 Longitude.

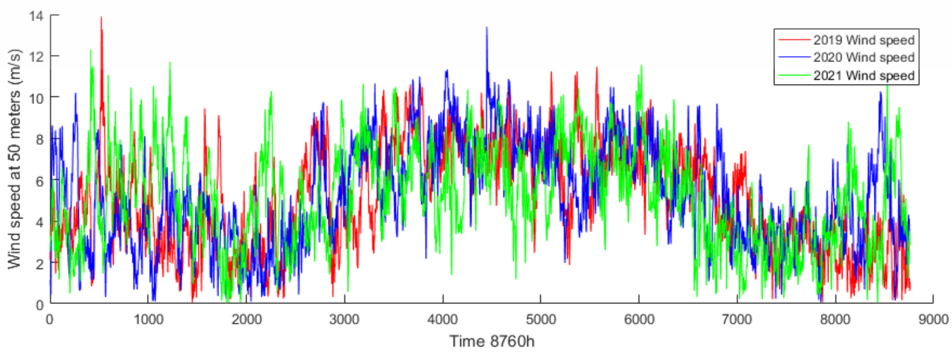


Figure 4.3 *Tomia Island's 2019, 2020, and 2021 wind speed values.*

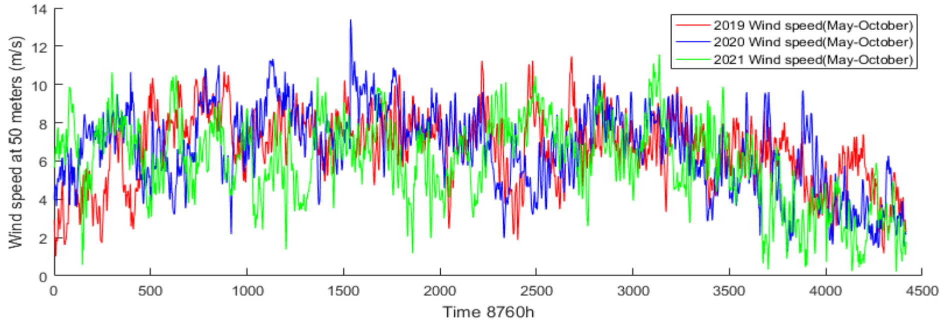


***Figure 4.4** Tomia Island's 2019, 2020, and 2021 wind speed values May to October.*

4.1 Objective Functions and Problem Formulation.

The methodologies and the optimization techniques employed in this study adopt a multi-objective optimization strategy, utilizing the Pareto optimal solution. This approach was chosen for its efficacy and dependability in solving nonlinear equations with enhanced convergence and precision. Moreover, it directs our investigation towards attaining an efficient, non-inferior, and permissible Pareto front by illustrating the non-dominated vectors. This investigation considers two objective functions, merging them to evaluate the optimality in DG sizing and selecting the best bus location while concurrently minimizing costs and the network's losses in the system. We conducted thorough simulations and optimizations to assess the balance between power losses and operational costs.

The multi-objective optimization approach involves determining the value of the vector $\vec{x}* = [x_1^*, x_2^*, \ldots\ldots, x_m^*]_T$_T, which can minimize $\vec{f}\,(\vec{x})$.

$$min\,\vec{f}\,(\vec{x}) = [f_1(\vec{x}), f_{\vec{2}}(x), \ldots.., f_n(\vec{x})] \quad for\ \vec{x}* \in X \tag{27}$$

$$\vec{g}\,(\vec{x}) \leq 0 \tag{28}$$

$$\vec{h}\,(\vec{x}) = 0 \tag{29}$$

Utilizing the non-dominate principle in sorting, a collection of Pareto solutions representing the optimal solutions is derived. A point $\vec{x}* \in X$ can be reflected as a Pareto optimal if for every $\vec{x} \in X$ and also $I = 1,2,\ldots\ldots,k$.

$$\forall i \in I\ (f_i(\vec{x}) = f_i(\vec{x}^*)) \tag{30}$$

In our proposed system, $\vec{g}$ and $\vec{h}$ represent the sets of both the inequality and the provided equality constraints, while X denotes the decision vectors' feasibility set [78, 79]. The primary objective function within our system aggregates the cost functions linked to the utilized electricity producers. It considers operational and maintenance (O&M) expenses, initial or investment costs, as well as the lifetime factor.

1. F1: The overall network Costs:

- Scenario 1: DG/PV/Battery

$$\text{Cost Objective function } (x) = a^*\text{Cost Fn. (main DG)} + b^*\text{Cost Fn. (PV)} + c^*\text{Cost Fn. (Batteries)} + d^*\text{Cost Fn. (Add. DG)}. \quad (31)$$

- Scenario 2: Wind Turbine/PV/Battery

$$\text{Cost Objective function } (x) = a^*\text{Cost Fn. (Wind Turbine)} + b^*\text{Cost Fn. (PV)} + c^*\text{Cost Fn. (Batteries)} + d^*\text{Cost Fn. (Add. DG)}. \quad (32)$$

2. F2: The overall active power losses:

$$P_{loss}^{Total} = \sum_{j=1}^{N} Ploss(j) \quad (33)$$

N represents the branches' number, and each power source's cost is denoted by the cost coefficients *a, b, c,* and *d,* where *x* represents the overall cost of the generated power in the system. MATLAB software was used to perform the mathematical calculations and the computational procedures. The Firefly Algorithm (FA) necessitated a longer time, varying from *11* to *21* minutes per run, whereas the Surrogate Algorithm was the fastest. The optimization steps are illustrated in the flow chart depicted in Figure 4.5. This study's optimization algorithms were run on a Windows laptop with a Core i5 processor. It was noted that employing a Windows laptop with a Core i7 processor decreased the execution time by *30* to *40* percent. As mentioned earlier, the differences and advantages of each algorithm used are highlighted. Parameters and constraints for the algorithms were set with consistent limits, boundaries, equality, and inequality constraints for the four utilized algorithms, as specified in Table 4.1.

Table 4.1: The FA, PSO, GA, and Surrogates algorithms Constraints and limits.

Algorithm/s	Limits and Constraints	
	Equality constraints	Inequality constraints
FA, PSO, GA, and Surrogate optimization algorithms	$P_{PV}(i) = 0.70 * PV_{out}(i)$	$420\ W \leq P_{DG} \leq 650\ W$ $150\ kW \leq Pwind\text{-}T \leq 950\ kW$ $-378\ W \leq P_{Batt} \leq 378\ W$ $100\ W \leq P_{Add.DG} \leq 500\ W$ $P_{DG/wind\text{-}T} + P_{PV} + P_{Batt} + P_{Add.DG} \leq 1.1*Pload\ (i)$

4.2 Minimum Costs, Network Losses, and the Optimum Generated Powers.

In this section, we will discuss the optimization outcomes of the two operating scenarios. The first one is the existing case DG/PV/Battery, and the second scenario is the Wind turbine/PV/Battery, considering adding additional DG to minimize the network losses and compensate for any leakage in the demanded power.

4.2.1 Scenario 1: Optimizing the existing case, DG/PV/Battery/Add.DG.

To address network losses, an extra Distributed Generation unit was integrated into the system. The optimal value and placement of this supplementary DG, along with the resulting losses, were determined and presented in Figure 4.6 and Table 4.2, respectively. A Pareto optimality plot was generated to analyze the trade-off between minimizing costs, and also the losses, as depicted in Figure 4.7.

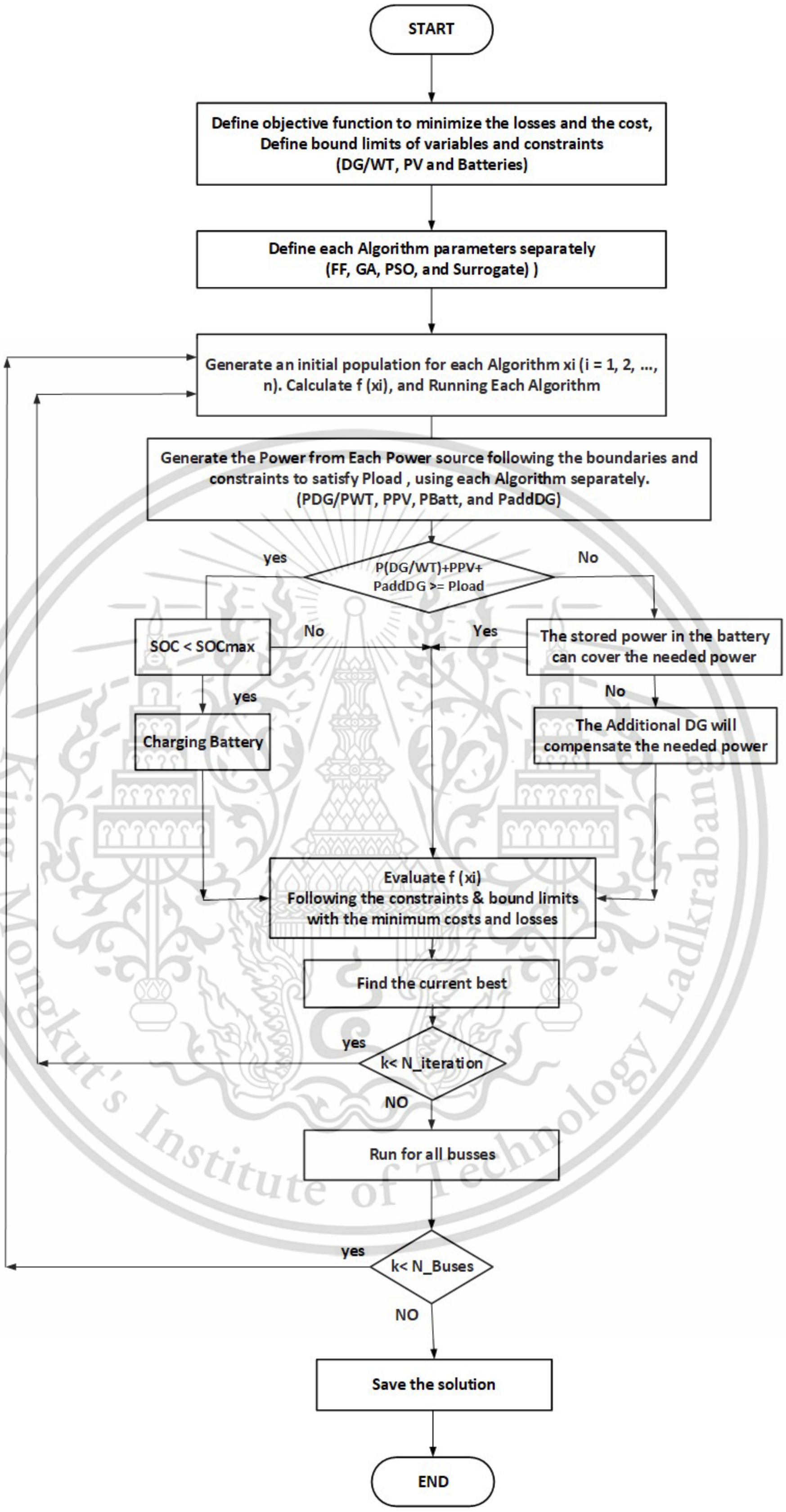


Figure 4.5 *Optimization procedures' flow chart.*

The analysis indicated that the GA, PSO, and Surrogate algorithms produced nearly identical results in terms of losses and the additional DG size. However, the FA achieved the lowest losses. It's important to note that FA required significantly more running time, averaging *451.86* seconds for one repetition.

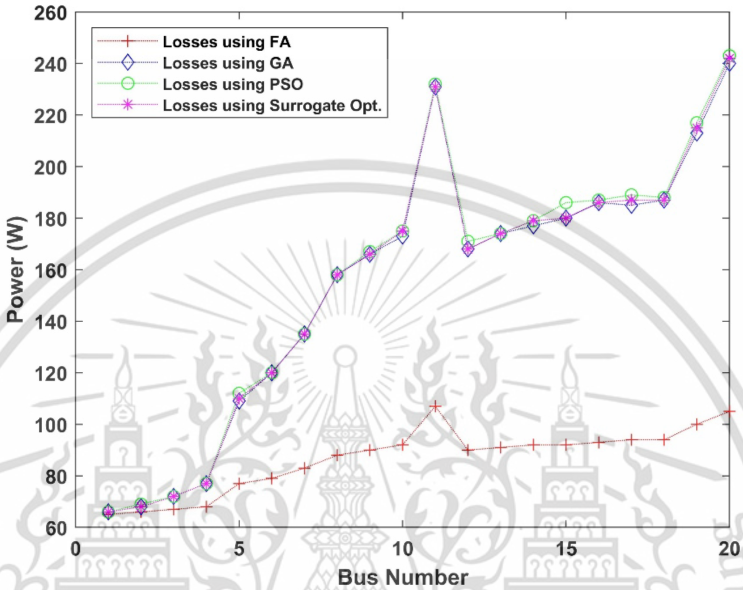


Figure 4.6 *The Network Losses after utilizing the four Algorithms.*

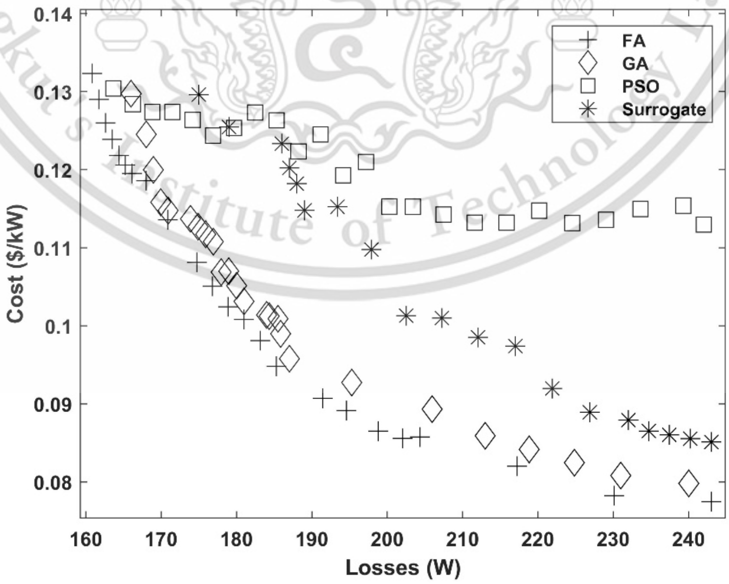


Figure 4.7 *The Pareto optimality for both the losses and cost.*

Table 4.2: The 4 Algorithms outcomes and comparisons.

	Adding Additional DG			Average Running Elapsed time (Second)	Cost of Energy – COE ($/kWh)	Performance Indicators	
	Minimum Losses (W)	Suggested Add. DG Value (kW)	Bus No.			LPSP	R^2
FA	66	103	3	451.85759	0.1439432669	0	1
GA	68	301.559	2	228.04349	0.1354487239	0	1
PSO	68	307.779	2	41.074049	0.1983062909	0.4159	0.57519
Surrogate	73	302	2	22.184509	0.1610758859	0.02234	1

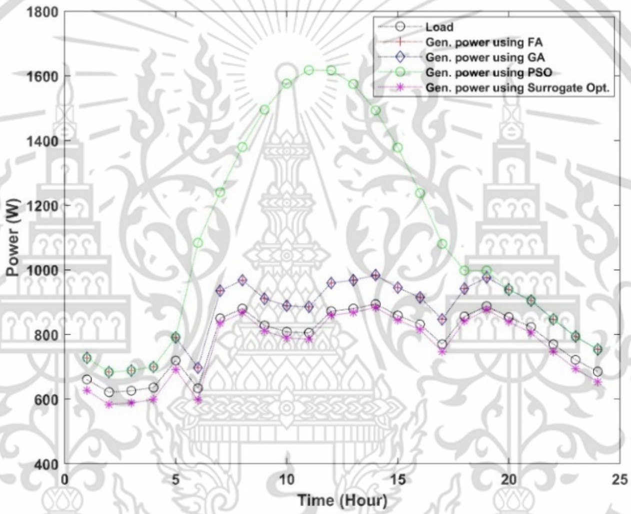


Figure 4.8 The four Algorithms' optimum generated power.

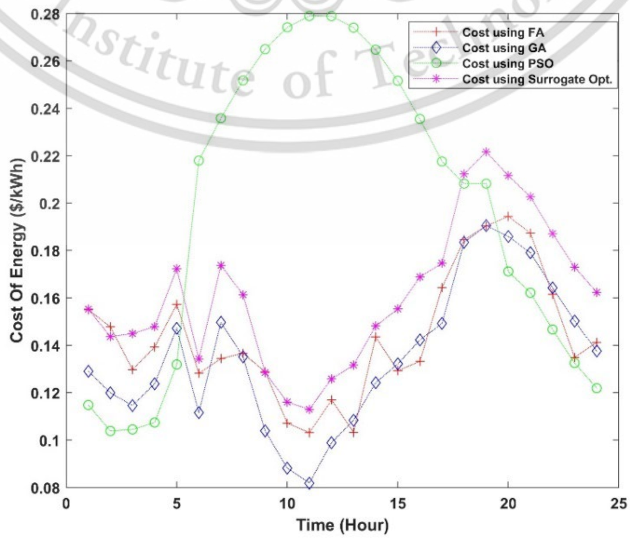


Figure 4.9 The four Algorithms' optimum overall Costs.

The findings presented in Figure 4.8 illustrate the optimal total generated power achieved by the implemented optimization algorithms, ensuring compliance with load demands and the system's boundaries. However, it is noteworthy that the Particle Swarm Optimization (PSO) algorithm yielded unrealistic results, significantly impacting the overall computed cost by *0.19829 $/kWh*, as outlined in Figure 4.9 and Table 4.2. This elevated cost is anticipated as a result of the impractical power generation from the power sources by PSO, leading to non-compliance with the generation's limits. This behavior is attributed to the inherent nature of PSO when operating under tight constraints, as indicated in Figure 4.10-(c). Conversely, The Firefly Algorithm's hourly generated power, Genetic Algorithm, and Surrogate algorithm remained well-constrained, meeting the requirements and load demands while maintaining *LPSP* and R^2 values within proper limits. These factors influenced the costs of the system, with Figure 4.9 demonstrating that the minimum Cost of Electricity (COE) was achieved by GA at *0.135439 $/kWh*, closely followed by FA at *0.14389 $/kWh*.

The subsequent figures illustrate the Optimum-Generated Power Analysis of the implemented optimization Algorithms. It's crucial to note that, in accordance with the system boundaries, the overall power generated from the four sources should not exceed *10%* above the total demand. These constraints remained consistent across all four algorithms. The variations observed in the optimal generated power for the FA, GA, PSO, and Surrogate Algorithm are depicted in figures 4.10-(a), 4.10-(b), 4.10-(c), and 4.10-(d), respectively.

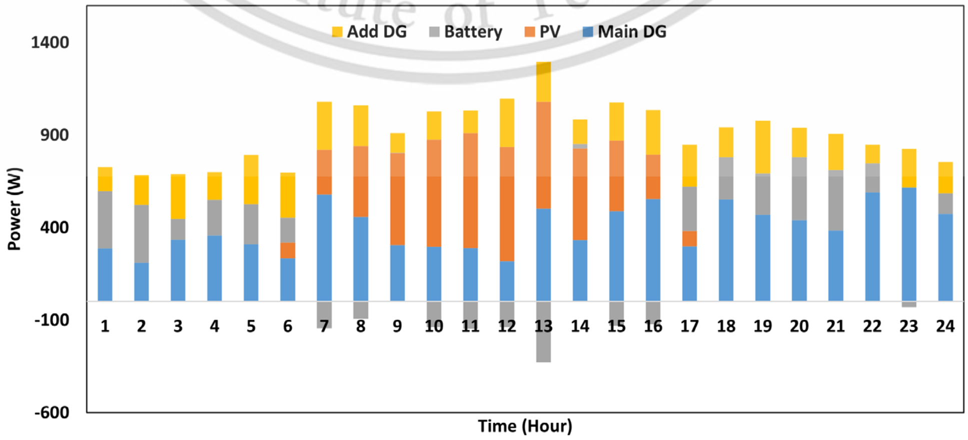


Figure 4.10-(a) *FA's Optimum hourly Generated power.*

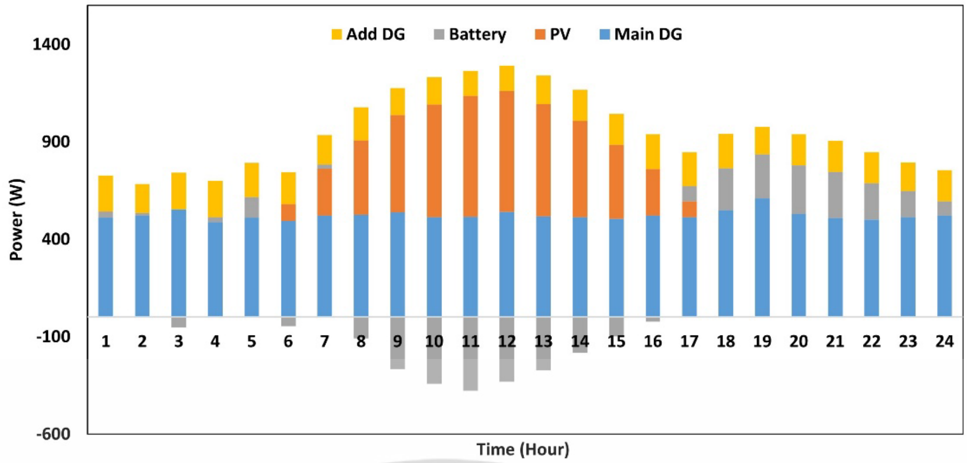


Figure 4.10-(b) GA's Optimum hourly Generated Power.

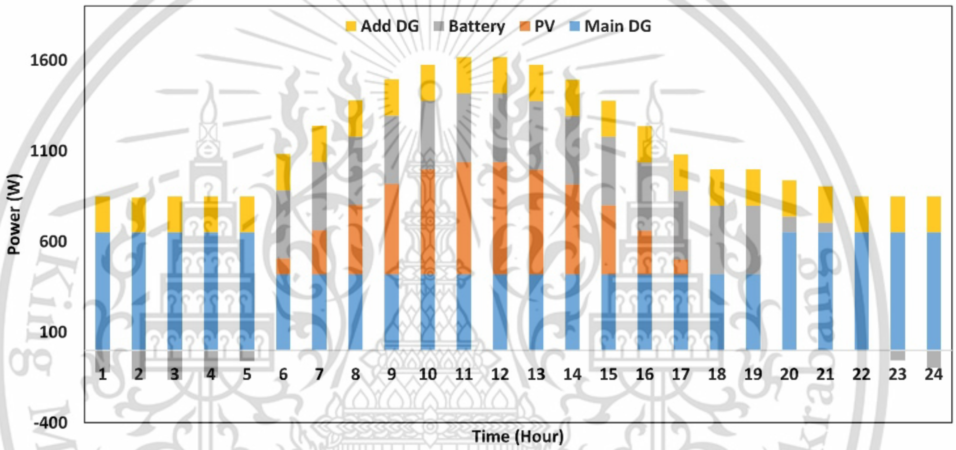


Figure 4.10-(c) PSO Optimum hourly Generated power.

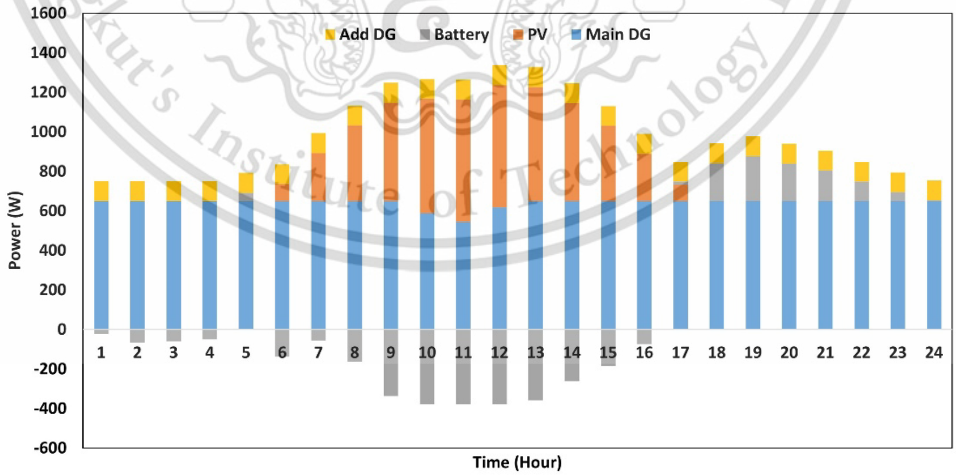


Figure 4.10-(d) Surrogate algorithm's Optimum hourly Generated Power.

FA, GA, and Surrogate algorithms yielded the most optimal generated power. In contrast, the power generated by the Particle Swarm Optimization (PSO) algorithm appeared inconsistent, as previously discussed and evident in Figure 4.10-(c). This disparity can be attributed to the fundamental differences in the optimization approaches: PSO operates akin to a swarm moving collectively toward a solution, whereas FA, GA, and Surrogate algorithms employ individual-based search mechanisms.

The findings revealed that each algorithm proposed a distinct size for the Distributed Generation and identified an optimal bus location to reduce network losses. FA recommended a DG size of 103 watts, while GA, PSO, and Surrogate algorithms selected the optimum DG sizes with values of *301.559* watts, *307.779* watts, and *302* watts, respectively. As a result, to minimize losses and costs and optimize the network, a *300*-watt additional DG could be installed at bus number *2* based on the recommendations provided by these algorithms. The total values of the optimum generated power values from the 4 algorithms are shown in Appendix A1.

To account for the diverse performance of the implemented meta-heuristic algorithms, numerous iterations were executed for each algorithm, followed by thorough comparisons and analyses. Significantly, the total optimum generated power remained consistent across these iterations, as demonstrated in Appendix A2. The algorithms were implemented on a Windows laptop with a Core i5 processor. Notably, utilizing a Core i7 Windows laptop resulted in observed reductions in running time ranging from *30%* to *40%*.

As previously mentioned, the variances and advantages of all the employed algorithms are delineated. All algorithms were configured with identical constraints and parameters, ensuring uniformity in limits, equality, and inequality constraints outlined previously in Table 4.1. Figure 4.11 showcases the optimized power generation from the four sources individually, employing the employed algorithms to enhance the current system on Tomia. It's worth noting that specific results were previously disclosed in our earlier publications [32-35, 80]. This figure emphasizes the core objective of this paper, which revolves around optimizing the proposed system through DG Allocation (DG/PV/Batteries/Add.DG).

Among the algorithms assessed, the Firefly Algorithm (FA) demonstrated significant performance by decreasing the load on the main DG by 30.479%. This reduction highlights the favorable influence of DG allocation implementation. Conversely, the GA, PSO, and Surrogate Optimization yielded lower reductions in the load on the main DG at *8.099%*, *3.209%,* and *1.169%*, respectively, indicating comparatively lesser effectiveness in this aspect.

Figure 4.10-(c) underscores the suboptimal performance of the PSO algorithm in power generation. This outcome can be attributed to the stringent constraints applied to the DG within the PSO algorithm. When constraints are overly restrictive, PSO's exploration capabilities are limited. Consequently, the algorithm may prematurely converge, settling for suboptimal solutions.

To address this challenge, a re-evaluation of the PSO algorithm was conducted by expanding the DG constraint limits to ($300\ W \leq PDG \leq 900\ W$). This adjustment led to improved performance by PSO, as depicted in Figure 4.12. LPSP decreased to *0.000229*, and R^2 reached *1*, indicating a more favorable outcome.

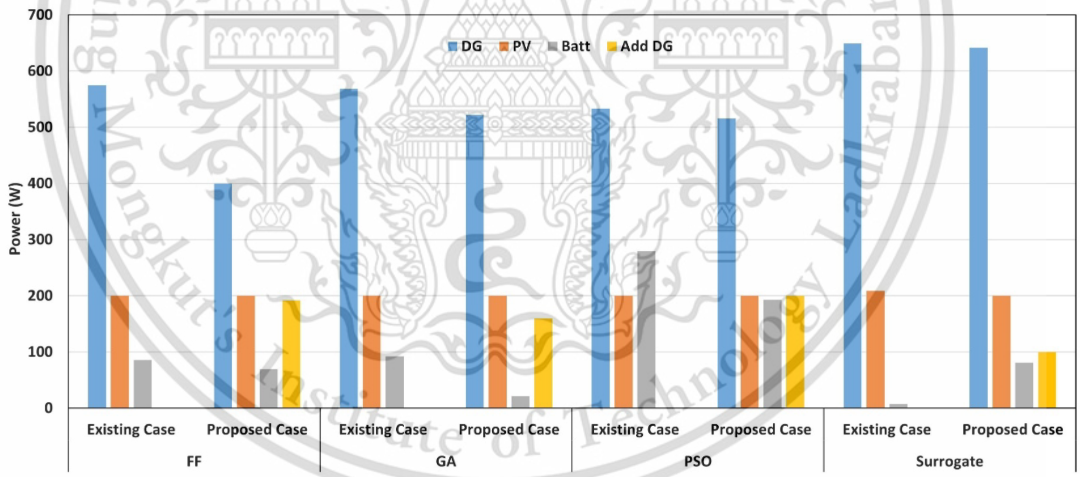


Figure 4.11 *The existing (DG/PV/Battery) and the proposed DG allocation (DG/PV/Battery/Add.DG) optimal generated power values.*

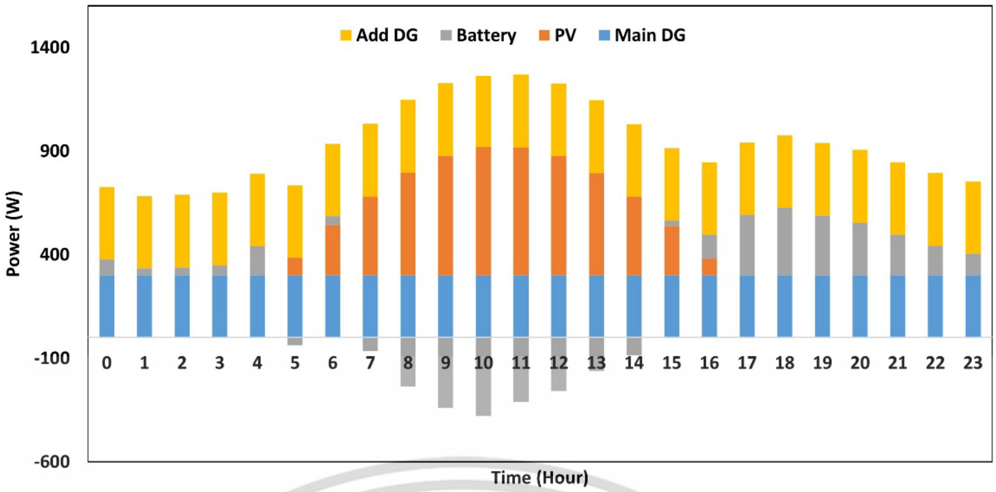


Figure 4.12 The effect of changing the PSO boundaries on the Optimum hourly Generated power.

In summary, the outcomes illustrate the effectiveness of the four algorithms in optimizing the system's costs and the losses on the Island's radial network. Each algorithm's unique characteristics contribute to achieving the optimal minima.

4.2.2 Scenario 2: The Results of Replacing the DG with Wind Turbine.

In this scenario, we replaced the DG with a Wind turbine to exploit the wind speed benefits; furthermore, we ran both the Wind/PV/Battery system and studied the Wind/PV/Battery/Add.DG system considering the wind speed fluctuations during the year and the dry season which starts from may to october every year.

4.2.2.1 Running 1: The Results of optimizing the proposed Wind/PV/Battery system.

During the analysis of the Wind/PV/Batteries system (Without adding add. DG), it was found that wind speed plays a crucial role in determining the generated power. However, GA, PSO, and Surrogate algorithms could not operate effectively for the full-year wind speed scenario, as the generated power from the wind turbine was insufficient to satisfy the system constraints and the demanded load. Only the FF algorithm was able to operate completely and showed that the generated power was not sufficient to cover the load, as illustrated in Figure 4.13. to overcome this problem, a suggestion discussed and explained in one of the author's publications to increase the battery size from the Existing 4200 kWh to 6111 kWh, which is the best-suggested scenario generated from the optimization algorithm, as this will satisfy the load throughout the year, all the data are explained in [35].

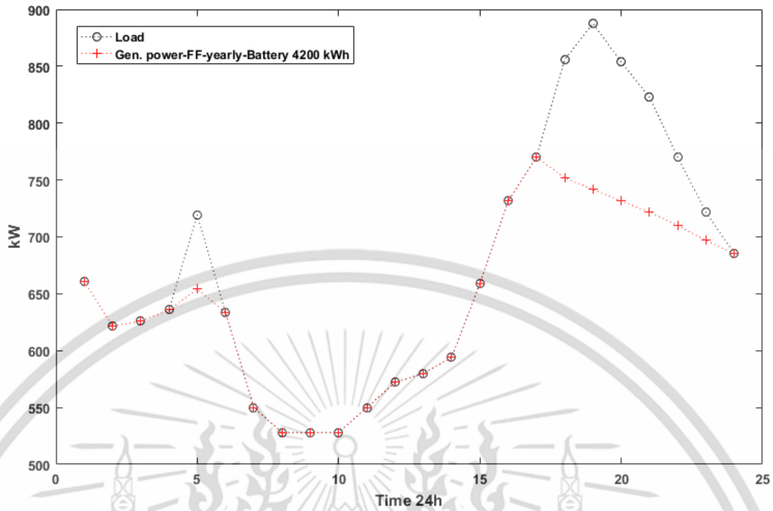
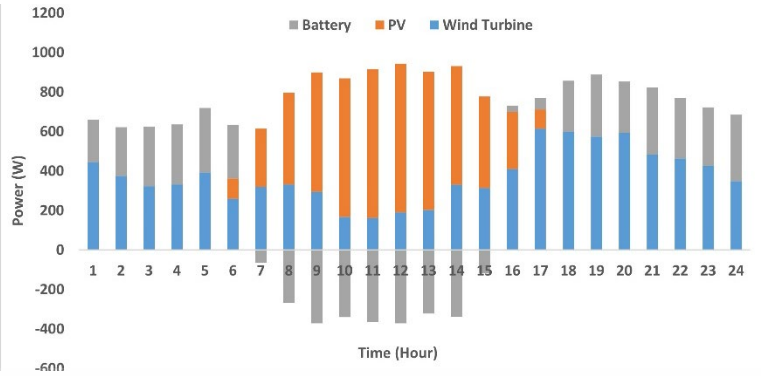


***Figure 4.13** Optimum hourly Generated power using the normal case Wind/PV/Battery using FF Full year wind speed.*

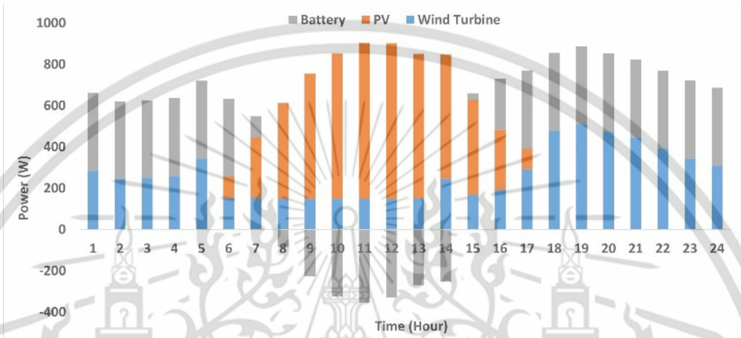
Therefore, the second running situation during the dry season from May to October was executed, as the wind speed was considered high, and all four algorithms were able to operate effectively and satisfy the load. Performance indicators LPSP and R^2 showed that all algorithms effectively optimized the system when considering the wind speed during the dry season, which starts from May to October, as depicted in Table 4.3 and Figure 4.14. The surrogate algorithm took the slowest and longest time than the other algorithms to achieve the optimum generated power; the total generated power values are shown in Table 4.3, Appendix A3, and Table A3-I.

***Table 4.3:** Outcomes and Differences using the 4 Algorithms Wind/PV/DG only from May to October and the full year.*

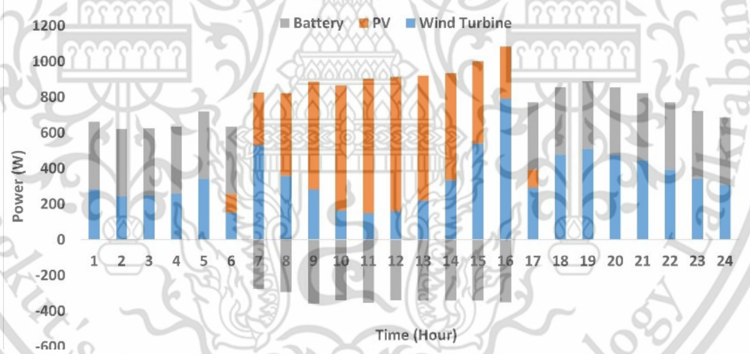
	Average Running Elapsed time (Second) / Core i5 Processor	Cost of Energy – COE ($/kWh)	Performancel Indicators	
			LPSP	R2
FA	4.915	0.184	0.0000111	1
GA	16.202	0.172006484	0.00000147	1
PSO	82.235	0.180916514	0.000000031	1
Surrogate	2688.55	0.1713	0.00000087308	1



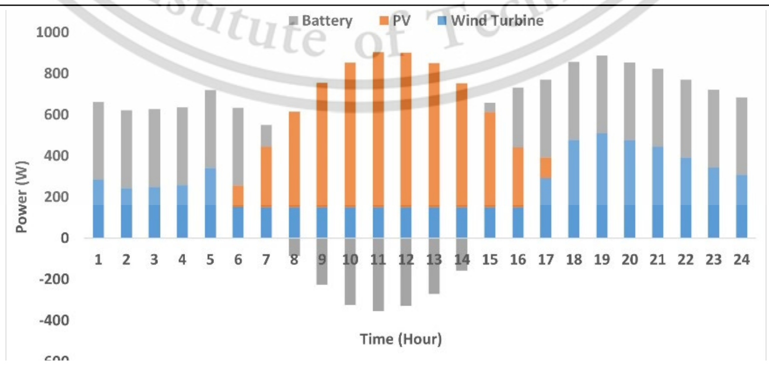
a) FA's generated power



b) GA's generated power



c) PSO's generated power



d) Surrogate algorithm's generated power

Figure 4.14 *Optimum hourly Generated power using considering May to October wind speed normal case Wind/PV/Battery normal case.*

Table 4.4: *Outcomes and Differences using the 4 Algorithms Wind/PV/DG from May to October.*

	Adding Additional DG		
	Minimum Losses (W)	Suggested Add. DG Value (kW)	Bus No.
FA	66	142	3
GA	65	100	2
PSO	65	100	2
Surrogate	73	1000	2

Running in the full year and May to October, wind speed variations were also considered in this operating scenario. To identify the effect of wind speed fluctuations in generating the optimum power considering DG allocation operation. FF, GA, and PSO performed better, and the losses and the additional DG values were almost the same using the three algorithms. Still, the surrogate performance was odd, which was estimated due to the longest elapsed operating time. Based on the FF, GA, and PSO, inserting an additional DG in bus number *2* with a *100-150* kW value can minimize the system losses and optimize the network. As presented in Table 4.4.

4.2.2.2 Running 2: The Results of optimizing the proposed Wind/PV/Battery/Add-DG system.

The second run involves inserting additional DG into the network to test the operating ability to cover the demanded load and decrease the network loss, based on the recommendations values in Running 1. Figure 4.15 shows the network loss analyses using the four algorithms; each one operated differently; surrogate optimization was the one that generated the highest loss values and was unrealistic, and the other operated with acceptable values.

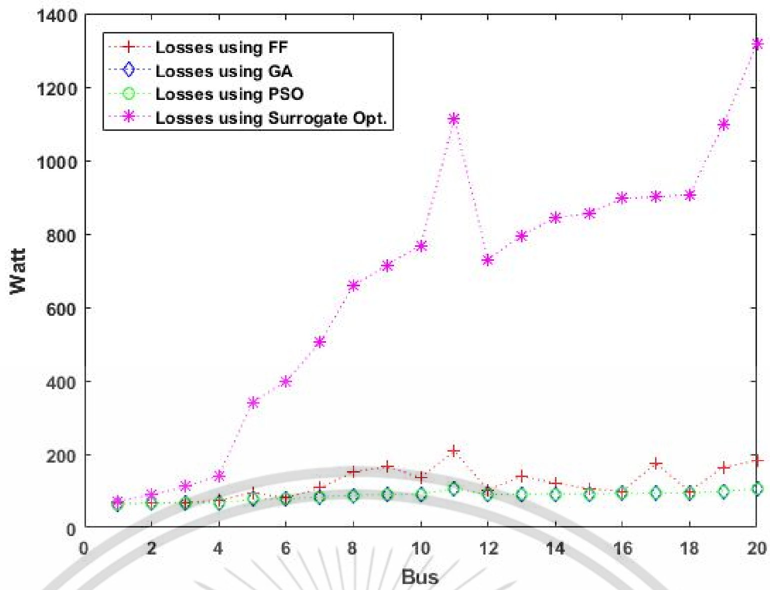


Figure 4.15 *Total Network Losses using the 4 Algorithms in Case Wind/PV/Battery/Add DG.*

4.2.2.2.1 Full-Year Wind Speed with Additional DG.

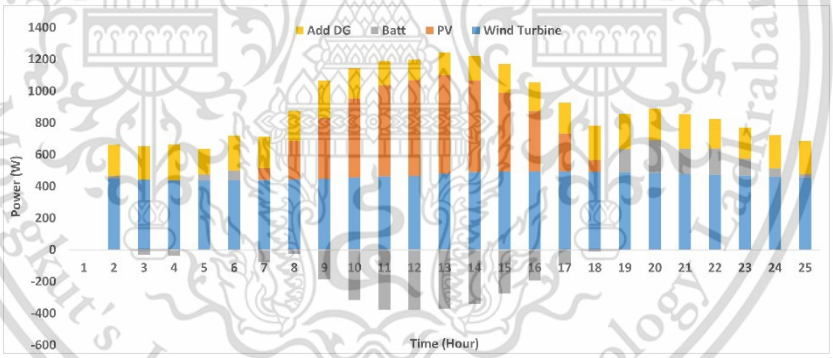
During the full-year operating scenario, the addition of an extra DG optimized the network using the four algorithms. This additional DG compensated for the generation shortage shown previously in Figure 4.13 as a result of the low wind speed values observed during the rainy season.

The four algorithms were executed on two different computers with Intel Core i5 and i7 processors; both processors generated the same values. However, the i7 processor performed faster, as demonstrated in Table 4.5. The Surrogate algorithm required more time for execution on both processors, with *115.168* seconds and *4784.984* seconds for the i7 and i5 processors, respectively. LPSP and R^2 values indicated that the system was optimized using all four algorithms. The Cost of Energy (COE) generated by the Surrogate algorithm was the lowest and comparable to that of GA, but the Surrogate algorithm required more time for optimization. GA needed 56.18 and 13.246 seconds to optimize the system using the i5 and i7 processors, respectively.

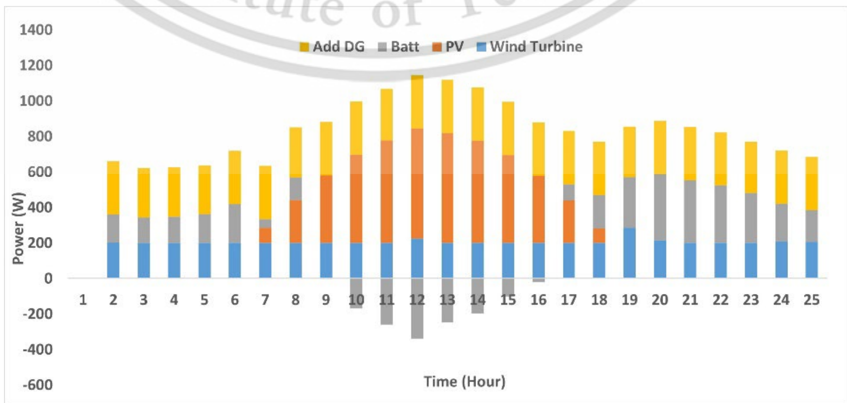
Table 4.5: Outcomes and Differences using the 4 Algorithms Wind/PV/Battery/Add DG full year wind speed.

	Average Running Elapsed time (Second)		Cost of Energy – COE ($/kWh)	Performance Indicators	
	Processor Core i5	Processor Core i7		LPSP	R^2
FA	14.158982	4.972398	0.21351748	0.00097104	0.9991
GA	56.185253	13.246	0.173979693	0.000000014	1
PSO	2.563104	0.70536	0.183731613	0	1
Surrogate	4784.984	115.168	0.172843305	0	1

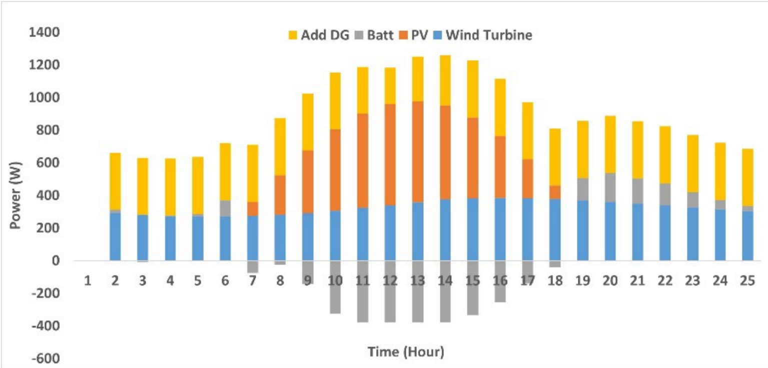
The optimum generated power of this operation scenario is shown in Figure 4.17. Both running operations satisfied the requested load as an effect of adding the additional DG following the system's constraints. The total generated power values are shown in Appendix A3 and Table A3-II, which show the actual values of those generated powers.



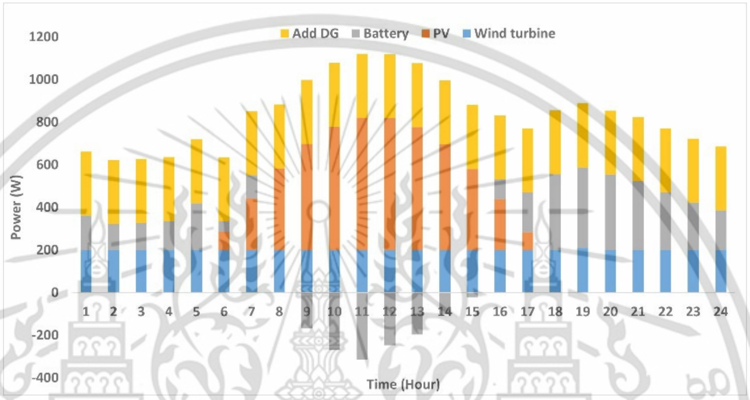
a) FA's generated power



b) GA's generated power



c) PSO's generated power

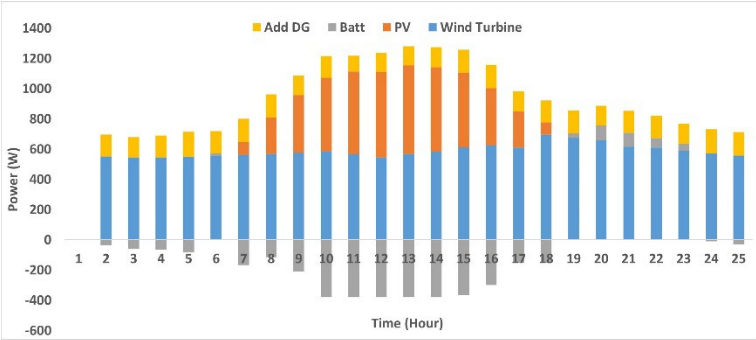


d) Surrogate algorithm's generated power

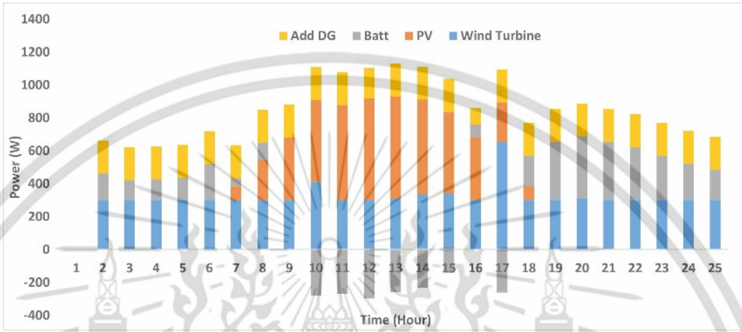
Figure 4.16 *Optimum hourly Generated power using considering Full year wind speed and Add DG.*

4.2.2.2.2 May to October Wind Speed with Additional DG.

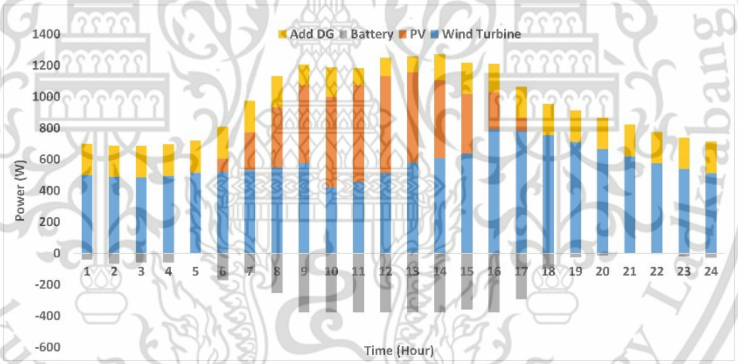
In this operation scenario, the wind turbine is estimated to be operated during the dry season; the wind speed is high during this period. We noticed that the system was optimized using the four algorithms, and the generated power was completely satisfying the load and was more than the demanded load, which led to an increase in the energy costs, as seen in Table 4.6, and the costs were more than the costs of running the wind turbine during the full year. Figure 4.18 shows the costs of both operating scenarios, and it is clearly obvious that the cost of running the system from May to October after adding additional DG will lead to an unnecessary cost increase.



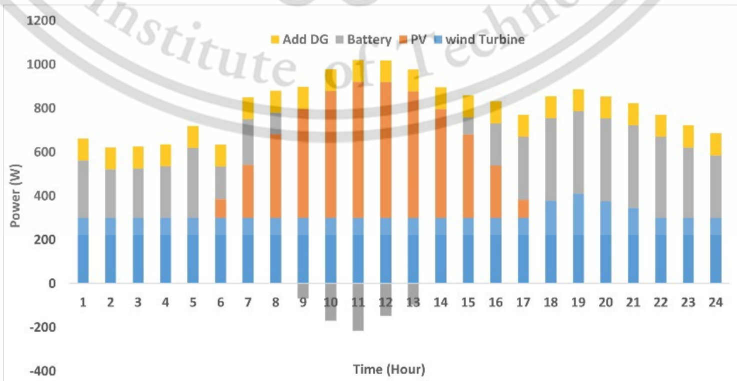
a) FA's generated power



b) GA's generated power



c) PSO's generated power

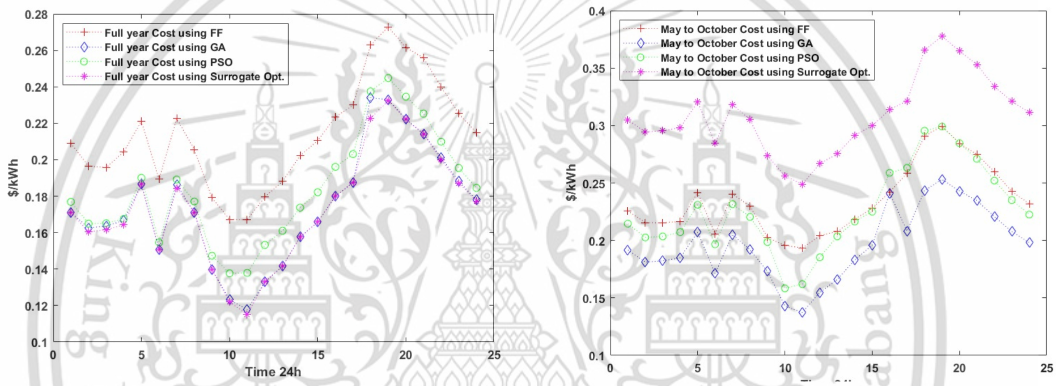


d) Surrogate algorithm's generated power

Figure 4.17 *Optimum hourly Generated power considering May to October wind speed and Add DG.*

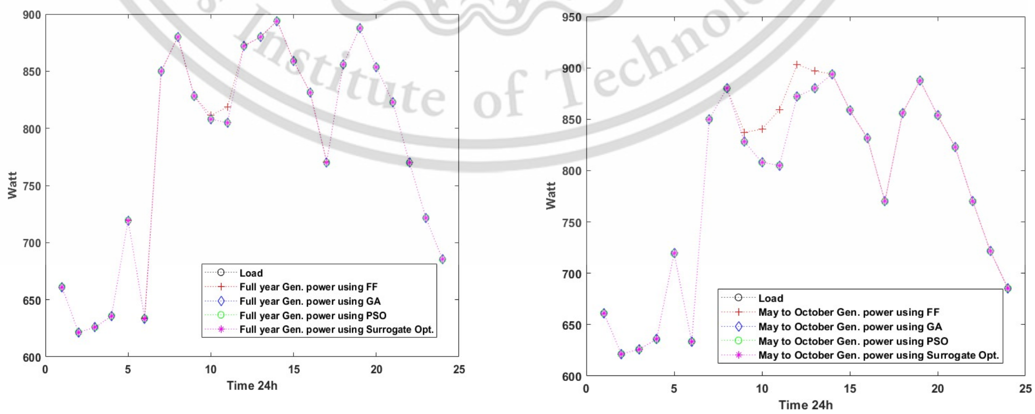
Table 4.6: Outcomes and Differences using the 4 Algorithms Wind/PV/DG May to October wind speed.

	Average Running Elapsed time (Second)		Cost of Energy – COE ($/kWh)	Performance Indicators	
	Processor Core i5	Processor Core i7		LPSP	R^2
FA	14.432	2.727164	0.234395459	0.007668385	0.9811
GA	50.967504	11.6308	0.196623364	0.000000234	1
PSO	3.437424	0.901944	0.22664929	0	1
Surrogate	3653.5611	99.593577	0.308178492	0	1



a) Full-year wind speed b) May to October wind speed

Figure 4.18 Optimum Costs using the 4 Algorithms of Wind/PV/Battery/Add DG. a) full-year wind speed operation, b) May to October wind speed operation.



a) Full-year wind speed b) May to October wind speed

Figure 4.19 Optimum generated power using the 4 Algorithms of Wind/PV/Battery/Add DG. a) full-year wind speed operation, b) May to October wind speed operation.

Chapter 5
Conclusions And Recommendations

5.1 The Study Conclusions

This study concentrates on enhancing the operational setup of a hybrid radial network consisting of DG/PV/Battery/Add.DG on Tomia Island through DG Allocation. Four optimization algorithms—FA, GA, PSO, and Surrogate Optimization—were applied in order to reduce the system's costs and losses by applying a multi-objective function approach. Real data was employed, with comparisons to the existing DG/PV/Battery system drawn from previous studies on system optimization and also for a proposed Wind/PV/Battery considering adding additional DG.

Firstly, In the Existing DG/PV/Battery/Add DG Scenario, The results revealed that:-

1. PSO occasionally generated excessive power relative to the required load due to stringent and tight DG constraints; this led to an LPSP value surpassing the *5%* threshold and a low coefficient of determination R^2 of *0.5128*. However, PSO demonstrated improved performance when constraints were relaxed, yielding better outcomes.
2. A Pareto Optimal approach was employed to optimize the multi-objective function while considering the minimum losses and costs.
3. FA and GA showed better performance and minimum running times. GA achieved the lowest COE at 0.135439 $/kWh, closely followed by FA at 0.14389 $/kWh.
4. Bus 2 and Bus 3 were recommended to install the additional DG; the best recommendation is to install the additional 300 k-watt DG at bus number 2 to optimize the system, minimize losses, and meet load requirements.

Each algorithm exhibited strengths and weaknesses inherent in seeking the minimum optima. Suggestions were provided to enhance PSO's performance in generating optimal power and reducing total loss costs. It's important to note that all algorithms operate under the same boundaries, limits, and system constraints.

Secondly, in the Wind/PV/Battery scenario, the generated power could satisfy the load, and only FA was able to run completely and show leakage in the generated power. The results revealed that:-

1. The Wind/PV/Battery Secanrio can not satisfy the load, so a suggestion after operating the optimization algorithms was to increase the Existing battery from 4200 kWh to 6111 kWh to satisfy the demanded load or add a small DG to the system.
2. Studying the optimization after adding a 100-150 k-watt DG at bus 2 to the network, the proposed Wind/PV/Battery/Add-DG showed that the generated power of the two runnings options during the year or during the dry season from May to October could satisfy the load, the values of the LPSP and R^2 were acceptable for the four algorithms.
3. GA generated the best outcomes regarding the total elapsed time and the cost of energy (COE), then FA, then PSO. The Surrogate took the longest operating time to generate the optimum solution and generated the highest cost of energy.

5.2 Future Directions

Future investigations will delve into studying the effect of implementing other optimization algorithms that can be adapted to the radial standalone networks and generate the optimum generated power considering the minimum network's losses and costs on Tomia Island, and working on publishing another paper in a reputable journal discussing the effect of the wind turbine represented in this thesis dissertation, in addition, studying the optimized algorithms for other networks located in different conditions and locations.

APPENDIX A1

The total generated power from the four power sources per hour using each algorithm, DG/PV/Battery/Add DG case.

Hour	Load (watt)	Firefly Algorithm (FA)		Genetic Algorithm (GA)		Particle Swarm Optimization (PSO)		Surrogate Optimization Algorithm	
		Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)
0	661.1	727.2099	0.1550	727.2090	0.1291	727.21	0.1148	627.21	0.1553
1	621.5	683.6498	0.1478	683.6490	0.1199	683.6541	0.1038	583.65	0.1437
2	625.9	688.4898	0.1297	688.4890	0.1146	688.49	0.1045	588.49	0.1450
3	635.8	699.3801	0.1392	699.3790	0.1238	699.38	0.1074	599.38	0.1479
4	719.4	791.3399	0.1573	791.3390	0.1472	791.34	0.1319	691.34	0.1723
5	633.6	696.9604	0.1282	696.9595	0.1116	1083.364	0.2180	596.96	0.1342
6	850	934.9980	0.1344	935.0019	0.1497	1240.129	0.2358	835	0.1738
7	880	968.0030	0.1366	967.9990	0.1352	1379.763	0.2518	868	0.1613
8	828	910.7981	0.1288	910.7990	0.1039	1495.214	0.2650	810.8	0.1285
9	808	888.8011	0.1071	888.799	0.0881	1576.115	0.2742	788.8	0.1160
10	805	885.5005	0.1032	885.4990	0.0818	1617.718	0.2789	785.5	0.1130
11	872	959.1985	0.1169	959.1990	0.0989	1617.286	0.2789	859.2	0.1258
12	880	968.0014	0.1032	967.9990	0.1084	1574.820	0.2740	868	0.1316
13	894	983.4019	0.1436	983.399	0.1242	1493.342	0.2647	883.4	0.1481
14	858.9	944.7906	0.1293	944.789	0.1321	1378.180	0.2516	844.79	0.1554
15	831.5	914.6511	0.1332	914.6490	0.1422	1237.106	0.2355	814.65	0.1688
16	770	846.9999	0.1643	846.9990	0.1492	1080.197	0.2176	747	0.1747
17	855.8	941.3810	0.1845	941.3790	0.1834	998	0.2082	841.38	0.2123
18	887.7	976.4698	0.1903	976.4690	0.1905	998	0.2082	876.47	0.2216
19	853.6	938.9601	0.1944	938.9590	0.1859	938.96	0.1712	838.96	0.2116

20	822.8	905.0799	0.1873	905.0790	0.1791	905.08	0.1622	805.08	0.2026
21	770	847.0000	0.1615	846.999	0.1643	847	0.1467	747	0.1872
22	721.6	793.7601	0.1348	793.7591	0.1502	793.76	0.1325	693.76	0.1730
23	685.3	753.8307	0.1412	753.829	0.1376	753.83	0.1219	653.83	0.1623

APPENDIX A2

The total generated power for 5 runs using PSO for both performances.

The first with the same system DG boundaries (420 W ≤ PDG ≤ 650 W), and the second after expanding the DG boundaries to give a space for the algorithm to search for the optimal solution (300 W ≤ PDG ≤ 900 W).

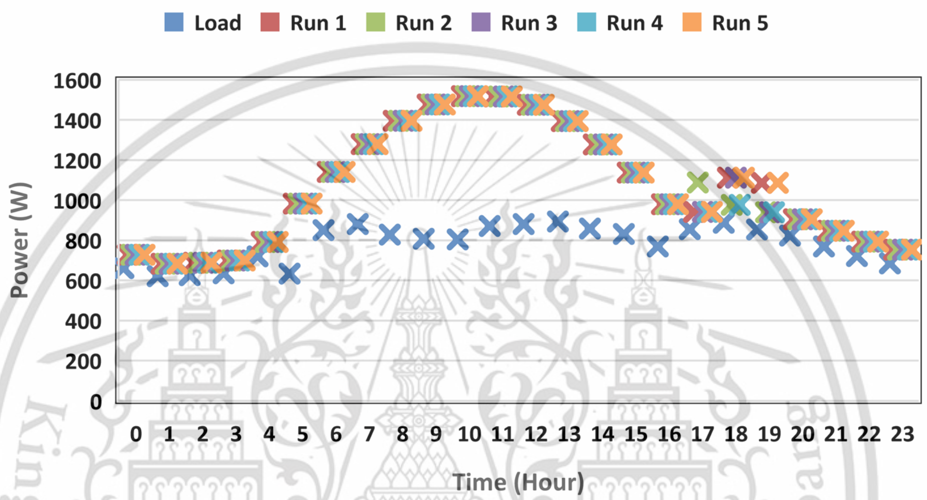


Figure B.1 Total generated power after performing 5 runs using considering the same system's DG boundaries using PSO.

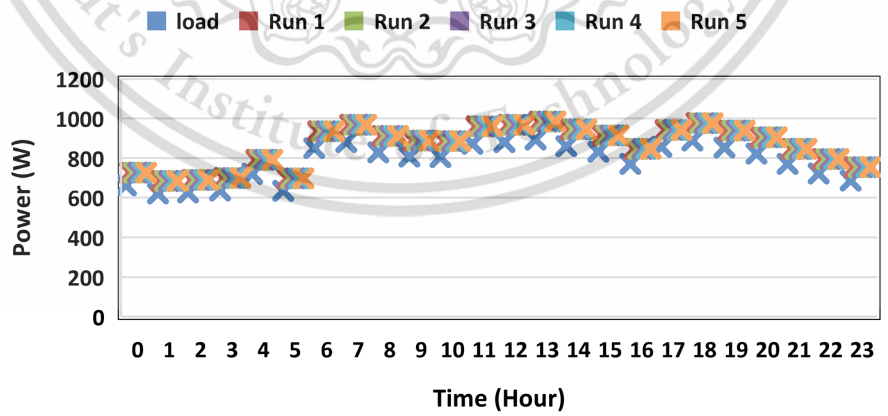


Figure B.2 Total generated power after performing 5 runs using considering expanding the DG boundaries using PSO.

APPENDIX A3

The total generated power for the Wind/PV/Battery/Add DG Case.

This appendis showing the total genrated power of the 2 ruunings ways of the wind turbine, the first one is running the wind turbin in the dry season only from May to October, and the second running is throughout the full year.

Table A3-I: Running 1- wind speed during the dry season, May to october:-

Hour	Load (watt)	Firefly Algorithm (FA)		Genetic Algorithm (GA)		Particle Swarm Optimization (PSO)		Surrogate Optimization Algorithm	
		Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)
0	661.1	661.099	0.2256	661.099	0.1916	661.1	0.214	661.1	0.304
1	621.5	621.507	0.21548	621.5	0.18114	621.5	0.2026	621.5	0.2943
2	625.9	625.907	0.21535	625.8999	0.18231	625.9	0.2035	625.9	0.2955
3	635.8	635.803	0.21665	635.8	0.18494	635.8	0.2073	635.8	0.2981
4	719.4	719.397	0.24150	719.3990	0.20720	719.4	0.2310	719.4	0.3204
5	633.6	633.607	0.20573	633.5999	0.17137	633.6	0.1966	633.6	0.2845
6	850	850	0.24008	849.9999	0.20514	850	0.2316	850	0.3183
7	880	879.989	0.23008	880	0.19189	880	0.2204	880	0.3051
8	828	837.281	0.20254	828.0000	0.17318	828	0.1986	828	0.2736
9	808	840.292	0.19570	808	0.14285	808	0.1583	808	0.2560
10	805	859.127	0.19345	805	0.13734	805	0.1620	805	0.2489
11	872	903.344	0.20425	872	0.15475	872	0.1854	872	0.2668
12	880	896.898	0.20778	879.9999	0.16613	880	0.2035	880	0.2754
13	894	893.995	0.21857	894	0.18297	894	0.2164	894	0.2915
14	858.9	858.901	0.22786	858.9	0.19580	858.9	0.2250	858.9	0.2997
15	831.5	831.499	0.24212	831.4992	0.24110	831.5	0.2588	831.5	0.3138
16	770	770.002	0.25855	770	0.20817	770	0.2631	770	0.3213

17	855.8	855.8	0.29093	855.7990	0.24352	855.8	0.2954	855.8	0.3656
18	887.7	887.7	0.29929	887.699	0.25312	887.7	0.2991	887.7	0.3777
19	853.6	853.6	0.28435	853.5999	0.24293	853.6	0.2846	853.6	0.3647
20	822.8	822.8	0.27508	822.7999	0.23473	822.8	0.2710	822.8	0.3530
21	770	770.004	0.25981	769.9999	0.22067	770	0.2521	770	0.3338
22	721.6	721.6	0.24261	721.6	0.20779	721.6	0.2351	721.6	0.321
23	685.3	685.297	0.23193	685.2997	0.19812	685.3	0.2225	685.3	0.3113

Table A3-II: Running 2- wind speed during the full year:-

Hour	Load (watt)	Firefly Algorithm (FA)		Genetic Algorithm (GA)		Particle Swarm Optimization (PSO)		Surrogate Optimization Algorithm	
		Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)	Total Generated power (watt)	Cost ($/kWh)
0	661.1	661.0974	0.2090	661.0999	0.1712	661.1	0.1769	661.1	0.1710
1	621.5	621.5015	0.1965	621.4999	0.1625	621.5	0.1649332	621.5	0.1604
2	625.9	625.8966	0.1957	625.8999	0.1637	625.9	0.1651322	625.9	0.1616
3	635.8	635.8041	0.2042	635.7997	0.1667	635.8	0.1675765	635.8	0.1642
4	719.4	719.4049	0.2211	719.3999	0.1865	719.4	0.1900314	719.4	0.1865
5	633.6	633.9407	0.1892	633.6	0.1507	633.6	0.1545799	633.6	0.1507
6	850	850.0037	0.2225	850	0.1862	850	0.1891339	850	0.1844
7	880	880.0061	0.2055	880	0.1712	880	0.1770753	880	0.1712
8	828	828.0056	0.1791	828	0.1398	828	0.1473102	828	0.1398
9	808	811.4372	0.1672	807.9999	0.1231	808	0.1376897	808	0.1221
10	805	818.54717	0.1671	805	0.1179	805	0.1379042	805	0.1150
11	872	872.0015	0.1796	871.9999	0.1330	872	0.1532523	872	0.1329
12	880	880.0118	0.1881	880	0.1415	880	0.1609924	880	0.1415
13	894	893.9906	0.2022	894	0.1576	894	0.1737294	894	0.1576
14	858.9	858.9094	0.2106	858.9	0.1658	858.9	0.1821461	858.9	0.1658
15	831.5	831.4973	0.2234	831.5	0.1800	831.5	0.1960715	831.5	0.1800
16	770	770.8936	0.2299	770	0.1875	770	0.2030875	770	0.1875
17	855.8	855.7934	0.2630	855.8	0.2341	855.8	0.2374906	855.8	0.2228
18	887.7	887.6914	0.2729	887.6999	0.2329	887.7	0.2448157	887.7	0.2324
19	853.6	853.5960	0.2615	853.5999	0.2222	853.6	0.2345850	853.6	0.2222
20	822.8	822.7917	0.2558	822.8	0.2143	822.8	0.2252551	822.8	0.2140
21	770	769.9981	0.2400	769.9999	0.2011	770	0.2098693	770	0.2000
22	721.6	721.6085	0.2252	721.5999	0.1881	721.6	0.1954734	721.6	0.1871
23	685.3	685.2983	0.2149	685.3	0.1781	685.3	0.184548	685.3	0.1774

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