

Artificial Neural Network (ANN) Backpropagation to Forecast 100% Renewable Energy in North Sumatra

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Abstract: North Sumatra possesses abundant natural resources, including renewable energy sources such as water, geothermal, biomass, biogas, waste and solar energy. However, currently, these resources are not optimally utilized for electricity generation, with fossil fuel plants still dominating the energy mix. This research aims to establish an objective function model to optimize the use of renewable energy sources in North Sumatra by phasing out fossil fuel plants. The method employed in this study is a statistical approach based on secondary data from PT. PLN Persero in the North Sumatra region, which was optimized using the Firefly (FA) and Particle Swarm Optimization (PSO) algorithms. Analysis of the results reveals that the lowest absolute value of θ for |FA/RE-Thermal| in 2064 is 335.404192, while the lowest absolute value for |PSO/RE-Thermal| in 2065 is projected to reach 689.475978. A smaller absolute value of θ indicates closer proximity to the optimum value. Therefore, renewable energy optimization using the Firefly algorithm is predicted, using the Backpropagation Neural Network method, to be achievable in 2064, while with the PSO algorithm, it is expected to be realized in 2065, thus eliminating the need for thermal generators. The θ value serves as a parameter for measuring the discrepancy between predicted and actual values, with a smaller θ value indicating closer proximity to the optimum value. In the context of renewable energy optimization, the optimum value represents the level of renewable energy utilization required to supplant thermal generation. This research contributes by predicting that achieving 100% renewable energy utilization in North Sumatra can be attained by 2064 using the Firefly algorithm, based on the Backpropagation Neural Network method, and by 2065 using the PSO algorithm.

Keywords: HRES, Algorithm, Optimization, FA, PSO.

1. Introduction

Green and clean power generation technologies will play an essential role in electricity supply in the future due to the increasing global public awareness of the need for environmental protection and the desire to reduce dependence on fossil fuels for energy production [1]. These

technologies include power generation from renewable energy (RE) resources, such as wind, photovoltaic (PV), micro-hydro (MH), biomass, geothermal, biomass, ocean waves and tides, clean alternative energy (AE), fuel cells (FC) and micro turbines (MTs) [1]–[3]. Where investment in renewable energy sources leads to decarbonisation of the power sector [4], [5]. In this regard, the Minister of Energy and Mineral Resources of Indonesia targets the use of Renewable Energy (RE) at 51.6% based on decision number 188.K / HK.02 / MEM / 2021 dated September 28, 2021, in the 2030 Electricity Supply Business Plan (PT. PLN (Persero), 2021). PT. PLN North Sumatera operates 49 plants consisting of fossil fuel plants with a capacity of 4,580,870 MW and renewable energy plants of 2,539.52 MW to meet the demand of electricity customers reaching 3,958,766 customers with a total demand for electrical power of 7,112.7400 MW. Preliminary studies on hybrid renewable systems (HRS) in North Sumatra based on weather data provide significant results to be developed [7], continued with research related to the use of hybrid renewable energy plants in North Sumatra has a positive impact on reducing energy prices per kWh [8] and generator synchronization testing data (wind & solar) has also been carried out in North Sumatra [9]. Overall, hybrid models can improve variable renewable energy generation performance [10].

The large use of fossil fuels contributes to global climate change that is being faced by all countries in the world [11], [12]. To that end, the burning of fossil fuels has caused great damage to the environment due to pollution caused by the production of large amounts of oil as well as being a major source of greenhouse gas emissions, which contribute to climate change, air pollution, and various environmental problems [13], [14]. Furthermore, the interconnection system of renewable energy (RE) plants has not been optimal [15], [16], thus making it difficult to predict the utilization of 100% of NRE.

This research is important considering the magnitude of the impact caused by the use of fossil fuel plants on global warming and its availability is quite limited, so studies are needed to minimize thermal plants and optimize RE plants. Where in this case North Sumatra has very abundant natural resources. It can ultimately contribute to policies and steps to be taken by local governments in supporting the utilization of RE. This requires a model to predict the potential of local natural resources into autonomous power systems capable of quickly balancing energy supply and demand in order to maintain the quality of electrical power through optimization of hydropower, geothermal, biomass, biogas and solar power generation

This study aims to produce a model to predict the period of time needed for North Sumatra to utilize 100% Renewable Energy using Artificial Neural Network (ANN) Backpropagation.

2. Literature Review

2.1 Firefly Algorithm (FA)

The Firefly algorithm is a metaheuristic algorithm inspired by nature, namely on the blinking behaviour of fireflies to find food and to communicate between fireflies [17], [18, p. 82]. FA is a population-based technique with an effective and efficient global search for combinatorial problems [19].

The firefly optimization mechanism is described in by [18], [20], [21] as follows:

- a. All fireflies are unisex, where each firefly can be attracted between each firefly.
- b. The attraction of each firefly is relative to the intensity of light.
- c. The attractiveness of each firefly is determined by its individual position in the search space
- d. Less attractive fireflies will be attracted by brighter fireflies.
- e. Better fitness capacity in certain positions results in an attractive firefly.
- f. The brightest fireflies move randomly.

The initial population of fireflies was randomly generated and using the fitness function of the associated optimization problem, the attractiveness of fireflies was defined as β_0 , aims to determine the position of each firefly in the population. All fireflies move throughout the

space looking for solutions for a certain number of iterations. For each iteration, compare the attractiveness between each of the two fireflies f_i and f_j . If f_i more interesting than f_j maka kunang-kunang f_j will move towards the fireflies f_i . In terms of light intensity or attraction capacity (β) depending on the distance (r) between fireflies and absorption coefficient (γ) light. The attractiveness of each firefly is determined by the equation:

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

Where β_0 shows attractiveness firefly, when $r = 0$.

Firefly movement in position x_j , Interested in a brighter firefly f_i at the position defined by the equation:

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

At Firefly Algorithm (FA) [21], [22], Fireflies are considered simple agents that move and interact throughout the search room and record the best solutions ever visited. So to get candidates for efficient schedule solutions in scheduling cases on computational problems, you can use FA. In addition, FA can also map received work to existing resources so that work can be completed with minimum makespan time. Therefore, in using the Discrete Firefly Algorithm (DFA)), the main step is to determine the firefly's position using the Firefly movement algorithm and then use the smallest position to find the permutation of the positional power capacity. So the last step is to calculate the fitness function using the permutations produced by the Smallest Position Value (SPV) and determine the new movement.

2.2 Particle Swarm Optimization (PSO)

The first time the Particle Swarm Optimization (PSO) algorithm was introduced by Dr. Kennedy and Dr. Eberhart in 1995 [23]. Particle swarm optimization is one of the most appreciated swarm-based algorithms in the literature [24]. The basic idea of the algorithm was inspired by the social behaviour of animals [25]. Social behaviour is a natural process of communicating with each other in sharing individual knowledge when looking for food and migrating to a group such as a group of birds, a group of bees and so on. When one member gets the desired path, the rest of the members will follow quickly.

Particle Swarm Optimization is an algorithm for finding minimum or maximum function values based on new populations. PSO has the advantage of finding complex non-linear optimization values. Particle Swarm Optimization is proven to find the best solution to optimization problems. The PSO algorithm can be applied to obtain the position of the sensor at Weighted Least Squares State (WLS) estimation [26]. WLS optimization can be used in determining the minimum sensor determination so that a fairly accurate estimate is obtained. In the PSO algorithm, there are models to get optimization values, one of which is Global Best PSO [25], [27]. In other research, it is stated that PSO is able to provide the best results when using polynomial models [28].

2.3 Artificial Neural Network (ANN) Backpropagation

A hybrid renewable energy system is a power generation system that combines two or more renewable energy sources. These energy sources have the potential to reduce dependence on fossil fuels and increase energy security. One of the challenges in this energy system is minimizing the use of thermal power plants. Thermal power plants are an unsustainable renewable energy source and produce greenhouse gas emissions. To minimize the use of thermal power plants in this energy system, it is necessary to predict when thermal power plants will be eliminated. This prediction can be done using methods including ANN Backpropagation [29]. The backpropagation neural network method demonstrates a higher level of predictability compared to other existing models. [30]. ANN Backpropagation is a supervised learning algorithm and is usually used by perceptions with multiple layers to change the weights connected to neurons in their hidden layer [31]. The training algorithm for Network Backpropagation is as follows:

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

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

$$z_{\text{net}_j} = v_{j0} + \sum_{i=1}^n x_i v_{ji}; z_j = f(z_{\text{net}_j}) = \frac{1}{1 + e^{-z_{\text{net}_j}}} \dots \dots \dots (3)$$

$$z_{\text{net}_j} = v_{j0} + \sum_{i=1}^n x_i v_{ji}; z_j = f(z_{\text{net}_j}) = \frac{1}{1 + e^{-z_{\text{net}_j}}} \dots \dots \dots (4)$$

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

$$y_{\text{net}_k} = w_{i0} + \sum_{j=1}^p z_j w_{kj}; y_k = f(y_{\text{net}_k}) = \frac{1}{1 + e^{-y_{\text{net}_k}}} \dots \dots \dots (5)$$

Backpropagation Error (Phase 2: step 6-7)

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

$$\delta_k = (t_k - y_k) f'(y_{\text{net}_k}) = (t_k - y_k) y_k (1 - y_k) \dots \dots \dots (6)$$

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 .

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

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

$$\delta_{\text{net}_j} = \sum_{k=1}^m \delta_k w_{kj} \dots \dots \dots (8)$$

Factor δ hidden unit

$$\delta_j = \delta_{\text{net}_j} f'(z_{\text{net}_j}) = \delta_{\text{net}_j} z_j (1 - z_j) \dots \dots \dots (9)$$

Calculate the weight change term v_{ji}

$$\Delta v_{ji} = \alpha \delta_j z_i, (j = 1, 2, \dots, p; i = 0, 1, \dots, n)$$

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::

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

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

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

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

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

Step 9: Testing completed

3. Method

This research uses data sources of thermal plants, RE plants and electricity load data in the period of 2014 – 2022 from PT. PLN North Sumatra Power Area.

Table 1. Installed Power of PLN Power Plants by Power Plant (MW), 2014 – 2022

Year	Diesel		Steam Turbin (Coal)	Steam Turbin (Gas)	Combinecycle (Coal & Gas)	Microhydro	Hydropower	Geothermal	Biomass	Biogas	Solar	Average	light	Peak Load
	Isolation system	Interconnection System												
2014	-	24,85	490	253,83	817,88	31,5	912	12	115			2657,06	2.568,06	2.652,56
2015	-	229,36	1150	340,23	817,88	31,5	912	12	119,8			3612,77	2 791,37	3.120,66
2016	-	396	1370	243	818	44,5	957	12	129,8			3970,3	3 080,00	3.506,36
2017	-	396	1370	245	818	49,5	957	232	130,8			4198,3	3 083,00	3.939,73
2018	-	304,37	1370	964,53	847,88	59,3	1007	342	135,8			5030,88	3 740,28	4.426,66
2019	17,35	328,36	1804	1024,03	847,88	59,3	1007	378	140,8			5606,72	4 275,12	4.973,77
2020	85,71	304,36	1828	1263,42	817,88	94,3	1007	378	142,8	3,4		5924,87	4 552,87	5.588,50
2021	82,21	304,36	1828	1548,42	817,88	113,3	1007	432	150,9	5,6	4	6293,67	4592,6534	6.279,21
2022	82,21	304,36	1828	1548,42	817,88	118,3	1681	570	159,8	5,6	5	7120,393	4 834,372	7.112,74

Source: Data Statistics PT. PLN

The research procedures carried out include: data collection, finding optimization models of hybrid geothermal plants, micro hydro power, hydropower, biomass, biogas and diesel and their characteristics, by eliminating fossil-fuelled plants, validating using Firefly Algorithm (FA) and Particle swarm optimization (PSO) to complete the proposed optimization model using MATLAB software, comparing better results from both algorithms used, finally make predictions using Artificial Neural Network (ANN) Backpropagation then conclusions are drawn.

In data analysis of the objective function of optimizing hybrid hydropower/geothermal/biomass/biogas/solar systems to maximize the efficiency of using renewable energy sources by minimizing the use of thermal plants is carried out by proposing a goal function model.

Based on a system of mathematical equations and inequalities, the study of the purpose function is the efficiency of using renewable energy sources can be calculated by the equation:

$$Efisiensi = \frac{\text{total energi yang dihasilkan sumber RE}}{\text{total energi yang dibutuhkan (E)}} \dots\dots\dots (12)$$

In this case, the total energy produced by the ER plant is: $X_1 + X_2 + X_3 + X_4 + X_5 + X_6$

Where:

- X1= Mini hydroelectric power plant capacity
- X2= Hydroelectric power generation capacity
- X3= Geothermal generator capacity
- X4= Biomass generating capacity
- X5= Biogas generator capacity
- X6= Solar power generation capacity

To minimize the use of thermal plants, we can set Efficiency - $T = \theta$ dengan $\theta \leq 0$. Thus the goal function can be formulated as follows:

$$\theta = \frac{X_1+X_2+X_3+X_4+X_5+X_6}{E} - T \leq 0 \dots\dots\dots (13)$$

$$\theta = \frac{X_1+X_2+X_3+X_4+X_5+X_6}{E} - T + T \leq 0 + T \dots\dots\dots (14)$$

$$\theta = \frac{X_1+X_2+X_3+X_4+X_5+X_6}{E} \leq T \dots\dots\dots (15)$$

The destination function is used to maximize the efficiency of using renewable energy sources in hybrid systems by minimizing the use of thermal plants. These objective functions can be reduced to several more specific additional purpose functions, each maximizing the efficiency of using one type of renewable energy source. This additional purpose function can be used to optimize the design of hybrid systems more specifically. Next by specifying:

- β_n = Efficiency factors of each type of dissident it (in the range 0 – 1, with $n = 1,2,3,4,5,6,\dots$,
- E = Total energy required
- θ = Purpose function

In this study, the β_n efficiency factor was determined based on the efficiency of each type of plant as follows:

- $\beta_1 = 1,00$
- $\beta_2 = 1,00$
- $\beta_3 = 0,80$
- $\beta_4 = 0,80$
- $\beta_5 = 0,42$
- $\beta_6 = 0,20$

Purpose Function

The goal of this optimization is to maximize the efficiency of using renewable energy sources in hybrid systems by minimizing the use of thermal plants using the following (16):

$$\theta = (\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6) - T \dots\dots\dots(16)$$

Constraints:

1. The total capacity of the hybrid system is not allowed to exceed the maximum available capacity.
 $(X_1 + X_2 + X_3 + X_4 + X_5 + X_6) \leq \text{Maximum available capacity}$
2. Hybrid plants must meet energy demand in North Sumatra.
 $(X_1 + X_2 + X_3 + X_4 + X_5 + X_6) \geq \text{Energy demand in North Sumatra}$
3. Thermal plants must be eliminated completely.
 $T = 0$

4. Results and Discussion

4.1 Use of Renewable Energy Plants and Thermal Plants in the North Sumatra Electricity System

Renewable energy plants in the North Sumatra electricity system have identified several components, such as micro hydro Power, hydropower, geothermal, Biomass, Biogas and Solar. The results of the evaluation of the use of renewable energy plants are shown in figure 1.

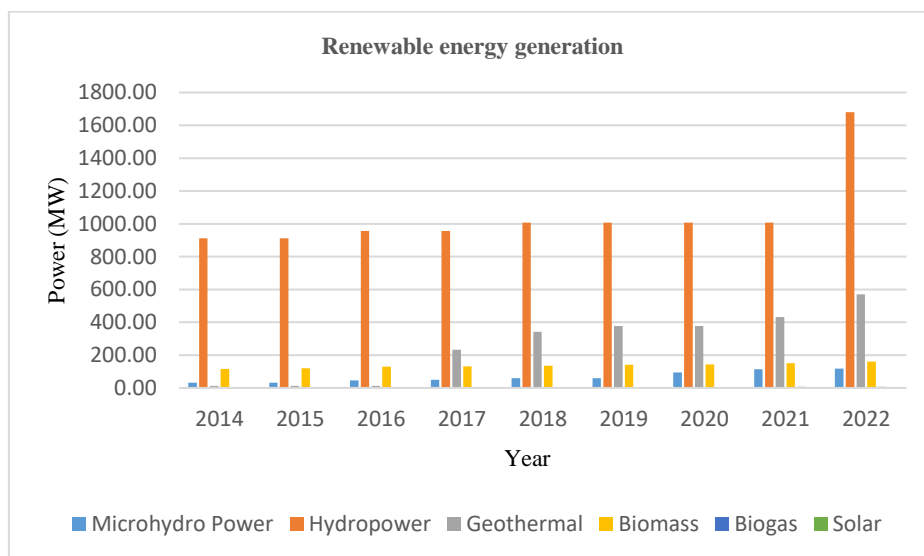


Figure 1. Histogram Evaluation of the Use of Renewable Energy Plants in the System (2014-2022)

From the histogram in figure 1 shows that micro hydro power and hydropower are consistent with the use of water resources, then the use of a hybrid system of geothermal plants with

Biomass, Biogas and Solar illustrates the use of sustainable energy in the power generation process.

In addition, there has been a significant increase in the use of renewable energy generation in some components over time, indicating the growing emphasis on renewable energy in the electricity system.

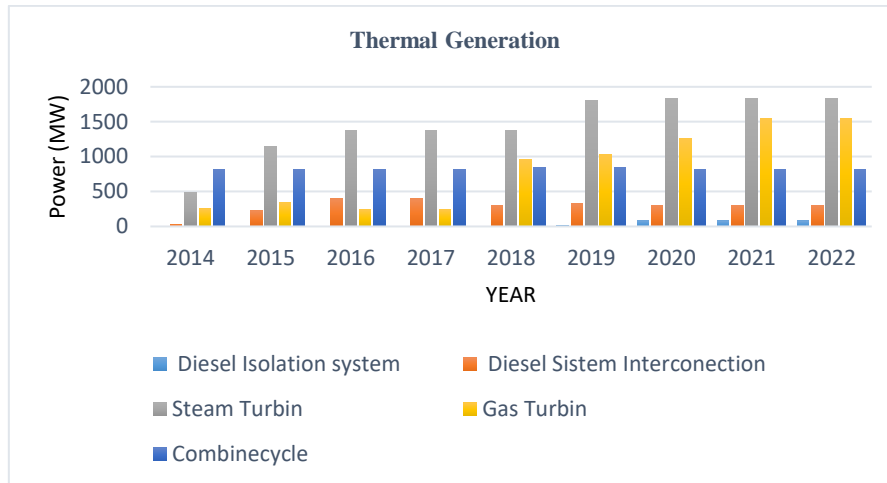


Figure 2. Histogram Evaluation of the Use of Thermal Plants in Systems (2014-2022)

Figure 2 shows that the use of thermal plants still dominates the electricity system in North Sumatra such as: Diesel, steam turbine, gas turbine, and steam gas turbine (combine cycle) represent compatibility with fossil base sources and derivatives. Thermal plant isolation and interconnection systems are used in electric power distribution to support system reliability.

4.2 Evaluate Results with Firefly Algorithm

From the results of statistical analysis conducted as shown in tables 2, 3, 4, 5 and 6, it is known that the evaluation of results using the Firefly algorithm in a hybrid hydro/geothermal/biomass/biogas/solar system in North Sumatra shows variations in the value of the destination function (θ) during five annual tests. The first to fifth tests showed significant changes in system efficiency, measured by a comparison between the total renewable energy generation capacity and the eliminated thermal plants. In the first test, the system experienced an average efficiency increase of 1017.4483, indicated by the θ value increasing from 2014 to 2022. The second test showed consistency in efficiency improvements, with an average θ of 776.6930. The third test showed an average efficiency decrease of 893.7330, which may have been due to variations in renewable generation capacity. The fourth test showed an increase in efficiency by an average θ of -193.3194, indicating the success of the algorithm in minimizing the use of thermal plants. The fifth test showed an efficiency increase of 792.7605, indicating consistency in increasing the contribution of renewable energy sources. Overall, Firefly's algorithm successfully improved the efficiency of using renewable energy sources and reduced dependence on thermal plants in North Sumatra during the test period.

Table 2. Evaluate Results with Firefly Algorithm

Experiment	Year	θ	$ \theta $
1	2014	33,6146	33,6146
	2015	404,1101	404,1101
	2016	2095,5668	2095,5668
	2017	923,4924	923,4924
	2018	-789,7192	789,7192
	2019	-608,7377	608,7377
	2020	-2332,1468	2332,1468
	2021	-1341,5426	1341,5426
	2022	628,1046	628,1046
Average		-109,6953	1017,4483

Table 3. Evaluate Results with Firefly Algorithm

Experiment	Year	θ	$ \theta $
2	2014	1193,8418	1193,8418
	2015	-523,6237	523,6237
	2016	350,0818	350,0818
	2017	325,0145	325,0145
	2018	-191,9802	191,9802
	2019	-659,5932	659,5932
	2020	-942,1488	942,1488
	2021	-1577,0834	1577,0834
	2022	-1226,8701	1226,8701
Average		-361,3735	776,6930

Table 4. Evaluate Results with Firefly Algorithm

Experiment	Year	θ	$ \theta $
3	2014	1458,3907	1458,3907
	2015	1298,3170	1298,3170
	2016	249,3882	249,3882
	2017	-136,8045	136,8045
	2018	-221,5060	221,5060
	2019	-148,1349	148,1349
	2020	-2395,8061	2395,8061
	2021	-1245,1326	1245,1326
	2022	-890,1173	890,1173
Average		-225,7117	893,7330

Table 5. Evaluate Results with Firefly Algorithm

Experiment	Year	θ	$ \theta $
4	2014	996,0780	996,0780
	2015	348,1692	348,1692
	2016	1342,9288	1342,9288
	2017	546,0924	546,0924
	2018	-27,2624	27,2624
	2019	-1371,5843	1371,5843
	2020	-1459,2055	1459,2055
	2021	-624,9578	624,9578
	2022	-1490,1333	1490,1333
Average		-193,3194	911,8235

Table 6. Evaluate Results with Firefly Algorithm

Experiment	Year	θ	$ \theta $
5	2014	1684,6989	1684,6989
	2015	419,4174	419,4174
	2016	-852,3637	852,3637
	2017	843,8582	843,8582
	2018	-740,7387	740,7387
	2019	387,6356	387,6356
	2020	-655,3719	655,3719
	2021	-813,3164	813,3164
	2022	-737,4438	737,4438
Average		-51,5138	792,7605

4.3 Evaluation of Results with Particle Swarm Optimization Algorithm

Based on tables 7, 8, 9, 10 and 11, it is known that evaluation of results using the Particle Swarm Optimization (PSO) algorithm in a hybrid hydro/geothermal/biomass/biogas/solar system in North Sumatra shows variations in the value of the objective function (θ) during five annual tests. The first to fifth tests showed significant changes in system efficiency, measured by a comparison between total renewable power generation capacity and eliminated thermal plants. In the first test, the system experienced an average efficiency decrease of 911.0538, indicated by θ values tending to be negative from 2014 to 2022. The second test showed

consistency in efficiency degradation, with an average θ of 1081.0358. The third test displayed an average efficiency decrease of 1187.6541, which may be due to variations in renewable generation capacity. The fourth test showed an increase in efficiency with an average θ - 1211.5206, indicating the success of the algorithm in minimizing the use of thermal plants. The fifth test showed an efficiency increase of 1122.7944, indicating consistency in increasing the contribution of renewable energy sources. Overall, the PSO algorithm successfully improved the efficiency of using renewable energy sources and reduced dependence on thermal plants in North Sumatra during the test period.

Table 7. Evaluate Results with Particle Swarm Optimization Algorithm

Experiment	Year	θ	$ \theta $
1	2014	257,1290	257,1290
	2015	-118,8160	118,8160
	2016	268,8591	268,8591
	2017	159,9460	159,9460
	2018	-1307,9740	1307,9740
	2019	-679,4792	679,4792
	2020	-1898,4703	1898,4703
	2021	-1935,2133	1935,2133
	2022	-2945,4656	2945,4656
Average		-911,0538	1063,4836

Table 8. Evaluate Results with Particle Swarm Optimization Algorithm

Experiment	Year	θ	$ \theta $
2	2014	475,0181	475,0181
	2015	292,1125	292,1125
	2016	-1317,5483	1317,5483
	2017	-882,4192	882,4192
	2018	-1330,9154	1330,9154
	2019	-1110,4594	1110,4594
	2020	-2251,2783	2251,2783
	2021	-2378,1335	2378,1335
	2022	-1225,6991	1225,6991
Average		-1081,0358	1251,5093

Table 9. Evaluate Results with Particle Swarm Optimization Algorithm

Experiment	Year	θ	$ \theta $
3	2014	181,2330	181,2330
	2015	-747,3195	747,3195
	2016	-921,4391	921,4391
	2017	-1063,4539	1063,4539
	2018	-1203,0173	1203,0173
	2019	-1373,8094	1373,8094
	2020	-1431,1674	1431,1674
	2021	-2368,1797	2368,1797
	2022	-1761,7340	1761,7340
Average		-1187,6541	1227,9281

Table 10. Evaluate Results with Particle Swarm Optimization Algorithm

Experiment	Year	θ	$ \theta $
4	2014	632,9114	632,9114
	2015	-393,5812	393,5812
	2016	-1534,1942	1534,1942
	2017	-120,4391	120,4391
	2018	-1122,7545	1122,7545
	2019	-2273,0436	2273,0436
	2020	-2629,8569	2629,8569
	2021	-2153,8857	2153,8857
	2022	-1308,8420	1308,8420
Average		-1211,5206	1352,1676

Table 11. Evaluate Results with Particle Swarm Optimization Algorithm

Experiment	Year	θ	$ \theta $
5	2014	1435,4614	1435,4614
	2015	-707,0494	707,0494
	2016	-597,1096	597,1096
	2017	-890,0267	890,0267
	2018	-1272,7705	1272,7705
	2019	-2547,2065	2547,2065
	2020	-2684,0241	2684,0241
	2021	-1928,1086	1928,1086
	2022	-914,3153	914,3153
Average		-1122,7944	1441,7858

4.4 Energy Prediction Analysis Based on Backpropagation Neural Network for Determining North Sumatra 100% using Renewable Energy

Thermal energy as one of the main resources in providing electricity in North Sumatra, plays a central role in maintaining the sustainability and availability of energy supply. In this context, predictive energy analysis becomes essential for understanding and planning the exhaustion time of thermal plants, a strategic information that affects the stability and reliability of electricity supply.

This study explains the results of energy prediction analysis based on Neural Network with Backpropagation method. This method has a unique regulatory function with a probabilistic approach. This regression pattern is a model used to make predictions. It is important to note that the Backpropagation method is very flexible in designing network structures. The trial was conducted with 45 experiments to produce the smallest Mean Square Error (MSE) value in this study. The research data predicted in this study are optimization results that have the smallest θ value (for RE optimization with the FA method on the 5th test and RE optimization with the PSO method on the 1st test). Next, an analysis of the power capacity of the thermal plant is carried out to find the θ value in the following year, so that it can be known when the thermal generator can be replaced or eliminated by the RE plant. This test will involve forecasting for the next 50 years with the following accuracy results in training data.

Table 12. FA Optimality in Test 5: Mean Square Error (MSE) Level in 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

Table 12. Provides a detailed analysis of the optimality of the Activation Function (FA) in Test 5 based on the Mean Square Error (MSE) level of the training data. At a learning rate of 0.01, it was seen that the number of hidden layers/neurons of 20 gave the smallest MSE of 0.018435, indicating a good match for that learning level. The increase in learning rate to 0.02 led to a significant increase in MSE for all hidden layer/neuron combinations, with the smallest MSE in hidden layer/neuron 30 at 0.000192. At a learning rate of 0.03, the number of hidden layers/neurons of 20 gives the smallest MSE of 0.059351. However, subsequent changes in learning rate result in significant fluctuations in MSE.

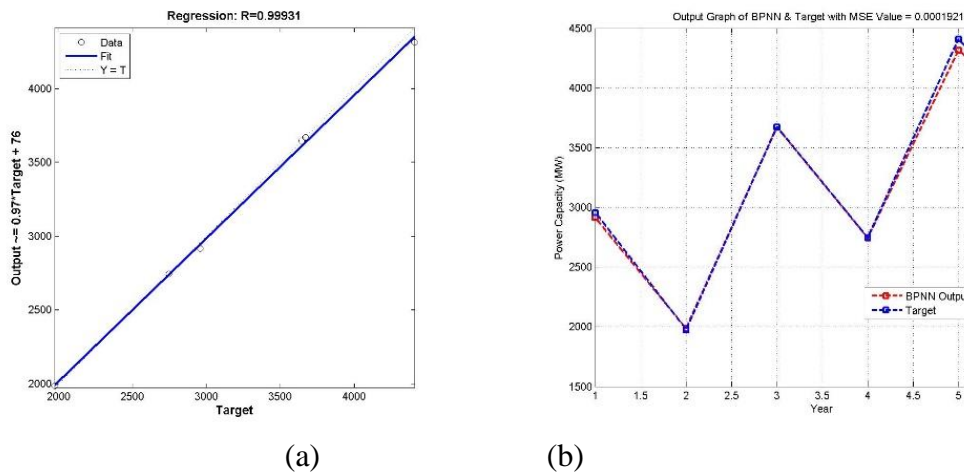


Figure 3. (a) Correlation between Target Data and BPNN Output Data; (b) Comparison of Target Data and BPNN Data Output FA Optimization Data 5th Testing

Based on Figure 3, it can be seen that in sub-figure (a), there is a very high correlation between Target Data and Backpropagation Neural Network (BPNN) Output Data, with a correlation value (r) of 0.99931. This indicates that BPNN is able to very well represent or predict target data. Furthermore, in sub-figure (b), there is a comparison between Target Data and BPNN Output Data after the optimization process using the Firefly (FA) Algorithm in the 5th test. With a Mean Squared Error (MSE) value of 0.00019214, this result shows a high level of accuracy in the FA optimization process, where the difference between the target data and the BPNN output data is very small.

Table 13. PSO Optimality in Test 1: Mean Square Error (MSE) Level in 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

Tabel 13, 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 shows that in this test, the use of a learning rate of 0.02 and 50 hidden layers/neurons produced the most accurate model in modelling training data. This combination provides good predictive results and optimal model performance. In neural network model development, careful evaluation of the combination of parameters needs to be performed to ensure consistent and reliable results.

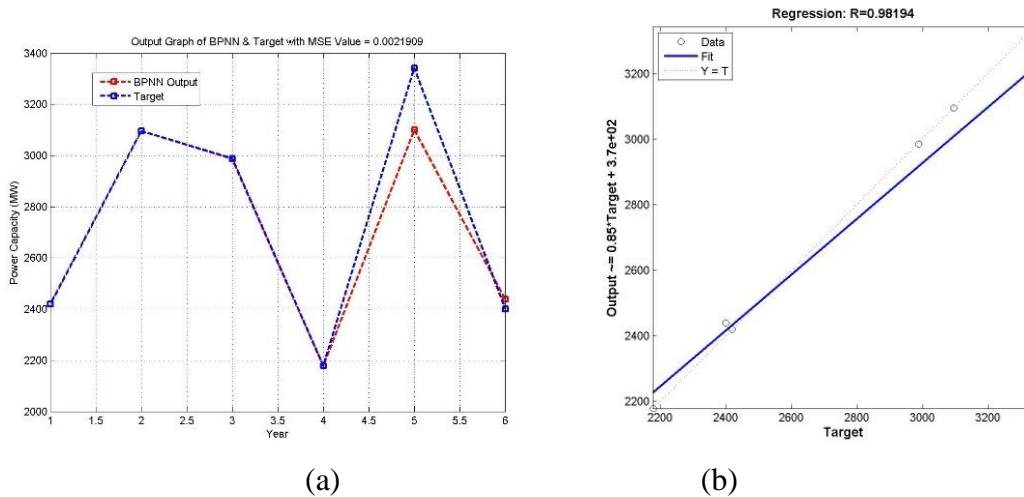


Figure 4. (a) Correlation between Target Data and BPNN Output Data; (b) Comparison of Target Data and BPNN Data Output PSO Optimization Data 1st Test

Seen in Figure 4, sub-figure (a) shows a fairly high correlation between Target Data and Backpropagation Neural Network (BPNN) Output Data, with a correlation value (r) of 0.98194. This indicates that BPNN has a good ability to represent target data. Meanwhile, in sub-figure (b), there is a comparison between Target Data and BPNN Output Data after the optimization process using the Particle Swarm Optimization (PSO) Algorithm in the first test. With a Mean Squared Error (MSE) value of 0.0021909, this result shows that optimization using PSO has succeeded in providing fairly accurate results, where the difference between the target data and BPNN output data is relatively small.

Table 14. Thermal Optimality: Mean Square Error (MSE) Rate in 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

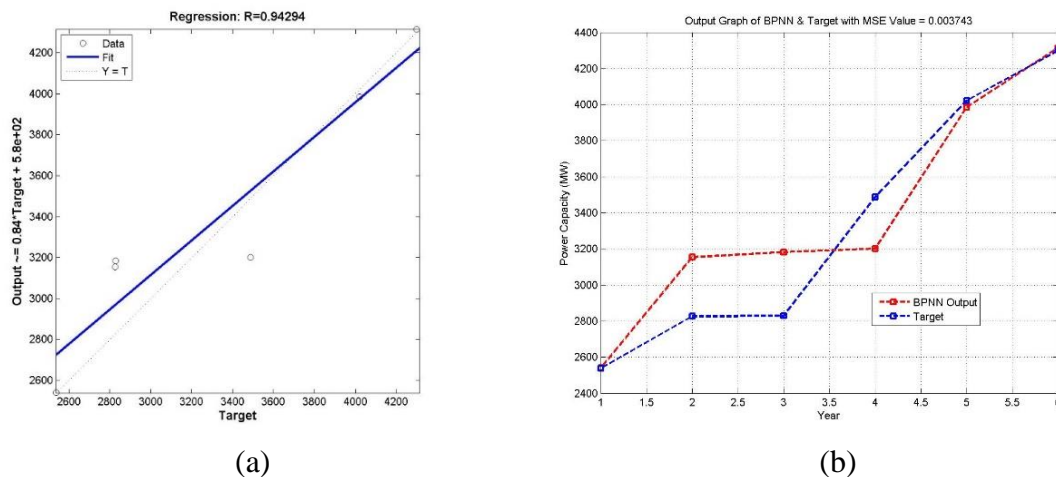


Figure 5 (a) Correlation between Target Data and BPNN Output Data; (b) Comparison of Target Data and BPNN Data Output of Thermal Optimization Data

From Figure 5, sub-figure (a) shows the correlation between Target Data and Backpropagation Neural Network (BPNN) Output Data, with a correlation value (r) of 0.94294. A high correlation value indicates a strong relationship between the target data and BPNN output data, indicating BPNN's ability to represent patterns in the target data. Meanwhile, in sub-figure (b), there is a comparison between Target Data and BPNN Output Data after going through the optimization process using the Thermal Method. With a Mean Squared Error (MSE) value of 0.003743 (Shown in Table 14), this result shows that the use of the Thermal Method in optimizing BPNN provides quite good results, where the difference between the target data and the BPNN output data is relatively small, showing a satisfactory level of accuracy. The results of energy prediction analysis based on neural network backpropagation to determine the time of non-operation of thermal plants are shown in figure 6.

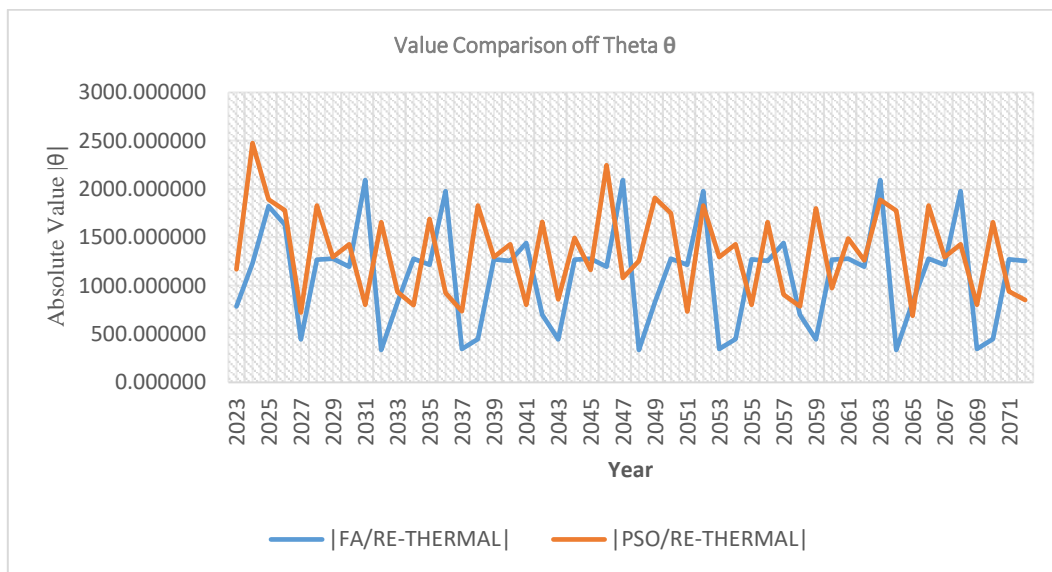


Figure 6. Value Comparison Absolute $|\theta|$

Based on Figure 6, the lowest absolute value θ for $|\text{FA/RE-THERMAL}|$ in 2064 it was 335.404192, while the lowest absolute value for $|\text{PSO/RE-THERMAL}|$ in 2065 it reached 689.475978. A smaller absolute value of θ indicates that the method is closer to the optimum value. Therefore, optimization of renewable energy using the Firefly method is predicted with the Backpropagation Neural Network method can be done in 2064, while with the PSO method it is predicted to be achieved in 2065 to eliminate thermal plants. The value θ is a parameter used to measure the distance between the predicted value and the actual value. A smaller value of θ indicates that the method is closer to the optimum value. In the context of RE optimization, the optimum value is the RE value that eliminates thermal generation.

5. Conclusion

This research achieved significant results in optimizing hybrid hydropower/geothermal/biomass/biogas/solar systems in North Sumatra using Firefly (FA) and Particle Swarm Optimization (PSO) algorithms. The results of the analysis of optimizations carried out through test 1, test 2, test 3, test 4, and test 5 showed that both algorithms were able to improve system performance consistently with an increase in the number of iterations or particles. Based on the evaluation of results using the Particle Swarm Optimization (PSO) algorithm in hybrid hydropower/geothermal/biomass/biogas/solar systems in North Sumatra for five annual tests, providing an overview of system efficiency dynamics. Significant changes were seen in the value of the goal function (θ) representing efficiency, with the average θ tending to be negative on each test. In the first test, there was an average efficiency decrease of 911.0538, indicating

a high dependence on thermal plants. Subsequent tests also showed a decrease in efficiency, with an average θ in the second test of 1081.0358 and in the third test of 1187.6541, which may be influenced by variations in renewable generation capacity. The fourth test showed an increase in efficiency with an average θ of -1211.5206, signifying the success of the PSO in minimizing the use of thermal plants. The fifth test showed an efficiency increase of 1122.7944, indicating consistency in increasing the contribution of renewable energy sources. Overall, the PSO algorithm successfully improved the efficiency of using renewable energy sources in North Sumatra, with an average θ across tests of -1122.7944, illustrating an increase of approximately 1441.7858 in efficiency during the test period. This research contributes that based on the results of renewable energy optimization in North Sumatra using the Firefly algorithm, it is predicted that the Backpropagation Neural Network method will reach 100% RE by 2064, while using the PSO algorithm is predicted to be achieved in 2065.

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