International Journal of Electrical and Electronic Engineering and Telecommunications Vol. 15, No. 3, 2026

Forecasting Generation of Motor Generators Using Neural Networks

Stiven Ismael Veintimilla Herrera, Secundino Marrero Ramírez*, Damian Alban Andrade,
and Enrique Torres Tamayo
Faculty of Engineering and Applied Sciences, Technical University of Cotopaxi, Latacunga, Ecuador
Email: stiven.veintimilla4518@utc.edu.ec (S.I.V.H.), secundino.marrero@utc.edu.ec (S.M.R.),
efren.alban9514@utc.edu.ec (D.A.A.), enrique.torres@utc.edu.ec (E.T.T.)

Manuscript received January 29, 2026; revised February 26, 2026; accepted March 4, 2026
*Corresponding author

Abstract—**Predicting the generation and efficiency of motor generators is a challenge in energy planning due to variable operating conditions and the need to optimize resources. This article addresses the aforementioned problem from a prediction approach based on Artificial Neural Networks (ANN). The object of study is a Hyundai motor generator used in electricity generation, for which the history of operating variables was used. The methodology employed consisted of the collection, normalization and training of an ANN with the respective validation of the prediction model using statistical metrics, such as the Mean Squared Error (MSE), which had a value of 0.0039 with a coefficient of determination of 0.9237 and an acceptable confusion matrix, since it was able to classify the data with 100% accuracy. In addition, the efficiency indicator was analyzed using the ratio between the energy generated and fuel consumption, with an average of 3.34 and a deviation of 0.17. The final results show a good prediction of the model with a low MSE of 0.000450, which allows the energy performance of the system to be evaluated. Therefore, the use of ANNs is very useful for planning and predicting electricity generation in these machines, as they present an error of less than one, which expresses greater accuracy.**

Index Terms—**resource optimization, energy planning, generation, fuel consumption, model validation**

I. INTRODUCTION

Since the last century, and with greater emphasis today, both governments and companies have recognized that the main conventional sources of energy generation, such as fossil fuels, must be used efficiently due to their impact on the environment and the level of existing reserves worldwide, which will eventually be depleted. The limited nature of these resources has increased their strategic value, which has been driven over the years by armed conflicts and geopolitical disputes [1]. This, in turn, has led to the search for rational energy use and the incorporation of other alternative energy sources.

The use of fossil fuels is fundamental to the global energy matrix, where the most developed countries have a significant weight, representing approximately 80% of global consumption, which is largely associated with per capita energy consumption per inhabitant, which is more significant compared to other less developed countries [2].

The burning of fossil fuels promotes the emission of greenhouse gases into the atmosphere, which contributes to climate change. This is one of the main concerns currently facing thermal power plants that generate electricity, which must switch to more efficient technologies [3]. In addition to the limited energy resources derived from fossil fuels, it is important to consider the impact their use has on the environment, due to the generation of Carbon Dioxide (CO_2) and other greenhouse gases that seriously affect the ecosystem. For this reason, for some time now, various studies have shown that these problems accumulate over time and can have a significant impact on global warming and the ozone layer. Therefore, if their negative effect is not stopped, it will be difficult to ensure a satisfactory environment for future generations [1].

Therefore, it is necessary for motor generators used in energy production to operate efficiently, and this will depend significantly on the rational consumption of different types of fuel, an aspect that is a constant concern during the operation of thermal generation systems, which are forced to implement different strategies to save fuel and reduce operating costs. The ability to effectively control the consumption of fuels such as diesel is a necessary factor during the operation of motor generators, and this will depend largely on the technical condition of the equipment, which in turn will allow for more accurate consumption forecasts, an aspect that affects operating costs and the value of the energy delivered to the system. Other factors associated with fuel composition must also be taken into account, such as the amount of sulfur, cetane number, and viscosity, which define the power generated. This has led researchers to analyze the use of different types of fuels, biofuels, and different commonly available blends, without having to adapt the internal combustion engine and ensuring that their negative effect on efficiency and the environment is as low as possible [4, 5].

That said, it is important to emphasize that all these factors can vary significantly depending on the situations that arise and that sometimes may be beyond the control of operators. In addition, the power generated must depend exclusively on the demand of the grid at any given time, thereby satisfying consumer needs with the operation of the different units available within a power plant. The parameters involved in the operation of the machine will fluctuate within a range and are determined by the manufacturer based on the type of fuel or fuel mixture,

doi: 10.18178/ijeetc.15.3.184-191

which may vary in quality and calorific value. This affects combustion and must be taken into account when predicting fuel consumption and planning costs in order to make forecasts that are as close to reality as possible, since predicting electricity generation inadequately with inaccurate models would have a negative result when defining the required fuel reserves, and this could distort the estimated operating costs [5].

In Ecuador, with population growth, improved quality of life, and industrial development, electricity consumption and demand are expected to increase in the short term. Hydroelectric power plants are the main source of electricity generation in the country, and thermoelectric power plants are considered the second most important source, ahead of renewable energies [6].

For its part, the Ecuadorian Electricity Corporation (CELEC) is a public company whose main objective is the management of energy generation, transmission, distribution, and commercialization, as well as the export and import of electrical energy. One of the thermal power plants that forms part of this company is CELEC-Sacha, which has been developing a generation strategy based on the operation of 12 generator sets, each with a nominal power capacity of 1.7 MW [7]. In addition, CELEC-EP Termopichincha controls the Quevedo power plant, which has a generation capacity of 102 MW. This type of generation is particularly important in the country's oil extraction industry, which is located far from the national power grid. As a result, the energy supply for these oil fields is generally provided off-grid by thermal power plants [6]. This company systematically performs preventive maintenance focused on guaranteeing the permanent operational availability of the system to ensure good operating conditions and efficient operation of the generators through the control of operating parameters such as temperature, pressure, fuel consumption, efficiency, and voltage stability, among others [7].

There are various research studies that have addressed the modeling and analysis of the efficiency of power generation systems using different mathematical approaches. Thus, researchers such as [6], in their studies, they propose how generators with fossil fuel systems should be modeled in order to include them in studies of electrical systems that feature this type of generation. The hybridization of systems that use biomass fuel is another option for reducing greenhouse gas emissions, especially in regions where there are plantations that produce significant volumes of biomass during harvests, as is the case in the Province of Cotopaxi in Ecuador [8]. Another option is to appropriately hybridize thermal generators with other alternative energy sources for viable solutions in systems that work with conventional and unconventional generation. For this reason, many researchers mention the need to model generation systems to monitor their operation and forecast consumption, thereby reducing unwanted downtime and avoiding damage or breakdowns that shorten the useful life of generators [6].

A generation system with different generation sources, as is the case in Ecuador, has the important feature of being able to determine the economic dispatch of the available units, where it is essential to consider a group of variables such as the availability of the main sources for energy production, the operating limits of hydroelectric power plants, and the available thermal generation units. For this reason, hydroelectric dispatch and thermal unit dispatch are used, which are synchronized within an appropriate margin in order to meet demand in each of the analysis cycles [9].

The fundamental characteristic of thermal units in a hydrothermal system is the number of units in the system, and although their capacity may not be extensive, they complement dispatch to meet economic requirements and thus respond to system demand. Therefore, it is of interest to be able to simulate a system with these characteristics using different mathematical foundations and heuristics, where an objective function is used for the dispatch of thermal units with the presence of cubic or quadratic functions, which are very useful for determining how the operation is in each analysis cycle, with the lowest possible operating cost. This is essential when the production costs of thermal units are linear, as is the case with the Ecuadorian electrical system, where the use of different techniques must be adapted to the objective of obtaining the dispatch of thermal units based on costs [9].

Thus, the fundamental objective of economic dispatch for thermal units is to minimize the total cost of electricity production with the thermal units that can participate, which must be operating within generation limits, while also satisfying system demand with minimal losses [9].

In diesel electric generators, it is essential to determine and predict the level of emissions and performance that will ensure smooth and efficient operation. This requires continuous monitoring with safe and reliable operation to predict future behavior, which may require expensive equipment and computer tools that demand dedication and time. Currently, there is an alternative technique for this, related to the use of Artificial Neural Networks (ANN), which have already been used in various research projects for engine performance modeling, (CO_2) emissions estimation, and monitoring of generation efficiency behavior [10, 11]. Multilayer ANN models are accurate and efficient in handling highly nonlinear relationships by approximating continuous functions with a sufficient number of neurons and data. Their adaptability allows them to learn directly from the data, they are robust in the presence of incomplete or noisy data, they avoid excessive simplification, and, once trained, can predict behaviors not observed in training and allow rapid model evaluation with the integration of advanced techniques such as intelligent control and optimization. This model has a similar operating principle to that of a biological neural system, enabling the development of systems to process information in a parallel, distributed, and adaptive manner.

The main component of this alternative is the artificial neuron, which is organized in layers and this allows it to progressively transform the information to represent complex relationships, where the construction of the neural network is due to the interconnection of several layers [5], with a basic architecture shown in Fig. 1, which also considers the weight of the input (V_n) and output variables to regulate the influence of the information throughout the network, as well as adjust and determine the contribution of the previous neurons in the final value of the output.

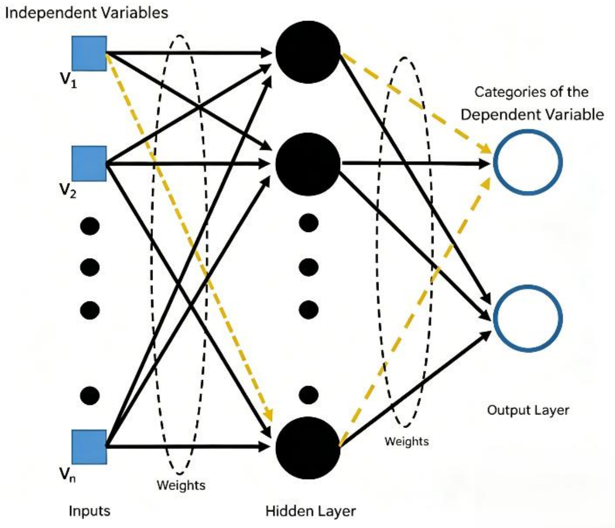

Fig. 1. Basic ANN Architecture [12].

The objective of this research is to forecast fuel generation and consumption in motor generators using ANN to analyze operating efficiency, given that ANN have already been used in the study of electrical distribution systems in recent years, demonstrating their efficiency in predicting situations where traditional techniques are not very efficient or have not been able to function adequately, due to the great difficulty of the calculations required during the study of different problems in electrical power generation systems and the precise monitoring of their operating variables [5].

II. MATERIALS AND METHODS

The research considered quantitative methods with numerical and statistical data, observation, and systematization to determine and describe the most important factors, variables, and their relationships in the operation of motor generators, which are the subject of the research. Documentary techniques were also used in the analysis of historical operating data, and computational tools were used for modeling and simulation, with the appropriate selection of variables to be incorporated into the predictive models of generation and consumption rates [13].

The modeled motor generator is a Hyundai brand, with internal combustion, direct injection, simple activation, piston-type plunger with turbocharger, and air cooler. An ANN with a learning algorithm and directional synaptic connection was used for its modeling [6]. The architecture used presents a sequential set for learning that has taken into account the features of the most commonly used configurations listed below [14]:

- The multilayer perceptron (MLP), which has an input layer, an undetermined number of hidden layers, and finally an output layer [15]. Furthermore, it is capable of solving problems when data can be separated linearly. Put this way, it is a reliable solution to this problem by using multiple perceptrons in multiple layers [16]. Fig. 2 shows the structure of a MLP, where (W_{ji}) and (W'_{kj}) represent the synaptic weights between the input-hidden and hidden-output layers, (θ_j) and (θ_k) correspond to the thresholds or biases of the neurons, x_i^M are the input values, y_j^M are the outputs of the hidden layer, z_k^M are the outputs obtained in the output layer, and t_k^M represent the target outputs, which were used in training.
- Self-organizing maps (Kohonen) that constitute a network model, known as (SOM) [17].
- Radia base, characterized by activation elements in nodes that cannot be visualized, which are radially symmetric, and corresponds to this factor if the output depends on the distance between the vector that stores the input elements and a vector of synaptic weights [18].
- In addition, there are other models that are also used, such as radial base function (RBF), general regression neural network (GRNN), adaptive resonance theory (ART), learning vector quantization (LVQ), and the Hopfield model [5].

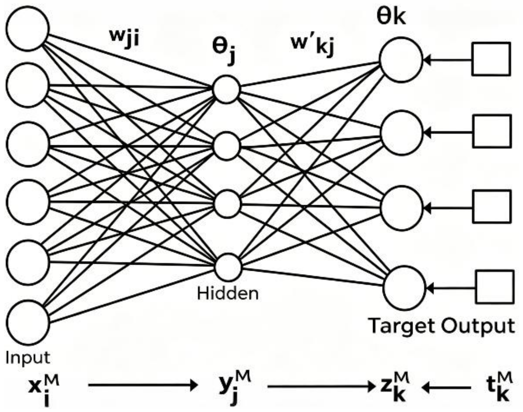

Fig. 2. Structure of a MLP [5].

There is no defined theoretical process for choosing the appropriate ANN architecture, as it depends mainly on the characteristics of the system under study and its complexity. In order to determine the number of neurons in the input and output layers, the dimensions of the problem under study must be considered [5]. In this way, the learning algorithm will differ in terms of its mode of operation and training, the latter being of great importance, as it constitutes a relatively significant factor in ANN architecture. The selection of patterns that go into the ANN input is also significant, as they must consider all the explicit requirements of the motor generator's generation and efficiency prediction in order to achieve the processing and quality of the network's output information. During the training pattern changes, different codes were considered in the input vector in order to evaluate the network under different conditions [5].

The motor generator that was studied is manufactured by Hyundai and has a capacity to produce up to 1.7 MW of electrical power at 4160 volts. It consists of a 9-cylinder internal combustion engine and an 8-pole generator with the technical specifications detailed in Table I. To reduce generation costs, Heavy Fuel Oil (HFO) from oil fields is used, which is mixed with varying percentages of diesel (from 10% to 20%) to improve its viscosity properties and make it more manageable, despite the requirement to use a fuel for the engine with a calorific value that must be between 41 MJ/kg and 43 MJ/kg.

TABLE I: NOTATION AND VARIABLES

Engine model	9H21/32
Number of cylinders	9
Number of diesel engine stages	4
Rated power [KW]	1800
Generator power [MW]	1.7
Total, weight [t]	50
Cooling system	Radiator
Voltage [V]	4160
Current [A]	295.1
Frequency [Hz]	60
Poles	8
Speed [RPM]	900

A widely used model to represent this type of system is one that considers the operating principle of the generator with Eq. (1) and Eq. (2), where the thermal power Q_{th} and fuel mass flow m are determined, respectively:

$$Q_{\text{th}} = m \times \text{LCV}, \tag{1}$$

$$m = C_s P_n, \tag{2}$$

where C_s represents specific consumption in kg kWh^{-1}, P_n represents nominal power in kW, and LCV represents the low calorific value of the fuel in kJ kg^{-1}.

Efficiency η is determined by the ratio between output energy E_o and input energy E_i, as expressed in Eq. (3):

$$\eta = E_o / E_i \tag{3}$$

Related to the mathematical modeling of thermal systems, it is important to highlight the work developed by [19]. The authors analyze the thermal performance in compressed air systems, through numerical simulation based on experimental data. The results show the tendency to reduce energy consumption with increasing concentration of the transported mixture. The research conducted by [20], [21], establishes the procedure for modeling and simulation of Solar Air Heater and heat exchange systems where heat transfer by conduction, convection and evaporation predominates depending on the cooling zone.

In order to perform energy balancing for the purpose of optimizing resources, it is necessary to know the total power delivered versus fuel consumption. To this end, it is possible to use the growing computational capacity of today's computers, as well as the machine learning algorithms available for ANN. With this objective in mind, Fig. 3 shows the flowchart of the different stages for forecasting using ANN. Where the input and output data are collected from operational reports of a generator, the prior performance of adequate maintenance of the equipment was also verified in order to ensure its operation in optimal conditions. The input data to be used has been collected, such as HFO, diesel, oil (A), energy delivery (E), performance (R), and hours of availability to perform preprocessing and data transformation with a view to normalizing it within a common range for the stability of training in learning the relationships between the selected variables and to be able to make predictions. Parameters such as the number of layers and neurons were considered in the model adjustment in order to evaluate when the model reaches an acceptable level of accuracy for the intended objectives. The generation forecast using the trained model should enable the prediction of future generation and the evaluation of efficiency. Finally, the results obtained from the generation forecast and the consumption index are detailed and compared with operating data that was preserved for validation.

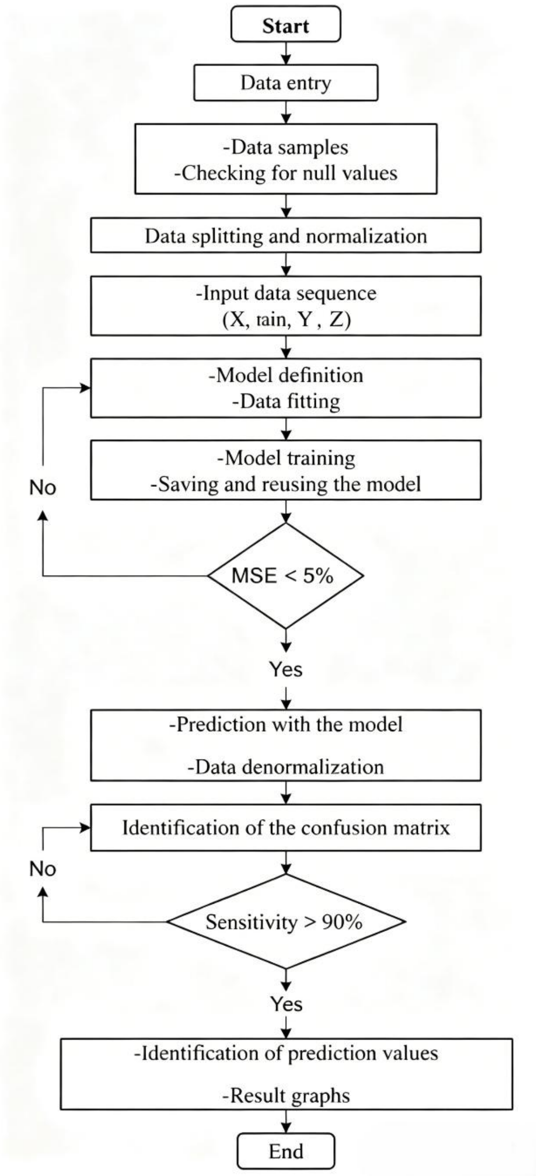

Fig. 3. Flowchart of ANN.

III. RESULTS AND DISCUSSION

During the preprocessing of the input data, historical records of the motor generator's operation over a period of 449 days were taken into account, including Diesel and HFO consumption, hours of operation, oil consumption, and gross energy generated (KWh). During this process, data with null values were eliminated and the input variables (diesel, HFO, operating hours) and output variables (gross energy and consumption index) were normalized to ensure efficient convergence of the training, data normalization was performed using the mapminmax algorithm and the random initialization. Tests were performed with recurring units in values between 10 and 32, considering the presence of few input variables, the low noise of the series and the weekly seasonality that requires 7 steps, taking into account the volume of data. The trainlm algorithm is also used to update weights and biases. Table II shows the results of the analysis of the data used in the network training, where the mean, maximum, minimum, and standard deviation of the daily data are shown, with the exception of A, which is reported monthly.

TABLE II: ANALYSIS OF THE DATA USED IN TRAINING

Parameter	HFO (Liters)	D (Liters)	Hours of operation	*A* (Liters)	*E* (Kwh)	KWh/ Liters
Mean	7350.08	2811.78	23.58	1274.77	33846.6	3.34
Max	8514.22	4839.51	24	2382.45	37200	4.12
Min	2197.72	810.22	6.25	378	10400	2.76
Std	729.17	469.27	2.05	898.77	3071.13	0.17

The fuel used is a mixture of HFO and diesel, with HFO accounting for the largest percentage due to its high density, low hydrogen content, and high sulfur content. Therefore, the ratio between HFO and diesel was considered a relevant factor in the energy delivered. Fig. 4 shows the exclusion of data that are outside the proposed range (± 3 of the standard deviation). It should be noted that this entire process is carried out in order to obtain a more accurate representation of the daily behavior of the power generation process.

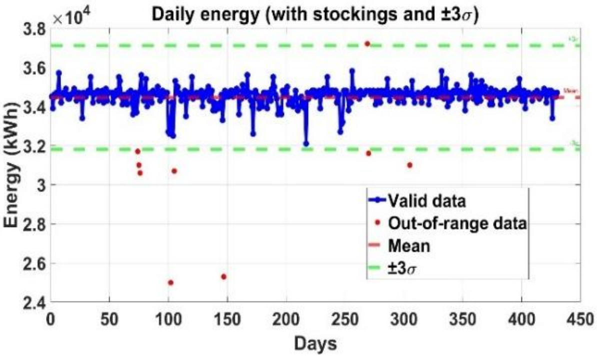

Fig. 4. Energy control chart

TABLE III: STATISTICAL METRICS OF THE TRAINING

Parameter	MSE	MAE	R²
Mean	0.0039	0.0304	0.9237
Max	0.0042	0.0321	0.9310
Min	0.0036	0.0289	0.9165
Std	0.0002	0.0011	0.0053

During training of the ANN model, a feedforward neural network was implemented with four hidden layers of 20 neurons each, and the ReLU (poslin) activation function. The dataset was divided into 70% for training and 30% for validation. In addition, training was run for a maximum of 3000 epochs, optimizing the weights until a feasible MSE, absolute error (MAE), merit index (IM), and correlation (R^2) were achieved, as shown in Table III with satisfactory values that allowed us to verify that the model achieved an adequate relationship between the input variables, the energy generated (output), and the consumption index. Input variable A was not used because this input did not influence the generation results during training, and unlike the other variables, the operating data is monthly rather than daily consumption.

The results obtained demonstrate that the proposed ANN is capable of correctly modeling the behavior of gross energy based on the input variables. One of the relevant aspects is the 100% sensitivity obtained in the confusion matrix. Therefore, this result shows that the model was able to correctly detect all real positive cases, which is essential in applications, where omitting the gross energy of some days of operation can have significant economic consequences. In addition, the 100% accuracy demonstrates an adequate balance between detection and determination.

The classification threshold was set at 26,700 gross energies, which was selected based on statistical criteria. Fig. 5, with the confusion matrix, demonstrates the validity of the model by showing that the prediction approximates the actual values, even where there are abrupt variations. The minimal difference between the two curves is expected, considering that the model should not memorize the data, but rather learn from its structure. In addition, different studies show that ANN, when adjusted for adequate training, follow patterns as expected without being overfitted [22].

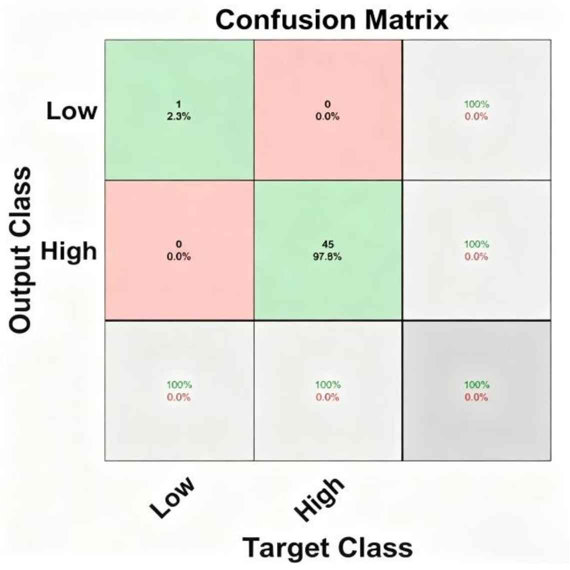

Fig. 5. Confusion matrix.

To evaluate the network's performance in terms of generation forecasting, Fig. 6 shows a comparison between actual gross energy and that predicted by the ANN using a dataset reserved for this purpose, where it can be seen that the curves maintain a very similar pattern, with a total MSE of 0.000450.

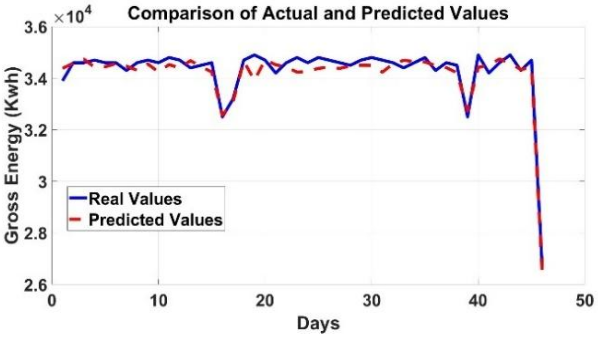

Fig. 6. Comparison between prediction and actual values.

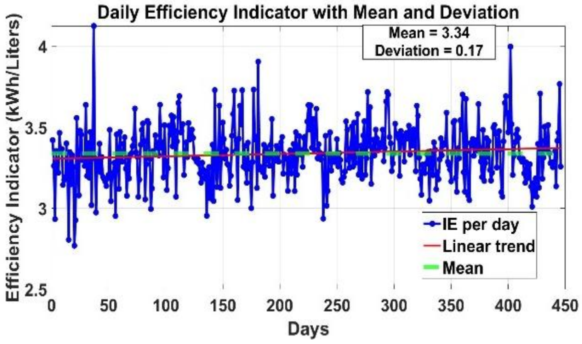

Fig. 7. Efficiency Indicator.

On the other hand, Fig. 7 shows the consumption indicator to analyze efficiency by day, which shows the daily variability of the system's energy performance, which is related to the energy generated and total fuel consumption (KWh/Liters), where the fuel mix used can change and, consequently, its effect on the generation obtained. It can be seen that, throughout the period analyzed, the indicator maintains a stable trend. However, there are favorable efficiency peaks. Similarly, declines in efficiency are identified, indicating that at those times there was greater fuel consumption relative to the energy generated.

The use of four hidden layers with 20 neurons each proved efficient for the model without overfitting, as verified by its behavior in the test and validation data. It is worth noting that more complex adjustments did not show significant performance improvements; therefore, the selected model presents an optimal balance, exhibiting stable convergence, low error when new data is added, and a compromise between accuracy and complexity. The generation forecast and its proximity to the actual data values are similar to the results achieved in the generation forecast for motor generators carried out by the authors [6], in which good performance is considered to be a low MSE.

Ultimately, the process of normalizing and appropriately dividing data (training, validation, and testing) are crucial factors for efficient neural network training. This is achieved by avoiding overfitting the model through the random deactivation of neurons during training, the adjustment of hyperlinks, the removal of irrelevant variables, and proper data separation [23].

In addition, various studies have shown that ANNs are highly effective in forecasting generation in electrical systems, thanks to their ability to learn the behavior of system variables. Therefore, this learning ability contributes to optimizing the operational efficiency and energy planning of the system [24]. The similarity of the results achieved in the research with the authors mentioned above is reflected in the values obtained for MSE, R^2 correlation level, sensitivity and accuracy.

The results of this type of forecasting model can be limited by the presence of incomplete, outlier, or noisy data, poorly calibrated sensors, and non-stationarity due to changing patterns. The structure of the selected network, the quality of preprocessing, sensitivity to extreme events, and computational requirements can also affect the forecast results.

IV. CONCLUSION

The implementation of ANN for forecasting generation in motor generators has proven to be an effective and reliable tool. The results obtained reflect a robust model with high levels of sensitivity and accuracy, which allows for advance knowledge of the behavior of the energy generated based on the type of fuel and hours of operation. In addition to being extremely useful for improving energy planning, the prediction helps optimize diesel consumption, thereby reducing operating costs and improving system performance by providing information on the average consumption rate of 3.34/Liters.

Among the main successes, it is essential to highlight the model's ability to classify raw energy data with 100% accuracy, as well as the match between actual and estimated generation and efficiency curves with an MAE of 0.0304.

Therefore, it is evident that the model is an adequate tool for energy planning and optimization of HFO and diesel consumption, as it achieves 100% sensitivity and accuracy, which is very useful for planning operating costs. However, small discrepancies were observed between the curves in situations where there are abrupt variations in operation, with a MSE of 0.000450, which is acceptable in the forecast. These results are consistent with the theoretical aspects and findings of other authors on the subject.

In short, the methodology used from standardization to the choice of network architecture was extremely useful in obtaining a suitable model, avoiding overfitting and ensuring an adequate response from the system with new data. Therefore, this study shows that the use of neural networks is feasible in this type of forecasting, and in future research, based on the increase in operating data, greater model adjustments could be achieved in real generation contexts, thus contributing to the development of more reliable solutions and the operational improvement of systems using motor generators.

Implementing this real-time model can present technical, computational, and operational challenges that must be evaluated if it is incorporated into a control system for managing energy generation. This will require considering the generator’s dynamics in response to load demand, the proper capture of nonlinear dynamics, its temperature, the quality and availability of real-time sensors and signals, computational latency, system robustness to operational changes caused by equipment degradation, and the need for calibration at specific intervals. Undoubtedly, considering all these aspects will require updating the model within the system at certain times to achieve proper integration with the control system.

CONFLICT OF INTEREST

The authors declare no conflict of interest

AUTHOR CONTRIBUTIONS

Stiven Veintimilla and Secundino Marrero conceived the study, developed the methodology, carried out the investigation, wrote the manuscript, and performed software application; Damian Alban collected the data, reviewed the results, processed the information, and validated the findings; Enrique Torres conducted the simulations and prepared the initial draft of the text; all authors had approved the final version.

FUNDING

This research was carried out by the Appropriate Energy and Technology research group within the framework of the project entitled Development of intelligent systems applied to electrical engineering, funded by the Technical University of Cotopaxi.

REFERENCES

[1] D. F. Álvarez. (2026). Neural network-based modeling of mechanical assets and processes in energy cogeneration plants. [Online]. Available: https://repositorio.comillas.edu/xmlui/handle/11531/65347

[2] C. S. Naranjo. (2023). *Thermal Power Plants*, 1st ed., Madrid: National University of Distance Education, 2023. [Online]. Available: https://buscador.biblioteca.uned.es/permalink/34UNED_INST/148u9r5/alma991005900974904215

[3] N. Moraes, U. Bezerra, J. M. Rodríguez, and J. Leite, “The emissions index as a parameter for assessing environmental pollution from thermal power plants. Case study,” *DYNA*, vol. 83, no. 218, Oct. 2016. doi: 10.15446/dyna. v83n199.51384

[4] W. Gracz, D. Marcinkowski, and W. Golimowski, “Multifaceted comparison efficiency and emission characteristics of multi-fuel power generator fueled by different fuels and biofuels,” *Energies*, vol. 14, no. 12, Jan. 2021. doi: 10.3390/en14123388

[5] S. de la F. Dotres, J. D. Fontanil, and J. A. Sierra, “Fuel consumption forecast for generator sets using a neural network,” *Cuban J. Comput. Sci.*, vol. 4, no. 1–2, pp. 53–58, 2010.

[6] S. T. Quilligana and G. A. Aviles, “Model of the energy production process in thermal power plants considering the operating profile,” *Lat. Sci. Multidiscip. Sci. J.*, vol. 6, no. 4, pp. 5541–5560, Sep. 2022.

[7] M. Á. M. Criollo and G. A. R. Granda. (2022). Prediction of mechanical failures in Hyundai H21/32 internal combustion engines at the Celec Ep Central Sacha thermoelectric power plant. [Online]. Available: https://bibdigital.epn.edu.ec/handle/15000/23368

[8] L. F. R. Riveros, C. L. T. Rodríguez, N. L. D. Aldana, and C. R. Casas, “Modelling of electric power generation plant based on gas turbines with agricultural biomass fuel,” *Electronics*, vol. 12, no. 9, Jan. 2023. doi: 10.3390/electronics12091981

[9] J. S. Ortiz, J. A. Tayupanda, and C. I. Quinatoa, “Solution to the problem of short-term hydrothermal dispatch using nonlinear programming applied to single-and multi-node systems,” *Tech. Energy Mag.*, vol. 20, no. 2, pp. 11–20, Jun. 2024.

[10] P. Ganesan, S. Rajakarunakaran, M. Thirugnanasambandam, and D. Devaraj, “Artificial neural network model to predict the diesel electric generator performance and exhaust emissions,” *Energy*, vol. 83, pp. 115–124, Apr. 2015.

[11] M. Micev, M. Ćalasan, M. Radulović, S. H. E. A. Aleem, H. M. Hasanien, and A. F. Zobaa, “Artificial neural network-based nonlinear black-box modeling of synchronous generators,” *IEEE Trans. Ind. Inform.*, vol. 19, no. 3, pp. 2826–2837, Mar. 2023.

[12] E. R. P. Rosas, R. D. Mendoza, I. J. Galván, M. A. F. Ortega, A. O. Montalvo, and G. F. Ortiz, “Application of artificial neural networks in assigned leadership and academic success in medical graduates,” *Surg. Surg.*, vol. 91, no. 4, pp. 550–560, Aug. 2023.

[13] R. M. Laurencio, O. T. Breff, S. M. Ramirez, and D. J. Jiménez, “Prediction of electricity consumption and demand using artificial neural networks and iterative algorithms,” *Polytech. Mag.*, vol. 54, no. 3, pp. 45–58, Dec. 2024.

[14] T. D. M. Velásquez, “Artificial neural networks in the oil and gas industry: bibliometric analysis (2020−2024),” *Enfoque UTE*, vol. 16, no. 2, pp. 18–25, Jun. 2025.

[15] D. G. C. Cachimuel and F. A. F. Vargas. (2023). Prediction of solar radiation using neural networks for the sizing of photovoltaic plants in the province of Pichincha. [Online]. Available: http://repositorio.utc.edu.ec/handle/27000/11418

[16] C. A. C. Sotelo. (2021). Artificial neural networks and support vector machines for classifying microcredit applicants. National University of Engineering (Peru). [Online]. Available: https://dialnet.unirioja.es/servlet/tesis?codigo=337971

[17] M. M. Kebalepile, L. N. Dzikiti, and K. Voyi, “Supervised Kohonen self-organizing maps of acute asthma from air pollution exposure,” *Int. J. Environ. Res. Public. Health*, vol. 18, no. 21, Jan. 2021. doi: 10.3390/ijerph182111071

[18] F. P. D. Gennaro, M. P. Catalano, and A. García, “Predictive capacity of events in patients with hypertension using artificial neural network analysis of ambulatory blood pressure monitoring compared to clinical risk stratification,” *Argent. J. Cardiol.*, vol. 93, no. 1, pp. 33–42, Apr. 2025.

[19] E. J. Díaz, E. T. Tamayo, D. M. Vélez, D. R. Salazar, C. M. Díaz, and M. P. Cedeño, “Energy consumption and simulation of pneumatic conveying lateritic mineral in dense and fluid phase,” vol. 11, 2017. https://cris.ute.edu.ec/entities/publication/58d5bac0-6200-43f8-be09-74cb781d22be

[20] T. Enrique, A. Mauro, L. Héctor, and V. Jorge, “Thermal performance comparative analysis of solar air heater with fins addition on the absorber plate,” *Int. J. Mech.*, vol. 19, pp. 13–19, Sep. 2025. doi: 10.46300/9104.2025.19.3.

[21] E. Tamayo, J. Morales, and M. Albarracín, “Cooling temperature and heat transfer coefficients in cylindrical heat exchangers,” *Int. J. Mech.*, vol. 15, pp. 254–259, Dec. 2021.

[22] X. Dou and Z. Cui, “Neural network-based forecasting and uncertainty analysis of new power generation capacity of electric energy,” *Energy Inform.*, vol. 8, no. 1, no. 85, Jun. 2025.

[23] A. Mystakidis, E. Ntozi, and K Afentoulis, “Energy generation forecasting: elevating performance with machine and deep learning,” *Computing*, vol. 105, no. 8, pp. 1623–1645, Aug. 2023.

[24] E. C. Casals Cunill, S. L. Hierrezuelo, D. J. García, and R. D. L. Solano, “Artificial neural network design for electricity demand forecasting,” *Energy Eng.*, vol. 45, no. 3, Dec. 2024.

Stiven Ismael Veintimilla Herrera was born in Latacunga, Ecuador, in 2003. He completed his schooling at the Belisario Quevedo Educational Unit and later at the Hermano Miguel Educational Unit, where he obtained a bachelor’s degree in consumer electronics. He is currently a graduate student at the Technical University of Cotopaxi, Faculty of Engineering and Applied Sciences, studying Electrical Engineering.

Secundino Marrero Ramírez received the degree in industrial electronics engineering and the Ph.D. degree in automation. He has participated in research projects related to industrial automation, rational energy use, and renewable energy sources. He has worked at various universities, including the University of Moa, Cuba; the University of Zambeze, Mozambique; and the National University of Loja, Ecuador. He is currently a full-time professor in the Electrical Engineering program at the Technical University of Cotopaxi, Ecuador. He is also a member of the research network in biomedical engineering, energy, telecommunications, and artificial intelligence (BIOENERTIC).

Damián Albán Andrade was born in Latacunga, Cotopaxi, Ecuador, in 1989. He received his degree in electromechanical engineering from the University of the Armed Forces, Latacunga, Ecuador, in 2017, and his master's degree in electricity with a specialization in electrical power systems in 2023. He has professional experience in various private companies, with positions in electrical maintenance, overhaul groups, maintenance groups, etc. With more than four years of experience in university teaching, he is a research professor in engineering and master's programs, especially in the area of exact sciences, at a university in Latacunga, Ecuador. He also provides professional services, including the installation and maintenance of pumps, control panels, low-voltage networks, and the assembly of transformers and industrial equipment.

Enrique Torres Tamayo received the degree of mechanical engineer, the Master's degree in electromechanics, and the doctor of technical sciences (Ph.D.) degree. He has 28 years of experience in training electromechanical and mechanical engineers. He conducts research related to thermal processes and fluid transport. He has published 42 articles in journals indexed in prestigious international databases and has presented more than 30 papers at international scientific events. He has worked at several universities in Latin America and Africa, including the University of Moa, Cuba; Arba Minch University, Ethiopia; the Federico Rivero Palacios Higher Institute, Venezuela; the Mariscal Sucre Higher Institute, Venezuela; and the National University of Loja, Ecuador. From 2015 to 2025, he was a full-time professor at the Technical University of Cotopaxi. He is currently a professor in the Faculty of Engineering and Applied Sciences at the Technical University of Cotopaxi, Ecuador. He is a member of the Renewable Energies Education Network.