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Experimental study for artificial neural network (ANN) based prediction of electric energy production of diesel engine based cogeneration power plant

Dizel motorlu kojenerasyon santralinin elektrik enerjisi üretiminin yapay sinir ağı (YSA) ile tahmini üzerine deneysel çalışma

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Abstract

In this study artificial neural network (ANN) has been developed in order to estimate the electricity production of cogeneration power plant, which produces a total of 11.52 MW electric power, consisting of two V type and 12 cylinders each of which is 5.760 kW diesel engines running with heavy fuel oil no 6. In the ANN which was developed for the estimation of electric power generation of cogeneration, power plant(W), Time period (t), working hours (h), fuel consumption (m) and internal power consumption (Wp) values were used as input variables. After evaluating the performance of different ANNs, an ANN, consisting of one hidden layer and 10 neurons, was considered to be the most ideal one. As a result of the comparison with experimental data, it is concluded that this model estimates the electricity generation values of the cogeneration power plant with an R-value of 0,99073 and mean square error 4.734e-8

Keywords: Cogeneration, Diesel engine, Power plant, Electricity consumption, Artificial Neural Network

Özet

Bu çalışmada iki adet V tipi 12 silindirli dizel motordan oluşan ve her biri 5.760 kW olmak üzere toplam 11.52 MW elektrik enerjisi üreten kojenerasyon enerji santralinin elektrik üretiminin tahmin edilmesi için yapay sinir ağı (YSA) geliştirilmiştir. 6 no'lu fuel oil ile çalışan kojenerasyon enerji santralinin elektrik enerjisi üretiminin (W) tahmini için geliştirilen YSA'da, zaman (t), çalışma saatleri (h), yakıt tüketimi (m) ve iç tüketim (Wp) değerleri giriş değişkenleri olarak kullanılmıştır. Farklı YSA'ların performansı değerlendirildikten sonra, bir gizli katman ve 10 nörondan oluşan YSA en ideal model olarak değerlendirilmiştir. Deneysel verilerle yapılan karşılaştırma sonucunda, bu modelin kojenerasyon enerji santralinin elektrik üretim değerlerini 0,99073 R değeri ve 4.734e-8 MSE ile tahmin edebileceği sonucuna varılmıştır.

Anahtar kelimeler: Kojenerasyon, Dizel motor, Enerji sanrali, Elektrik tüketimi, Yapay Sinir Ağı

1 Introduction

With the increase in population, the developing industrial industry has brought more energy needs. The studies of the International Energy Agency (IEA) show that world electricity demand in 2040 will increase by 80% compared to 2012 [1]. The types of electric power plants are vital in meeting the increasing demand for electricity. Consumption of electricity where it is produced is one of the most preferred and useful methods since it eliminates the factors causing the decrease in efficiency such as energy losses in transmission lines. In the industrial area, cogeneration power plants are frequently preferred as high-efficiency energy production system in case there is a need for electrical power as well as heat power (hot water, steam etc.). It is possible to define the cogeneration system as a system where electricity and heat energy are produced simultaneously using a single fuel source. The cogeneration system is used in domestic applications as well as in industrial systems which need electricity and heat energy [2]. Because of the high financial savings due to the high fuel efficiency obtained from the system, it is seen that legal subsidies are applied in many countries for cogeneration systems which are frequently preferred owing to their environmental advantages [3-5]. The cogeneration system, which can also be known as combined heat and power (CHP) plant, is not a new concept. At the end of the 1800s, when steam was the major energy source in the industry, the concept of cogeneration emerged as a result of replacing mechanical driven systems with electrically driven systems and replacing steam-driven belt-pulley mechanisms with electricity and motors [6, 7]. Demand for cogeneration systems is increasing day by day due to the ability to produce the required electricity and thermal energy from a single fuel source such as oil or natural gas and with a high efficiency ratio. The energy efficiency of cogeneration systems can reach up to 80% compared to conventional electricity generation systems [8]. The high fuel efficiency values in electrical and thermal energy production are the main advantages of the cogeneration system. Because waste heat from conventional systems is converted into useful thermal energy in cogeneration systems, a smaller amount of fuel is needed to produce the equivalent amount of energy as conventional systems (turbine, steam boilers, etc.) to produce electrical and thermal energy in the cogeneration system [9, 10]. As they reduce the impact of greenhouse gases by up to 50% with their technical and economic advantages, the environmental advantages of cogeneration systems reach considerable proportions [11, 12]. Although they have many different applications, the most common application in cogeneration power plants is the power plants established with internal combustion engines and open cycle gas turbines. Heavy fuel diesel power plants, a low-grade oil refinery product, operate on diesel fuel, which is relatively inexpensive than other types. This technology, which can produce hundreds of megawatts of energy, stands out with

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the advantages of being able to be installed quickly in less than twelve months [13]. According to their capacity, diesel engine cogeneration power plants can be classified into three main categories as low capacity (15 - 1000 kW), medium capacity (1 - 6 MW) and high capacity (over 6 MW). The diesel cogeneration power plant has four available waste heat sources: exhaust gas, engine jacket cooling water, lubricating oil cooling water and charge air cooling water. Exhaust gases from diesel cogeneration power plants have a substantial sum of thermal energy that can be used to recover waste heat. The heat recovered from the exhaust gas is generally considered to be hot water or steam production. The resulting recycling energy can be used for an assortment of process needs, heating and cooling applications [14]. In many studies on energy efficiency in the literature, the advantages of cogeneration plants have been scientifically proven [15-18]. In the literature, many studies have been done on diesel engines and cogeneration power plants.

While some of the studies on diesel engines have carried out analyzes on the second law of thermodynamics [19, 20], some researchers have studied the effects of diesel engine parameters on performance and emission values [21-23]. Previous studies on cogeneration power plants have mostly focused on the efficiency of power plant and exergy analysis. Ust et al. [24] in their study on a gas turbine regeneration system, optimizing the external performance criteria of the power plant, demonstrated the advantages of this method. In his study for cogeneration power plants, Ertesva [25] evaluated the external comparisons of efficiency indicators for cogeneration power plants and consequently stated that external improvements were achieved to a limited extent by several energy-based efficiency indicators. Khaliq and Han [26] analyzed the heat and power system of a gas turbine cogeneration plant using the first and second laws of thermodynamics. The case study on a diesel engine-operated cogeneration plant was also carried out with only the first laws in mind [27]. In the management of the electrical energy system, it is of excessive prominence to estimate the production capacities of the power plants operating in the grid. In cases where the total capacity of electrical energy that the power plants in the system can produce is lower than the amount of electrical energy required, power outages begin to occur. Power cuts in the system, especially unplanned power outages, bring technical and economic problems. Considering that the sudden power outages, stopping in industrial processes, deterioration of the materials in the production system, interruption of production and re-commissioning, serious losses are observed [28]. Unstable operation of power generation systems with interruptions can also cause malfunctions in mechanical systems and generator units. In view of all these reasons, accurate estimation of the generation capacity of an electric power plant is of great importance both in terms of providing the required energy stably and sustainably and in the management of the electricity grid [29].

In the literature, many studies have been conducted on the estimation of the electricity generation capacity of power plants. Since data mining techniques are used in the methods used in such studies, it is possible to estimate the electricity generation capacities only for local cases in the database. In the data mining technique, the structure of the database can be examined, and estimated values can be obtained [30]. In the absence of the data required to create a model in the database, errors can also occur in the estimation results. For example, since the decrease in the performance of an electrical power plant will increase as the working hours increase, long-term data of the power plant are needed to estimate the performance decline using long-term data for performance estimation by data mining technique. In the absence of sufficient data, the estimation results will not be accurate. It is seen that this method is frequently used in the literature due to the advantage that the characteristics and performance factors of the power plant can be evaluated simultaneously [31-33]. One of the methods for estimating the desired values is the artificial intelligence (AI) thanks to the algorithms developed using the obtained data. In the literature, artificial intelligence applications for estimating the performance and production values of power plants are frequently encountered. Smrekar et al. [34] and Tunckaya et al. [35] used statistical data and artificial neural network (ANN) model in their study on estimating the performance of coal-fired power plants. Boksteen et al. [36] used the Bayesian calibration model to estimate the power plant performance, while Tüfekci [37] preferred the machine learning model developed with long-term data to estimate the performance of combined cycle power plants. Many different studies have been made on the estimation of performance and production values of cogeneration power plants by ANN. Optimization of power plant parameters and development of ANN to achieve efficiency increase [38-41], modeling of the manners of power plant components such as steam boiler and turbine with ANNs [42-46], development of ANN for estimation of thermal efficiency and air pollution [47-51], optimization of power plant load distribution [52, 53], power plant production according to demands [54] are some examples of ANN studies on cogeneration power plants by researchers.

In this study, an ANN model has been developed in order to predict electrical energy production values of a diesel engine cogeneration power plant. However, many applications of ANNs in different areas are also included in the literature [55]. Although there are various studies in the literature on cogeneration power plants, there is no study on estimating the electrical energy production values of diesel engine cogeneration power plants using ANNs. This study is important in that it aims to fill this gap in the literature.

2 Description of cogeneration power plant

The cogeneration power plant investigated in this study was established to meet the electricity, hot water and steam needs of five different textile factories. The cogeneration power plant has two MAN brand diesel engines of type 12V32/40, each of which can produce 5760 kW of power. 12V32/40 refers to the 12 is the number of cylinders, V engine type (Vee engine), 32 cylinders bore (cm) and 40 is the piston stroke (cm). In Figure 1, cross-sectional view of the V32/40 diesel engine, in Figure 2 and Table 1, main dimensions of MAN 12V32/40 diesel engine are given [56].

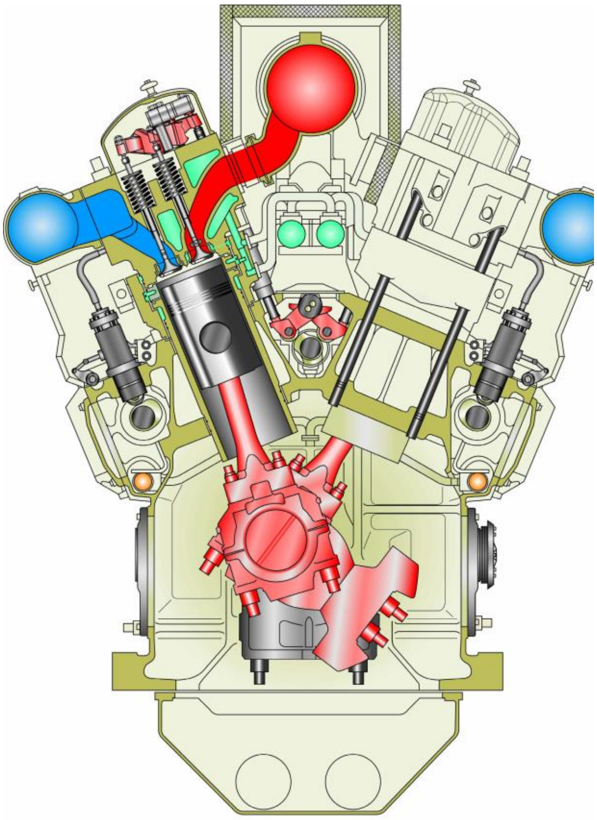

Figure 1. MAN 12V32/40 diesel engine cross section view on coupling side

In the calculations carried out for the cogeneration power plant, which has a total capacity of 11.52 MW, the data of one unit was used because the values of both diesel engines were the same. Heavy fuel oil No:6 is used as fuel in the cogeneration power plant. Although the purpose of using this type of fuel, which is also considered as heavy fuel, is its economic advantage compared to other types of fuel, operational difficulties due to the components contained in the fuel content (necessity of using fuel separator, maintenance requirements due to mechanical equipment contamination, yield reduction, etc.) can also be evaluated as disadvantages. The technical characteristics of the fuel used are given in Table 2.

Table 1. Main dimensions of MAN 12V32/40 diesel engine

A (mm)	B (mm)	C (mm)	H (mm)	W (mm)	Weight (tons)
6.475	4.215	10.690	4.795	3.370	98

In the cogeneration power plant, hot water and steam production are integrated with electricity generation, and all three energy types are transmitted to the enterprises to meet the electricity and process needs of five different power plants. Exhaust excavation at a temperature of approximately 520 °C enters the boiler and helps to produce a total of 4.5 t/h of steam at a pressure of 6 bar and a temperature of 165 °C. The process of removing the corrosive gases contained in the feed water fed to the steam serpentines in the boilers and reaching them to a temperature of 102 °C before the boiler is carried out by means of degasser. The schematic diagram of the cogeneration power plant is given in Figure 3 [57].

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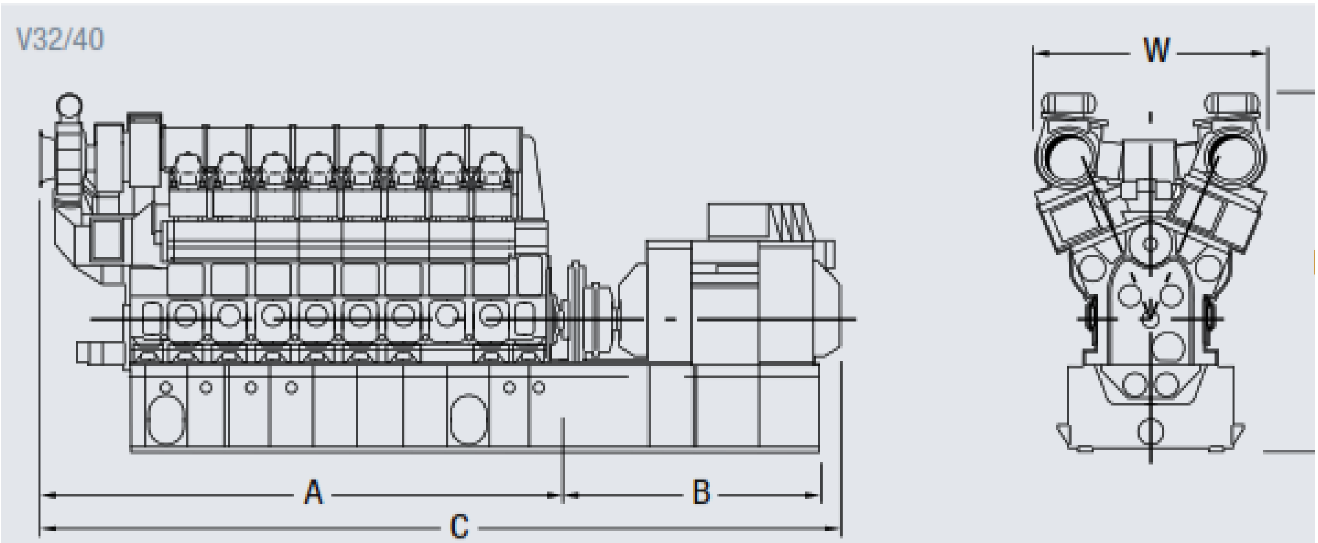

Figure 2. Main dimensions of MAN 12V32/40 diesel engine

The schematic diagram of the cogeneration power plant is given in Figure 3 [57]. The system in cogeneration power plant; diesel engine, exhaust gas turbine, compressor, heat recovery heat exchangers, charge air cooler, oil cooler, cooling tower, cooling tower heat exchanger and five circulation pumps. As a result of the combustion in the four-stroke diesel engine, the rotational movement of the crankshaft is converted to electrical energy by means of the generator (alternator). The first movement to diesel engines is given by 30 bar compressed air produced by the piston start air compressor.

Table 2. HFO technical characteristics

Heavy Fuel No:6 Typcial Specifications	
Ca (weight%)	86.5 - 90.2
H (weight%)	9.5 - 12.0
S (weight%)	8.51 - 7.68
Viscosity (CSt @38°C)	260 – 750
BS&W (%)	0.05 - 2.0
HHV (BTU/LB)	17410 - 18990

When the diesel engine starts, the exhaust gas flow resulting from combustion gives a rotational motion to the exhaust gas turbine. With the rotational movement of the air compressor connected to the same shaft, the compressed air required for the combustion reaction is sent to the cylinder. The entire exhaust gas turbine and air compressor unit, which is connected to the same charge and is integrated into a single case, is called a turbocharger. The charge air, which reaches high temperatures after the compressor, is gradually cooled in the charge air cooler using HT then LT water and then sent to the cylinder. The exhaust gas exiting the diesel engine first enters the turbocharger unit and gives the turbine movement.

After leaving the turbocharger, it enters the waste heat boilers and turns the hot water fed into the serpentines into steam. The steam produced is transferred from the waste heat boilers to the steam tank and then to the enterprises. LT provides water, oil cooling and charge air cooling. HT water, which has a higher thermal capacity, cools the engine, and at the same time, warm water from the engine is obtained by means of heat recovery heat exchanger with a capacity of 140 t/h and 85 °C. Information about the cogeneration power plant system is given in Table 3 [57].

3 Cogeneration power plant data analysis

In this study, which has been carried out in order to estimate the electrical energy production of the cogeneration power plant with ANN, the production values of the power plant for five-years (60-months) have been used. Time, working hours, internal power consumption and fuel consumption values were used as input variables. Monthly working hours of 5.760 kW diesel engine were recorded during the 60-month period on which the study was based. Working hours of the cogeneration power plant may vary according to months. The reason is that the downtime of the power plant due to breakdowns, maintenance and the downtime of the plants where energy is supplied. The cogeneration power plant worked for a total of 32.106 hours, with an average of 535,1 hours per month, ranging from 334 to 657 hours per month during the 60-month period of the study. The graph of the operating hours of the cogeneration power plant in the 60-month period is given in Figure 4.

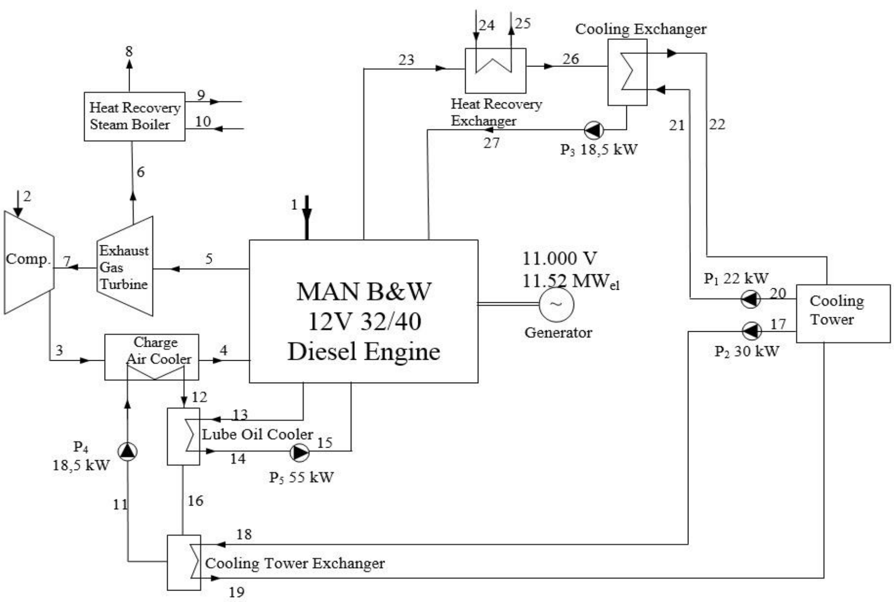

Figure 3. Schematic diagram of the cogeneration power plant

Table 3. Values about cogeneration power plant

No	Flow identification	m (kg/h)	T (°C)	P (kPa)
1	Inlet fuel	0.318	125	640
2	Air inlet (before compressor)	11	27	2
3	Air (after compressor)	11	225	300
4	Air (for charge)	11	55	300
5	Exhaust gas (before turbine)	11.31	520	-
6	Exhaust gas (after turbine)	11.31	330	2.5
7	Shaft	-	-	-
8	Exhaust gas	11.31	210	2.5
9	Steam for factory	12.50	165	600
10	Make up water	12.50	102	700
11	LT water (inlet)	31.67	35	260
12	LT water (outlet)	31.67	40	260
13	Lube oil (inlet) cooler	38.88	75	420
14	Lube oil (outlet) cooler	38.88	65	420
15	Inlet lub oil	38.88	65	420
16	Charge air (inlet) water for CT HE	31.66	50	260
17	Water (outlet) CT	31.94	30	300
18	LT (Inlet) water	31.94	30	300
19	LT (Outlet) water	31.94	40	300
20	Heat Recovery (Engine) Exchanger	31.66	25	300
21	HT (Inlet) water	31.66	25	300
22	HT (Outlet) water	31.66	25	300
23	Heat Recovery (Outlet)	20	90	420
24	Water (Return line)	38.88	70	600
25	Water (to factory)	38.88	90	550
26	HT Exchanger (inlet)	20	70	420
27	HT Exchanger (outlet)	20	80	420

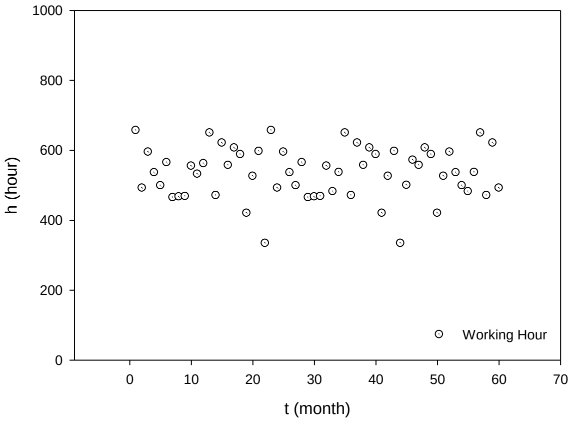

Figure 4. Operating hours of the cogeneration power plant

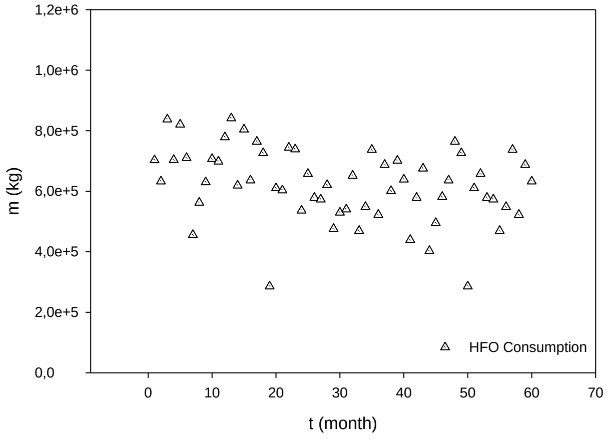

Figure 5. Fuel consumed in the cogeneration power plant

The graph of the amount of fuel consumed in the cogeneration power plant operating with heavy fuel oil no:6 over a period of 60 months is shown in Figure 5. In this process, between 285.698 kg and 841.073 kg fuel was consumed in the power plant and a total of 37.729.499 kg of fuel consumption was realized, with an average of 621.325 kg per month. The reason for the difference in fuel consumption in the power plant is that the working hours differ each month due to the circumstance that the power plant stops owing to the reasons explained previously.

During the operation of the cogeneration power plant, the equipment such as the fuel module, instrument air compressors, separators, lubrication and cooling water pumps, water treatment system and lighting consume electrical energy. Such consumption in the power plant is expressed as the internal consumption or internal need of the power plant. During the 60-month period in which the study data were taken, the total electricity consumption of 6.305.137 kWh was realized for the internal consumption of the cogeneration power plant ranging from 73.350 kWh to 132.062 kWh, with an average of 105.086 kWh per month. Figure 6 indications the graph of the internal consumption of the cogeneration power plant.

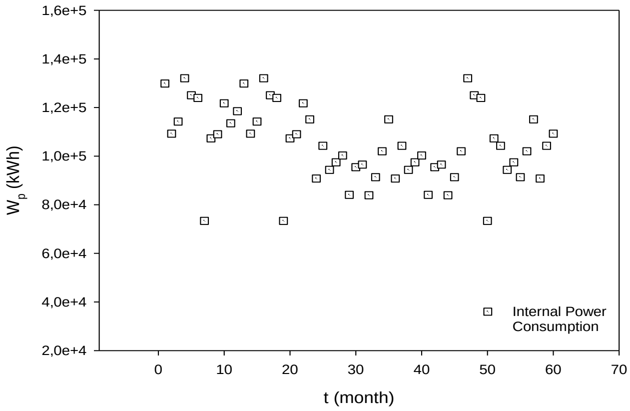

Figure 6. Internal consumption of the cogeneration power plant

4 Artificial Neural Network

One of the ideal methods for estimating the electricity generation of a cogeneration power plant is the use of ANN. ANNs generally be made of three separate layers: input, hidden and output layers. The input layer is where data is received and behaves like a self-determining variable. The sum of input layer neurons unwavering by the structure of the model depends on the sum of arguments. The other layer, the hidden layer, does not characterize any impression and only affords midway results to calculate output values and calculates the sum of each unit in ANNs by multiplying the weights corresponding to the input values. The sum of the calculated morals is then mapped to the output value using a transfer function [58]. Multi-layer perceptron (MLP) model is one of the most widely used ANN models. In ANNs developed using this model, prediction of nonlinear mathematical equations can be performed at high performance levels.

The multi-layer perceptron model includes an input layer, as a minimum one hidden layer, and an output layer, each layer being entirely linked to the next layer. These bonds between layers consist of neurons, the basic processing element. Neurons are identified by bias (b), weights (w) and a transfer function (f). The weight values fixed using a unsystematic number generator are multiplied by the input values of each neuron, and the values obtained are added to each other and to the bias value. The neuron value is calculated as follows:

$$Y_j = f\left(\sum_{i=1}^{n} W_{j,i}x_i + b_j\right) \tag{1}$$

Where Y is the neuron output, n is the number of neurons that connect to the jth neuron, and x is the incoming signals.

In the ANN developed using multi-layer perception, the process of determining the appropriate weight and bias for learning the functional relationship between input and output is entitled "training". One of the most efficient and common algorithms used for training ANN is feed-forward backpropagation (FF-BP) algorithm. In this algorithm, information processing is performed in the feed-forward phase and this process is propagated from the input layer to the output layer. The errors between the predicted and actual data are calculated in the backward processing stage and sent back to the input layer to adjust the biases and weights. This process continues step by step until the error rate in the ANN is minimized. In estimating the energy production values of cogeneration power plants, since the operating hours of the plant, the amount of fuel consumed and the internal consumption values of the plant are the parameters that affect the result, these three parameters are defined as the input value. The output parameter is the amount of electrical energy manufactured by the cogeneration power plant, and this value is obtained in the one-dimensional output layer. The basic structure and configuration topology of the developed ANN is presented in Figure 7 and 8, respectively.

In the developed ANN model, the sum of hidden layers and neurons are the most imperative factors that unswervingly affect the predictive performance [59]. The presence of a small number of hidden layers and neurons in an ANN causes the ANN to be incorrectly trained, and the accuracy of prediction is low. With the purpose of minimize the guesstimate error, the excessive number of neurons is not an accurate approach. It is important to optimize the data to be used in the ANN in order to obtain the ideal estimation accuracy. In this study, feed-forward back-propagation multi-layer perceptron ANN has been developed by using data obtained from a diesel engine cogeneration power plant, and this model has been used to estimate the electricity generation values of the cogeneration power plant. In the ANN developed using 60 data, the data were separated into three groups as training, testing and validation. 42 (70%) of the 60 data were used for the training phase, 9 (15%) for the test phase and 9 (15%) for the validation phase. The values obtained from the mean square error (MSE) and R equations given in Equation (2) and (3), respectively, were chosen as norms for the optimization and performance analysis of the developed ANN.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(W_{exp(i)} - W_{ANN(i)})^2 \tag{2}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}\left(W_{exp(i)} - W_{ANN(i)}\right)^2}{\sum_{i=1}^{N}\left(W_{exp(i)}\right)^2}} \tag{3}$$

Where N is the number of data points, W_{exp} is the experimental production value of the cogeneration power plant, and W_{ANN} is the production value obtained from the ANN model. The flow chart of this ANN with 10 neurons is presented in Figure 9.

5 Results and discussion

In this study, a single hidden layer feed-forward multi-layer perceptron method was chosen as an ANN modeling, and Levenberg-Marquardt backpropagation algorithm, which is one of the most proper models for training ANN, was preferred. As transfer functions of hidden and output layers, Tangent sigmoid (Tan-Sig) and linear (Purelin) functions are selected respectively.

The Tan-Sig transfer function and purelin are presented in Equation (4) and (5)

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{4}$$

$$\mathrm{purelin}(x) = x \tag{5}$$

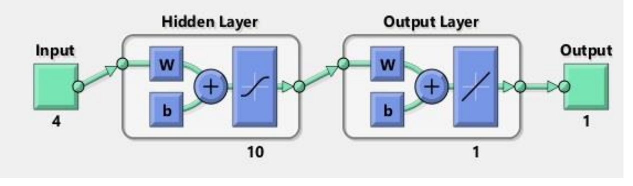

Figure 7. Basic structure of the ANN

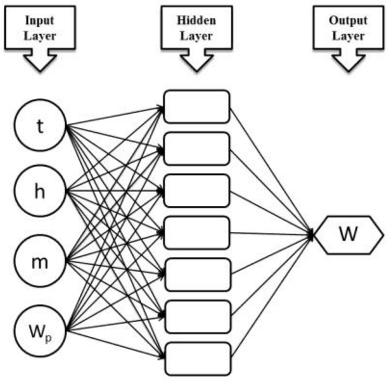

Figure 8. Configuration topology of the ANN

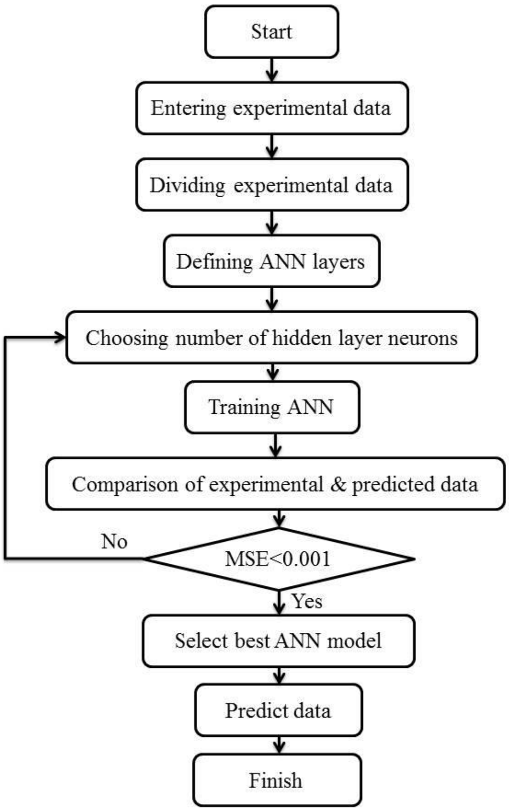

Figure 9. The flow chart of the ANN

In Figure 10, the deviation between the values obtained from the cogeneration power plant and the values obtained from the ANN is plotted. As can be seen in Figure 10, when the training phase of the ANN starts, the high MSE value decreases with increasing periods (epoch). It means that the training stage of the developed ANN model is premeditated acceptably. According to the graph, the MSE rate drops continuously and it is the best result with the lowest MSE value of 27112400562 immediately after 5 iterations. The reason that the ANN achieves the ideal result with the minimum MSE value with a low iteration like 5 is an indication that the data optimization used in the experiment set is done in an ideal way. Figure 11 shows the training status of the ANN model. As shown in Figure 11, the errors were repeated 6 times after epoch 6 and stopped at epoch 11. This error showed that the over-matching of the repeated data starting from the 6th epoch is very good. Thus, the fifth epoch was chosen as the base, but their weights were chosen as final weights. Furthermore, due to the errors repeated six times before the process is stopped, the validation process is equal to 6. Figure 12 shows the error histogram of the training, validation and testing of the ANN. The distribution of the error distribution around the zero line indicates that the designed ANN can estimate the electrical energy production of the cogeneration power plant with an ideal accuracy rate. Figure 13 appearances the assessment of the experimental results with the data used for training the ANN.

The fact that the training data located on the compatibility line is compatible with the experimental data and the R-value obtained as 0.99586 is an indication that the training process of the ANN is finalized with high accuracy and precision. Figure 14 shows the comparison of tentative data with the data used for testing the ANN.

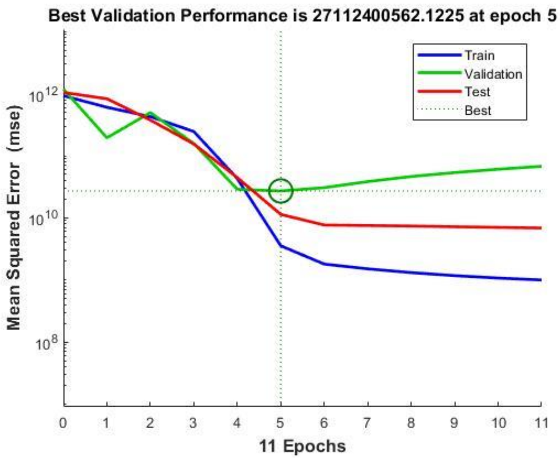

Figure 10. Performance chart of artificial neural network

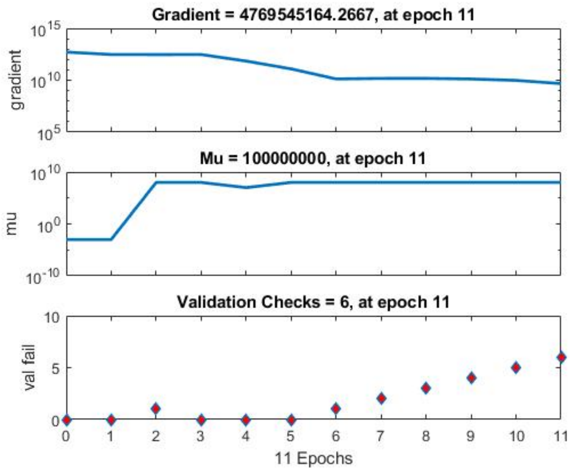

Figure 11. Training status of artificial neural network model

The performance of the test data is important in assessing the suitability and performance of the ANN. The position of the test data close to the equality line and the R-value of the test data, which is 0.97918, can be interpreted as the ideal performance of the improved ANN. Figure 15 shows the validation outcomes of the ANN. The proximity of the validation data to the equality line is indicative of the proper modeling of the ANN. It can be seen that the R-value for the validation results is 0.99227. All the data of the ANN, designed with 60 tentative data, are shown in Figure 16. As can be seen from the graph, all data points obtained from the ANN are located very close to the equality line. This closeness of the data points to the compatibility line indicates that the developed ANN model is capable of generated electrical energy from the cogeneration power plant; time, working hours, fuel consumption and internal power consumption of the plant. The R-value for all ANN results is 0.99073. The performance values of the ANN developed for the purpose of estimating the electricity generation values of the cogeneration power plant are given in Table 4 and Figure 17. The electrical energy production values of the cogeneration power plant are associated with the data obtained from the ANN developed with experimental data. The results have shown that the ANN can accurately predict the electrical energy generation of the cogeneration power plant based on four different input variables. Figure 18 shows the comparison of the values obtained from the ANN with the production values of the cogeneration power plant.

Table 4. ANN performance values

Data Set	MSE	MoD (%)	R	Number of Data
Train	3.48E-03	-0,65	0.99586	42
Test	5.69E-03	-1,02	0.97918	9
Validation	5.64E-04	0,06	0.99227	9
All	4.48E-04	-0,61	0.99073	60

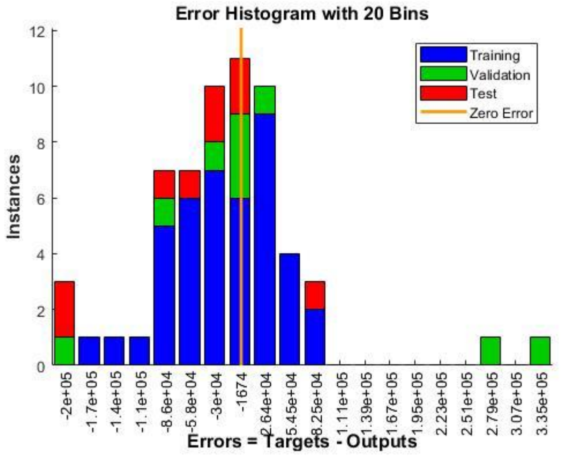

Figure 12. Error histogram

One of the methods used to evaluate the performance of the developed ANN is a standard deviation analysis. The values obtained from the ANN were compared with the electrical energy generation values of the cogeneration power plant, and the deviation values realized for each value were calculated. In the graph given in Figure 19, the electric energy generation values of the cogeneration power plant are placed on the x-axis, and the production values obtained from the ANN developed on the y-axis are placed. The positioning of the data points around the equality line is an indication that the developed ANN accurately predicts the electrical energy generation values of the cogeneration power plant. The deviation between the output values of the ANN and electrical energy generation values of the cogeneration power plant was calculated using the theoretical correlation given in Equation (6) [60].

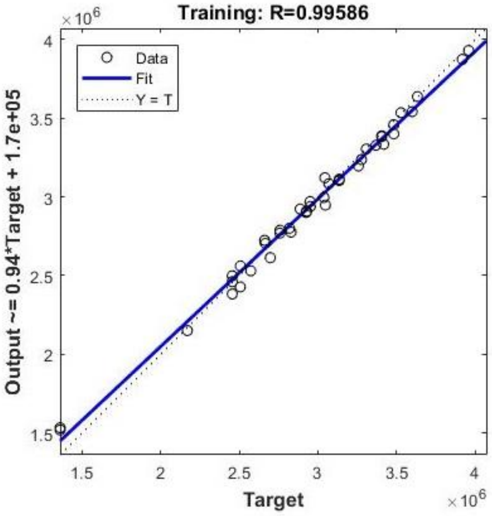

Figure 13. Training data performance

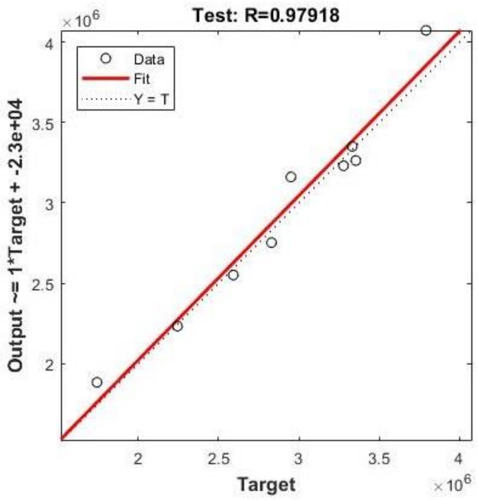

Figure 14. Test data performance

$$\text{Margin of Deviation} = \left[\frac{W_{exp} - W_{ANN}}{W_{exp}}\right] x\ 100\% \qquad (6)$$

The electricity generation values of the cogeneration power plant were compared according to the number of data obtained by using an ANN. The comparison was performed separately for three different data sets used in the development of the ANN.

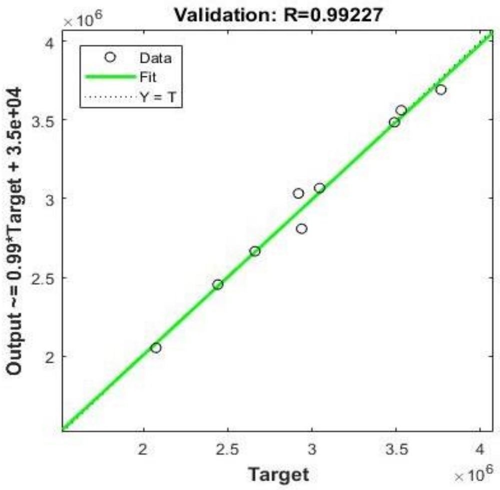

Figure 15. Validation Data Performance

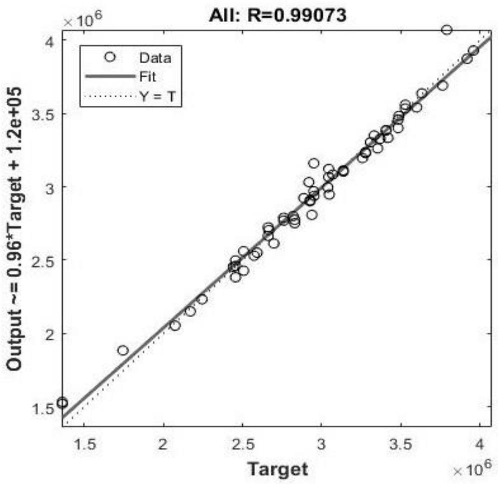

Figure 16. General performance

As can be seen in Figure 20, the estimated values using the ANN and the production values of the cogeneration power plant are very close to each other. It means that the ratio between the values estimated by the ANN and the production values of the cogeneration power plant is acceptable. In Figure 21, error rates of electrical energy generation values estimated using the ANN are shown based on the number of data. Determination of error rates is one of the studies conducted to evaluate the performance of the ANN model whose training phase has been completed. The amount of deviation between the electrical energy generation values of the cogeneration power plant and the data obtained from the ANN was calculated using Equation (6).

The calculated deviation amounts are shown in separate graphs for each training, test and validation data set used in the ANN. As can be seen in Figure 21, the production values predicted by the ANN are very close to the zero line and the deviation amounts are very low and acceptable. These error rates indicate that the results obtained from the ANN are accurate with acceptable deviation rates. As can be seen in the three-dimensional graph given in Figure 22, the ANN was able to estimate the electrical energy generation values of the cogeneration power plant in the range of -5.34% to 2.57% with an average deviation of -0.61%. In the graph, the intensity of the zero error area indicated by the green region is an expression of the good agreement between experimental results and ANN outputs.

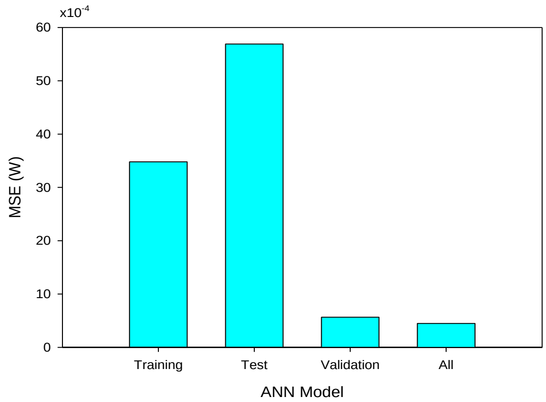

Figure 17. Mean square error values for training, validation, test, and all data

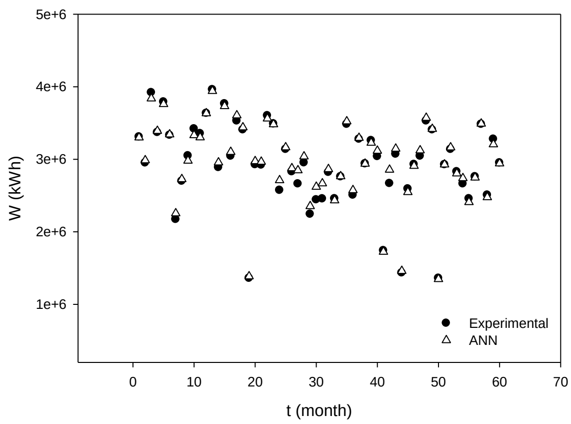

Figure 18. Comparison of production values with ANN outputs

Comprehensive studies have been carried out on the energy and exergy analysis of this cogeneration power plant, where electricity energy generation values are predicted using ANNs [57, 61].

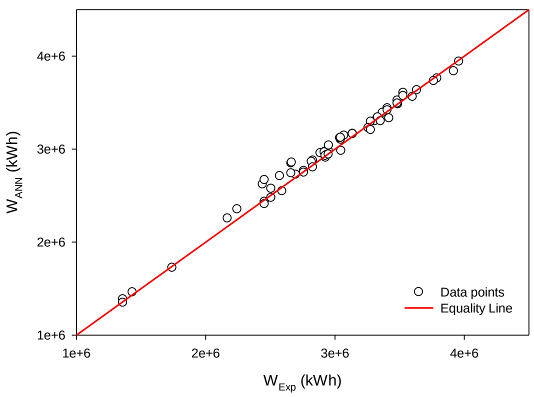

Figure 19. Comparison of experimental production data with artificial neural network data

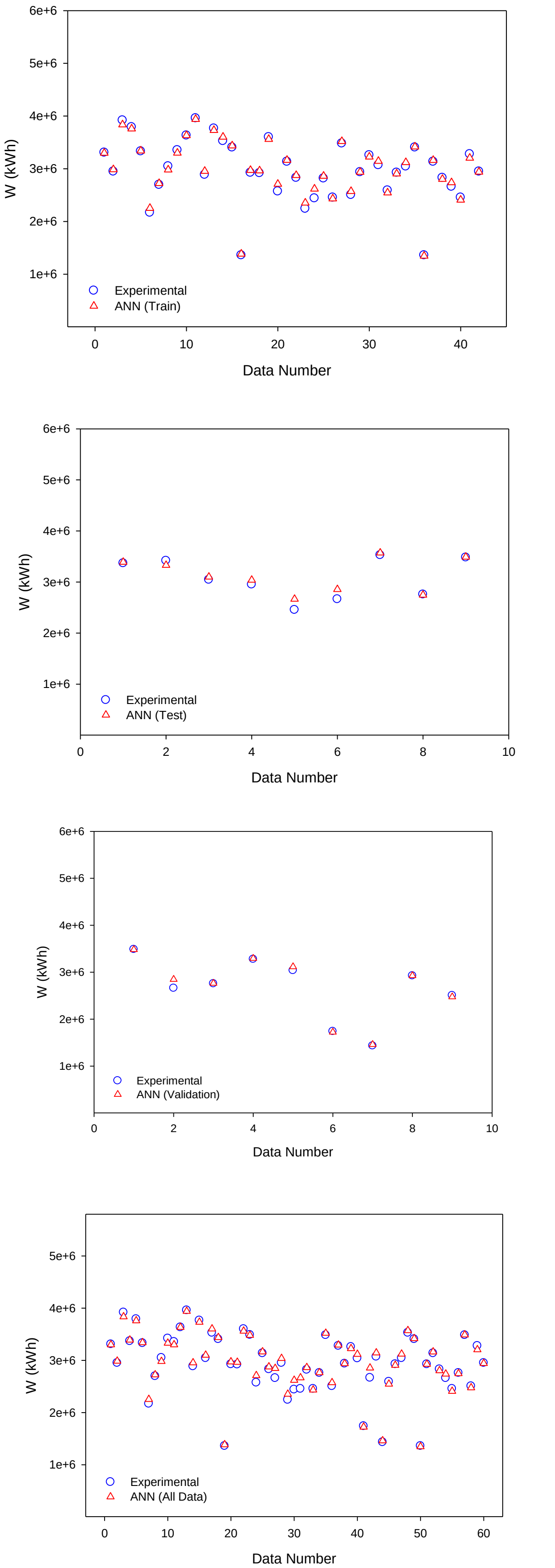

Figure 20. Comparison of ANN and plant production values according to data number

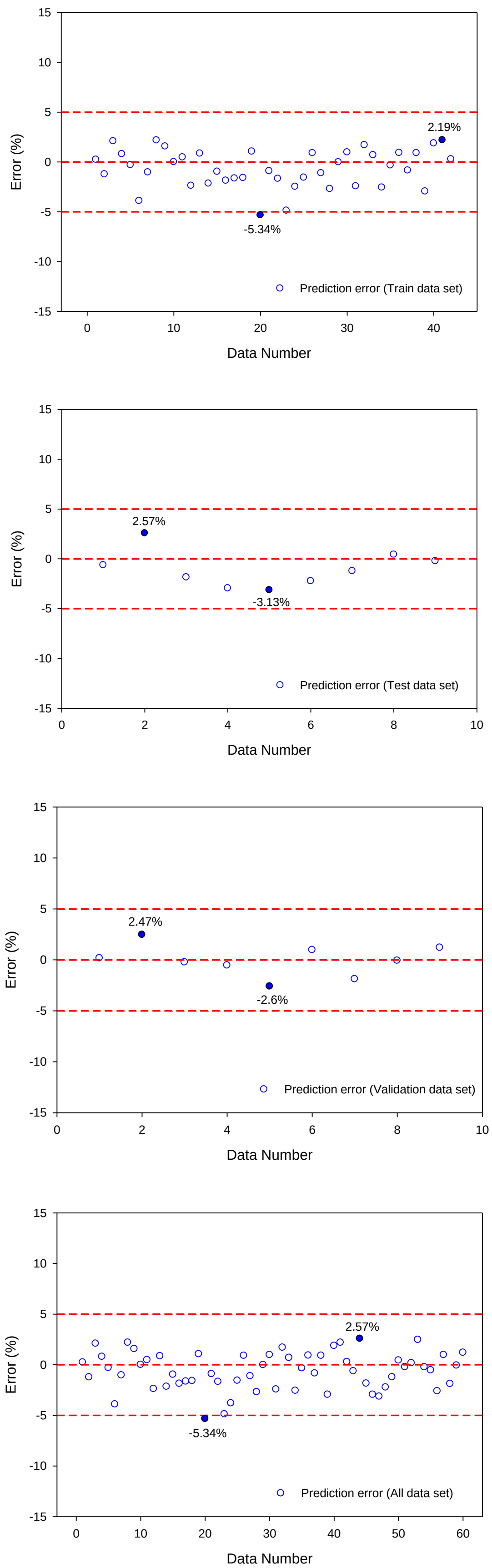

Figure 21. Prediction error by ANN according to data number

6 Conclusion

Numerous studies on cogeneration power plants in the literature have focused on the efficiency and exergy analysis of cogeneration power plants, while various optimization studies with ANNs are also available. In this study, in order to estimate the electricity generation values of a 12-cylinder 32/40 type diesel engine cogeneration power plant operating with heavy fuel oil, a multi-layer perception forward-feed backpropagation ANN was developed through the Levenberg-Marquardt algorithm.

In the ANN model, time (t), working hours (h), fuel consumption (m) and power plant internal consumption (W_p) are defined as input variables, and the electricity generation values (W) of the cogeneration power plant are estimated based on these four input values.

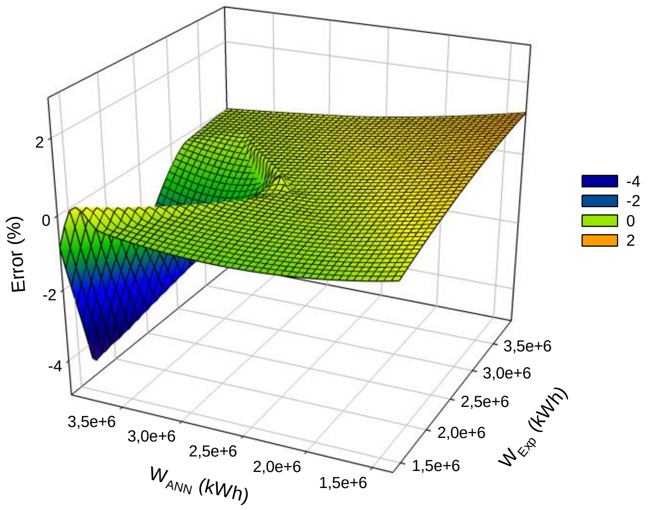

Figure 22. Deviation rates of experimental and ANN data

The ANN was designed using the 5-year (60 months) data of the cogeneration power plant. 42 (70%) data were used for training, 9 (15%) were used for validation, and 9 (15%) were used for testing. The obtained results showed that the R-value obtained for the ANN is 0.99073, The mean error square value is 4.734e-8, and the ANN is modeled optimally. The ANN was able to estimate the electrical energy generation values of the cogeneration power plant in the range of -5.34% to 2.57% and with an average error margin of -0.61%. In the future, different estimation and optimization studies of cogeneration power plants can be made by using ANNs.

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Conflict of interest statement

The author declares that there is no conflict of interest.

Similarity Rate: 19%.

Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
b	Bias
BS&W	Basic Sediment and Water
BTU	British Thermal Unit
CHP	Combined Heat and Power
CT	Cooling Tower
f	Transfer Function
FF-BP	Feed Forward Back Propagation
h	Working hour (h)
H	Hydrogen
HE	Heat Exchanger
HT	High Temperature
HHV	Higher Heating Values
IEA	International Energy Agency
LT	Low Temperature
MLP	Multi-layer perception
MSE	Mean Square Error
S	Sulphite
t	Time period (month)
m	Fuel Consumption (kg)
w	weights
W	Power generation of power plant (kWh)
W_p	Internal power consumption (kWh)

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