Day-Ahead Dynamic Economic Emission Dispatch Considering Photovoltaic Predicted Output Using Sailfish Optimizer and Simulated Annealing

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***Abstract*—Economic Dispatch (ED) aims to optimize the output power of generating units to minimize the total cost of power system operations. With the application of ED, the minimum generation cost will be obtained for the production of electric power generated by generating units in an electricity system while still paying attention to constraints. For hybrid plants, the challenge to performing ED is the intermittency of solar energy. So that before the ED is carried out, solar radiation forecasting is carried out using LSTM. In previous research, there are problems such as not making solar radiation forecasts and ED equally important so that it cannot be fully applied to solve ED problems. To overcome these problems, this research makes solar radiation forecasts using LSTM and solves ED problems using Sailfish Optimizer and Simulated Annealing Algorithm. To measure the accuracy of forecasting, RMSE, MSE MAE, and MAPE are used with average results of 6.311, 40.11, 4.61, and 4.87. With the application of ED, the minimum generation cost is obtained for the production of electric power generated while still considering the constraints. Through ED, fuel allocation can be optimized, helping to reduce production costs and carbon emissions, and making a positive contribution to environmental sustainability. To improve ED results in the sailfish optimizer, the use of simulated annealing is added so that the results have lower total cost and emission values than ED without simulated annealing. Rp 128.024 and 398 kg, respectively.**

Keywords— ***economic dispatch, forecasting, LSTM, sailfish optimizer.***

I. Introduction

The government of Indonesia continues to focus on promoting environmentally friendly electrification across all layers of Indonesian society. This is evident through the achievement of an electrification ratio of 99.40 percent in the third quarter of 2021, coupled with promising growth in the capacity of Renewable Energy (RE). [1]. In line with this, to address RE issues, the conversion of Diesel Power Plants in isolated systems into plants using RE will be carried out. One of the converted Diesel Power Plants is the Selayar Diesel Power Plants located in Selayar Regency. Besides being converted to operate fully on RE, these systems can also operate in a hybrid mode.

The most effective way to harness energy from the sun is by installing a photovoltaic system connected to the grid. However, solar radiation is limited by various factors, such as climate change and weather conditions. Solar radiation is an unpredictable and unstable energy source, making it a challenge for operators to control power uncertainty and voltage stability. This becomes a power quality issue that must be considered. Therefore, incorporating solar energy facilities into the power grid poses challenges in maintaining a stable energy supply. [2]

ED aims to optimize the power output of generation units to minimize the total operation cost of the power system. [3]. The procedure involves selecting which generators are suitable for the load or electricity demand at that moment. By applying ED, the power system can obtain the lowest cost of generating electricity while meeting all necessary constraints. Hybrid generators, such as the Selayar Solar Power Plant, face the challenge of intermittent solar energy in the process of ED. Concerns about the effects of global warming are driving wider use of renewable clean technologies such as wind and solar energy. The government through the Ministry of Energy and Mineral Resources (ESDM) has created a roadmap to achieve Net Zero Emission (NZE) in the energy sector. The roadmap, which is a form of joint commitment between the Government and stakeholders, is in the form of a timeline divided into 6 stages, starting in 2021 to 2060. [27] Indonesia's energy sector emitted 530 million tons of CO2e in 2021. It is projected that peak emissions will happen around 2039, reaching 706 million tons CO2e. Following the expiration of fossil energy generation contracts in 2040, emissions will sharply decline to zero by 2060. [4]. To reduce carbon emissions and increase the use of clean energy, PT PLN (Persero) is underway with a program to convert approximately 5,200 diesel power plants operating in various regions, particularly remote areas, to renewable energy-based and gas plants, and to integrate them with the national grid. This dedieselization or conversion program aims to lower overall greenhouse gas emissions and promote environmentally friendly energy solutions.[5] To determine the division of each unit in providing the requested load, so that the load demand can be met at the lowest possible cost by considering the limitations of available plants and systems, it is necessary to conduct ED on systems that operate in a hybrid manner by first forecasting the solar energy that will be used. There are several previous studies that conducted ED on RE plants such as in [6] Marine Predators Algorithm (MPA) is used to train an Artificial Neural Network to predict energy demand and complete dynamic economic emission dispatch (DEED). The input

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variables used are ambient temperature, humidity, cooling and air conditioning output where the target is energy demand. Then based on the predicted energy demand, DEED is completed for the building by considering the availability of thermal and Photo Voltaic (PV) banks, energy reserves are also included in the modeling. In [7] proposed the use of Deep Recurrent Neural Network with Long Short-Term Memory Units (DRNN-LSTM) to predict residential electricity load and PV solar panel power output in the short term for a community microgrid. Furthermore, the load dispatch optimization of a grid connected microgrid consisting of residential electric loads, PV arrays, electric vehicles, and energy storage systems was performed. Three scheduling scenarios are analyzed to see the influence of electric vehicles and energy storage systems [8] An improved SSA method is proposed to perform dynamic economic dispatch (DED) considering various PV profiles (sunny and cloudy), using one year of data. Mutation mechanism is combined with SSA to obtain the global optimal solution. The method was tested on 40 thermal generators and PV using BESS simulated by creating several PV penetration scenarios (0%, 10%, 20%, 30%, 40%, and 50%). In [9], this article proposes DED using novel genetic algorithm (nGA) combined with short-term load forecasting. For short-term load forecasting, MANN (multilayer artificial neural network) is used. The electricity generated by the wind turbine is obtained by the system operator based on the wind speed forecast from https://www.windfinder.com/forecasts/. The modified IEEE 30-bus system was used to verify the model with real data obtained from a power plant in the Ereymentau region of Kazakhstan. In the next research [10], HDEED considering wind and solar power generation is made and also includes possible loading patterns, to find the most competitive dispatch plan made with MFO PDU. The wind and PV output power data utilized in this investigation are cited in Ref. [48], and the load demand data in three situations are given in Ref. [49]. In [11], an optimal energy dispatch strategy for a grid connected microgrid is proposed, comprised of PV, wind, and diesel generators. The mathematical model is developed and solved using the Advanced Interactive Multidimensional Modeling System (AIMMS) with the CONOPT solver. The solar radiation data is calculated using a simplified tilted plane model from stochastically generated values of global and diffuse radiation. The forecasted data of solar and wind are applied. For further study [12] the Combined Dynamic Economic and Emission Dispatch (CDEED) problem using wind and PV. Particle Swarm Optimization (PSO) algorithm was used to build an optimal dispatch model. The suggested methodology considers various trade-offs between dynamic fuel cost dispatch and gas emission dispatch in two different scenarios of wind and PV unit participation. Simulations were performed initially on a three-unit power system, followed by various scenarios using a 13-unit IEEE test system. The data sources for PV and Wind utilization are not described in this paper. In paper [13] presents an economic load dispatch analysis considering the inherent uncertainty of renewable energy sources, a probabilistic approach is employed to attain a more precise mathematical representation of the photovoltaic and wind power generation. Following the formulation of the generation limitations, a PSO algorithm with multiple objectives is developed to solve the problem at hand. The output of PV is planned and under or over estimation of the generated output is considered. In paper [14] recommended Combined Heat and Power Economic Dispatch (CHPDED) solved using Chaotic Fast Convergence Evolutionary Programming (CFCEP). Scenarios were created with or without demand side management consisting of variations of Wind, PV, and Pumped Hydro Energy storage generation. The forecast upper and lower bounds of wind speed and solar irradiance used are shown in this article but it is not explained how to obtain them.

In [15], a new algorithm based on Combined Emission Economic Dispatch (CEED) is proposed to optimise the ED problem for thermal power generation units and Photo Voltaic (PV) generation. To solve CEED, they utilise an improvised Euclidean Affine Flower Pollination Algorithm (eFPA) and Binary Flower Pollination Algorithm (BFPA) approach, solving the optimisation problem for 5 thermal generators and 20 PV operating under varying solar radiation conditions. The levels of solar radiation and temperature were taken through Geospatial Toolkit software. This application provides solar radiation data used in a particular area and the data taken on November 17, 2015. In [16] work has been done to develop an advanced energy management system (EEMS) that takes into account the probability of wind power to optimise grid-connected MG dispatch. This study ensures clarity and ease of understanding by providing explanations of abbreviated technical terms at the first use. This study presents a wind power probabilistic forecasting approach, using Gaussian process regression (GPR) and complementary ensemble empirical mode decomposition with adaptive noise (CEEMDAN) in the wind power forecasting module. To address the ED problem, an improved multi-objective bat algorithm (IMOBA) methodology with fuzzy set theory (FST) is proposed. Research [17] indicates that tidal energy has significant potential as a fuel-free and reliable energy source to provide significant amounts of energy in diverse forms. To address the issue of dynamic economic load dispatch while considering limitations on load and generation. a pioneering approach has been adopted. The ARIMA forecasting method has been preferred, as it forecasts the potential of tidal energy accurately. Then integrate tidal energy to solve ED using IWO. In some of the journals mentioned above, there are problems such as not making solar radiation forecasts and ED equally important so that it cannot be fully applied to solve ED problems. To overcome these problems, this research makes solar radiation forecasts using LSTM and solves ED problems using Sailfish Optimizer and Simulated Annealing Algorithm. This paper is structured as follows: In Section II, one-day ahead ED model of RE power generation is created. Section III shows the one-day ahead forecasting method using LSTM and shows the solving steps of Economic Dispatch using Sailfish Optimizer and Simulated Annealing. Finally, some conclusions are given in Section IV.

II. Methods

A. *Objective Function*

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

TABLE I Generation Power Balance

No	Unit	Installed Power (kW)	Net Power (kW)	Status
1	Deutz 1	1224	900	Standby
2	Deutz 2	1224	900	Standby
3	Deutz 3	1224	900	Standby
4	Deutz 4	1224	900	Standby
5	Deutz 5	1224	900	Standby
6	Cummins 1	1292	900	Standby
7	Cummins 2	1292	950	Standby
8	Cummins 3	1292	950	Standby
9	Mitsubishi 1	1330	1000	Standby
10	Mitsubishi 2	1330	1000	Standby
11	Mitsubishi 3	1330	900	Standby
12	PLTS	1300	1000	Standby

The purpose of ED is to minimize generation costs obtained by determining the amount of generation power of each generator. The generation power for each unit is determined by ensuring that the maximum and minimum generator generation constraints are fulfilled. [18] If the solar energy conversion system belongs to the system operator and does not require fuel to generate electricity, its electricity generation cost can be omitted from the objective cost function. Consequently, $Fcost$ t is represented by a quadratic equation as shown. (1). [10]

$$F_{cost} = \sum_{i=1}^{n} (a_i + b_i P_i + c_i P_i^2) \tag{1}$$

Where

F_{cost} : fuel cost of unit i
i : each generation unit
a_i, b_i, and c_i : fuel cost coefficient of unit i
P_i : power at unit i

Various pollutants such as carbon dioxide, sulfur dioxide and nitrogen oxides are released as a result of the operation of diesel generators. Reduction of these pollutants is mandatory for every unit. [37] The equation to solve this problem can be seen in (2)

$$F_{emission} = \sum_{i=1}^{n} (x_i P_i^2 + y_i P_i + z_i) \tag{2}$$

$F_{emission}$: total emission value
x_i : coefficient of emission i-th power plant (kg/MW2h)
y_i : coefficient of emission i-th power plant (kg/MWh)
z_i : coefficient of emission i-th power plant (kg/h)

The DEED issue comprises the optimization of multiple objectives involving expenses ($Fcost$) and emissions ($Femission$).[21] The weight w in the a priori method is used to solve a multi-objective problem into a single objective problem. The selection of the a priori technique sidesteps the need for generating intricate multi-objective algorithms. Consequently, this research employs the a priori method to solve the DEED problem. Equation (3) highlights the trade-off between the two objectives. In the process of optimizing DEED, it is not feasible to minimize both $Fcost$ and $Femission$ at the same time. Thus, determining the ideal value of w becomes crucial to finding the most optimal fuel cost and pollutant emission values. [22]

$$minF = w \times F_{cost} + (1 - w) F_{emission} \tag{3}$$

B. Constrain

There are several constraints considered in this optimization, they include:

1) Generator Capacity Constrain

For normal operation, the output power of each generator is constrained by the minimum and maximum limits which can be seen in the following (4) [5]:

$$P_{Gi}^{min} \leq P_G \leq P_{Gi}^{max} \ untuk\ i = 1,2,\dots,n \tag{4}$$

P_{Gi}^{min} is the minimum generation capacity of the i-th unit generator. P_{Gi}^{max} is the maximum generation capacity of the *i-th unit generator*

2) Ramp Rate Constrain

The ramp-rate limitation includes the rates of increase (UR) and decrease (DR) to prevent detrimental effects caused by rapid and excessive dynamic changes in power loading and releasing that surpass the generator's capacity.[23] The power plant's service life may be reduced by violating the unit ramp rate. The limit for ramp rate should accommodate the changes in load demand [24]. The operating constraints with ramp-rate are shown (5) and (6)

$$P_{i\ min,} = max(P_{i\ min,} P_i^{t-1} - DR_i) \tag{5}$$

$$P_{i\ max} = (P_{i\ min,} P_i^{t-1} + UR_i) \tag{6}$$

3) Load Demand Constrain

This constraint ensures that the total power generated by all power plants (including solar PV) and solar PV power (E_{plts}^t) at each hour t is not less than the power deman*d (P_{load}^t)*

$$\sum_{i=1}^{n} P_{gen_i} + E_{plts}^t \geq P_{load}^t \ untuk\ t = 1,2,\dots,24 \tag{7}$$

The overall power produced must satisfy the entire load requirement while also taking into account the losses on the transmission line. In this research discussion, the amount of losses on the transmission line is ignored. The power output generated by each generator unit (h −unit) at a period of time (t) in the power system must meet the requirements of the existing power requirements in the power system and must meet the power of the min and max limits of the power that can be generated by a generator ($h\ unit$). These limits will be a requirement in the fulfillment of power in a power system so that the system can operate optimally and be able to make each generator unit last long.

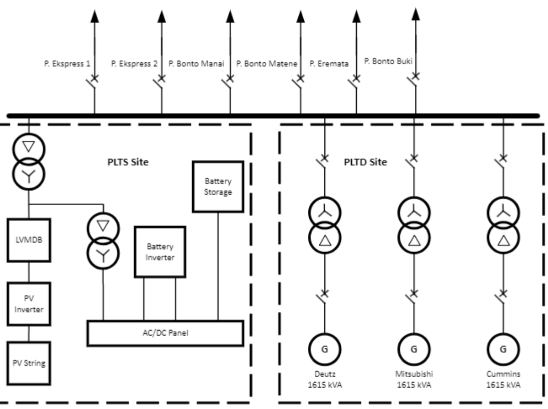


Fig. 1. Single Line Diagram Selayar System

C. *Research Location*

The Selayar Islands Regency is situated in South Sulawesi Province, Indonesia. The present research was conducted in an area of 2000 km², specifically in Tanete Village, Bontomatene District, Selayar Islands Regency, located at coordinates 6°2'48.45 "S 120°27'30.15"E. The district capital is Benteng City, and it covers an extensive area of 10,503.69 km² (including land and sea area) and a populace of 122,055. It is important to note that the Selayar system is an isolated system, unrelated to the surrounding areas. The Selayar system is an isolated system because the location of this system is an island separated from P. Sulawesi. To serve customers in the Selayar system, the rating used is 20 kV. The peak night load on this system is 6.22 MW with a capable power of 9.5 MW. The following is the single line diagram (Fig. 1.) and generation power balance (TABLE I) of the Selayar System used in this study. In this study using 11 diesel generators and 1 PV.

D. *Measure Accuracy of The Forecasting Value*

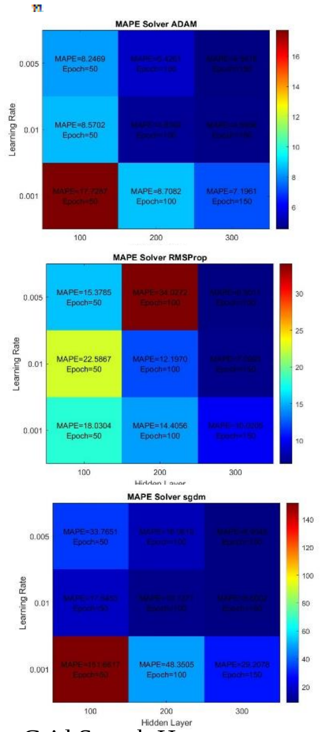
Various methods exist for computing the entire forecast error. Specific instances of forecast error measures comprise the mean absolute percentage error (MAPE), mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE). The forecasting model that presents the smallest overall measurement error value is the best. Choosing the most fitting error criterion depends on the researcher's objectives, data knowledge, and personal preferences [19].

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - Y_i')^2 \quad (8)$$

$$MAE = \frac{\sum_{i=1}^{n} |F_i - A_i|}{n} \quad (9)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{1} (Y_i - Y_i')^2} \quad (10)$$

$$MAPE = \frac{\sum_{i=1}^{n} \left|\frac{A_i - F_i}{A_i}\right| \times 100}{n} \quad (11)$$



(a)

(b)

(c)

Fig. 2. Heatmap Grid Search Hyperparameter (a) Adam (b) RMSProp (c)sgdm

Where Y_i is actual value, Y_i' is predicted value and n is number of data [21]

III. RESULT AND DISCUSSION

A. *Day Ahead Forecasting*

Due to changing weather profiles, such as solar radiation and temperature variations, photovoltaic (PV) power prediction becomes more complicated. LSTMs have been used in various applications. Optimal photovoltaic generation planning considers changes in solar energy to reduce grid operational costs while addressing operational issues such as voltage violations and reverse power flow. The LSTM's recurrence architecture and memory units allow it to model temporal changes in data objectively. Its capacity to capture abstract concepts sets it apart from traditional recurrent neural networks, thereby circumventing long-term dependency issues, making it a viable option for time series prediction problems.

The data used in this study was acquired from https://power.larc.nasa.gov/data-access-viewer/. Data used from 2013 to 2022 There are 10 types of data obtained, namely Speed at 10 Meters (m/s), All Sky Surface Albedo (dimensionless), All Sky Insolation Clearness Index (dimensionless), Solar Zenith Angle (Degrees), Wet Bulb Temperature at 2 Meters (C), Dew/Frost Point at 2 Meters (C), Precipitation Corrected (mm/hour), Surface Pressure (kPa), Specific Humidity at 2 Meters (g/kg), and Temperature at 2 Meters (C). To see the relationship between data and solar radiation which is the purpose of the forecast, the random forest technique is used. Random Forest is one of the machine learning algorithms used for classification and regression tasks. It falls under the category of ensemble learning, which means it builds multiple models (decision trees) and combines their results to make more accurate predictions than a single model. The method used in random forest to see the most influential data on solar radiation is Permutation Importance. The "Permutation Importance" method is used to evaluate the importance of each feature in a machine learning model. This method evaluates how much of a decrease in model performance (such as accuracy or average error) occurs when the value of a particular feature is randomized or permuted randomly while the value of other features remains constant. If randomizing a feature causes a significant decrease in model performance, then the feature is important for model prediction.

The solar radiation forecasting model used was built in Matlab. The radiation data used to forecast the Selayar System was obtained from https://power.larc.nasa.gov/data-access-viewer/. The data used was obtained from 2013 to 2022 LSTM was used to forecast solar radiation. Historical data is divided into 70% as training data and 30% as testing data.

Several steps are taken before the data is fed into the LSTM for forecasting. First all 0 values for radiation are removed and outliers or extreme values that can affect the model are removed. Then an analysis is carried out to see the relationship of the data using random forest. The method used is Permutation Importance. There are 10 data obtained. This is done to see the 4 most influential data on solar radiation forecasts. Solar Zenith Angle, All Sky Insolation Clearness Index, Precipitation Corrected, and Temperature at 2 Meters is obtained with a level of association of 14369.85, 6151.30, -2581.37, and -2581.61 respectively.

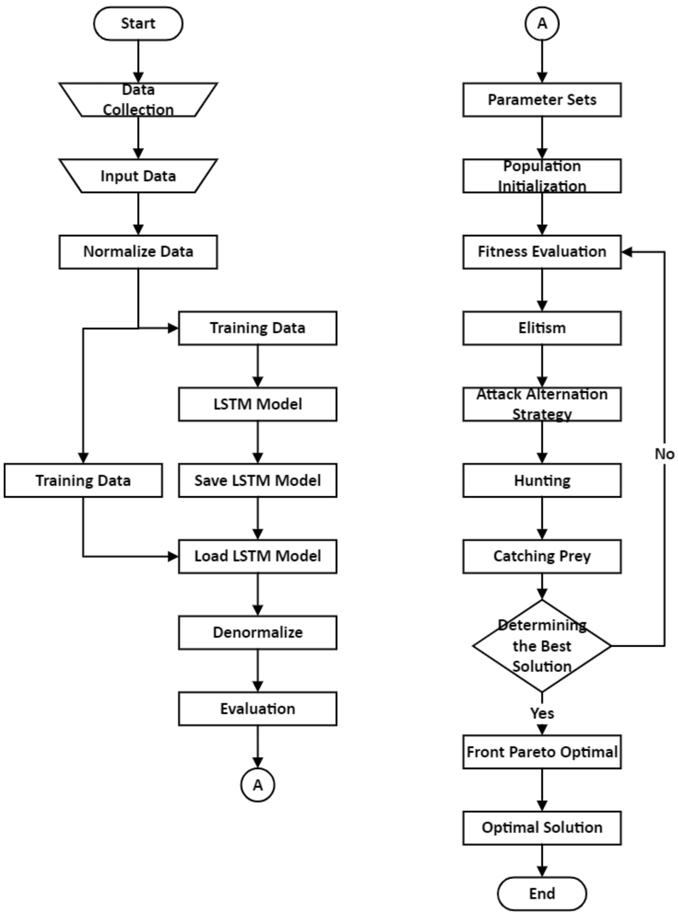


Fig. 3. Flowchart

To get the best model, hyperparameter tuning is performed using grid search. Grid search is one of the simplest hyperparameter search techniques. The principle is to try all combinations of hyperparameters in a predefined grid (list of values). Grid search can be very time-consuming but is quite effective for finding hyperparameter optima. Then the results of the grid search combination are compared using MSE, MAE, MAPE, and RMSE to determine the best hyperparameter combination. The grid search optima results are visualized in Fig. 3. in the form of a heatmap to see the effect of each hyperparameter. After hyperparameter tuning, the optimum hyperparameters used in solar radiation forecasting are the hidden layer of the neural network of 300, for the solver method using "Adam", the initial learning rate used is 0.05 and the maximum number of epochs is 150.

A total of 217,260 data were used in LSTM modeling. To see the accuracy of the forecast carried out, an evaluation calculation of the accuracy of the forecasting value is carried out using MSE, MAE, MAPE, and RMSE. Forecasting results using LSTM in this research produce RMSE, MSE MAE, and MAPE with average results of 6.311, 40.11, 4.61, and 4.87, respectively. To calculate the PLTS output used based on the results of the forecast using (12).

$$Eplts = A \cdot r \cdot Pr \cdot H \qquad (12)$$

Where H is the solar radiation on the panel, PR is the performance ratio, range 0.5 to 0.9, default value is 0.75, r is the efficiency of the solar panel (%), A is the total area of the panel (m²) and E is energy (kWh), (28). Fig. 4. displays the solar radiation forecast used in Dynamic Economic Emission Dispatch modeling

TABLE II Selayar System Generator Profile

Unit	Cost Function (Rp/Jam)	Pmax (kW)	Pmin (KW)	Ramp Up (kW/hr)	Ramp Down (kW/hr)
BV #1	$94.69+0.00000036P_1+7.48x10^{-4}P_1^2$	900	0	500	500
BV #2	$31.26+0.14198 P_1+ 4.52x10^{-7} P_1^2$	900	0	500	500
BV #3	$55.07+0.10983 P_1+8.87x10^{-6} P_1^2$	900	0	500	500
BV #4	$74.28+0.07885 P_1+6.4x10^{-12} P_1^2$	900	0	500	500
BV #5	$17.24+0.16127 P_1+1.32x10^{-6} P_1^2$	900	0	500	500
CMN 1	$67.07+0.00129 P_1+1.16x10^{-3} P_1^2$	900	0	500	500
CMN 2	$62.15+0.0998 P_1+5.2x10^{-8} P_1^2$	950	0	500	500
CMN 3	$11.24+0.16277 P_1+1.7x10^{-10} P_1^2$	950	0	500	500
MTS 1	$11.24+0.16277 P_1+2.43x10^{-9} P_1^2$	1000	0	500	500
MTS 2	$10.03+0.16522 P_1+9.44x10^{-8} P_1^2$	1000	0	500	500
MTS 3	$51.86+0.11759 P_1+2.17x10^{-9} P_1^2$	900	0	500	500
PLTS		1000	0	500	500

B. *Economic Dispatch*

The generators used in this system are 11 plants with each different profile in terms of fuel costs. The following is the profile of the existing generators in the Selayar System. The load used in this study is the peak load every hour ever recorded in the Selayar System. The Selayar System load profile can be seen in Fig. 5. The peak load of the system occurs at 19:00 WITA amounting to 6350 kW. Population Initialization.

Initially, a set of arbitrary solutions (initial population) is generated. The initial population is created randomly with varying power generation rates for each power station. Fitness Evaluation Each solution in the population is evaluated to measure its performance in meeting the optimization objective. The evaluate_fitness function is used to calculate the fitness value of each solution in the population. This function considers limitations such as power production boundaries, ramp rates, and existing power requirements. This fitness evaluation includes several important steps.

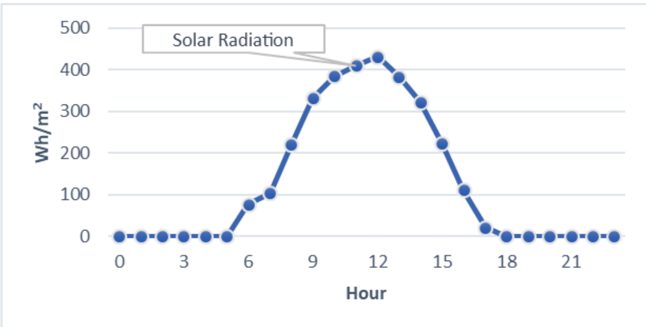


Fig. 4. Solar Radiation Forecast Results

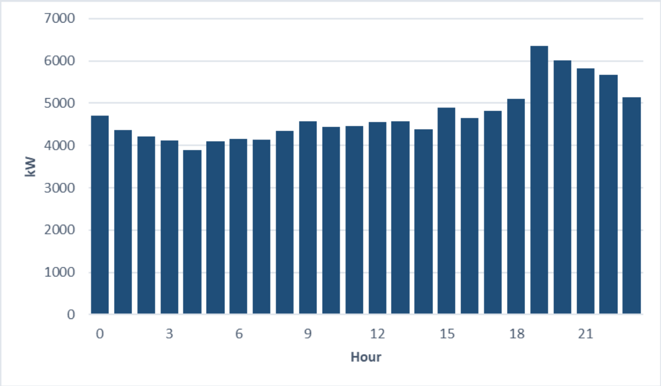


Fig. 5. Load of Selayar System

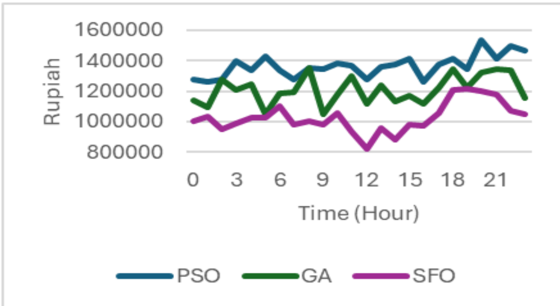
The function checks whether the power generation rate is within the specified constraints (Pmin and Pmax). If these constraints are violated, the solution is assigned an "inf" value to indicate invalidity. Total Cost Calculation: The total cost of electricity production is calculated based on the power generation rate for each power plant, using the cost coefficients ($Fcost = ai + bi\ Pi + ciPi\ 2$) used in the Selayar System. This is the production cost of conventional generation.

Toxic gas emissions are calculated based on the level of power generation using the emission coefficients ($Femission = \sum (xiPi\ 2 + yi\ Pi + zi)\ n\ i{=}1$ given in the code. These emissions may include emissions from conventional power generation. Elite Selection Elite selection is the process of selecting about the best 20% of the population based on their fitness value. Elites are the best performing solutions and serve as "watchdogs" to ensure that the quality of the population does not degrade from generation to generation. Attack Alternation This is a strategy in SFO that allows each solution in the population to experience random changes in power generation rate. At each iteration, each solution has a probability p of experiencing the change. The probability p decreases with time. This is one of the steps in SO that allows the population to undergo random changes in an effort to increase exploration of the search space.

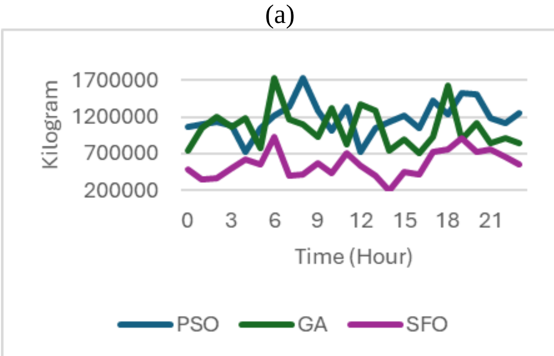
Hunting function is used to implement the process of hunting by the population based on the position of "prey." This is one of the unique components in the SO algorithm. In this step, the population tries to approach or "chase" solutions that have lower fitness values (better solutions). Catching prey function allows the population to catch better "prey" if found. This ensures that the population always tries to move towards a better solution. If there is a better solution (with a lower fitness value) in the population, the SO algorithm will try to catch this "prey". Determination of the Best Solution The SFO algorithm runs iterations for multiple generations (maxIterations). During each iteration, the solution is updated based on the strategy described above. After a certain number of iterations, the SFO algorithm will identify the best solution in the population. This best solution has the lowest fitness value, which indicates that it is the most economical solution and has the lowest emissions. In this study, the SFO Algorithm is used to minimize costs and emissions in 24 hours in two parts. The first part solves the economic emission dispatch problem by only involving conventional generation to serve the load in the system. The second part solves the DEED problem by using conventional generation and solar PV to serve the load on the system. Generation capacity constraints, ramp rate constraints, load demand constraints, and solar PV capacity constraints are considered in both sections. Operating costs, emissions, and generation capacity constraints are used as indicators to evaluate the performance of SFO in solving the DEED problem in this study. Case System 1 The scenario in case system 1 is that the power plant serving the load in the Selayar System only uses conventional generation. Plant capacity specifications can be seen in TABLE II. There are 11 generators reviewed in this study. The simulation results in the form of loading data, generated power and total generation costs are shown in TABLE III. To compare the results of Dynamic Economic Emission Dispatch, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) algorithms are used as a comparison. PSO and GA results can be seen in Fig. 6.

It can be seen from the graph of costs and emissions generated every hour between PSO, GA, and SFO. The value of costs and emissions generated by SFO is smaller when compared to other algorithms in solving the same problem. The total cost value that must be incurred in a day by the plant to serve the system from PSO and GA is Rp. 33.890.250 and Rp. 28.992.823 while the total cost of SFO is Rp. 25.926.927 while the total emissions generated by the plant in a day from PSO and GA is 33.210 kg and 27.493 kg while the total SFO emissions are 14,433 kg.

In case 2 scenario, there will be an additional solar power plant connected to the system of 1.3 MW with the radiation value entered based on the forecast results for the next day. The specifications of the generating capacity can be seen in TABLE II and the simulation results obtained in the form of loading data, generation power and total generation costs will be shown in TABLE IV. Same as case 1, to compare the results of Dynamic Economic Emission Dispatch, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) algorithms are used as a comparison. The results of PSO and GA can be seen in Fig. 7.



(a)



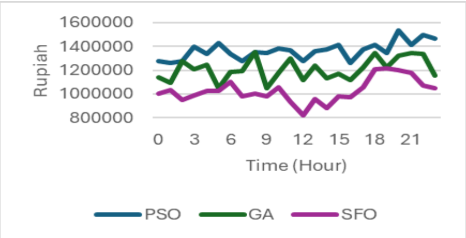
(b)

Fig. 6. Result ED in Conventional Generation Systems (a) Cost (b) Emissions

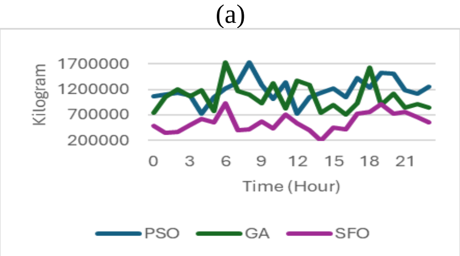
TABLE III ED Results at Conventional Plants

Time	Total Load (kW)	Power Generated(kW)	Cost (Rp)	Emissions (Kg)
00:00	4.71	4.71	1.089.826	777
01:00	4.36	4.36	1.014.062	467
02:00	4.22	4.22	1.008.754	613
03:00	4.11	4.11	996.121	657
04:00	3.9	3.9	948.718	409
05:00	4.09	4.09	978.499	442
06:00	4.15	4.15	1.011.541	576
07:00	4.135	4.135	1.029.312	714
08:00	4.35	4.35	1.004.862	443
09:00	4.565	4.565	1.053.632	544
10:00	4.44	4.44	1.040.360	623
11:00	4.45	4.45	1.049.303	634
12:00	4.545	4.545	1.048.832	670
13:00	4.565	4.565	1.043.210	840
14:00	4.375	4.375	1.014.549	567
15:00	4.895	4.895	1.120.676	834
16:00	4.645	4.645	1.054.918	567
17:00	4.82	4.82	1.070.601	505
18:00	5.1	5.1	1.125.409	673
19:00	6.35	6.35	1.422.438	1167
20:00	6.01	6.01	1.253.939	1059
21:00	5.82	5.82	1.182.396	764
22:00	5.665	5.665	1.210.326	1024
23:00	5.15	5.15	1.154.644	952

Case System 2 It can be seen from the graph of costs and emissions generated every hour between PSO, GA, and SFO. The value of costs and emissions generated by SFO is smaller when compared to other algorithms in solving the same problem. The total cost value that must be incurred in a day by the plant to serve the system from PSO and GA is Rp. 32.776.566 and Rp. 28.992.823 while the total cost of SFO is RP. 25.600.230 while the total emissions generated by the plant in a day from PSO and GA is 28,552 kg and 25,287 kg while the total emission of SFO is 16.265 kg.

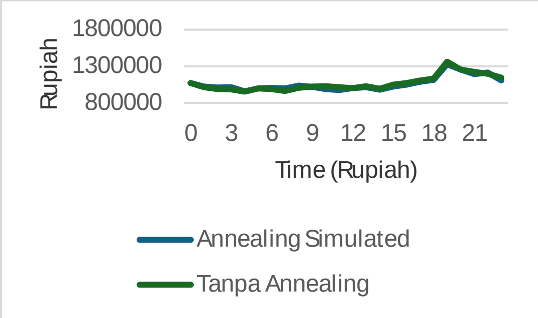


(a)

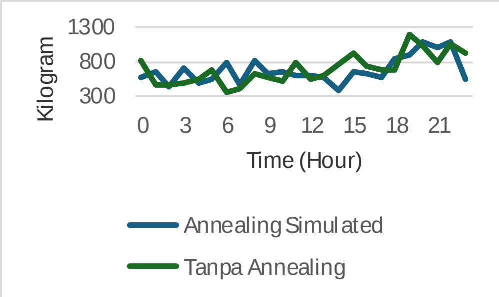


(b)

Fig. 7. ED of Conventional and Solar PV Generation Systems (a) Cost (b) Emissions



(a)



(b)

Fig. 8. Comparison of Simulated Annealing on ED Sailfish (a) Cost (b) Emissions

To improve the process of finding the best solution to hunting strength, a simulated annealing algorithm is added. The temperature in the Sailfish Optimizer serves to control the degree of randomness of the particle movement (sailfish). The higher the temperature, the more random the movement of the particles. This encourages extensive exploration of the solution space at the beginning of the iteration. Then the temperature is gradually lowered each iteration (annealing schedule) so that the movement of the particles is increasingly influenced by the best global solution that has been found. This is to exploit the optimal solution region. So temperature acts as a balancing act between exploration and exploitation. Initially more explorative with high randomness, over time more exploitative by leading to the global best solution. The lower the temperature, the more influence the global best solution has on the movement. To see a comparison of the results of the ED Sailfish Optimizer using simulated annealing algorithm and without simulated annealing algorithm can be seen in Fig. 8. ED using simulated annealing has lower total cost and emission values than economic dispatch without simulated annealing. It is Rp. 128.024 and 398 kg respectively.

IV. Conclusion

In this research, ED is carried out on diesel and solar power plants using Sailfish Optimizer. For hybrid plants such as the Selayar solar power plant, the challenge to ED is the intermittency of solar energy. Because of this it is necessary to consider forecasting the energy to be generated so that ED can be applied with appropriate results. So that before the ED is carried out, solar radiation forecasting is carried out using LSTM. To measure the accuracy of forecasting, RMSE, MSE MAE, and MAPE are used with average results of 6.311, 40.11, 4.61, and 4.87. With the application of ED, the minimum generation cost is obtained for the production of electric power generated while still considering the constraints. Through ED, fuel allocation can be optimized, helping to reduce production costs as well as carbon emissions, and making a positive contribution to environmental sustainability.

For further research, consideration could be given to the addition of batteries as a crucial element in RE systems and to enhancing the accuracy of solar forecasting, which is crucial in planning and managing solar photovoltaic systems. Solar radiation forecasting based on cloud patterns can be utilized.

TABLE IV ED Results at Hybrid System

Time	Total Load (kW)	Power Generated (kW)	Cost (Rp)	Emissions (kg)
00:00	4.71	4.71	1.070.326	575
01:00	4.36	4.36	1.023,395	654
02:00	4.22	4.22	1.009.049	432
03:00	4.11	4.11	1.014.552	711
04:00	3.9	3.9	980.82	504
05:00	4.09	4.09	997.744	541
06:00	4.15	4.15	1.004.250	798
07:00	4.135	4.135	997.5	472
08:00	4.35	4.35	1.036.167	812
09:00	4.565	4.565	1.021.333	637
10:00	4.44	4.44	988.037	654
11:00	4.45	4.45	977.364	590
12:00	4.545	4.545	1.000.441	608
13:00	4.565	4.565	1.016.609	584
14:00	4.375	4.375	982.316	375
15:00	4.895	4.895	1.065.646	657
16:00	4.645	4.645	1.049.542	635
17:00	4.82	4.82	1.087.832	567
18:00	5.1	5.1	1.115.611	847
19:00	6.35	6.35	1.345.799	895
20:00	6.01	6.01	1.272.693	1.092
21:00	5.82	5.82	1.193.074	1.006
22:00	5.665	5.665	1.245.523	1.076
23:00	5.15	5.15	1.104.609	544

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