Energy Management and Optimization of PV/Diesel/Battery Hybrid Power Systems for Remote Consumers

Nonthanan Phonphan[†], **Pracha Khamphakdi**, and **Bongkoj Sookananta**, Non-members

ABSTRACT

This paper evaluates the efficiency of a photovoltaic-diesel-battery hybrid off-grid system over one year using a particle swarm optimization technique (PSO) to develop an optimal energy dispatch model. The model achieves cost savings and improved system efficiency and can accurately estimate consumer fuel costs. The study shows that the hybrid system is more cost-effective and efficient than a diesel-only system, highlighting the importance of considering daily and seasonal variations in demand. The optimization model developed can be further developed to optimize various components of the hybrid system. Overall, the study emphasizes the importance of considering variations in demand and suggests that the use of an optimization model can lead to more efficient energy delivery systems, particularly in the context of PV-diesel-battery hybrid systems.

Keywords: Energy Management Strategy, Hybrid Off-Grid System, Particle Swarm Optimization, Optimisation Algorithm

1. INTRODUCTION

1.1 Motivation and Background

The power systems for remote communities vary depending on location, available resources, and energy demand. The primary objective is to provide a reliable and affordable power supply to meet the energy needs of the community. Renewable energy resources (RES) , such as solar, wind, and hydropower, are commonly used in off-grid power systems that utilize a combination of energy sources, energy storage, and diesel generators (DG). Currently, [1] implementing a Microgrid (MG) system is a potential solution for electric power management in remote communities without access to the electricity distribution system. The electricity generated by the RE would be stored in batteries for later use, allowing the community to have access to electricity even during periods when the RES are not generating power. In addition, [2] generating their own electricity, communities can reduce their reliance on expensive and polluting diesel generators and potentially lower their overall energy costs. Overall, implementing a MG system is a promising idea for electric power management in remote community areas that are not connected to the electricity distribution system. It can provide a sustainable, reliable, and cost-effective source of electricity that can improve the quality of life for residents in these communities.

1.2 Literature Overview

Henerica Tazvinga et al.[2] propose an optimal energy dispatch model for a PV-diesel-battery hybrid system and analyze the optimal energy flows with the “quadprog” function in MATLAB Their model achieved more savings than a diesel-only scenario, and they found that daily and seasonal demand variations affect the operational costs of the system. Specifically, weekend fuel costs are higher than weekday costs, and winter fuel costs are higher than summer fuel costs due to higher demand and lower radiation levels. Their study emphasizes the importance of considering these factors when analyzing energy flows and operational costs in a hybrid system. The developed optimization model can be used to achieve optimal fuel costs and analyze energy flows in any given system. However, the ”quadprog” function in MATLAB has limitations when applied to energy management systems. It is primarily suitable for quadratic programming problems and may not handle non-quadratic objectives or constraints. Additionally, its performance may deteriorate for large-scale problems due to increased computational demands. The function is also sensitive to problem formulation, necessitating meticulous setup for precise outcomes. Considering these limitations is crucial when deciding whether the “quadprog” function is appropriate for a particular energy management system, especially in cases involving non-quadratic problems, large-scale optimization, or a need for robustness in problem formulation., comprehensive assessments, validations, and consideration of a broader range of scenarios and technologies are recommended.

Ali Saleh Aziz et al.[3] propose an evaluation of a PV/diesel/battery off-grid configuration for a rural area in Iraq using three different control strategies,

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The authors are with Department of Electrical and Electronics Engineering, Faculty of Engineering, Ubon Ratchathani University, Ubon Ratchathani, Thailand.

[†]Corresponding author: nonthanan.ph.59@ubu.ac.th

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i.e., a combined dispatch (CD) control strategy for a photovoltaic (PV)/diesel/battery hybrid energy system (HES) by combining the load following (LF) strategy and cycle charging (CC) strategy. HOMER software was used to evaluate the overall analyses. The cost analysis results show that the combination of PV, a DG, batteries, and a power converter with the CD strategy was the optimal solution for this case study. The CD strategy had the minimum fuel consumption and the lowest CO_2 emissions, making it the most suitable option for the environment. The sensitivity analysis showed that variations in important parameters had significant effects on system performance. Overall, this study provides valuable insights for decision making towards better energy management strategies for off-grid configurations in rural areas. However, there are potential disadvantages to consider when using the described work utilizing the HOMER software for optimizing Hybrid Energy Systems (HESs). These include simplified representation, a limited scope of analysis, dependency on input data, sensitivity to assumptions and constraints, a lack of consideration for emerging technologies, and a limited economic scope. To mitigate these limitations, comprehensive assessments, validations, and consideration of a broader range of scenarios and technologies are recommended.

Designing and optimizing PV-diesel-battery hybrid power systems for remote areas or isolated islands. [4] proposes a genetic algorithm-based optimization model that minimizes the total annual cost of the system, resulting in a hybrid system consisting of wind turbines, batteries, and diesel generators. However, the cons of Genetic Algorithm (GA) for energy management systems include the possibility of premature convergence, which can lead to suboptimal solutions, the need for parameter tuning, and the lack of transparency in the optimization process. Additionally, GA may require a large number of function evaluations, making it computationally expensive for complex energy management systems. [5] proposes a spread sheet-based simulation model that considers battery and DG lifespan and fuel efficiency as important variables in the economics of the system. [6] presents a distributed utility engineering micro-grid topology structure that achieves safe, reliable, and efficient operation, with renewable energy contributing more than 90% of total output. Moreover, the cons of a simple spread sheet-based mathematical model for energy management systems include limited flexibility and scalability. These models are often simplistic and may not capture the complexity of real-world systems accurately. They may lack the ability to handle dynamic scenarios, uncertainty, and multi-objective optimization. Additionally, spread sheet-based models can be time-consuming and require manual updates, making them less suitable for large-scale or rapidly changing energy management systems. [7] proposes a methodology that optimizes the sizing of a stand-alone hybrid wind/PV/diesel energy system using a deterministic algorithm called the DIRECT algorithm, which dynamically evaluates the wind and solar potential of the site based on long-term data. However, the cons of the DIRECT algorithm for energy management systems include the potential to get trapped in local optima, discretization error in approximating the objective function and search space, and limitations in handling multi-objective optimization. All of these studies show that PV-diesel-battery hybrid systems can be cost-effective and environmentally friendly solutions for meeting the energy demand of remote areas and isolated islands.

Energy management solutions for photovoltaic-battery hybrid power systems. In [12], a novel energy management approach was introduced, focusing on a 4 kW photovoltaic (PV) hybrid power conditioning system (HPCS) with an energy storage device (ESD). The goal of the proposed method was to optimize energy management and minimize electricity costs while ensuring power balance. The approach incorporated time-of-use rate pricing to guide decision-making. The performance of the energy management system (EMS) was evaluated through a case study using MATLAB software and simulation techniques. This allowed for a comprehensive analysis of the residential PV HPCS and its effectiveness in achieving cost savings and efficient energy utilization. However, it is worth noting that the researcher did not utilize optimization techniques in the energy management process, which could potentially limit the system's ability to achieve optimal solutions and maximize energy efficiency. [13] proposed to enhance renewable energy utilization and reduce electricity costs in residential settings. The system utilized an open-loop optimal control method to determine the optimal power dispatch throughout the day, aiming to minimize daily electricity expenses. By analysing historical data and predicting renewable energy generation and electricity demand, the Home Energy Management System (HEMS) calculated the optimal power allocation. This allowed homeowners to maximize renewable energy usage and achieve cost savings. However, open-loop optimal control methods have limitations such as lack of real-time adaptability, sensitivity to prediction errors, limited flexibility, susceptibility to disturbances, and reliance on accurate models. These factors should be considered when implementing such methods in an Energy Management System (EMS). [14] propose an enhanced algorithm called the multi-constrained integer programming genetic algorithm (MCIP-GA) for energy management systems. The algorithm aims to minimize electricity costs and maximize the utilization of renewable energy. The main contributions of the paper include incorporating battery sustainability and comprehensive modelling of the system. The MCIP-GA overcomes the drawbacks of local optima and sensitivity to initial solutions often associated with traditional genetic algorithms. It also generates significantly shorter solutions compared to previous methods. However, the MCIP-GA algorithm has its own limitations, including computational complexity, the need for parameter tuning, the possibility of converging to suboptimal solutions, sensitivity to constraints, and interpretability challenges. It is important to carefully consider these cons before implementing the MCIP-GA algorithm in an energy management system. Overall, the proposed algorithms improve the efficiency of home energy management systems, reduce peak demand, reduce electric bills for consumers, and ensure the safety and reliability of electric and hybrid vehicles.

In summary, the previous works identified certain areas that needed to be addressed appropriately:

1. The models discussed in the literature focused on reducing electricity costs and enhancing user satisfaction. However, they did not adequately consider factors such as renewable energy utilization, battery sustainability, and power interaction costs. This oversight led to potential energy wastage and additional expenses.
2. The algorithms employed in these models exhibited limitations in terms of convergence performance, often getting trapped in local optima. They were also sensitive to the initial solutions provided and posed challenges in terms of computation time and complexity.

This paper focuses on optimizing the operational cost over a one year period, considering the daily variation of demand and supply, as well as real operational issues to improve efficiency. Mathematical optimization PSO and optimal control approaches are employed to enhance operation efficiency with the objective of minimizing fuel costs. Additionally, the concept of energy efficiency, which includes performance efficiency, operation efficiency, equipment efficiency, and technology efficiency (POET), is used as a framework for evaluating the system.

In addition, various factors affect the operational costs of an off-grid hybrid system, including load demand, solar radiation, and fuel costs. Load demand determines the amount of power needed from the system, while solar radiation affects the power generation of the PV modules. Fuel costs impact the cost of running the DG set. Thus, an optimal dispatch strategy for the system should consider these factors to minimize operational costs. This study assumes a fixed load demand representative of typical household use, and uses solar radiation data from a local weather station. The fuel cost is assumed to remain constant throughout the year. The goal is to minimize the DG set's fuel cost while meeting the load demand and keeping the battery state of charge within acceptable limits. To achieve this paper, the study utilizes PSO, a metaheuristic optimization technique inspired by natural selection, to solve the optimization problem.

1.3 Contributions and Organization

The main contribution of this paper can be represented as follows:

1. We incorporate the battery sustainability and the full utilisation of the renewable energy into the system, and establish a more comprehensive and practical model, which was not mentioned in the previous work.

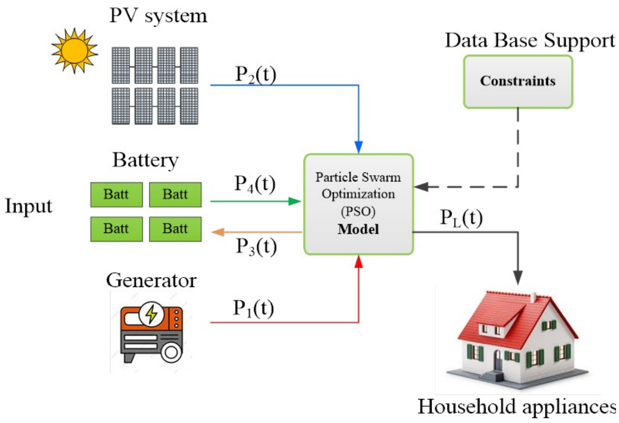

Fig. 1: *System model of a PV-diesel-battery hybrid power supply system.*

2. The goal is to minimize the DG set's fuel cost while meeting the load demand and keeping the battery state of charge within acceptable limits.
3. This model can assist solar energy practitioners or companies in estimating consumer fuel costs accurately on a daily or yearly basis.
4. To achieve this, the study utilizes PSO, a metaheuristic optimization technique can effectively optimize energy management in MGs, leading to significant cost savings and improved system efficiency.

The paper is organized as follows: Section 2 establishes the system model, including the mathematical model of all devices. Section 3 presents the optimization model. Section 4 presents power management algorithm. Section 5 presents results and discussion of the simulation experiment and Section 6 presents conclusion of the full text .

2. SYSTEM MODEL

In Fig.1, the input data is presented as crucial for the simulation and optimization of the PV-diesel-battery hybrid power supply system. To model the PV output and estimate available solar energy for each hour of the day, weather data is used. Load demand data is employed to determine the energy demand for each hour of the day and calculate battery charging and discharging rates. The system component data is utilized to model the limitations and characteristics of each component and ensure that the system operates within its design limits. The PV module characteristics consist of the module efficiency, maximum power output, and temperature coefficients. The battery bank data includes capacity, efficiency, and maximum charging and discharging rates. DG data is made up of the rated power output, fuel consumption rate, and efficiency. All this data is used in the optimization model to find the optimal dispatch strategy, minimizing the fuel cost of the DG while ensuring that the load demand is met, and the system components operate within their operating limits. Overall, input or database play a crucial role in the simulation and optimization of the PV-diesel-battery hybrid power supply system. Accurate and reliable data is essential to ensure that the model accurately reflects the system behavior and optimization results are valid and useful for designing and operating the system.

The proposed methodology involves the use of Particle Swarm Optimization (PSO) to determine the optimal dispatch strategy that minimizes the fuel cost of the DG while satisfying the load demand and the battery operating limits. The PSO algorithm updates the position and velocity of the particles in the search space using a combination of their individual best solution and the best solution found by the entire swarm. In the case of the PV-diesel-battery hybrid power supply system, the PSO algorithm uses database support to store the best solutions found and guide the particles towards the optimal solution, ensuring that the battery operates within its limits and maximizing the utilization of the PV power. The simulation output includes the PV power output, battery state of charge (SOC), and DG power output, providing insights into the system performance, energy balance, efficiency, and fuel cost savings achieved by the hybrid system. The proposed simulation process can be applied to design and optimize PV–diesel–battery hybrid power supply systems for various applications, including remote off-grid communities, rural electrification, and small-scale commercial and industrial uses.

2.1 Photovoltaic system model

The efficiency of the PV generator, represented by the variable η_{PV}, is influenced by various factors, including the solar irradiation, ambient temperature, and the test parameters of the PV generator at standard and nominal cell operating temperature conditions. The area of the PV array, denoted by AC, is determined by the size of the PV system and the available installation space. The hourly solar irradiation incident on the PV array, IPV, is determined by the weather conditions, such as the intensity and duration of sunlight. By multiplying these factors, the equation computes the hourly energy output, PPV, from the PV generator as shown in Eq. (1) [2],[8],[11].

$$P_{PV} = \eta_{PV} I_{PV} A_C, \tag{1}$$

where P_{PV} is hourly energy output, measured in kilowatt-hours (kWh) or joules (J), η_{PV} is PV generator efficiency, expressed as a dimensionless value (percentage or decimal), A_C is PV array area, measured in square meters (m^2) or square feet (ft^2), I_{PV} is hourly solar irradiation, measured in watts per square meter (W/m^2) or kilowatts per square meter (kW/m^2).

Predicting the hourly solar irradiation incident on the PV array is crucial for optimizing the performance of a PV system as it directly affects the amount of energy that can be generated by the system. This value is typically measured in units of kilowatt-hours per square meter (kWh/m2) and is influenced by various factors, including the angle and orientation of the PV array, the geographic location, and the time of year. These

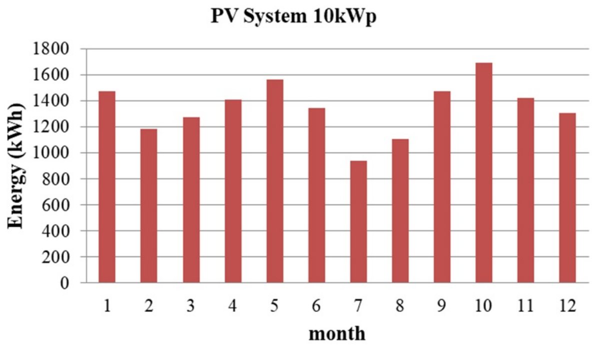

Fig. 2*: Monthly energy of PV system 10 kWp.*

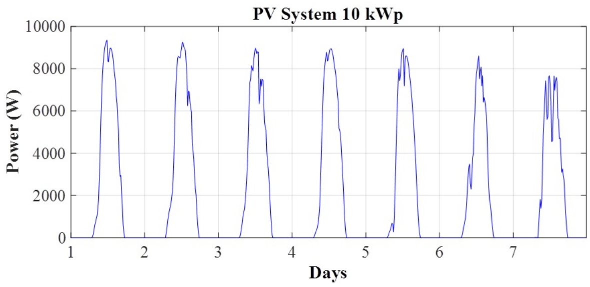

Fig. 3*: Output power of PV system 10 kWp (1-7 Jan 21).*

factors are taken into account while predicting the solar irradiation. Accurate prediction of solar irradiation is essential for maximizing the energy output of a PV system, ensuring efficient use of resources, and reducing costs associated with excess energy storage or backup systems.

The hourly power generation from solar cells is typically measured in kilowatt-hours (kWh), which is a unit of energy equivalent to one kilowatt of power being used for one hour. This unit is commonly used to express the amount of energy produced by a solar panel or array over a given period of time can be expressed as Eq. (2)[8].

$$E_{PV,h}, \quad \forall h \in \{1, 2, \ldots, 24\}, \tag{2}$$

where $E_{PV,h}$ is hourly power generation from solar cells, measured in kilowatt-hours (kWh). It represents the energy produced by solar panels or arrays during a specific hour (h).

The total daily power production from solar cells installed by the household is in kilowatt-hours (kWh). It represents the amount of energy generated by the solar cells during a day can be expressed as Eq. (3)[8].

$$E_{PV} = \sum_{h=1}^{24} E_{PV,h}, \tag{3}$$

where E_{PV} is total daily power production from solar cells, measured in kilowatt-hours (kWh). It represents the sum of energy generated by solar cells over a day.

This study is currently considering the measurement of electricity generation from PV systems installed in

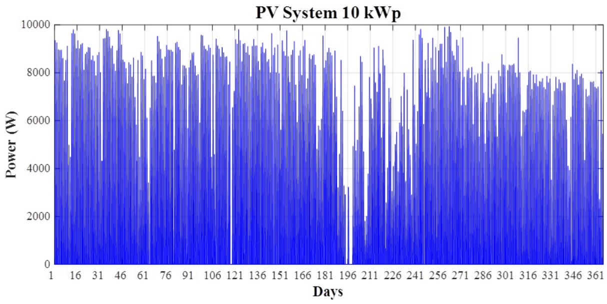

***Fig. 4**: Yearly output power of PV system 10 kWp (2021).*

Roi-Et Province, Thailand for duration of one year in 2021, as depicted in Fig. 2-4.

Fig. 2 shows the monthly energy production of the 10 kWp PV system. It provides a graphical representation of how the energy generated by the PV system varied from month to month throughout the year. This information helps in understanding the seasonal variations in PV system performance and energy production.

Fig. 3 focuses on the output power of the 10 kWp PV systems specifically for the period of 1-7 January 2021. It provides a detailed view of the daily fluctuations in the PV system's output power during that specific week. This information allows for a more granular analysis of the system's performance on a daily basis.

Fig. 4 represents the yearly output power of the 10 kWp PV system for the entire year of 2021. It provides an overview of the cumulative energy production from the PV system over the course of the year. This data helps in evaluating the overall performance and energy generation potential of the PV system throughout the year.

2.2 Battery Bank Model

If the PV power output is greater than the load demand at a given hour (t), the excess power is used to charge the battery bank. The charge power at that hour (t), which is equal to $SOC(t) - SOC(t-1)$, is computed by subtracting the load demand from the PV power output. When the load demand at that hour (t) is greater than the PV power output, the deficit power is supplied by the battery bank. In this case, the discharge power at that hour (t), to $SOC(t) - SOC(t-1)$, [2], [8] is computed by subtracting the PV power output from the load demand. When the PV power output and the load demand at that hour (t) are equal, there is no net energy flow into or out of the battery bank, and the SOC remains the same as the previous hour. The charge or discharge power into and out of the battery bank is subject to the maximum charge and discharge rates of the battery bank, which are determined by its capacity and efficiency. If the charge or discharge power exceeds these limits, the excess power is either wasted or the battery bank may be damaged. By considering these conditions, the energy flows between the PV system, battery bank, and load demand can be optimized to ensure the most efficient and reliable operation of the system. To optimize energy flows from the previous hour (t-1) to the current hour (t), several conditions need to be taken into consideration. At any given hour t, the battery SOC will be given by the expression [2], [8], [12-14]:

$$SOC\,(t) = SOC\,(t-1) + \eta_C P_3\,(t) - \eta_D P_4\,(t)\,, \qquad (4)$$

where η_C is the battery charging efficiency and η_D is the battery discharging efficiency.

The following general expression derived from Eq. (4) applies to the battery dynamics [2], [8], [12-14]

$$SOC\,(t) = SOC\,(0) + \eta_C \sum_{\tau=1}^{t} P_3\,(\tau) - \eta_D \sum_{\tau=1}^{t} P_4\,(\tau)\,, \quad (5)$$

where $SOC(0)$ is considered as the initial SOC of the battery, $\eta_C \sum_{\tau=1}^{t} P_3(\tau)$ is the power accepted by the battery at time t, and $\eta_D \sum_{\tau=1}^{t} P_4(\tau)$ is the power discharged by the battery at time t of system model show in Fig.1.

The available battery bank capacity at any time t ($SOC(t)$) must not be less than the minimum allowable capacity(SOC_{min}) and must not be higher than the maximum allowable capacity (SOC_{max}). The minimum allowable capacity, (SOC_{min} The maximum allowable capacity (SOC_{max}) is the maximum capacity of the battery bank. The relationship between SOC_{min}, SOC_{max} is given by [2], [8], [12-14]:

$$SOC_{min} \leq SOC\,(t) \leq SOC_{max} \qquad (6)$$

Ensuring that the battery bank is not over-discharged, which can damage the battery and reduce its lifespan, and that it is not overcharged, which can also damage the battery and reduce its performance, is important. By maintaining the battery bank within these capacity limits, the system can operate more efficiently and reliably.

Battery life can be measured in terms of calendar life or cycle life. The calendar life refers to the length of time that a battery can last regardless of the number of charge or discharge cycles it undergoes. This type of life is mainly determined by the chemical reactions that occur within the battery over time [14]. On the other hand, cycle life refers to the number of charge and discharge cycles that a battery can undergo before its capacity is reduced to a certain level. In most cases, manufacturers measure and specify battery life based on laboratory tests and simulations. However, [2-7] various factors can affect the actual battery life, such as temperature, depth of discharge, charging and discharging rates, and the overall usage pattern. Therefore, it is essential to regularly monitor the battery's health status and take appropriate measures to ensure its longevity.

$$SOH\,(\%) = \frac{C_{REF}\,(t)}{C_{REF,NOM}} \times 100, \qquad (7)$$

where $SOH(\%)$ is the state of health or cycle life of the battery. $C_{REF}(t)$ is the maximum capacity of the battery at time t, and $C_{REF,NOM}$ is the initial capacity of the battery.

2.3 Diesel Generator Model

A DG generates electricity by using a diesel engine to power an alternator [2-4]. It is commonly used as a backup power source in areas where grid power is unreliable, or in remote locations where access to grid power is limited or nonexistent. The power output of a DG depends on its engine size and the speed at which it is running. Generally, [5-7] larger engines running at higher speeds produce more power than smaller engines running at lower speeds. Although DGs are generally less efficient than other types of generators, such as natural gas generators or solar power systems, they are preferred in certain situations due to their reliability, durability, and ability to provide power in remote locations or during emergencies.

In hybrid power supply systems, [2-4] a DG is commonly used as a backup to supply power when the PV and battery cannot meet the demand. To ensure efficient DG operation, it is important to follow the manufacturer's recommended minimum diesel operation. Moreover, [5-7] the generator should be operated within a specific range of power output to achieve maximum efficiency. Running the generator below its rated capacity can decrease its efficiency and increase fuel consumption, while running it above its rated capacity can cause damage and reduce its lifespan. Therefore, it is crucial to monitor and control the generator's load to keep it operating within its optimal range.

The constraint for the DG power output of system model show in Fig.1 is represented by [2]

$$P_1^{min} \leq P_1(t) \leq P_1^{max} \tag{8}$$

A load-following strategy involves turning on the DG only when the PV and/or battery cannot meet the load demand. This approach is more cost-effective because the generator is dispatched only when necessary. The DG should not be used for battery charging, and it should generate only enough power to meet the load demand. This strategy enables the DG to operate at high load factors, resulting in low specific fuel consumption and a longer lifespan of the generator [2-7].

To determine the fuel consumption rate (FCR) of a DG, can refer to the manufacturer's specifications or measure the actual fuel consumption rate during operation. Additionally, need to find out the cost of diesel fuel per liter (CPL) from the current market price of diesel fuel. Once have these values, can calculate the cost of fuel per hour (CFH) using the formula stated earlier. This calculation is essential in estimating the cost of operating the DG and optimizing its fuel efficiency [5].

Calculate the cost of fuel per hour (CFH) using the following formula:

$$CFH = FCR \times CPL, \tag{9}$$

where CFH is cost of fuel per hour, representing the expense of fuel consumed by the diesel engine generator per hour, FCR is fuel consumption rate, indicating the rate at which fuel is consumed by the generator, CPL is cost per unit of fuel, representing the price of fuel.

To determine the cost of electricity per kilowatt-hour (kWh), start by determining the electrical power output of the diesel engine generator in kilowatts (kW). This information can be obtained from the manufacturer's specifications or by measuring the actual power output during operation. Once the power output is determined, calculate the cost of electricity per kilowatt-hour (kWh) using the following formula [5]:

$$COE = \frac{CFH}{kW \times PF \times h}, \tag{10}$$

where COE is the cost of electricity per kilowatt-hour (kWh), PF is the power factor of the generator, and h is the number of hours of operation.

The power factor (PF) measures the efficiency of the generator in converting mechanical energy to electrical energy. The manufacturer's specifications usually provide this information, and it usually falls within the range of 0.8 to 0.9.

2.4 Household Appliance Model

Household appliances are electrical devices that are utilized in homes for various purposes, such as cooking, cleaning, refrigeration, and entertainment. Common household appliances include refrigerators, ovens, microwaves, toasters, coffee makers, vacuum cleaners, washing machines, and televisions. Typical load profiles for residential homes in Roi Et Province, Thailand, are depicted in Fig.5, based on energy demand surveys carried out in rural communities. The weekday and weekend demand profiles were obtained from these surveys. Hourly power demand for each load in a household for a 24-hour period is included in the profiles [8].

The hourly power demand for each load in a household for a day (24 hours):

$$E_a = \left[E_{\_a1}, E_{\_a2}, \ldots, E_{ah}\right], \tag{11}$$

where E_a is the hourly power demand for each load in a household throughout a 24-hour period, E_{ah} is the power demand of each load at different hours of the day (h).

The total hourly power demand for appliances can be calculated by [8] summing up the power demand of all the individual appliances at each hour of the day.

$$E_h = \sum_{a=1}^{N} E_{\_ah}, \tag{12}$$

where E_h is total hourly power demand for appliances, E_{ah} is hourly power demand for a specific appliance.

The total daily power demand for appliances can be calculated by [8] summing up the power demand of all

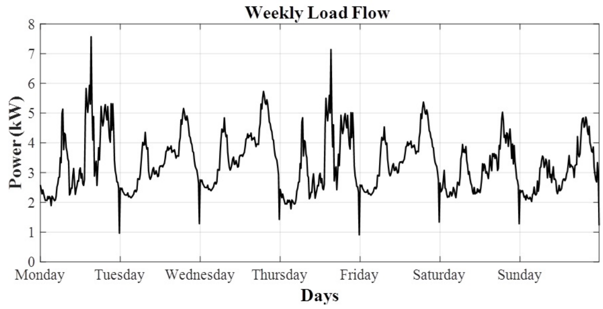

***Fig. 5**: Weekly Load Flow.*

the individual appliances at each hour of the day.

$$E_T = \sum_{a=1}^{N} \sum_{h=1}^{24} E_{\_ah}. \tag{13}$$

3. OPTIMIZATION MODEL

The typical operation strategy for a hybrid renewable energy system with a battery and a backup DG prioritizes the utilization of solar energy to meet the load demand. The battery is used to provide the necessary energy when the PV output is insufficient. Any excess energy from the PV system is stored in the battery for future use when it is fully charged and the PV output is higher than the load demand. If the PV output is not enough, and the battery is fully discharged, the DG can provide the deficit power to meet the load demand.

In Fig. 5, we find typical load profiles that are derived from energy demand surveys conducted in rural communities. These profiles showcase the patterns of electricity consumption during both weekdays and weekends. The surveys were carried out to gain insights into the usual energy consumption behavior of residents and to comprehend their electricity requirements. By analyzing the collected data, distinct patterns emerge regarding energy demand fluctuations throughout the day, thereby indicating peak and off-peak periods. These load profiles hold significance for various purposes, including energy planning, system design, and optimization of power generation and distribution.

However, [2] the DG is switched off when the PV and/or the battery can meet the load demand, saving fuel and reducing operating costs. To optimize this operation strategy, an economic dispatch algorithm can be used to minimize fuel costs and ensure system reliability. The algorithm utilizes non-linear optimization programming, which can be solved using the MATLAB programming language. Overall, [5] this operation strategy for a hybrid renewable energy system with a battery and backup DG, combined with an economic dispatch algorithm, increases the use of renewable energy, reduces operating costs, and ensures a reliable power supply for the load demand.

The economic dispatch problem is a classic optimization problem in power systems that aims to find the optimal dispatch of available generation sources while minimizing the cost of generation and meeting the load demand. In this scenario, the available generation sources include the PV, battery, and DG, and each has a controllable power output. To solve this problem, the optimization algorithm determines the optimal power output schedule for each source while ensuring that the demand is entirely satisfied and the operating limits of the sources are not violated. The operation strategy prioritizes the use of PV and battery to meet the load demand to the extent possible, with the DG only being utilized to fill any deficit. By [5] using the economic dispatch algorithm, the system can generate an optimal dispatch schedule for each source that ensures a reliable power supply while minimizing fuel costs. The algorithm considers various factors, such as the available power from each source, the fuel cost of each source, and the operating constraints of each source, to generate the optimal dispatch schedule. In summary, the economic dispatch problem is a crucial optimization problem in power systems that helps minimize fuel costs while ensuring a reliable power supply for the load demand. The objective function is given by the following expression:

$$\min C_f \sum_{t=1}^{N} COE * P_1(\mathrm{t}) \tag{14}$$

, subject to the following constraints:

$$P_2\,(t) + P_3\,(t) \leq P_{PV}\,(t)\,, \tag{15}$$

$$P_1\,(t) + P_2\,(t) + P_4\,(t) = P_L\,(t)\,, \tag{16}$$

$$P_1\,(t) \geq 0,\; P_2\,(t) \geq 0, P_3\,(t) \geq 0,\; P_4\,(t) \geq 0, \tag{17}$$

$$P_i^{min} \leq P_i\,(t) \leq P_i^{max}, \tag{18}$$

$$SOC_{min} \leq SOC\,(t) \leq SOC_{max}, \tag{19}$$

for all $t = 1, \ldots, N$, where N is 24 and C_f is the fuel price. $B_C(t)$ is equal to the sum of and the power accepted or discharged by the battery. $P_1(t)$, $P_2(t)$, and $P_4(t)$ are the control variables representing energy flows from the DG, PV and battery to the load at any time (t) respectively and $P_3(t)$ represents the energy flow to the battery during the 24-h period of system model show in Fig.1.

The optimization algorithm used for the economic dispatch problem ensures that the power generation from each source meets the demand and operates within the specified limits. Constraint Eq. (15) limits the total power output from the PV array to the sum of the charging power and power supplied directly to the load. Constraint Eq. (16) ensures that the power supplied from all sources meets the demand at any hour, while constraint Eq. (17) ensures that the power supplied by each source is positive and not negative. Constraint Eq. (18) specifies the minimum and maximum values for the power output of each source, while constraint Eq. (19) sets the minimum and maximum limits for the battery capacity.

Constraint Eq. (19) takes into account the charging

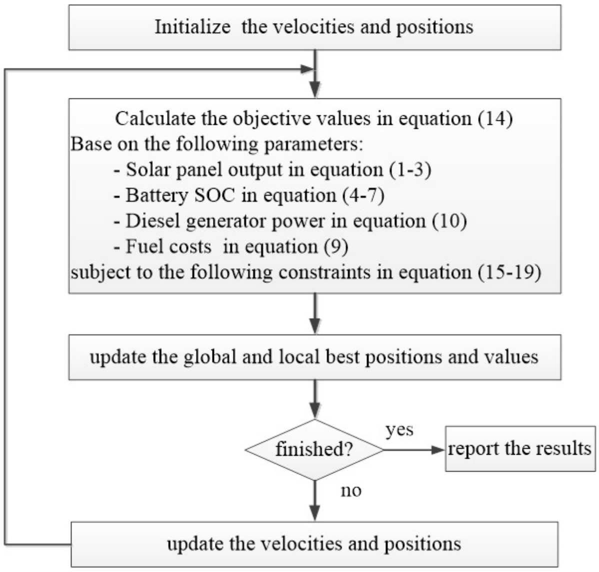

***Fig. 6**: Flowchart of PSO. [11].*

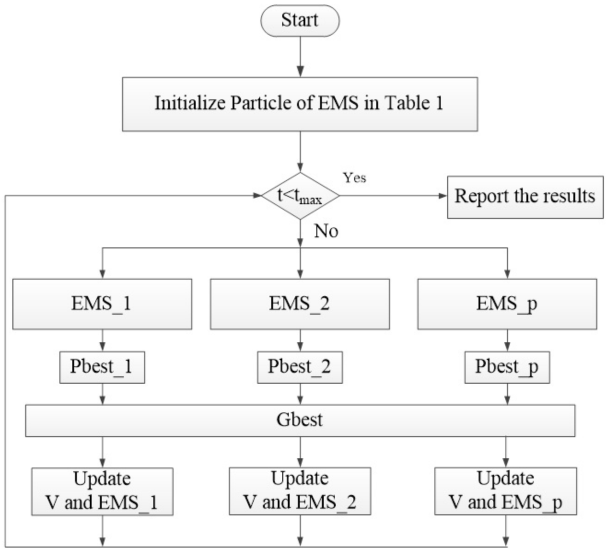

***Fig. 7**: Flowchart of the EMS algorithm by PSO. [8]*

efficiency of the battery, represented by the term η_C, and the discharging efficiency, represented by the term η_D, to ensure that the battery capacity at any time (t) is within the specified minimum and maximum levels. The objective function Eq. (14) represents the total fuel cost for the 24-hour period and is a function of the power outputs of DG. The coefficients COE represent the cost of electricity per kWh for the DG. The algorithm determines the optimal power output schedule for each source by minimizing the objective function. This minimizes the total fuel cost while ensuring that the demand is completely satisfied and the operating limits of the sources are not violated.

3.1 The Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) method [8-10] is a metaheuristic optimization algorithm inspired by the social behavior of animals such as birds and fish. In PSO, a population of particles (or individuals) represents potential solutions to an optimization problem. These particles move through the search space and exchange information with each other to find the optimal solution. PSO has been applied to a wide range of optimization problems, including engineering design, data mining, and machine learning, flowchart of PSO is shown in Fig.6.

To calculate the new velocity of particle i at iteration cycle t, the following equation is used:

$$P_{best,i}^{t+1} = \begin{cases} P_{best,i}^{t} \ , \ f\left(x_i^{t+1}\right) > P_{best,i}^{t} \\ x_i^{t+1} \ , \ f\left(x_i^{t+1}\right) \le P_{best,i}^{t} \end{cases} , \tag{20}$$

$$G_{best} = min\left\{P_{best,i}^{t}\right\} i \in \ [1, \ldots, n] \text{ and } n > 1, \tag{21}$$

$$v_{ij}^{t+1} = \omega^t v_{ij}^t + c_1 r_{1j}^t \left[P_{best,i}^t - x_{ij}^t + c_2 r_{2j}^t \left[G_{best} - x_{ij}^t\right]\right], \tag{22}$$

where v_{ij}^t is the velocity vector of particle i in dimension j, x_{ij}^t is the position vector of particle i in dimension j, $P_{best,i}^t$ is the personal best position of particle i in dimension j, G_{best} is the global best position of particle i in dimension j, c_1 and c_2 are positive acceleration constants which are used to level the contribution of the cognitive and social components respectively, r_{1j}^t and r_{2j}^t are random numbers from uniform distribution, $U(0,1)$, ω is the inertia weight that controls the impact of the previous velocity on the new velocity. It is updated at each iteration as follows:

$$\omega^{t+1} = \omega_{max} - \left[\frac{\omega_{max} - \omega_{min}}{t_{max}}\right] t \ , \ \omega_{max} > \omega_{min} \tag{23}$$

The process of updating the velocity and position is repeated for all particles until the maximum number of iterations tmax is reached or a satisfactory solution is found. After updating the velocity, the position of particle i at iteration $t+1$ is calculated as follows:

$$x_i^{t+1} = x_i^t + v_i^{t+1}, \quad x_i^0 \sim U\left(x_{min}, x_{max}\right) \tag{24}$$

```
Algorithm : PSO
  P = Particle Initialization();
  for it = 1 to it_max
     for p = 1 to size(P)
        cost_p = cost(EMS_p)
        if cost_p < p_Best
           p_Best = EMS_p
        end
     end
     g_Best = best EMS_p in P
     ω^t = ω_max − [(ω_max − ω_min)/t_max] t
     for p = 1 to size(P)
     v^t = ωv + c_1 r_1 [P_Best − EMS_p] +
            c_2 r_2 [G_Best − EMS_p]
```

$$EMS_p = EMS_p + v^t$$

end

end

This code snippet represents [8] the particle swarm optimization (PSO) algorithm. The PSO algorithm is a population-based optimization technique that iteratively updates a group of candidate solutions, called particles, by simulating their movement in a search space. The algorithm maintains the best-known solution, called gBest, and the best-known solution for each particle, called pBest. A flowchart of the EMS algorithm by PSO is shown in Fig. 7.

3.2 Model Parameters

Optimizing energy management is critical for achieving maximum energy efficiency and minimizing energy waste in any given system. Proper sizing of the system is also important to ensure that energy demand is met at all times without incurring unnecessary costs or wasting energy. This is particularly relevant for renewable energy systems such as PV and DG, which are dependent on weather conditions and generate variable energy output. Efficient energy management can improve the utilization of renewable energy systems, contributing to a more sustainable energy future.

The sizing of the PV array depends on the cell material used. The energy produced by the PV and DG is consumed by the load and is also used to charge the battery bank, depending on the state of charge of the battery and the magnitude of the load at any given moment. The load following strategy is used to manage the operation of the DG, which is only used when the PV and battery output is not sufficient to meet the load demand.

The parameters of the DG-PV battery system used in this study are shown in the Table 1. The main focus of this study is to achieve optimal energy management of the system, leading to efficient operation and cost savings. To achieve this goal, a 7.5 kVA Power Rush generator type is used, which employs an electronic control system to vary the output by sensing the load and adjusting the fuel supply and engine revolutions in response to the load. This type of generator is advantageous as it can supply the required power output at any given time.

4. POWER MANAGEMENT ALGORITHM

In this study, the power management algorithm consists of four different operating modes that dictate the system's behavior at different times of the day. A flowchart of the energy management system (EMS) control algorithm is presented [8],[11] in Fig.8.

The following is a summary of each mode:

Mode 1: This operation mode applies to the time period between t0 and t1, which is from 01:00 to 05:00. During this period, the photovoltaic system does not generate electricity, and the load demand is low. The battery is charged from the DG system, and the State of Charge (SOC) varies between 20% to 90%.

Table 1: Parameters of the DG-PV-battery system.

Parameters	Parameter Value
Nominal Battery Capacity	100 kWh
Battery Charge Efficiency	85%
Battery Discharge Efficiency	100%
PV Array Capacity	10 kWp
DG Capacity	7.5 kW
Fuel Consumption for DG	3.2 litre/h
Cost of Electricity/kWh (COE)	14.26 Baht/kWh
Cost of Diesel Fuel/litre (CPL)	33.44 Baht/litre
ω_{min}	0.4
ω_{max}	0.9
i	10
t	20

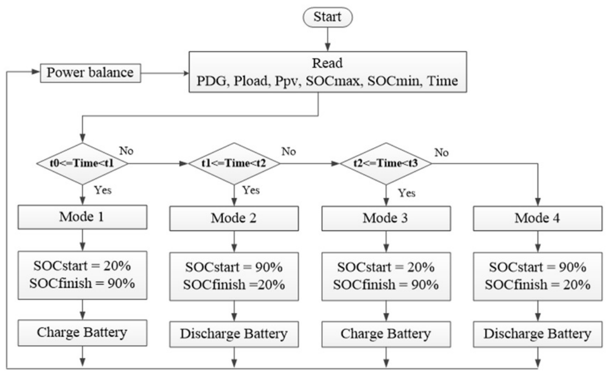

Fig. 8: Flowchart of the control algorithm.

Mode 2: The energy management algorithm applies this operation mode to the time period between t1 and t2, which is from 05:00 to 11:00. During this period, the photovoltaic system begins to generate electricity, but the energy produced is still limited. The battery discharges to supply power to the load in the morning, and the State of Charge (SOC) decreases from 90% to 20%.

Mode 3: During the time period between t2 and t3, which is from 11:00 to 15:00, the energy management algorithm applies this operation mode. In this mode, the battery is charged using the energy generated by the photovoltaic system. The algorithm is designed to optimize the charging of the battery, ensuring that the State of Charge (SOC) increases from 20% to 90%.

Mode 4: The energy management algorithm applies this operation mode to the time period between t3 and t4, which is from 15:00 to 24:00. During this period, the load consumption gradually increases. The battery begins discharging to supply power to the load until the State of Charge (SOC) reaches the lower boundary limit of 20%. The algorithm is designed to optimize the discharge of the battery, ensuring that it provides power to the load in a way that maintains the SOC within the safe range. The battery's energy is utilized to handle

***Table 2**: Case study.*

Case Study	Work Case			
	DG	PV	BESS	PSO
1	✓			
2	✓	✓		
3	✓	✓	✓	
4	✓	✓	✓	✓

the peak evening load in the residential home, which typically occurs during this period.

In the paper, safe operation and prolongation of the service life of lithium-ion batteries are considered. The maximum State of Charge (SOC) of the battery is set to 90%, while the minimum SOC is set to 20%. However, the paper does not take into account the cost of installing a hybrid system consisting of a generator, solar cells, and a battery. Instead, it focuses on discussing how to control the integrated systems built into the workflow and optimize the sizing of the mixing system for the load. As a result, important issues related to installation, such as economic analysis, are not accounted for in the model. Furthermore, the operating costs of the generator, the photovoltaic system, and the batteries are also not considered in the paper. While the paper provides insights into optimizing the energy management algorithm to ensure the efficient use of the available resources, it is important to consider the economic and operating costs of the system when implementing it in practice.

In this case study, the focus is on evaluating the performance of the proposed energy management algorithm using simulation techniques in MATLAB software. The system model being simulated is a PV-diesel-battery hybrid system, as illustrated in Fig. 1. The simulation is conducted under four different scenarios, which are described in Table 2.

The main objective of the study is to assess the effectiveness of the energy management algorithm in managing the energy flow within the system and ensuring its reliability. The algorithm is responsible for optimizing the utilization of power from the PV system, diesel generator, and battery storage. By analyzing the energy flow and making intelligent decisions, the algorithm aims to achieve efficient energy management and maintain the system's stability.

Through the simulation, the researchers can analyze the performance of the proposed algorithm under various conditions in Eqs. (15)-(19) and evaluate its ability to handle different scenarios. This assessment helps to determine the algorithm's effectiveness in maximizing the utilization of renewable energy, minimizing reliance on the diesel generator, and optimizing the use of battery storage. The paper presents the evaluation of four different cases for power system performance:

Case 1 (DG): This case focuses on assessing the performance of a power system that relies solely on a single diesel generator (DG) as its power source. The DG is operated to meet the load demand without the integration of solar cells or batteries.

Case 2 (DG+PV): In this case, the performance of a power system that combines a DG with a photovoltaic (PV) system is evaluated. However, the system does not include the installation of a battery energy storage system.

Case 3 (DG+PV+BESS): This case revolves around the evaluation of a power system that integrates a DG, PV systems, and battery energy storage systems. The control algorithm governing the battery charge and discharge is analyzed, as depicted in the flowchart presented in Fig. 8.

Case 4 (DG+PV+BESS+PSO): The performance evaluation in this case involves an electrical system that integrates a DG, a solar power generation system, and a battery energy storage system. The system is designed to be optimized using particle swarm optimization (PSO) techniques. The control algorithm for battery charge and discharge is illustrated in the flowchart shown in Fig. 8.

5. RESULTS AND DISCUSSION

In this section, the study presents and analyzes the simulation results. The system model is simulated under four different scenarios in Table 2 to assess the algorithm's ability to manage power flow and ensure system reliability. The simulation aims to determine the system's ability to meet the electrical load demand throughout the year, as well as to identify the optimum battery SOC, battery charge cycles, and economic viability.

Fig.9 illustrates the power flow during a 24-hour period. During weekdays, the DG meets the load demand during the night and in the morning. The simulation results could show the system's performance under different conditions, such as varying load demands, changes in fuel consumption and generator efficiency, and the effects of external factors like temperature or humidity. These results could be used to evaluate the system's overall efficiency, reliability, and cost-effectiveness. However, the performance of a DG-based power system depends on various factors, such as the generator's size and capacity, fuel quality, system maintenance and upkeep, and the load being served. The electricity demand for homes in the early morning and evening can vary depending on factors such as the number of occupants, their daily routines and habits, and the types of appliances and electronics used. In the morning, electricity demand may be relatively low as occupants are typically asleep and not using many appliances or electronics. However, as occupants start their daily routines, electricity demand may increase as they use appliances like lights, coffee makers, and showers. In the evening, electricity demand in homes typically peaks as occupants return home from work or school and start using appliances and electronics for cooking, entertainment, and other activities. This peak demand period is often referred to as the "evening peak" and can occur anywhere from around 5 PM to 9 PM,

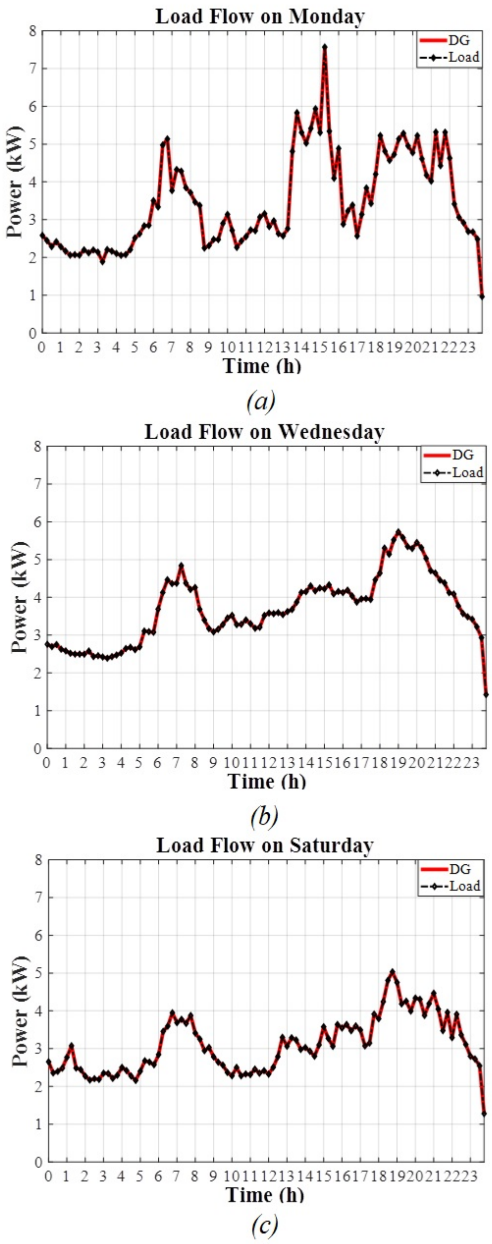

Fig. 9: *January weekday power flow (case 1).*
(a) Power flow on Monday.
(b) Power flow on Wednesday.
(c) Power flow Saturday.

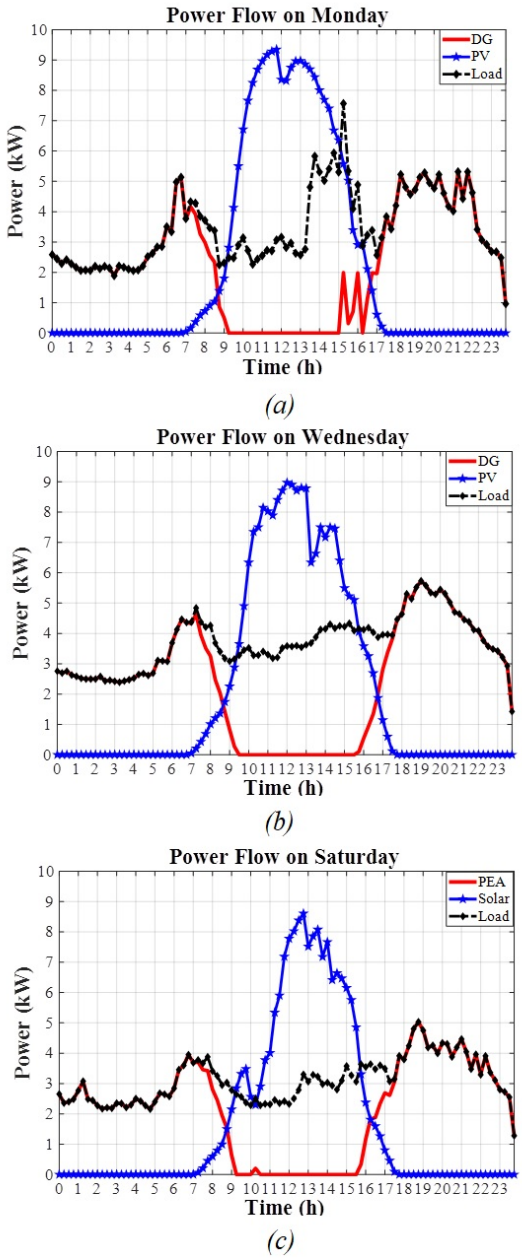

Fig. 10: *January weekday power flow (case 2).*
(a) Power flow on Monday.
(b) Power flow on Wednesday.
(c) Power flow Saturday.

depending on local electricity usage patterns.

In Fig. 10, the power system demonstrates the advantages of combining a DG with a PV system. By integrating these two sources, the power system can harness the strengths of each component. The DG serves as a reliable power supply, particularly during periods of low solar irradiation or high demand that exceeds the capacity of the PV system. It acts as a backup or supplemental power source, ensuring uninterrupted electricity supply even when solar energy generation is insufficient.

Overall, the integration of a DG with a PV system in a power system provides a balanced and reliable electricity generation solution. It capitalizes on the reliability of the DG and the sustainability and cost-efficiency of the PV system. By leveraging the strengths of both sources, this hybrid approach ensures uninterrupted power supply, reduces reliance on fossil fuels, and contributes to a more sustainable energy future.

Fig.11 depicts the energy flow in a hybrid power system that uses PV panels, a battery bank, and a DG. The system is designed to meet the load demand over a 24-hour period, with the PV output supplying the load

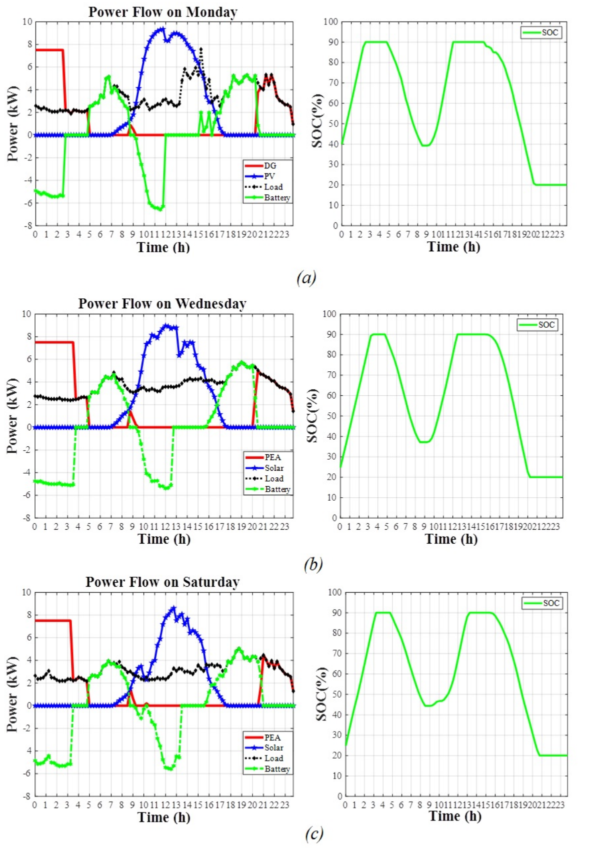

Fig. 11: *January weekday power flow (case 3).*
(a) Power flow on Monday.
(b) Power flow on Wednesday.
(c) Power flow Saturday.

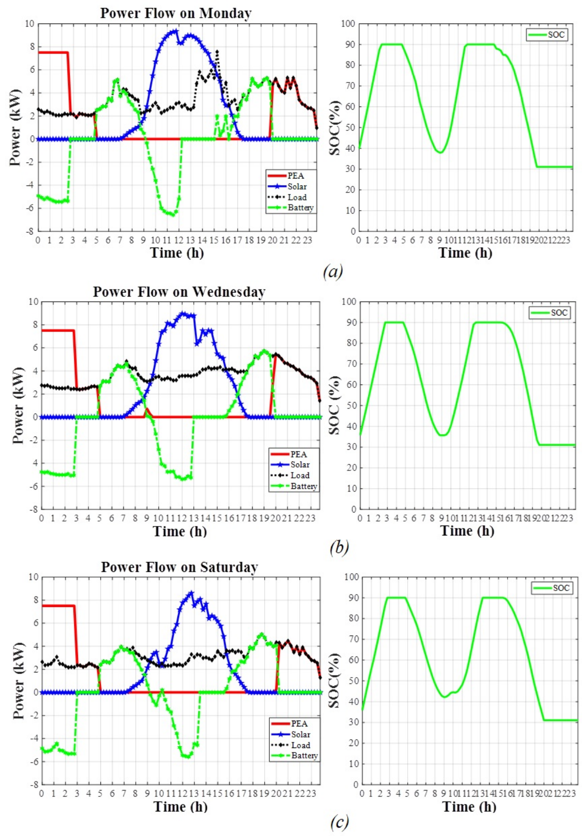

Fig. 12: *January weekday power flow (case 4).*
(a) Power flow on Monday.
(b) Power flow on Wednesday.
(c) Power flow Saturday.

and charging the battery during the day. At night, when there is no power from the PV, the battery supplies the load. If the PV and battery cannot meet the load, the DG switches on, and its running time and power output depend on the SOC of the battery and the amount of power from the PV array. Two constraints limit the system's operation. The first constraint ensures that the PV array output must be equal to or greater than the load for the system to meet the load or charge the battery. The second constraint restricts the SOC of the battery to a specific range, beyond which excess power from the PV array is wasted. The figures show how the system responds to changes in the amount of power from the PV array, the SOC of the battery, and the load demand. It is noteworthy that optimizing the energy management algorithm to balance the operation of the PV, battery, and DG can help ensure efficient use of the system and achieve cost savings.

Fig.12 depicts the energy flow in a hybrid power system that comprises PV panels, a battery bank, and a DG. The system is optimized using the PSO techniques, which enable adjusting the control parameters of the different components to attain the desired power output while minimizing fuel consumption and operating costs. The system is designed to meet the load demand over a 24-hour period, with the PV output supplying the load and charging the battery during the day. At night, when there is no power from the PV, the battery supplies the load. If the PV and battery cannot meet the load, the DG switches on, and its running time and power output depend on the SOC of the battery and the amount of power from the PV array.

In general, this type of power generation system presents a more cost-effective and efficient solution for fulfilling electricity demands, particularly in remote or off-grid locations. The system combines various power sources and energy storage systems, leveraging advanced optimization techniques to provide reliable electricity while curbing fuel consumption and operating expenses. PSO optimization of the hybrid power system offers the advantage of reducing the required battery size by approximately 10% compared to unregulated systems as show Table 3. This reduction is due to PSO minimizing unnecessary battery charging and discharging, leading to more efficient energy use. In the simulation results, the SOC graph of the battery during the charging process shows that the maximum SOC attained is 90%, while the minimum SOC achieved is 32%, indicating that the battery is almost fully charged. By monitoring and

Table 3: *SOC of the battery.*

SOC	Cases Study	
	3	4
Mode1: SOCmin	20	32
Mode1: SOCmax	90	90
Mode2: SOCmax	90	90
Mode2: SOCmin	20	20
Mode3: SOCmin	20	20
Mode3: SOCmax	90	90
Mode4: SOCmax	90	90
Mode4: SOCmin	20	32

Table 4: *Fuel cost saving.*

Cases Study	Fuel Cost (Baht)	Battery Charge Cycle (cycle)	Cost Saving (%)
1	415,758.61	0	0
2	279,043.62	0	32.88
3	273,626.61	721	34.19
4	236,744.20	717	43.06

controlling the SOC of the battery, PSO can optimize the charging and discharging process, ensuring that the battery is charged appropriately and minimizing the risk of overcharging or undercharging.

Table 4 illustrates the cost and fuel savings achieved by implementing photovoltaic-diesel-battery systems compared to a diesel-only scenario over a year. The results demonstrate that utilizing the proposed algorithm for a PV-diesel battery system can save up to 43.06% of fuel when compared to a diesel-only situation.

Furthermore, a comparison of the number of battery cycles between case study 3 and 4 revealed that implementing the PSO algorithm in case study 4 resulted in a reduction in the number of battery cycles. This suggests that the optimization model can effectively decrease the fuel cost for the energy delivery strategy used. Overall, the study suggests that employing the optimization model can lead to significant fuel savings and substantially reduce the cost of the energy delivery system, particularly when accounting for changes in consumption patterns.

The results of the study suggest that using PSO to optimize the hybrid power system can reduce the required battery size by approximately 10% compared to unregulated systems. This is because PSO can minimize unnecessary battery charging and discharging, leading to more efficient energy use and reduced energy storage requirements. The simulation results demonstrate that PSO can optimize the charging and discharging process, ensuring that the battery is charged to an appropriate level and reducing the risk of overcharging or undercharging.

6. CONCLUSION

This paper focuses on evaluating the operational efficiency of a photovoltaic-diesel-battery hybrid off-grid system over a period of one year. The study aims to compare the fuel costs associated with daily energy consumption variations for weekdays and weekends. To achieve this, the study uses a particle swarm optimization technique (PSO) to present an optimal energy dispatch model that can effectively optimize energy management for remote communities, leading to significant cost savings and improved system efficiency.

The model can assist solar energy practitioners or companies in estimating consumer fuel costs accurately on a daily or yearly basis and can be used to analyze energy flows in any given system. The results of the study indicate that the photovoltaic-diesel-battery hybrid system achieves a fuel saving when compared to a scenario where the DG satisfies the load on its own. This suggests that the hybrid system is more cost-effective and efficient than a diesel-only system. The study highlights the importance of considering daily and seasonal variations in demand when analyzing the operational cost of the PV-diesel-battery power supply system. However, the paper does not address the installation costs of the generator, solar cells, and battery, nor does it consider the ongoing operating costs of these components. While the paper offers valuable insights into energy management algorithm optimization, it is crucial to incorporate economic and operational costs when implementing such systems in real-world applications.

In the future, it would be expected that the proposed development of the model could lead to even more optimal results and can be further developed to optimize various components of the hybrid system, such as incorporating on/off switching of the DG, using more generators, reactive power compensation in system, and conducting a life cycle cost analysis of the whole system in the longer term, taking into account the daily operational cost variations.

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Nonthanan Phonphan completed his Bachelor of Engineering in Electrical Engineering at Rajamangala Institute of Technology Khon Kaen Campus in 2002. He furthered his education and earned a Master of Science degree in the Industrial Education Department of Electrical Engineering from King Mongkut's University of Technology Thonburi in 2005. Currently, he is pursuing a Ph.D. in the Department of Electrical Engineering at Ubon Ratchathani University. Presently, he holds the position of Assistant Professor in the Bachelor of Science Program Department of Electrical Technology at Roi Et Rajabhat University in Roi Et Province, Thailand. His research focuses on the management and control of electrical energy consumption, particularly in the realm of integrating renewable energy and energy storage systems.

Pracha Khamphakdi was born in Roi-Et, Thailand, in 1978. He received the B.S. and M.S. degrees in electrical engineering from the King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand, in 2001 and 2005, respectively. He finished the Ph.D. degree in electrical and electronic engineering from the Tokyo Institute of Technology, Tokyo, Japan in 2015. He is a senior lecturer at the Department of Electrical and Electronic Engineering, Ubon Ratchathani University, Thailand. His research interests include power converters and their applications, photovoltaic system, electric vehicles system, embedded system and ioT application in smart farm. Dr. Pracha receive the First Prize Paper Award from 2013 IEEE Industry Applications Society (IAS) Industrial Power Converter Committee (IPCC). He receives the Best Paper Award from 2019 International Conference on Power, Energy and Innovations (ICPEI) 16-18 Oct. 2019, Pattaya, Chonburi, Thailand.

Bongkoj Sookananta is a senior lecturer in electrical and electronics engineering, Ubon Ratchathani University. She finished her Ph.D. from the University of Strathclyde in Glasgow, UK. Her research interests include data analysis, modelling and Al applications, electrical power system operation and planning, renewable energy and storage in power systems and agricultural applications.