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Artificial Neural Network (ANN) Backpropagation for Forecasting 100% Renewable Energy in North Sumatera

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Growing environmental awareness and the increasing need to reduce reliance on fossil fuels have driven the development of renewable energy (RE) technologies, such as micro-hydro, photovoltaics, biomass, geothermal, and biogas. However, the utilisation of RE in North Sumatera remains limited compared with fossil fuels, highlighting the need for optimisation strategies to accelerate the transition towards 100% RE. This study develops a predictive model using the artificial neural network (ANN) backpropagation algorithm to maximise RE contributions, minimise dependence on fossil fuels, and forecast the timeline for a full transition to RE. Data from Perusahaan Listrik Negara (North Sumatera), Independent Power Producers (IPP), and palm oil mills were used to model a hybrid generation system incorporating micro-hydro, hydropower, geothermal, biomass, biogas, and solar energy. Simulations were carried out using the firefly algorithm (FA) and particle swarm optimisation (PSO), with optimisation assessed through the renewable energy contribution ratio (RECR). The results indicate that FA outperforms PSO in meeting RE targets, with an average RECR of −51.514 for FA compared with −911.054 for PSO. Predictions using ANN backpropagation suggest that the transition to 100% RE could be realised by 2064 (FA) and 2065 (PSO). This research offers valuable insights for accelerating the transition to sustainable energy, enhancing energy resilience, and reducing environmental impacts.

Keywords: renewable energy, artificial neural network, optimisation, firefly algorithm, particle swarm optimisation, energy transition.

Introduction

Green and clean power generation technologies will play a vital role in future electricity supply due to increasing global public awareness of the need for environmental protection and the desire to reduce dependence on fossil fuels for energy production (Chaichan et al., 2022). These technologies include power generation from renewable energy (RE) sources, such as wind, photovoltaic (PV), micro-hydro (MH), biomass, geothermal, wave and tidal energy, alternative clean energy (AE), fuel cells (FC), and microturbines (MTs) (Chaichan et al., 2022; Javed et al., 2020; Nehrir et al., 2011). Investment in RE sources leads to the decarbonisation of the electricity sector (Marrasso et al., 2019; Wang et al., 2019). According to Indonesia's Ministry of Energy, RE is targeted to account for 51.6% of the electricity mix by 2030 (PT. PLN [Persero], 2021). In 2018, the state electricity company in North Sumatera operated 49 power plants, with fossil fuel-based plants accounting for 4580.87 MW and RE plants for 2539.52 MW. Additionally, the number of electricity customers reached 3 958 766, with a total power supply of 7 12.74 MW. The limited use of RE power plants has led researchers to conduct a preliminary study on hybrid renewable systems (HRS) in North Sumatera. This study, based on weather data, provided significant results for further development (Rimbawati et al., 2018). The implementation of RE in North Sumatera has also had a positive impact on reducing energy prices per kWh (Hutasuhut et al., 2022). Furthermore, to explore the development opportunities for each available RE source in North Sumatera, optimisation studies have concluded that hydropower has significant potential for future development (Rimbawati et al., 2024). Overall, hybrid models can enhance the performance of RE utilisation variables (Javed et al., 2021).

The extensive use of fossil fuels significantly contributes to global climate change, which is a challenge faced by all nations worldwide (Lohani and Blakers, 2021; Rashmi et al., 2017). The combustion of fossil fuels has caused severe environmental damage due to pollution from large-scale oil production and is the primary source of greenhouse gas emissions, contributing to climate change, air pollution, and various environmental problems (Nur and Harahap, 2021; Tariq et al., 2018). Moreover, the interconnection systems of RE power plants remain suboptimal (Fernandes and Ferreira, 2014; Martinot, 2010), making it difficult to predict the full utilisation of 100% RE.

A study optimising the development of combined renewable energy systems (CRES), comprising solar PV, wind, and FC systems, aimed to determine the most optimal system using the firefly algorithm (FA), shuffled frog leaping algorithm (SFLA), and particle swarm optimisation (PSO). The study concluded that the proposed system combination is economically feasible, with an average energy cost of \$0.47/kWh (Samy et al., 2020a). An optimised control system design using PSO to improve the performance of hybrid RE systems has demonstrated better performance under load conditions (Arora et al., 2020). Additionally, optimisation techniques using genetic algorithms (GA) and PSO for PV, wind, and biomass energy sources have shown significant results, making these algorithms worthy of consideration in optimisation analyses (Sawle et al., 2017). Optimisation techniques are also closely linked to prediction techniques, which are used to forecast future optimisation conditions.

Research on forecasting RE utilisation using artificial neural networks (ANN) is currently being conducted extensively, particularly to reduce fossil fuel usage in the electricity industry by understanding its characteristics and architecture (Madhiarasan and Louzazni, 2022). Smart energy management algorithms for biomass and geothermal power plants have been developed (Zile, 2021). Wind power generation forecasting (Zafirakis et al., 2019), solar photovoltaic energy generation forecasting (Dumitru et al., 2016), and global solar and photovoltaic energy forecasting (Perveen et al., 2020) have also been studied. An ANN has even been applied to forecast natural gas consumption (Anagnostis et al., 2020). These efforts aim to support sustainable development goals by mapping the natural resources of each region (Mehra and Swain, 2024b).

Based on the review, this research is significant given the considerable environmental impacts of fossil fuel-based power generation and their limited availability. North Sumatera has abundant natural resources that can contribute to government policies supporting the utilisation of RE. However, its development requires a model to forecast the potential of local natural resources within autonomous power systems through the optimisation of hydro, geothermal, biomass, biogas, and solar power plants.

This research contributes to developing a model for predicting the timeframe required for North Sumatera to achieve 100% RE utilisation using ANN backpropagation, supported by FA and PSO optimisation techniques. These findings will assist policymakers and decision-makers in accelerating the development of sustainable energy in North Sumatera.

Literature Review

Firefly algorithm (FA)

The FA, inspired by the behaviour of fireflies, is an effective population-based technique for global optimisation. It calculates the attractiveness and movement of fireflies using light intensity, distance, and the absorption coefficient. Details of FA implementation can be found in Jain et al. (2021, p. 157–180) and Yang (2014). FA is also recognised as an efficient and effective global search technique for combinatorial problems (Yang, 2010).

The firefly optimisation mechanism is described in Jain et al. (2021), Johari et al. (2013), and Yang and He (2018) as follows:

1 All fireflies are unisex, meaning that any firefly can attract another.
2 The attractiveness of each firefly is relative to its light intensity.
3 The attractiveness of each firefly is determined by its position in the search space.
4 Less attractive fireflies are drawn towards brighter ones.
5 Better fitness at a particular position results in a more attractive firefly.
6 The brightest firefly moves randomly.

The initial population of fireflies is generated randomly, using the fitness function of the relevant optimisation problem. The fireflies' attractiveness is defined as β_0, which determines the position of each firefly within the population. All fireflies move throughout the search space to find solutions over a defined number of iterations. In each iteration, the attractiveness between two fireflies, f_i and f_j, is compared. If f_i is more attractive than f_j, firefly f_j will move towards firefly f_i. The light intensity or attractiveness (β) depends on the distance (r) between the fireflies and the light absorption coefficient (γ). The attractiveness of a firefly is given by *Equation (1)*:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{1}$$

where β_0 represents the attractiveness of a firefly when $r = 0$.

The movement of a firefly at position x_j, attracted to a brighter firefly f_i at position x_i, is defined by *Equation (2)*:

$$x_j = \beta_0 e^{-\gamma r^2 ij}(x_j - x_i) + \alpha_i \tag{2}$$

The firefly algorithm (Fister et al., 2013; Johari et al., 2013) treats fireflies as simple agents that move and interact across the search space, recording the best solutions visited. Therefore, FA can be used to generate efficient candidate schedules for computational scheduling problems. Additionally, FA can also define the range and map the existing tasks, allowing them to be completed within the minimum time span.

When implementing the discrete firefly algorithm (DFA), the primary steps involve determining the positions of fireflies using the firefly movement algorithm and then employing the smallest position value to search for permutations of position capacity. The final step involves calculating the fitness function based on permutations generated by the smallest position value (SPV) and determining the new movement.

FA has been applied in various fields (Akan et al., 2023; Thirunavukkarasu et al., 2023), such as techno-economic analysis (Güven and Mahmoud Samy, 2022; Samy et al., 2020b), cost reduction for RE generation (wind, PV, biomass, and pumped hydro) (Alturki and Awwad, 2021), and power flow optimisation in electrical power systems (Shaheen et al., 2019; Khan et al., 2020).

Particle swarm optimisation (PSO)

The particle swarm optimisation algorithm was first introduced by Dr. Kennedy and Dr. Eberhart in 1995 (Ahmed and Glasgow, 2012). Particle swarm optimisation is one of the most esteemed swarm-based algorithms in the literature (Shami et al., 2022). The basic idea behind this algorithm is inspired by the social behaviour of animals (Freitas et al., 2020). Social behaviour is a natural process of communication between individuals, sharing knowledge when searching for food or migrating in groups, such as flocks of birds or swarms of bees. When one member identifies a desired path, the others will quickly follow suit.

Particle swarm optimisation is an algorithm used to find the minimum or maximum values of a function based on a new population. PSO has the advantage of finding optimal values for complex non-linear optimisation problems. Particle swarm optimisation has been proven to find the best solutions for optimisation issues. The PSO algorithm can be applied to obtain sensor positions in weighted least squares (WLS) estimation. WLS optimisation can be used to determine the minimum number of sensor points needed to achieve accurate estimates. In the PSO algorithm, there is a model for obtaining optimised values, one of which is the global best PSO (Fakhouri et al., 2020; Freitas et al., 2020). Other research indicates that PSO is capable of providing the best results in the use of polynomial models (Shankar et al., 2022). Moreover, PSO is also capable of optimising electrical power distribution network configurations (Azhar and Ahmad, 2021) when hybridised with FA.

Artificial neural network (ANN) backpropagation

A hybrid RE system is a power generation system that combines two or more RE sources. These energy sources have the potential to reduce dependence on fossil fuels and enhance energy resilience. One of the challenges in such systems is minimising the use of thermal power plants. Thermal power plants are non-sustainable energy sources that generate greenhouse gas emissions. To minimise the use of thermal power plants within this energy system, it is necessary to predict when these plants will be eliminated. This prediction can be made using the ANN backpropagation method (Raudonis et al., 2022). The backpropagation neural network method has demonstrated a high level of predictability compared with other existing models (Aljanad et al., 2021). ANN backpropagation is a supervised learning algorithm typically used by perceptrons with multiple layers to adjust the weights connected to neurons in their hidden layers (Pearson and Dray, 1998).

Artificial intelligence applications have become increasingly popular as forecasting tools for the future. Their implementation spans various fields, including electricity demand forecasting (Saglam et al., 2022), energy consumption prediction (Panagiotou and Dounis, 2022), and power quality forecasting (Jahan et al., 2022). One study has also noted that artificial neural network models exhibit high precision in short-term energy load forecasting (Kuo and Huang, 2018). Similarly, the optimisation of ANN methods has been used for reliability forecasting by employing a boxing match algorithm combined with electrical and mechanical systems (Tanhaeean et al., 2023). Furthermore, ANNs can be applied in energy demand modelling for industry (Shiau et al., 2022) and used in renewable energy estimation based on weather forecasting (Maduabuchi et al., 2023). A recent implementation of ANNs has been utilised for forecasting protected area and agricultural land expansion in balanced management and conservation, ensuring sustainable development between urban expansion and natural resource conservation (Mehra and Swain, 2024a). ANNs combined with cellular automata have also been employed to forecast and determine land-use change potential for the years 2025 and 2040 (Mehra and Swain, 2024a). The training algorithm for the backpropagation network is as follows (Pearson and Dray, 1998):

Step 0: Initialize all weights with small random numbers;

Step 1: If the termination conditions have not been met, perform Steps 2–9;

Step 2: For each pair of training data, perform Steps 3–8.

Feed forward (Phase 1: Step 3–5):

Step 3: Each input unit receives a signal and forwards it to a hidden unit above it;

Step 4: Calculate all outputs in hidden units:

$$z_j (j = 1, 2, \dots p)$$

$$z\_net_j = v_{j0} + \sum_{i=1}^{n} x_i v_{ji}; z_j = f(z\_net_j) = \frac{1}{1+e^{-z\_net_j}} \tag{3}$$

$$z\_net_j = v_{j0} + \sum_{i=1}^{n} x_i v_{ji}; z_j = f(z\_net_j) = \frac{1}{1+e^{-z\_net_j}} \tag{4}$$

Step 5: Calculate all network outputs in the output unit y_k:

$$y\_net_k = w_{i0} + \sum_{j=1}^{p} z_i v_{kj}; y_k = f(y\_net_k) = \frac{1}{1+e^{-y\_net_k}} \tag{5}$$

Backpropagation error (Phase 2: step 6–7):

Step 6: Calculate factor δ output units based on errors in each output unit y_k (k = 1, 2, … m):

$$\delta_k = (t_k - y_k) f^{'}(y\_net_k) = (k_k - y_k) y_k (1 - y_k) \tag{6}$$

where δ_k is the error unit that will be used in changing the weight of the layer below it, calculate weight change w_{kj} with a steady understanding α.

$$\Delta w_{kj} = \alpha \delta_k z_j (k = 1, 2, ...m; j = 0, 1, ...p) \quad (7)$$

Step 7: Calculate factor δ hidden units based on errors in each hidden unit z_j (j = 1, 2, ... p):

$$\delta\_net_j = \sum_{k=1}^{m} \delta_k w_{kj} \quad (8)$$

Factor δ hidden unit:

$$\delta_j = \delta\_net_j f'(z\_net_j) = \delta\_net_j z_j (1 - z_j) \quad (9)$$

Calculate the weight change term v_{ji}:

$$\Delta v_{ji} = \alpha \delta_j z_i, (j = 1, 2, ...p; p = 1, 2, ...n)$$

Weight and bias changes (Phase 3: Step 8):

Step 8: Calculate all weight changes.

Changes in the weight of the line leading to the output unit are:

$$w_{kj}(baru) = w_{kj}(lama) + \Delta w_{kj} \quad (10)$$

$$(k = 1, 2, ...m; j = 0, 1, ...p)$$

Changes in the weight of the line leading to the hidden unit namely:

$$v_{ji}(baru) = v_{ji}(lama) + \Delta v_{ji} \quad (11)$$

$$(j = 1, 2, ...p; i = 0, 1, ...n)$$

Step 9: Testing completed.

Methods

Data and procedures used

This study utilises data obtained from power providers, including the State Electricity Company in the North Sumatera region, specifically from its generation unit division, Independent Power Production (IPP), as well as private entities (palm oil mills) that use biomass and solar cells.

Table 1. *Installed capacity data of fossil-fuelled power plants in North Sumatera*

Year	Diesel		Steam turbine (coal) (MW)	Gas turbine (MW)	Combined cycle (Coal and Gas) (MW)
	Isolated system (MW)	Interconnection system (MW)			
2014	0.00	24.85	490.00	253.83	817.88
2015	0.00	229.36	1150.00	340.23	817.88
2016	0.00	396.00	1370.00	243.00	818.00
2017	0.00	396.00	1370.00	245.00	818.00
2018	0.00	304.37	1370.00	964.53	847.88
2019	17.35	328.36	1804.00	1024.03	847.88
2020	85.71	304.36	1828.00	1263.42	817.88
2021	82.21	304.36	1828.00	1548.42	817.88
2022	82.21	304.36	1828.00	1548.42	817.88

Source: Statistics Indonesia, North Sumatera province

Table 2. *Installed capacity data of renewable energy power plants in North Sumatera*

Year	Micro-hydro (MW)	Hydropower (MW)	Geothermal (MW)	Biomass (MW)	Biogas (MW)	Solar (MW)
2014	31.50	912.00	12.00	115.00	0.00	0.00
2015	31.50	912.00	12.00	119.80	0.00	0.00
2016	44.50	957.00	12.00	129.80	0.00	0.00
2017	49.50	957.00	232.00	130.80	0.00	0.00
2018	59.30	1007.00	342.00	135.80	0.00	0.00
2019	59.30	1007.00	378.00	140.80	0.00	0.00
2020	94.30	1007.00	378.00	142.80	3.40	0.00
2021	113.30	1007.00	432.00	150.90	5.60	4.00
2022	118.30	1681.00	570.00	159.80	5.60	4.82

Source: processed data

Table 3. *Data on electricity development in North Sumatera*

Year	Normal load (MW)	Peak load (MW)
2014	2568.06	2652.56
2015	2791.37	3120.66
2016	3080.00	3506.36
2017	3083.00	3939.73
2018	3740.28	4426.66
2019	4275.12	4973.77
2020	4552.87	5588.50
2021	4592.65	6279.21
2022	4834.372	7112.74

Source: Statistics Indonesia, North Sumatera Province

The research process begins with data collection. Subsequently, a hybrid power generation optimisation model is determined, comprising micro-hydro, hydropower, geothermal, biomass, biogas, and solar energy sources.

The resulting model is used to perform optimisation using the firefly algorithm and particle swarm optimisation, with each algorithm being simulated five times. The maximum number of iterations for each simulation is set at 100, 500, 2500, 12500, and 62500, respectively. This approach aims to compare the best results obtained from both algorithms in reducing the reliance on fossil-based power generation.

The best results from each algorithm are subsequently used to predict 100% renewable energy utilisation through an ANN backpropagation model, as illustrated in *Fig. 1*. MATLAB software is employed to perform the simulations this study.

The objective function of this analysis is to optimise a hybrid system consisting of micro-hydro energy, hydropower, geothermal, biomass, biogas, and solar power. The proposed objective function model is developed to maximise the utilisation of renewable energy sources while minimising dependence on fossil-fuel-based power plants.

The objective function in this study focuses on determining the renewable energy contribution ratio (RECR). This function is used to measure the level of renewable energy utilisation in a specific region. The RECR equation considers the generation capacity from various renewable energy sources, namely micro-hydro, hydropower, geothermal, biomass, biogas, and solar power, in comparison with the total power demand (E).

$$RECR = \frac{Total\ Installed\ Capacity\ of\ Renewable\ Energy\ (MW)}{Total\ Power\ Demand\ (MW)} \quad (12)$$

$$RECR = \frac{X_1 + X_2 + X_3 + X_4 + X_5 + X6}{E} \quad (13)$$

where X_1 is micro-hydro capacity (MW); X_2 is hydropower capacity (MW); X_3 is geothermal capacity (MW); X_4 is biomass capacity (MW); X_5 is biogas capacity (MW); X_6 is solar capacity (MW); E is total power demand (MW).

In terms of reducing the use of fossil-fuel power plants, a variable (T) is introduced as the total contribution of fossil-fuel power generation. The objective function (θ) of the optimisation is aimed at minimising the value of (T).

To minimise the use of fossil-fuel power plants (T), we can express this as the following Equation:

$$RECR - T = \theta \quad (14)$$

with $\theta \leq 0$

Thus, the objective function can also be expressed as follows:

$$RECR \leq T \quad (14)$$

This objective function is designed to:

1 measure the effectiveness of renewable energy contributions in the power generation system;

2 encourage the reduction of dependence on fossil energy, thereby achieving energy sustainability goals.

Constraints:

1 The total capacity of the hybrid system must not exceed the maximum available capacity.

2 $(X_1 + X_2 + X_3 + X_4 + X_5 + X_5) \leq$ The maximum available capacity.

3 The hybrid power generation must meet the power demand in North Sumatera.

4 $(X_1 + X_2 + X_3 + X_4 + X_5 + X_5) \leq$ Power demand in North Sumatera

5 Fossil-fuel power generation must be completely eliminated.

$T = 0$

Fig. 1. *Proposed research flowchart*

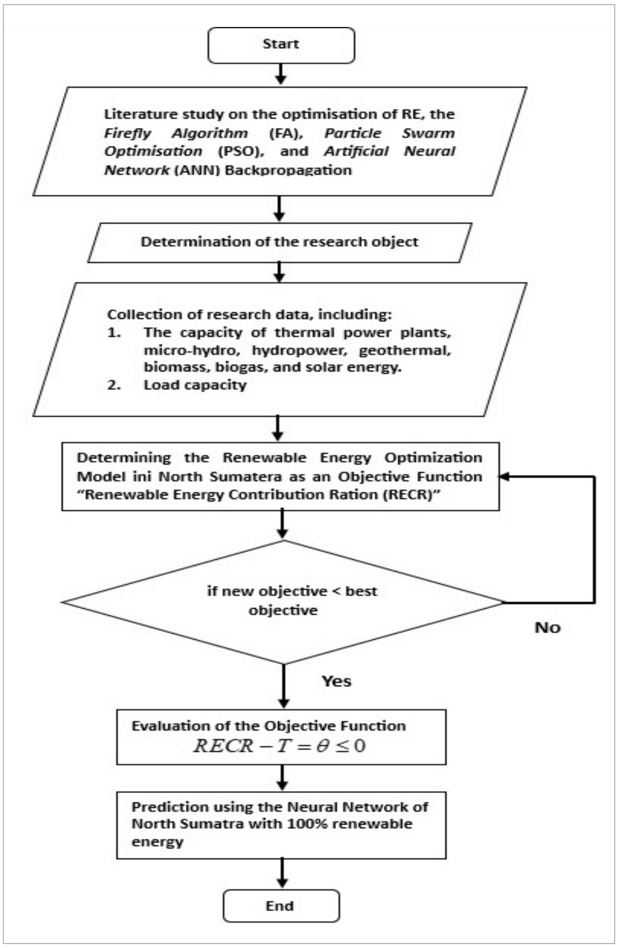


Fig. 2. *Renewable energy utilisation in the North Sumatera power system*

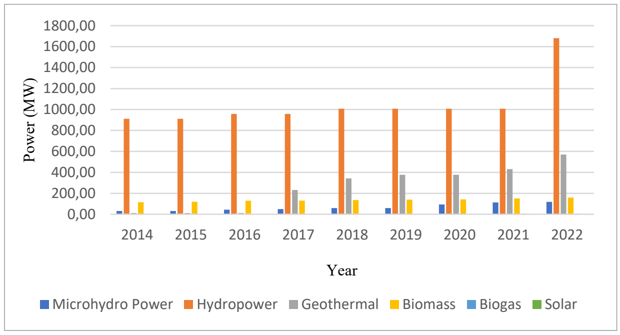
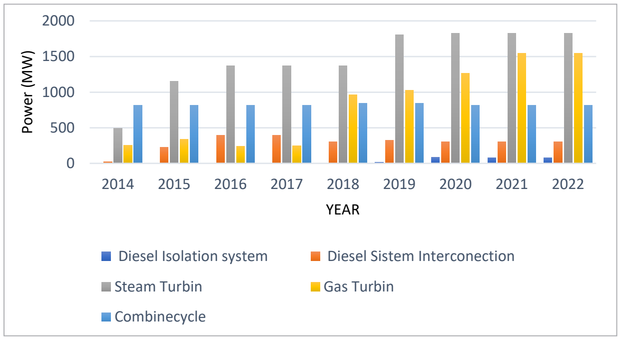


Fig. 3. *Fossil energy utilisation in the North Sumatera power system*



Results and Discussion

The renewable energy power plants in the North Sumatera electricity system have been identified to include several components, such as micro-hydro, hydropower, geothermal, biomass, biogas, and solar. The results of the evaluation of renewable energy utilisation are shown in *Fig. 2*.

From the histogram in *Fig. 2*, it can be observed that micro-hydro and hydropower have shown strong consistency in supporting the North Sumatera power system. Furthermore, the utilisation of geothermal, biomass, biogas, and solar power plants has experienced significant growth, contributing to the use of sustainable energy. The increasing emphasis on renewable energy within the North Sumatera power system is expected to reduce dependence on fossil energy.

Fig. 3 shows that fossil energy utilisation still dominates the power system in North Sumatera, sourced from diesel, steam turbines, gas turbines, and steam and gas turbines (combined cycle), representing the use of fossil energy and its derivatives. The strategy of using isolated systems is aimed at meeting the electricity demand in remote areas that cannot be served by power providers, in this case, the State Electricity Company. Meanwhile, interconnected systems are implemented to support the reliability of the power system, offering a solution for current energy needs.

Evaluation of results

This study aims to evaluate the performance of two optimisation algorithms, namely the firefly algorithm and the PSO algorithm, in optimising the hybrid energy system by minimising the use of fossil-fuel power plants. The primary objective is to achieve a renewable energy contribution ratio value of $\theta \leq 0$, serving as an indicator of successful optimisation.

The evaluation is conducted by testing both algorithms using installed power data over a testing period through five simulations for each algorithm. The results of the calculations, analysis, and interpretation of the variations in the θ value will be discussed, including the stability and tendencies of both methods in achieving the research objectives. Subsequently, the evaluation results of each algorithm used will be presented.

Evaluation of results using the firefly algorithm

Based on the evaluation using the firefly algorithm from 2014 to 2022 in *Table 4*, it is observed that the average θ value from the five simulations shows significant variation each year. The first simulation resulted in −109.695 MW, the second simulation in −36.374 MW, the third simulation in −225.712 MW, the fourth simulation in −193.319 MW, and the fifth simulation in −51.514 MW (which is closer to zero). The negative average values in the first four simulations indicate that the contribution of renewable energy remains below the target for thermal power plant utilisation.

Although there were performance improvements in certain years, the fluctuations in θ values suggest instability in the optimisation results when using the firefly algorithm.

Table 4. *Evaluation of RECR (θ) results using the firefly algorithm*

Year	The renewable energy contribution ratio (θ) value in megawatt (MW)				
	Simulation 1	Simulation 2	Simulation 3	Simulation 4	Simulation 5
2014	33.615	1193.842	1458.391	996.078	1684.699
2015	404.110	−523.624	1298.317	348.169	419.417
2016	2095.567	350.082	249.388	1342.929	−852.364
2017	923.492	325.015	−136.805	546.092	843.858
2018	−789.719	−191.980	−221.506	−27.262	−740.739
2019	−608.738	−659.593	−148.135	−1371.584	387.636
2020	−2332.147	−942.149	−2395.806	−1459.206	−655.372
2021	−1341.543	−1577.083	−1245.133	−624.958	−813.316
2022	628.105	−1226.870	−890.117	−1490.133	−737.444
Average	−109.695	−361.374	−225.712	−193.319	−51.514

Table 5. *Evaluation of RECR (θ) results using the particle swarm optimization algorithm*

Year	The renewable energy contribution ratio (θ) value in megawatt (MW)				
	Simulation 1	Simulation 2	Simulation 3	Simulation 4	Simulation 5
2014	257.129	475.018	181.233	632.911	1435.461
2015	−118.816	292.113	−747.320	−393.581	−707.049
2016	268.859	−1317.548	−921.439	−1534.194	−597.110
2017	159.946	−882.419	−1063.454	−120.439	−890.027
2018	−1307.974	−1330.915	−1203.017	−1122.755	−1272.771
2019	−679.479	−1110.459	−1373.809	−2273.044	−2547.207
2020	−1898.470	−2251.278	−1431.167	−2629.857	−2684.024
2021	−1935.213	−2378.134	−2368.180	−2153.886	−1928.109
2022	−2945.466	−1225.699	−1761.734	−1308.842	−914.315
Average	−911.054	−1081.036	−1187.654	−1211.521	−1122.794

Evaluation of results using the particle swarm optimisation algorithm

Based on the evaluation using the PSO algorithm from 2014 to 2022, as shown in *Table 5*, it is observed that the average θ values consistently yield negative results. The first simulation resulted in an average value of –911.054 MW, the second simulation in –1081.036 MW, the third simulation in –1187.654 MW, the fourth simulation in –1211.521 MW, and the fifth simulation in –1122.794 MW. These negative results indicate that the RECR is always lower than the target for fossil fuel power plant utilisation (T). Although some simulations approach the target, the high negative fluctuations suggest that PSO is neither stable nor optimal in achieving the objectives of the hybrid system optimisation.

Forecasting analysis based on artificial neural network (ANN) backpropagation

Fossil fuels, as one of the primary energy sources for electricity supply in North Sumatra, play a central role in maintaining the availability of energy supply. In this context, energy forecasting analysis becomes essential for understanding and planning the dependence on fossil energy. This is strategic information that impacts the stability and reliability of the electricity supply.

The results of the prediction analysis based on the ANN with the backpropagation method are presented. This method features a unique regulatory function with a probabilistic approach. The regression pattern is a model used for making predictions. It is important to note that the backpropagation method is highly flexible in designing network structures. The experiment was conducted with 45 trials to achieve the smallest mean squared error (MSE) value in this study. The predicted research data in this study is the optimisation result with the lowest RECR value. In this case, the fifth simulation result for optimisation using the FA method and the first simulation result for optimisation using the PSO method are used.

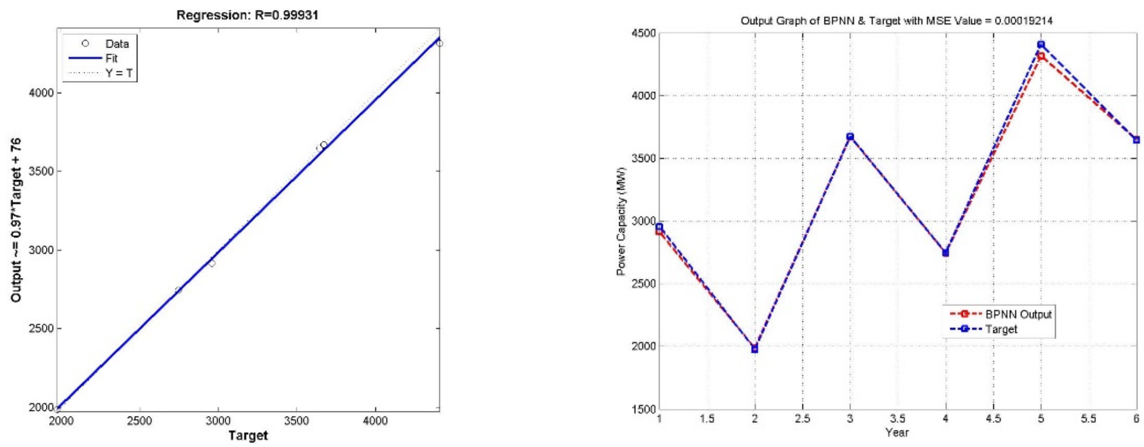
Subsequently, an analysis was conducted on the fossil fuel power generation capacity to determine the RECR values for the following year, so that the time when thermal power plants can be replaced or eliminated by renewable energy power plants (RE) can be identified. This test will involve forecasting for the next 50 years, with the training data accuracy results presented as follows.

Table 6 provides a detailed analysis of the optimality of the FA activation function in the fifth simulation based on the MSE level in the training data. At a learning rate of 0.01, it can be observed that 20 hidden layers/neurons produce the smallest MSE of 0.018435, indicating a good fit for this learning rate. Increasing the learning rate to 0.02 results in a significant rise in MSE for all combinations of hidden layers/neurons, with the smallest MSE of 0.000192 occurring at 30 hidden layers/neurons. At a learning rate of 0.03, 20 hidden layers/neurons provide the smallest MSE of 0.059351. However, the subsequent changes in the learning rate result in significant fluctuations in the MSE.

Table 6. *FA optimality in the fifth simulation: mean square error (MSE) level in the training data*

Learning rate	Hidden layer/neuron				
	10	20	30	40	50
0.01	0.118940	0.018435	0.100360	2.171500	0.443640
0.02	0.019816	0.094164	0.000192	0.683770	0.485550
0.03	0.283940	0.059351	1.257400	0.630840	1.212600
0.04	0.054270	0.020396	0.395660	0.604460	0.382210
0.05	0.097610	0.072552	0.153400	0.281780	0.173450
0.06	0.045630	0.225330	0.025674	0.119440	1.229800
0.07	0.073820	0.076556	0.055100	3.166000	0.445400
0.08	0.133560	0.414490	0.006609	0.021032	0.780870
0.09	0.008865	0.077021	0.085388	1.553400	0.863630

Fig. 4. *(a) Correlation between the target data and BPNN output, (b) Comparison of data and the BPNN output of the 5th simulation of FA optimisation data*



(a) (b)

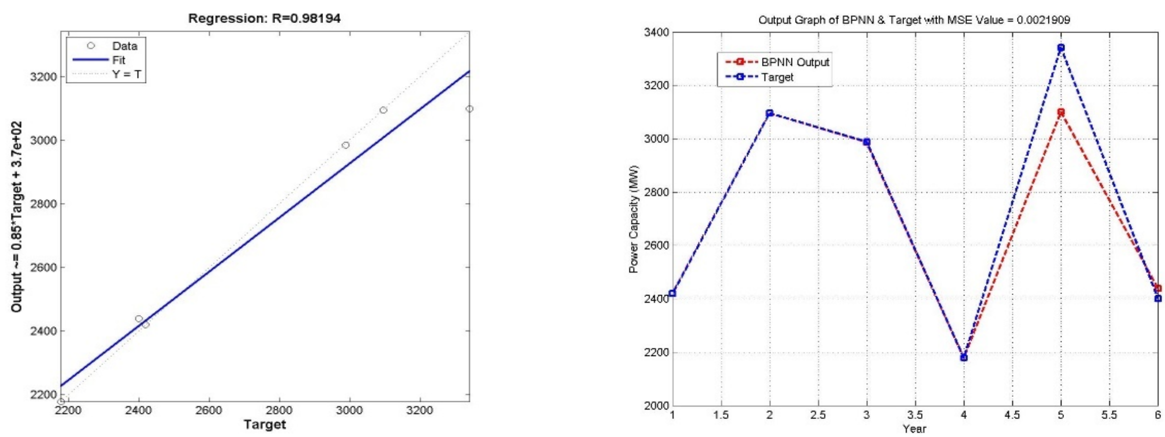
Based on *Fig. 4 (a)*, a very high correlation is observed between the target data and the backpropagation neural network (BPNN) output, with a correlation value (r) of 0.99931. This indicates that the BPNN is highly effective in representing or predicting the target data. Furthermore, in *4 (b)*, a comparison is presented between the target data and the BPNN output after the optimisation process using the FA in the fifth test. With MSE value of 0.00019214, this result demonstrates a high level of accuracy in the FA optimisation process, where the difference between the target data and the BPNN output is minimal.

Table 7 provides information that the combination with the smallest MSE value is at a learning rate of 0.02 with 50 hidden layers/neurons, where the MSE reaches 0.002191. This indicates that in this test, the use of a learning rate of 0.02 and 50 hidden layers/neurons produces the most accurate model for modelling the training data. This combination provides good predictive results and optimal model performance. In the development of neural network models, careful evaluation of parameter combinations is necessary to ensure consistent and reliable results.

Table 7. *Optimality of PSO in the first test: mean squared error (MSE) level in the training data.*

Learning rate	Hidden layer/neuron				
	10	20	30	40	50
0.01	0.043650	0.168240	0.018159	0.036281	0.673660
0.02	0.031234	0.299860	0.073291	0.069573	0.002191
0.03	0.036161	0.002475	0.093580	0.512740	0.026664
0.04	0.170870	0.018440	0.007748	0.119730	0.041801
0.05	0.105230	0.047061	0.020356	0.378050	0.247300
0.06	0.031376	0.069735	0.154730	1.212100	0.042902
0.07	0.167740	0.322240	0.031061	0.206670	0.202400
0.08	0.022567	0.022685	0.380590	0.064082	0.193210
0.09	0.137240	0.010810	1.082800	0.169430	0.130220

Fig. 5. *(a) Correlation between the target data and the BPNN output data; (b) Comparison of the target data and the BPNN output in the first test of the PSO optimisation data*



(a) (b)

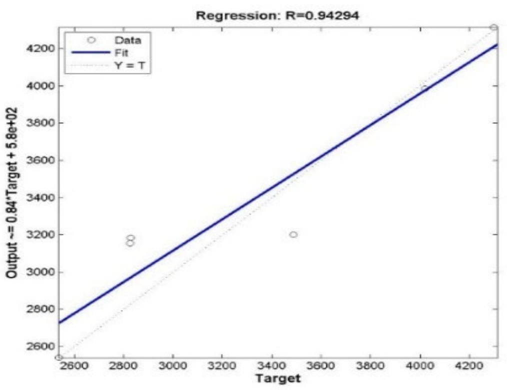
Fig. 5 (a) shows a fairly high correlation between the target data and the BPNN output data, with a correlation value (r) of 0.98194. This indicates that the BPNN is effective in representing the target data. Meanwhile, in 5 (b), a comparison is made between the target data and the BPNN output after the optimisation process using the particle swarm optimisation (PSO) algorithm in the first simulation. With a MSE of 0.0021909, the result demonstrates that the PSO optimisation has successfully produced fairly accurate results, with the difference between the target data and the BPNN output being relatively small.

Table 8 shows the MSE level in the training data for various combinations of learning rate and number of hidden layers/neurons. From the table, it can be seen that the combination with the smallest MSE value is at a learning rate of 0.09 with 20 hidden layers/neurons, where the MSE reaches 0.003743. This indicates that this combination provides the most accurate and consistent predictive results in modelling the training data. Therefore, the use of a learning rate of 0.09 and 20 hidden layers/neurons can be considered an optimal choice in developing the neural network model for this dataset. It should be noted that when selecting parameters for the neural network model, careful evaluation of the combination of the learning rate and the number of hidden layers/neurons is necessary to ensure optimal model performance.

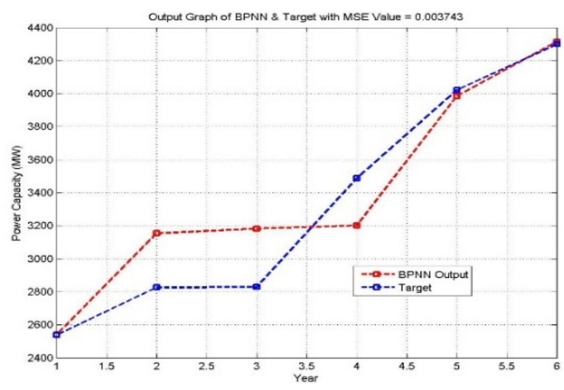
Table 8. *Fossil optimality: mean squared error (MSE) level in the training data*

Learning rate	Hidden layer/neuron				
	10	20	30	40	50
0.01	0.008417	0.080302	0.010657	0.303090	0.081962
0.02	0.017726	0.410450	0.030078	0.112550	0.083310
0.03	0.012392	0.009154	0.052081	0.183810	0.094796
0.04	0.008172	0.147050	0.911810	0.130470	0.240770
0.05	0.005976	0.028005	0.012502	0.006529	0.013926
0.06	0.005084	0.078251	0.021615	0.304740	0.007611
0.07	0.010622	0.023581	0.016326	0.539080	0.283640
0.08	0.006984	0.010641	0.018469	0.105320	0.033066
0.09	0.007344	0.003743	0.059175	0.006143	0.022764

Fig. 6. *(a) Correlation between the target data and the BPNN output data; (b) Comparison of the target data and the BPNN output data for fossil optimality*



(a)

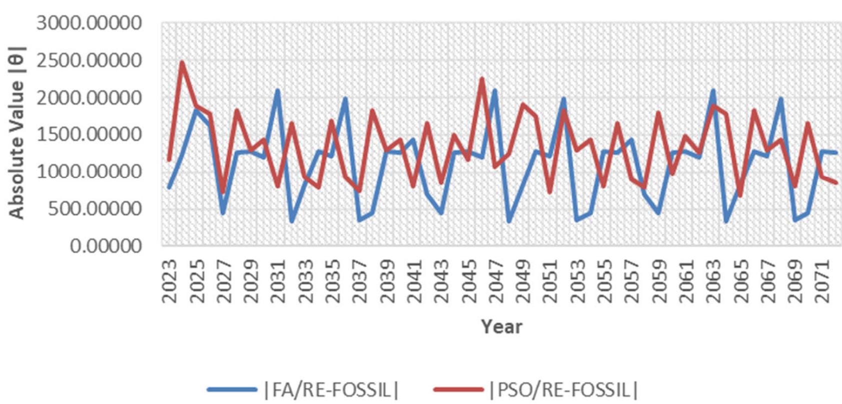


(b)

Fig. 6(a) shows the correlation between the target data and the BPNN output data, with a correlation value (r) of 0.94294. The high correlation value indicates a strong relationship between the target data and the BPNN output data, suggesting the BPNN's ability to represent the patterns present in the target data. Meanwhile, in 6(b), a comparison is made between the target data and the BPNN output data after the optimisation process, resulting in a MSE value of 0.003743. This indicates that the difference between the target and the output is relatively small, suggesting good model performance. Overall, both graphs demonstrate that the BPNN model has high accuracy and can predict data well, based on the high correlation value and the low error value.

The results of the energy forecasting analysis based on the backpropagation neural network to determine the downtime of the thermal power plant are shown in *Fig. 7*. Based on *Fig. 7*, the lowest absolute value for |FA/RE–FOSSIL| in 2064 is 335.404192, while the lowest absolute value for |PSO/RE-FOSSIL| in 2065 reaches 689.475978. A smaller absolute value of θ indicates that the method is closer to the optimal value. Therefore, renewable energy optimisation using the firefly algorithm is predicted to be achieved by the backpropagation neural network method in 2064. Subsequently, with the PSO algorithm, it is predicted to be achieved in 2065 to reduce dependence on fossil power plants. The value of θ is a parameter used to measure the distance between

Fig. 7. *Comparison of the absolute value |θ|*



the predicted value and the actual value. In the context of RE optimisation, the optimal value is the RE value that eliminates dependence on fossil power plants.

Conclusions

From the optimisation results analysis, the FA demonstrates consistent performance with an average value (θ) approaching zero (–51.514), indicating relatively more optimal performance. In contrast, the PSO showed a larger average value (θ) of –911.054, indicating that the RECR is lower than the minimum target for fossil power plant usage (T) under various simulation conditions. This suggests that optimisation using PSO is less effective in achieving a θ value that meets the condition θ ≤ 0. The evaluation of optimisation results shows that the combination of these two algorithms can enhance the RECR, leading to a reduction in reliance on conventional energy sources. Forecasting using the backpropagation artificial neural network predicts that renewable energy could fully replace fossil power plants by 2064 with FA optimisation, and by 2065 with PSO optimisation. However, this could be accelerated if policymakers are committed to achieving national energy mix targets.{Gurauskiene, 2006, Eco-design methodology for electrical and electronic equipment industry}

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