NUEJ
Naresuan University
Engineering Journal

Power Generation Scheduling of Hydropower Plants Using an Artificial Neural Network (ANN)

Souk Lao[1], Suttichai Premrudeepreechacharn[2*] and Kanchit Ngamsanroj[3]

[1] Department of Mechanical, Faculty of Engineering, Chiang Mai University
[2] Department of Electrical Engineering, Faculty of Engineering, Chiang Mai University
[3] Electricity Generating Authority of Thailand (EGAT), Nonthaburi, Thailand

* Corresponding author e-mail: suttic@eng.cmu.ac.th and zouzeng2012@gmail.com

(Received: 27 September 2021, Revised: 26 March 2022, Accepted: 4 April 2022)

Abstract

This paper presents the determination of power generation in hydropower plants using an artificial neural network ANN in the Central-1 region power grid of EDL. The goal aims to reduce the generation cost in terms of the total cost of each power plant to generate the electricity at its lowest point and to maximize the power generation to balance the supply and demand sides. The proposed ANN is applied to solve an optimal generation scheduling, an optimization problem, and an economical dispatching problem. In addition, a quadratic function uses the Lambda iteration method to consider an optimal dispatch problem in a hydropower plant system. Use the ANN tool in MATLAB to solve the power plant generation problem and train it with the back-propagation algorithm considered as 10 power plants in EDL's Central-1 region power grid. The results of the studies show the best-operating costs in comparison between the proposed ANN and the lambda iteration method, which are significantly less than the operating costs of the current system. For the ANN accuracy is measured using the Root Mean Square Error RMSE of the input-output relationship. It shows that the ANN is highly efficient and has an accuracy of better than 0.90.

Keywords: Hydropower Plants, Scheduling, Optimal Power Flow, Artificial Neural Network.

1. INTRODUCTION

Electricite du Laos EDL is a leading company that supplies electricity to the whole country and parts exports to a neighboring country, especially Thailand. According to the company's mission and vision, it is to be the battery of Asia. Owned, operated according to government guidelines. Responsible for the generation and supply of electricity as well as the import and export of electricity at various locations. As almost all electricity generation in the whole country comes mainly from hydropower plants, of which 78 hydropower plants, also 1 thermal, 4 biomass, and 6 solar power plants, the number will continue to increase. For easy handling of electrical systems. Therefore, the network is divided into 4 regions, namely the Northern Region Network, the Central 1 Region Network, the Central 2 Region Network, and the Southern Region Network. An ideal facility for generating electricity is an abundant natural water source. Therefore, the foregoing causes the number of power plants to increase every year. Currently, the power generation system consists of three main sectors: EDL-Generation Public Company EDL-Gen, Domestic Independent Power Producer IPPd, and Exporting Independent Power Producer IPPe. All of them are electricity producers in Laos PDR supplies to EDL and exports to neighboring countries. EDL's grid-connected generation sectors such as EDL-Gen and IPPd go directly to EDL for domestic distribution. And EDL's off-grid generation sector is directly exported to neighboring countries. Figure 1 shows that each year runs from January to April. Some years are from February to May, about 3 months. It shows that the load curve is higher than the production curve, which means that the supply side is lower than the demand side. Due to a dry season, the amount of water in each reservoir begins to decrease, meaning that the inflow is less than the outflow. Water resources are the main factor in power generation. As a result, the power plant cannot cover domestic electricity requirements all year round. Due to seasonal fluctuations to cover the seasonally fluctuating demand in electricity generation, more energy has to be imported from neighboring countries if bottlenecks persist.

Electricity generation will gradually change into reality and management methods will evolve with the increase in population in the country. In addition, technological advances are a key factor behind major changes. In previous work to prove this problem, there are several techniques for simulating the power generation planning of hydropower plants, taking into account the question of optimal load flow and optimal economic operation. These problems can be solved by different methods like unit commitment, Newton-Raphson, and lambda iteration. In addition, the application of machine learning in hydropower plants is widely used to manage electricity efficiently in terms of forecasts and estimates in various fields.

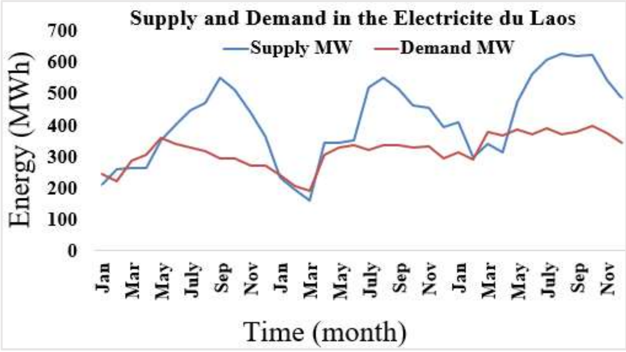

Figure 1 The supply and demand in Electricite du Laos 2016-2018

Table 1 Name, location, and capacity of 10 hydropower plants that are considered

No	Generation Name	Location/ Provinces	Installation Capacity (MW)
1	Nam Ngum1	Vientiane	155
2	Nam Leuk	Xaysomboun	60
3	Nam Mang3	Vientiane	40
4	Nam Lik1-2	Vientiane	100
5	Nam Ngum5	Vientiane	120
6	Nam Ngiep2	Xiengkhouang	180
7	Nam Phai	Xaysomboun	86
8	Nam Chien	Xiengkhouang	104
9	Nam San3A	Xiengkhouang	70
10	Nam San3B	Xiengkhouang	45

Many references describe the literature review as follows: Estoperez and Nagasaka (2006) presented a neural network to plan small hydroelectric power plants to predict electricity generation by forecasting monthly water runoff, Naresh and Sharma (2000) presented a two-phase neural network to do that find optimal planning to maximize hydroelectric power generation of the Bhakra-Beas compound reservoir system, Liang and Hsu (1994) demonstrate how to implement used artificial neural networks for short-term hydroelectric generation planning of a power system, Tufegdzic (1997) Presents the use of neural networks for management and optimization of reservoirs to provide sufficient water for generation, Shadaksharappa (2011) presented a neural network to optimize generation scheduling of thermal power plants and compare the results with the classical method, Dike et al. (2013) presented a solution to the economic dispatch problem using lambda iteration using MATLAB programming and compared the results to genetic algorithms, and Saeed (2019) proposed a neural network to solve the economic burden transfer problem optimize. Based on the Lambda iterative optimization method. These are the relevant theories referenced for this paper and apply an artificial neural network technique for planned power generation for this research.

ANN is one of the proposed machine learning processes, which is a black box model used for various purposes and is a highly effective prediction tool. It is used for forecasts and estimates. It processes records individually and learns by comparing the most arbitrary classifications of records. Error classification begins with entering error data into the network. Then check the exact value. If the result is good, the process ends. Adjust the algorithm again if the result is not good. After every adjustment, it's still not good. Repeat this many times until are satisfied and stop. Especially when predicting flood discharges at downstream stations of unmeasured rivers. Make messages fast and flexible. The complex correlation problem of hydropower nonlinear variables can be overcome by constructing ANN modeling for power plant efficiency predictions based on some data relevant to previous observations of the parameters. For the neural network backpropagation algorithm, this is a very clear and accurate step in model prediction, so many ANN models are more optimized and accurate than various artificial intelligence. To check the accuracy and precision of the hydropower generation model, the input and the output are necessary parameters for testing and validation.

This paper presents 10 power plants in the central-1 region network to be considered as a case study. Such details are shown in Table 1. This research has proposed the abilities of neural networks to predict electricity generation in hydropower plants. The purpose of this paper is to reduce generation costs and maximize power generation to match the supply and demand sides. In particular, to keep electricity imports from neighboring countries as low as possible during the dry season and to ensure that all plants in the country are producing at the highest possible output. This research aimed to study the feasibility of using artificial neural networks in hydroelectric power plants, particularly in the field of power generation and reservoir management. Then use the datasets obtained from the Lambdas data mining steps to feed them into the model to train the last designed architecturally neural network. After that, the neural network generates new prediction results. They are then compared to results obtained using traditional lambdas calculation methods to determine which is better. The results of the comparison show that the side hammer neural network method gives more satisfactory results. This indicates that the designed model can also be applied to hydropower plants generation management.

2. PROBLEM FORMULATION

2.1 Optimal Power Flow solution.

Optimal Power Flow (OPF) is a program that helps solve electrical system problems, especially in the area of optimal distribution and minimizing power dissipation. Optimal disposition is essential for the electrical system to return the highest production efficiency. Reducing the cost of sending electricity to consumers and maintenance is divided into two parts. The first relates to the minimal cost of generating electricity, known as economical power distribution, and the other relates to delivering the generated electricity to the load with minimal losses. The allocated economic load determines each power generation plant to reduce the production cost in the system that is fed to the load and focuses on the generation cost of all power plants operating in the system. With the minimal loss, problems can take many paths depending on the current control in the system. There are several optimization methods to solve complex nonlinear problems as shown in Figure 2

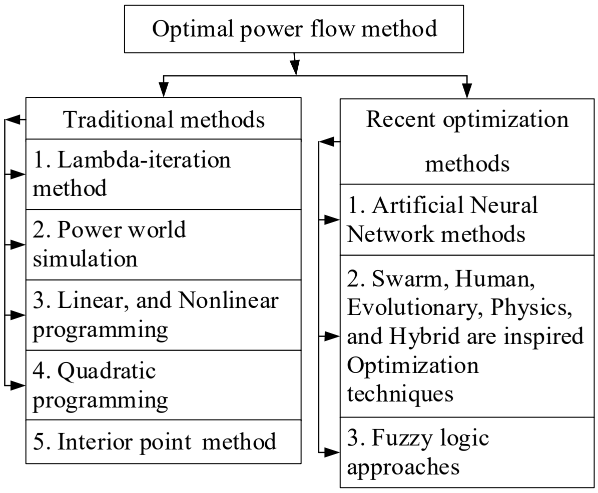

Figure 2 Optimal power flow solution method

2.1.1 Distribution of loads between units in the power plants

When the load increases, power is only supplied to the systems with maximum efficiency. The most efficient facility will supply electricity up to the point of maximum efficiency for that facility. Determination of the economic load distribution between different production units. Distributing the load between two units depends on the increase or decrease of the load on that unit. All costs increase or decrease accordingly. It shows that electricity production is related to costs. Considering the slope of the input-output curves of both units, this will be as shown in Figure 3

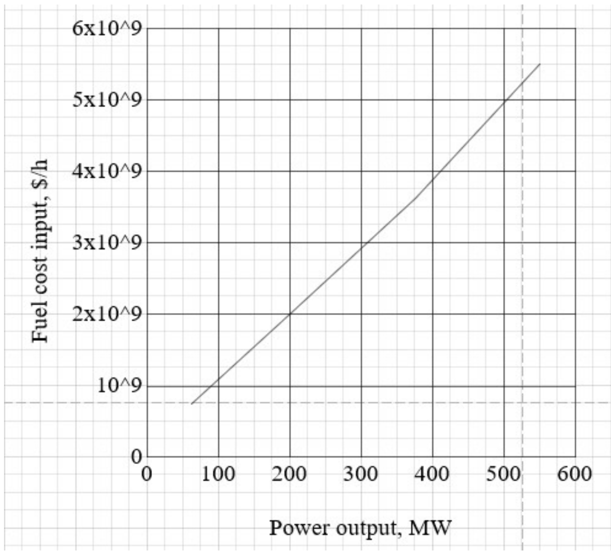

Figure 3 Input-output curve for a generating unit showing fuel cost input versus power, output

If dCi/dPGi is the increased fuel cost in dollars per megawatt-hour and Ci/PGi is the average fuel cost in the same unit, then the unit input-output curve is written as a quadratic function:

$$C_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2 (\$/h) \tag{1}$$

If the unit has an incremental fuel lambda can be defined by:

$$\lambda_i = \frac{dC_i}{dP_{Gi}} = 2c_i P_{Gi} + b_i (\$/MWh) \tag{2}$$

Where a_i, b_i, c_i are the power plant coefficients.

2.1.2 Distribution of loads between the power plants

Loss in power transmission lines must be considered to account for load sharing between power plants. The load needs to be reduced on power plants with low marginal costs and the load needs to be increased on power plants with high marginal costs. It is, therefore, necessary to find a way of keeping these losses as low as possible when sending electrical energy. By planning each crop generation for maximum savings at a given load level.

$$C_T = C_1 + C_2 + \ldots + C_n = \sum_{i=1}^{n} C_i \tag{3}$$

Where Ci is the total cost of generation; C1, C2, and Cn are the cost of generating of each power plaequal
where PG1, PG2, PGn are the power of each power plant and PGT is the total power of the power plant. Which can be written in a new way

$$P_L + P_D - \sum_{i=1}^{n} P_{Gi} = 0 \quad (4)$$

Where PD is the demand and PL is the transmission loss

2.2 Unit Commitment

Future projected a load supply plan knowing the capacity and reserve power to meet potential abnormal operating conditions. For example, consider a thermal unit planning problem where K the generators are 4 units (K = 4), and possible combinations of 15 sets of the theory are obtained as shown in Table 2.

Table 2 Units combined

Unit	1	2	3	4
X1	1	1	1	1
X2	1	1	1	0
X3	1	1	0	1
X4	1	0	1	1
X5	0	1	1	1
X6	0	1	0	1
X7	1	0	0	1
X8	0	0	1	1
X9	1	1	0	0
X10	1	0	1	0
X11	0	1	1	0
X12	1	0	0	0
X13	0	1	0	0
X14	0	0	1	0
X15	0	0	0	1

2.3 Optimal Dispatch Operation

Hydroelectric power generation schedules must follow the Optimal Power Flow (OPF) principle to determine operating costs. According to the principle of system optimization under different load conditions. The power plant must have minimal total production costs. This also results in the lowest overall generation cost. While total power generation still meets demand. If one considers n plants in the network and determines the load side of the power generation, each power plant enters a target function as follows:

Minimize:

$$C_T = C_1 + C_2 + \ldots + C_n = \sum_{i=1}^{n} C_i(P_{Gi}) \quad (5)$$

The actual power generation cost function is expressed as a quadratic function as follows.

$$MinP_{Gi} \sum_{i=1}^{n} C_i(P_{Gi}) = MinP_{Gi} \sum_{i=1}^{n} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (6)$$

$$P_{GT} = P_{GT} + P_{GT} + \ldots + P_{Gn} = \sum_{i=1}^{n} P_{Gi} \quad (7)$$

$$\sum_{i=1}^{n} P_{Gi} - P_D = 0 \quad (8)$$

Where ai, bi, ci coefficient of plant i
n: is the number of power plant
i: the index of power plants in dispatched
C_i: generation cost of plant i [\$/h]
C_T: total generation cost [\$/h]
P_{Gi}: the power generation of plant i [MW]
P_T: total power generation [MW]
P_D: total load demand in the system [MW]

2.3.1 Power Balance

The power generation of a hydropower station. Should be considered optimal to reduce the cost of power generation and provide higher power generation. Therefore, the power production is equal to the total transmission losses plus the total system load requirement. Which is described as follows:

$$\sum_{i=1}^{n} P_{Gi} = P_{Loss} + P_D \quad (9)$$

Where P_D: Total load demand [MW]
Ploss: Total transmission loss [MW]

2.3.2 Power constraints

The limitation of the power generation optimization problem is that each power plant must be between the minimum and the maximum.

$$P_{Gi(min)} \leq P_{Gi} \leq P_{Gi(max)} \quad (10)$$

Where $P_{Gi(min)}$ is the minimum limit of generation for plant i [MW]
$P_{Gi(max)}$ the maximum limit of generation for plant i [MW]

2.3.3 Lagrange functions

An objective function multiplied by an uncertain multiplier expressed as

$$L = C_T + \lambda\phi \quad (11)$$

Define the Lagrange function

$$L = L(P_{Gi}, \lambda) \quad (12)$$

Substitute equations (6), (5), and (9) into (12).

$$L(P_{Gi}, \lambda) = C_i(P_{Gi}) + \lambda(P_D - \sum_{i=1}^{n} P_{Gi}) \quad (13)$$

Solve equation (14) to get

$$\frac{\partial L(P_{Gi},\lambda)}{\partial P_{Gi}} = \frac{\partial C_i(P_{Gi},\lambda)}{\partial P_{Gi}} - \lambda = 0 \quad (14)$$

$$\frac{\partial L(P_{Gi},\lambda)}{\partial P_{Gi}} = P_D - \sum_{i=1}^{n} P_{Gi} = 0 \quad (15)$$

Solve equation (15) to get

$$\frac{\partial C_i(P_{Gi},\lambda)}{\partial P_{Gi}} = \lambda \quad (16)$$

For i[th] generating units, the incremental cost becomes

$$\frac{\partial C_i(P_{Gi},\lambda)}{\partial P_{Gi}} = 2a_i P_{Gi} + b_i \quad (17)$$

When equations (17) and (18) are combined, one obtains

$$\lambda = 2a_i P_{Gi} + b_i \quad (18)$$

After arranging an equation (19) will get

$$P_{Gi} = \frac{\lambda - \text{bthe the}_i}{2a_i} \quad (19)$$

Substituting equation (20) into (16) we get

$$P_D = \sum_{i=1}^{n} \frac{\lambda - b_i}{2a_i} \quad (20)$$

Finally got

$$\lambda = \left(\frac{P_D + \sum_{i=1}^{n} \frac{b_i}{2c_i}}{\sum_{i=1}^{n} \frac{1}{2c_i}} \right) \quad (21)$$

2.4 Optimal Dispatch by Lambda Method

Steps to solve the problem with Lambda is to use computer algorithms to calculate complex processes using MATLAB. First, read out system data such as cost functions of each power plant (ai, bi, and ci) and generation boundary conditions. Lambda initial conditions are used to define each asset's power (Pi) based on its incremental cost. Then the load and power generation of the entire power plant is determined. An optimal generation plan is obtained by comparing the tolerance (ε). If they differ, they are recalibrated and reset to the starting point for recalculation. Then the generation cost is simulated using Equation (1).

1. Firstly, start by inputting the number of plants, total demand, power generation limit, coefficient of each power plant, iteration limit, tolerance, and the default setting of λ;
2. Set default lambda
3. Compute P_{Gi} (i=1, 2,…, n) using (20);
4. Check the power generation limit using (11);
5. If $P_{Gi} \geq P_{Gi(max)}$, set $P_{Gi} = P_{Gi(max)}$,
   If $P_{Gi} \leq P_{Gi(min)}$, set $P_{Gi} = P_{Gi(min)}$;
6. Compute ΔP using (9);
7. Compute Δλ(k) using (22);
8. If Δλ(k) ≠ Tolerance. Update the λ
9. Return to step 3
10. If Δλ(k) = Tolerance, stop and display the value of P_{Gi} and λ. Then stop.

Like the flowchart shown in the figure below

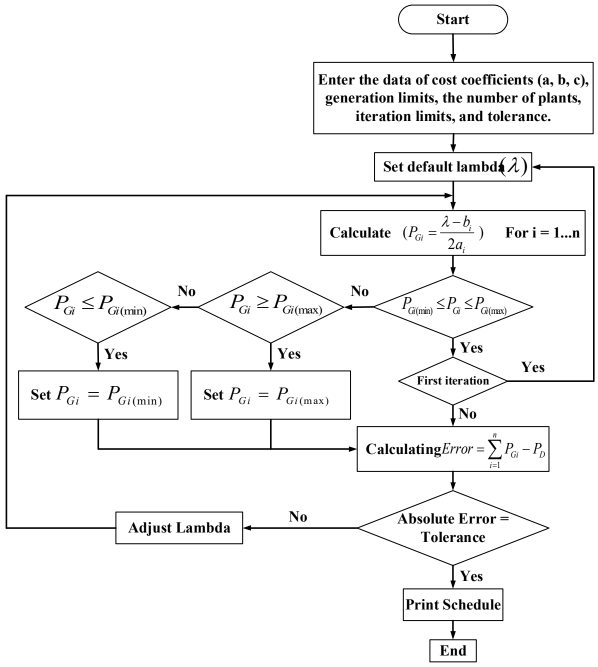

Figure 4 The procedure for calculating the power and cost of each power plant the lambda iteration method

3. ARTIFICIAL NEURAL NETWORK

3.1 Introduction

The concept of information processing by neural networks is the same as that of the human brain. A neural network architecture consists of many interconnected cells that work together through experiential learning through the concept of learning the relationship between cause and effect. The perfect connection of neurons across all layers is the typical architecture. It consists of an input layer that takes external data and transmits it to the network for learning. The layer between the input and output layers is hidden. It can learn things and store the results of different learning methods in the output layer as shown in Figure 5.

NUEJ
Naresuan University
Engineering Journal

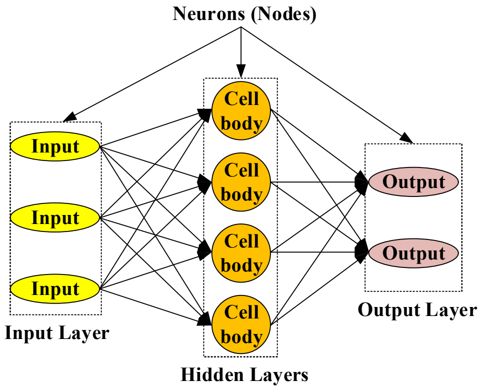

Figure 5 Typical architecture of a neural network

3.2 Neural Networks to Solve Problems

Most problem variables are inputs, weights, and outputs with examples (training data) that identify a problem that can be solved, e.g., Input and output are known. For training purposes, various algorithms can be used to find a set of weight matrices that should match the correct output when applied to any input network. In the learning process, it uses a gradient algorithm for training. It's a simple training algorithm. What is used in the case of supervised training simulation schemes can change the weight of the network, including reducing the error value. Propagation is an extension of the delta gradient learning rule after an error has occurred. The Back-Propagation Neural is one of the error learning algorithms based on the principle of backpropagation. With back-propagation from the output layer to the input layer through a hidden layer. The delta learning rule based on gradients was used to adjust the weights for each error learning. For each weight adjustment, the weights that precede the output layer are adjusted first. Then actually follows the adjustment of the weight on the back of the input layer.

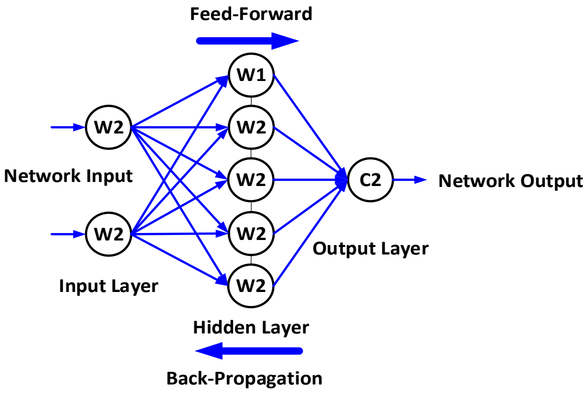

Figure 6 Typical backpropagation architecture of neural networks

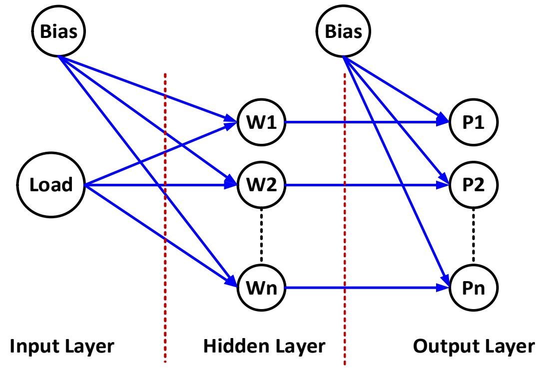

Figure 7 Backpropagation architecture for neural networks to compute power generation

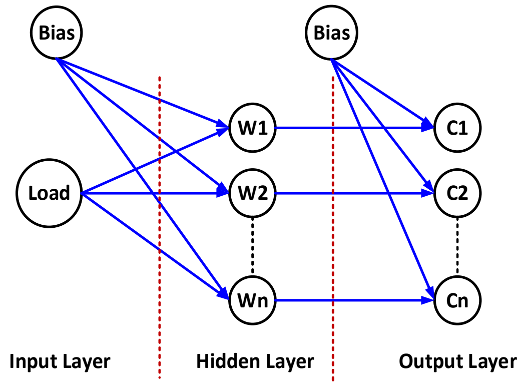

Figure 8 Backpropagation architecture for neural networks to calculate electricity generation costs

Fig. 5 and Fig. 6 are neural network designs for calculating the sum of power generation and the sum of cost generation.

4. DATA COLLECTION FOR TRAINING

4.1 Cost Function Configuration

Figure 4 demonstrates the procedure for determining the variable parameters of the quadratic function of power generation cost function for each power plant. First, the existing power plants in the Central-1 region network of EDL were modeled in the Power World Simulator. The model of the system is then simulated in an optimal power flow. Then power flow and power loss are analyzed. Finally, the cost function of each power plant (ai, bi, ci) is analyzed using the Excel function after simulating the coefficients of the hydropower plants using the Power World Simulation program and the Excel function. The cost function parameters (ai, bi, ci) for each plant are presented in Table 3 and Table 4

Figure 7 and Figure 8 show that there is an input in the input layer that feeds into the networks, resulting in 10 outputs of 32 neutrons. Where both networks use the same input as the load. The output in Figure 7 represents the electricity generation from 10 power plants and Figure 8 represents the costs of generation.

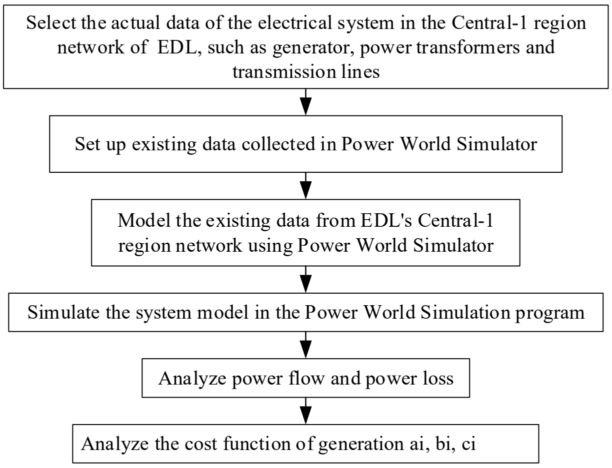

Figure 9 The procedure for calculating coefficients using Power World Simulation Software.

Table 3 Cost coefficients of electricity generation from 10 power plants in the Central Region 1 network

Generation Name	Coefficient of the power generation cost		
	a ($/h)	b ($/MWh)	C ($/MW²h)
Nam Ngum1	441.35	54.1360	0.0086
Nam Leuk	642.60	54.3790	0.0200
Nam Mang3	775.26	52.6390	0.0192
Nam Lik1-2	328.51	48.8930	0.0159
Nam Ngum5	348.51	47.6350	0.0204
Nam Ngiep2	545.86	58.6530	0.0174
Nam Phai	611.33	59.8610	0.0194
Nam Chien	583.34	68.0540	0.0255
Nam San3A	390.14	73.6690	0.0325
Nam San3B	833.84	72.2920	0.0264

Since the cost of production is a condition of this research that must be taken into account. Therefore, the tar values of 10 power plants are defined as shown in Table 5 below.

Table 4 Generation limits of 10 power plants in the Central-1-region network

Generation Name	The Limit of generation	
	Min (MW)	Max (MW)
Nam Ngum1	15	155
Nam Leuk	20	60
Nam Mang3	10	40
Nam Lik1-2	20	100
Nam Ngum5	20	120
Nam Ngiep2	20	180
Nam Phai	15	104
Nam Chien	15	86
Nam San3A	15	70
Nam San3B	10	45

Table 5 Existing tariffs of 10 power plants in the Central-1 region network

No.	Hydro Power Plant	Tariff ($/kWh)
1	Nam Ngum1	0.0533
2	Nam Leuk	0.0533
3	Nam Mang3	0.0533
4	Nam Lik1-2	0.04822
5	Nam Ngum5	0.04729
6	Nam Ngiep2	0.05800
7	Nam Phai	0.05330
8	Nam Chien	0.06800
9	Nam San3A	0.07320
10	Nam San3B	0.07320

4.2 Process of conducting research

First of all, it is necessary to collect the data from power, generation, and transmission systems in the EDL network of the Central-1 region to analyze variables using the Power World Simulator program. Then apply the results to the neural network training. Which details are as follows as Figure 10

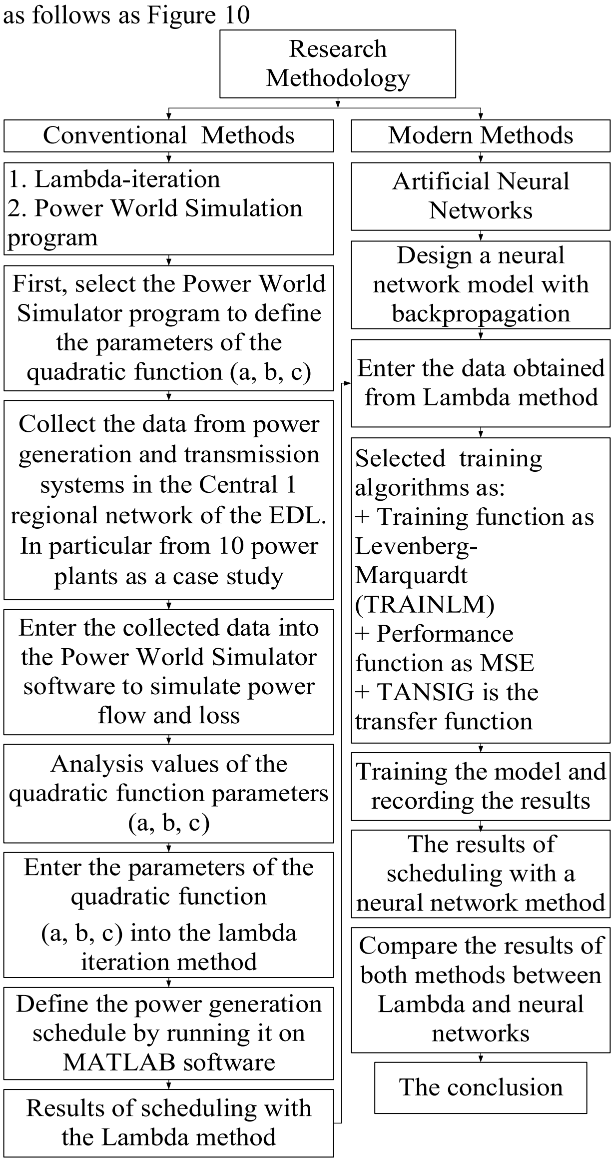

Figure 10 Flow chart showing the process of conducting research

5. SIMULATION RESULTS

Parameters of the quadratic cost function (1) as a, b, c are calculated in the lambda iteration method regardless of transmission line losses and any faults in the power plant. Consider calculating 10 power plants in the Central-1 region network using MATLAB R2018b (9.5.94). First, it is calculated with the lambda method, then the result is calculated in the neural network. Finally, compare the results of both methods with each other as the results are shown in Table 8. This is divided into two training parts. Start the training by entering the data obtained from the Lambda iteration method into the model designed in the MATLAB program and start the model training process. After completing the training process, the result is the power of each power plant PGn (MW). The second part of the training state is the load demand and production cost data. It is obtained from the lambda iterative method. Both are fed into the model in the MATLAB program as input and output data after the training is complete. The result obtained is the cost ($/kWh) as shown in Fig. 5 and Fig. 6. Next comes the explanation of the symbols, e.g., PGn represents the power production of n plants by the Lambda iteration method, and Cost PGn cost represents the production costs of n plants by the neural network method.

The aim of this paper is that the total cost of generation must be as low as possible and the total output must be maximum. The simulation results are as follows. The overall performance with the Lambda Iteration method is lower than that of the Neural Network method (PG < PGn) and the total cost of generation with the Lambda Iteration method is higher than that of the Neural Network method (Cost > Cost PGn) with a load of 160 MW to 960 MW. While the power of generation changes according to the changing load.

The neural network method took 108 seconds to calculate and the lambda iteration method took 528 seconds to calculate. Shows the difference between both methods. This can be summarized as follows: the neural network method is faster than the lambda method. Executed on a single computer by a 64-bit version of MATLAB R2018b. Processor: Intel(R) Core (TM) i5-8300H CPU @ 2.30 GHz; Installed RAM: 8 GB operating system

For back-propagation networks, the training algorithms are selected as the type, Levenberg-Marquardt (TRAINLM) is a training function, MSE is a performance function, and TANSIG is the transfer function. Next, show the detailed parameter settings and the results of running the models

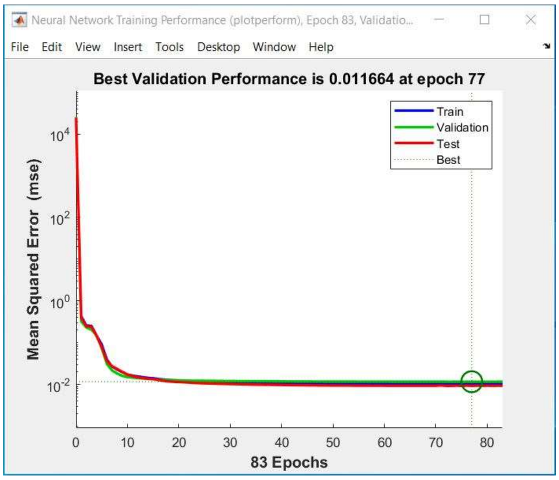

Figure 11 Training performance

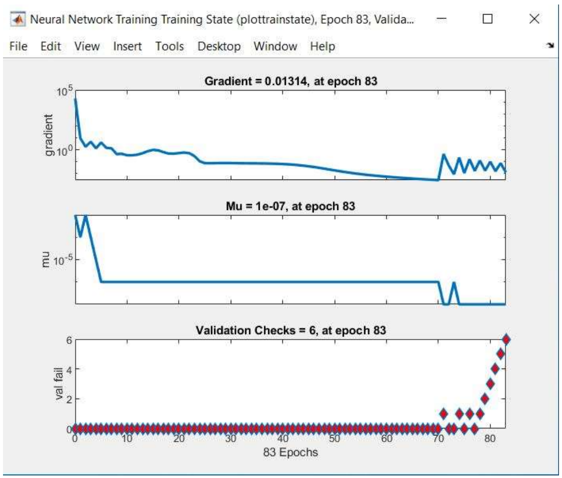

Figure 12 Training state

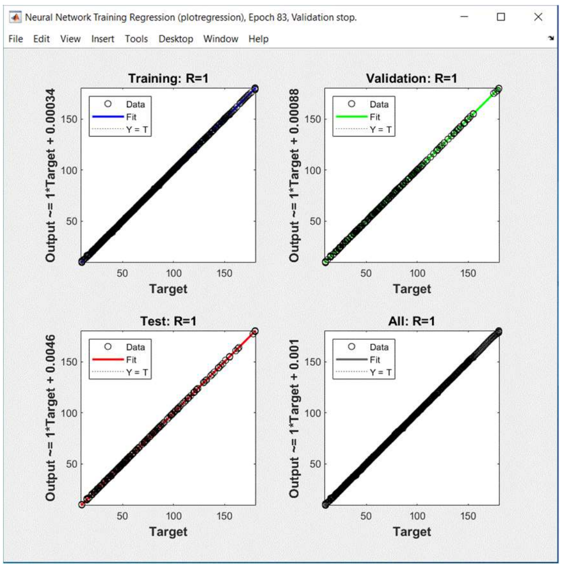

Figure 13 Training regression

For the training process ended at 83 epochs within 108 seconds. The results are shown in Tables 5 and 6.

Table 6 Simulation results of the power generation in neural networks ($P_{G1} - P_{G5}$)

Load	PG1	PG2	PG3	PG4	PG5
160	15.00	20.00	10.00	20.48	20.70
200	15.00	20.00	10.00	27.73	52.22
260	15.00	20.00	10.00	61.31	78.60
300	15.01	20.00	9.97	83.80	96.17
360	14.66	19.96	30.40	100.03	120.05
400	45.04	19.77	40.21	100.00	120.01
600	155.02	60.01	40.00	100.00	120.00
660	155.00	60.00	40.00	100.00	120.00
700	155.00	60.00	40.00	100.00	120.00
760	155.00	60.00	40.00	100.00	120.00
800	155.00	60.00	40.00	100.00	120.00
860	155.00	60.00	40.00	100.00	120.00
900	155.00	60.00	40.00	100.00	120.00

Table 7 Simulation results of the power generation cost in neural networks ($P_{G6} - P_{G10}$)

Load	PG6	PG7	PG8	PG9	PG10
160	20.00	15.00	15.00	15.00	10.00
200	20.00	15.00	15.00	15.00	10.00
260	20.00	15.00	15.00	15.00	10.00
300	20.00	15.00	15.00	15.00	10.00
360	20.00	15.00	15.00	15.00	10.00
400	19.99	15.00	15.00	15.00	10.00
600	61.27	23.69	15.00	15.00	10.00
660	92.81	52.12	15.00	15.00	10.00
700	113.88	71.02	15.00	15.00	10.00
760	145.52	99.40	15.03	15.00	10.00
800	178.99	103.84	17.00	15.00	9.97
860	179.95	103.99	76.30	15.06	9.66
900	180.00	104.00	85.87	15.02	40.26

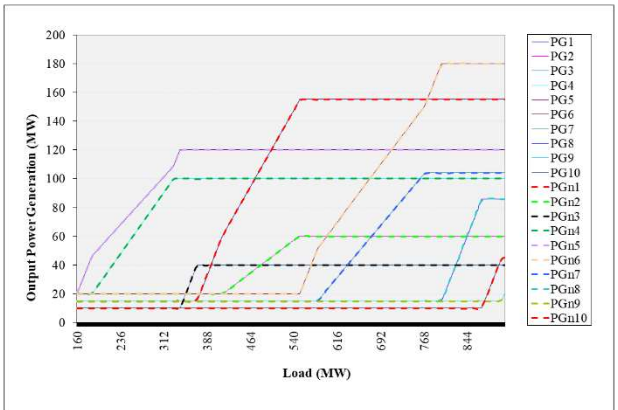

Figure 14 The results of the total power generation using the Lambda iteration method and the neural network for 10 power plants in the Central-1 regional network

The results of both methods can be summarized as shown in Table 8

Table 8 Compare the results calculated by the neural network with the Lambda method calculation

Methods	Total Power Generation (MW)	The total cost of the generation ($/h)	Time (s)
Lambda iteration	448,560	29,664,071.99	528
Neural Network	448,567	29,663,499.09	108
Difference	7.00	-572.90	420

demonstrated the hydroelectric power generation schedule using the neural network method. Both methods deliver different power, so the neural network method can generate one more power generation than the lambda method up to 7 megawatts, saving the capital cost of generation to $572.90/hr. At 420 seconds, the computing time of the neural network is less than lambda iteration.

The results of this study show that the papers refer to are consistent, which is evident in many fields, such as the application of neural networks to forecast electricity demand, forecast electricity supply adequacy, forecast water inflow, forecast precipitation, forecast power plant generation that is used to planning, and is a factor in the decision-making of human who is more positive.

6. CONCLUSION

This paper presents a guideline for power generation scheduling of 10 power plants in EDL's Central-1-Region network by applying a neural network to train the model based on the data from these power plants using feedforward and backpropagation algorithms running. It was developed to calculate the results according to the neural network architecture designed in MATLAB. The results obtained from the neural network method are compared to the results from the lambda method to determine feasibility. As the results showed, the neural network method provides slightly more satisfactory results than the lambda method, resulting in less computing time and higher productivity due to the neural network method. All work on the theory of optimal dispatch problems, the aim is to find the most suitable methods to minimize production costs and maximize power production. This paper discusses how to use MATLAB's powerful tools to design a model based on the desired architecture and demonstrates the feasibility of using this technique. This applies to optimization tasks in power plants in areas such as storage inflow forecast, storage management, which can also be precipitation forecast, and numerous power generation. The neural network is a simple calculation method and saves calculation time. It can also be used, as a tool to cut off the color of works, which is an alternative that draws a lot of attention.

7. ACKNOWLEDGEMENT

I would like to thank the cooperation project EGAT-CMU for making the master's degree in energy possible. Especially in the technical and academic cooperation projects between EGAT and EDL. Another with EDL Generation Public Company Limited. Which supported this research fund.

8. REFERENCES

Estoperez, N., & Nagasaka, K. (2006). An artificial neural network-based micro-hydro power generation scheduling: considering demand profile and environmental impact. Clean Technologies and Environmental Policy, 8(2), 123-130.

EDL. (2020, October 29). Annual Report 2019. http://www.edl.com.la/file_post.php?id=12

Naresh, R., & Sharma, J. (2000). Hydro system scheduling using the ANN approach. IEEE Transactions on power systems, 15(1), 388-395.Electrical Engineering of Riga Technical University (RTUCON), pp. 1-6. IEEE, 2016.

Sauhats, A., Petrichenko, R., Broka, Z., Baltputnis, K., & Sobolevskis, D. (2016, October). ANN-based forecasting of hydropower reservoir inflow. In 2016 57th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON) (pp. 1-6). IEEE.

Dogra, R., Gupta, N., & Saroa, H. (2014, January). Economic load dispatch problem and Matlab programming of different methods. In International conference of advance research and innovation (ICARI-2014).

Arora, I., & Kaur, M. (2016, November). Unit commitment scheduling by employing artificial neural network-based load forecasting. In the 2016 7th India International Conference on Power Electronics (IICPE) (pp. 1-6). IEEE.

Suman, M., Rao, M. V. G., Hanumaiah, A., & Rajesh, K. (2016). Solution of economic load dispatch problem in power system using lambda iteration and backpropagation neural network methods. International Journal on Electrical Engineering and Informatics, 8(2), 347.

Liang, R. H., & Hsu, Y. Y. (1994). Scheduling of hydroelectric generations using artificial neural networks. IEE Proceedings-Generation, Transmission, and Distribution, 141(5), 452-458.

Tufegdzic, N. (1997). Optimal scheduling and dispatch for hydroelectric generation (Doctoral dissertation, University of Tasmania).

Kilinç, I., & Ciğizoğlu, K. (2012). Reservoir management using artificial neural networks. 14th. Reg. Directorate of DSI (State Hydraulic Works), Istanbul, Turkey.

Shadaksharappa, N. M. (2011). Optimum generation scheduling for thermal power plants using artificial neural network. International Journal of Electrical and Computer Engineering, 1(2), 134.

Dike, D. O., Adinfono, M. I., & Ogu, G. (2013). Economic dispatch of generated power using the modified lambda-iteration method. IOSR Journal of Electrical and Electronics Engineering, 7(1), 49-54.

Saeed, I. K. (2019). Artificial Neural Network Based on Optimal Operation of Economic Load Dispatch in Power System. Zanco Journal of Pure and Applied Sciences, 31(4), 94-102.

Imen, L., Mouhamed, B., & Djamel, L. (2013, November). Economic dispatch using classical methods and neural networks. In 2013 8th International Conference on Electrical and Electronics Engineering (ELECO) (pp. 172-176). IEEE.