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ARTIFICIAL NEURAL NETWORKS TO PREDICT A COAL-FIRED POWER PLANT EFFICIENCY: COMPARATIVE STUDY

Renata Rech de Souza
Lara Werncke Vieira
Rafael Petri Zanardo
Julia Britto de Castro dos Santos
Paola Mendes Albino
Paulo Smith Schneider
Federal University of Rio Grande do Sul, Porto Alegre, Brazil
renata.rech@ufrgs.br
lara.vieira@ufrgs.br
rafael.zanardo@hotmail.com
julia.britto@ufrgs.br
paola.albino@ufrgs.br
pss@mecanica.ufrgs.br

Abstract. *The energy sector is responsible for almost three-quarters of the world's CO2 emissions, which makes it necessary for the sector to be at the center of climate change solutions. In this respect, coal-fired power plants have an important role since they provide about 40% of electricity worldwide and coal is the largest source of carbon emissions into the atmosphere. That makes the efficiency of these plants a critical parameter when it comes to environmental control and CO2 emissions mitigation. In this regard, machine learning models can capture unique characteristics of the power generation facilities without any previous knowledge of the process, which makes them an important tool to represent complex systems or capturing disturbances. The present work evaluates the efficiency of a real coal-fired power plant modeled by a Feedforward Neural Network (FFNN) and a Recurrent Neural Network (RNN). The performance of the models was evaluated by comparing the resulting Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) of each neural network. The resulting metrics shows that the RNN (MAE = 0,0539 and RMSE = 0,0662) is the most suitable model to represent the system and predict its efficiency in comparison with the FFNN (MAE = 0,0680 and RMSE = 0,1026).*

Keywords: *Machine Learning for thermal systems, Recurrent neural networks, Coal-fired power plant, Efficiency prediction*

1. INTRODUCTION

The energy sector is responsible for almost three-quarters of the world's CO2 emissions, which makes it necessary for the sector to be at the center of climate change solutions. In this respect, coal-fired power plants have an important role since they provide about 40% of electricity worldwide and coal is the largest source of carbon emissions into the atmosphere. That makes the efficiency of these plants a critical parameter when it comes to environmental control and CO2 emissions mitigation. In this regard, improvements in energy efficiency can make a critical contribution on minimizing energy demand growth, making a huge contribution to achieve de Net Zero Emission goal by 2050, as efficiency measures can be put into effect and scaled up quickly (IEA, 2021; IEA, 2019).

The application of accurate and reliable models that provide system control is an important area of research since a control structure allows to make predictions of system performance over a time horizon and establishes an optimal control (Hedengren et al., 2014), besides the improvements in energy efficiency and maintenance. Machine learning models are able to capture unique characteristics of the system without any previous knowledge of the process, which makes them an important tool to represent systems that are too complex or contain many unmeasurable disturbances. Artificial Neural Networks (ANN) are a powerful machine learning method capable of addressing a wide range of prediction problems (Tuttle et al., 2021). These models are created based on the type and the provided input. Then, it can solve difficult problems, generally providing an output with some probability distribution which suggests the prediction based on the input values (Abdullah et al., 2021).

The neural networks considered are a feedforward Neural Network (FFNN) and a Recurrent Neural Network (RNN). The objective is to identify the differences between the structures since the RNN has cyclic and reverse connections between nodes and layers, which allows the integration of past conditions with the current ones, and the FFNN models problems where input data has a timeless impact on the output data. Therefore, it is possible to compare the structures and identify the prediction of the parameters in time and determine how important this is for the improvement of the plant's performance. For this purpose, each method is evaluated and compared within the context of a coal-fired power plant located in Ceará, Brazil.

2. ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN) is used to work with complex systems with a lot of data. It generally includes an input layer, several hidden layers, and an output layer. Each layer is composed of several connected units, each one associated with an activation function (Li et al., 2020). After the model formation, neural network model can be used for a prediction purpose (Abdullah et al., 2021).

Feedforward Neural Network (FFNN) is used to generate a multi-layer neural network. In the multi-layered network, output of previous layer is input the to the next layer (Abdullah et al., 2021). The representation of this neural network is shown in Equation 1, where each layer beginning with the first hidden layer will pass its output to the subsequent layer as inputs. The Recurrent Neural Network (RNN) architecture displays differences compared to FFNN, in which the looping constraint on the hidden layer turns back to the RNN. The feedback constraint is back-propagated to ensure that the subsequent data is looped into the input data from the last step in each neuron's first step. RNN is normally used to solve problems associated with text data, time-series data, and audio data (Abdolrasol et al., 2021) and the prediction is performed using the output of the previous timestep, as shown in Equation 2.

$$o_i = f\left(\sum_{i=1}^{N_j} w_{ij} x_i + b_i\right) \tag{1}$$

$$o_i = f\left(\sum_{i=1}^{N_j} w_{ij} x_i + w_{ih} o_{i-1} + b_i\right) \tag{2}$$

In these equations, o is the output of the node, x is the input value, b is the bias term and w_{ij} is the weight of the ith node in the jth layer of the network, where there are N nodes. An example of the structure of each neural network is shown in Figure 1, where it is possible to identify the recurrent connections in the RNN that affect the subsequent result with the integration of past inputs.

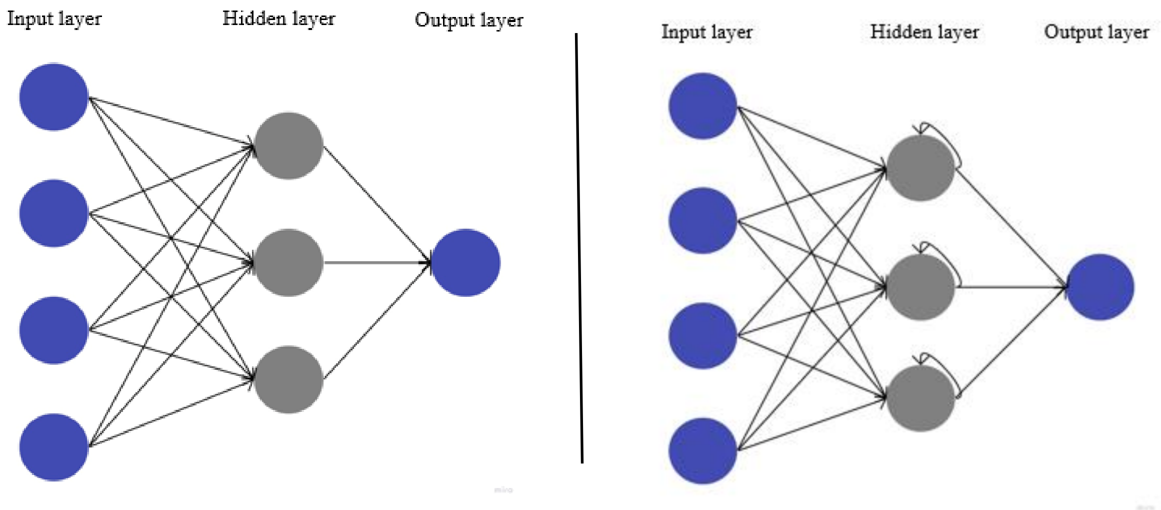

Figure 1. Left: Structure of a Feedforward Neural Network (FFNN). Right: Structure of a Recurrent Neural Network (RNN), highlighting recurrent connections amongst hidden layers.

3. SYSTEM DESCRIPTION AND METHODOLOGY

The system under analysis is the steam generator of Pecém power plant, a coal-fired power plant located in the state of Ceará, Brazil, with data from 2018 to 2020. The power plant is composed of three identical and independent power groups of 360 MW. A schematic layout of the steam generator and its coupled coal mills is presented in Figure 2.

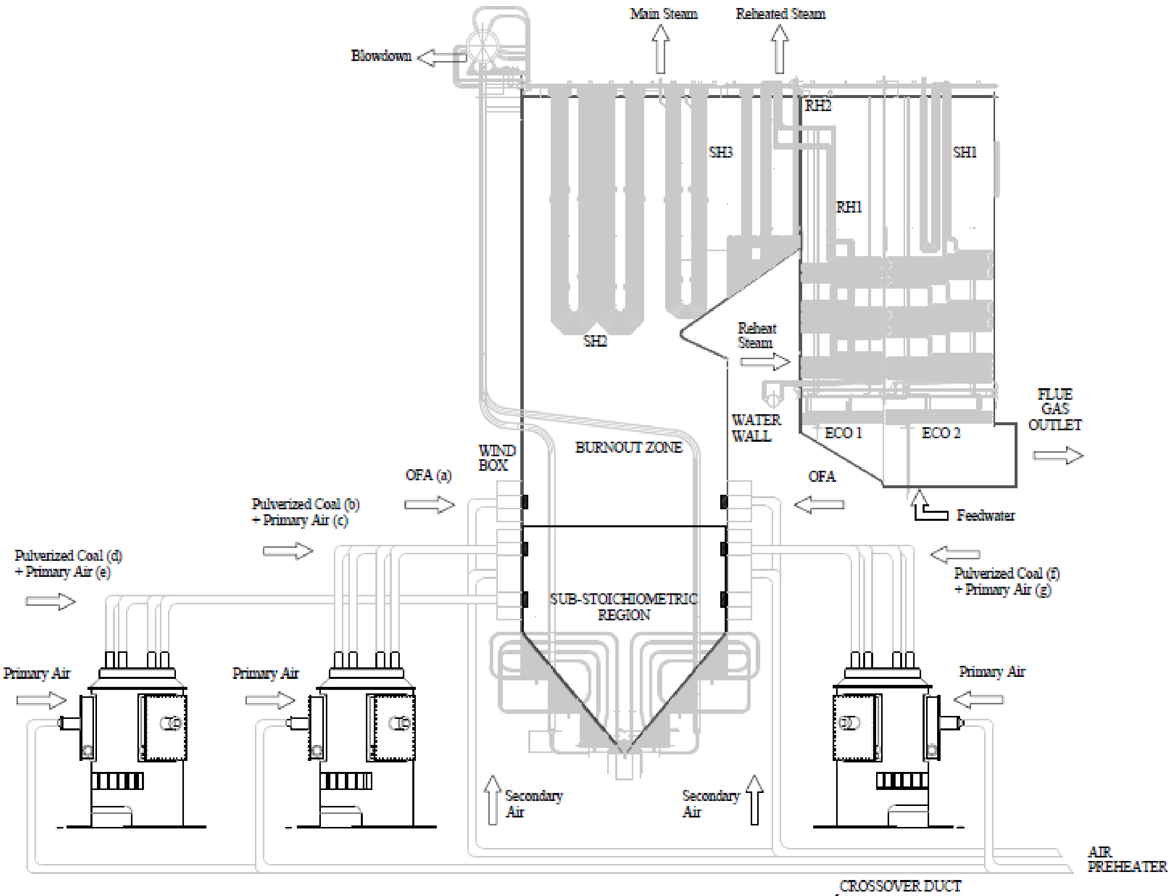

Figure 2. Pecém steam generator schematic layout (UTE PECÉM, Brazil)

The efficiency of the steam generator was modeled by two different ANN algorithms as a response of seven input parameters, presented in Table 1. These parameters were chosen based on their controllability and the operational range of each variable was defined with the assistance of the Pecém technical team (Vieira et al., 2022).

Table 1. Summary of controllable parameters operation range and respective levels

Description	Factor	Lower Level	Medium Level	Upper Level
Primary air flow [kg/s]	P1	24	26	28
Pulverizes coal outlet temperature [ºC]	P2	65	75	85
Speed of the dynamic classifier [rpm]	P3	90	100	110
Stoichiometry (dimensionless)	P4	0.80	0.88	0.95
Oxygen excess [%]	P5	1.5	2.3	3.0
Secondary air crossover duct pressure [mbar]	P6	18	21	23
Primary crossover duct pressure [mbar]	P7	70	78	85

The steam generator efficiency was predicted with the Feedforward Neural Network (FFNN) and the Recurrent Neural Network (RNN) algorithms, following the steps displayed in the flowchart in Figure 3. The objective of this methodology is to evaluate if the recurrent connections in the RNN improve its performance of prediction and that was determined by the evaluation of some metrics.

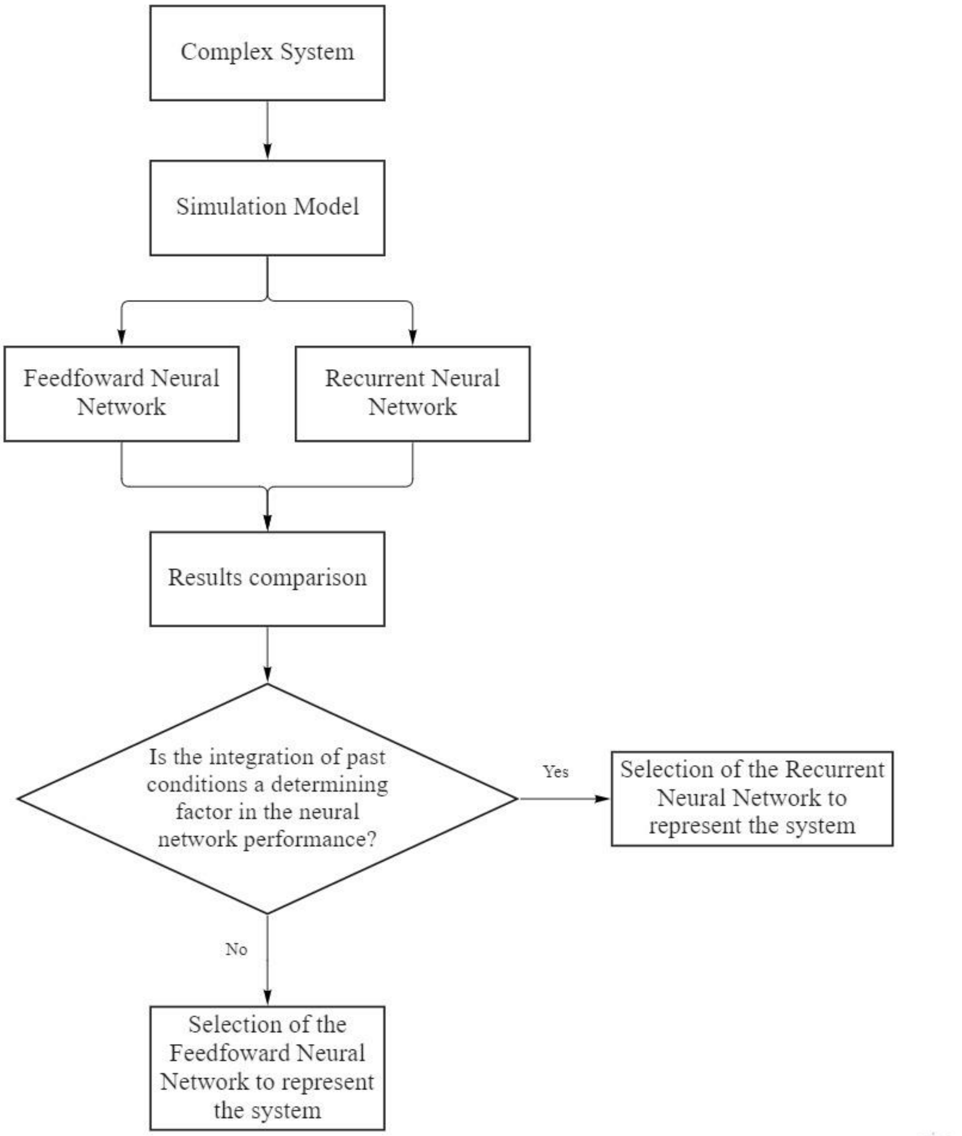

Figure 3. Methodology flowchart

The neural networks were trained using 70% of the available sequential data and the other part was separated for testing. The metrics used to evaluate the performance of the neural networks were the Mean Absolute Error (MAE) in Equation 3 and the Root Mean Squared Error (RMSE) in Equation 4. They were calculated to evaluate the suitability of the modeling methods for the prediction of the system's behavior.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|X_{exp} - X_{obs}\right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|X_{exp} - X_{obs}\right|^{2}} \tag{4}$$

In these equations, X_{exp} represents the expected value and X_{obs}, the value returned by the artificial neural network. A model's RMSE of prediction on the relevant dataset is used to characterize the model's prediction performance and to differentiate between the quality and desirability of models (Tuttle et al., 2021). The performance of the model is defined here as its ability to generate accurate and stable predictions across a future time horizon in a recursive prediction structure. Thus, in the prediction of this steam generator's efficiency, RMSE metric was used to select the best performing model due to its metric's sensitivity to large error values and due to the fact that the stability and reliability of performance along a time horizon has a great importance in this application.

4. RESULTS AND DISCUSSION

The data from 2018 to 2020 were acquired by the Pecém power plant Distributed Control System (DCS). The efficiency of the steam generator over that period is presented in Figure 4 where the variation of this parameter can be seen over time. The chosen topology and the metrics evaluated for the Feedfoward Neural Network (FFNN) and the Recurrent Neural Network (RNN) are in Table 2.

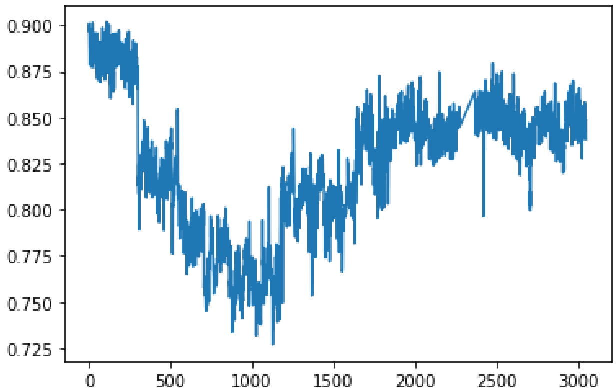

Figure 4. The efficiency of the steam generator over time.

Table 2. Resultant metrics for the evaluated ANNs for 100 epochs and a batch size of 64.

Neural Network	Input layer	Hidden layers	Activation function	Output layer	MAE	RMSE
Feedforward Neural Network (FFNN)	7	3	tanh-tanh-relu	1	0.0680	0.1026
Recurrent Neural Network (RNN)	7	2	tanh-tanh	1	0,0539	0,0662

It can be noticed that the RNN obtained lower MAE and RMSE, which indicates that this model of ANN has a better performance in representing the system. According to the study conducted by Tuttle et al. (2021), the FFNN model presents a greater accuracy at the beginning of the timestep, but over time it decays, in contrast to the RNN model, which has a lower RMSE over the timesteps, that were also identified in the present work. Thus, it can be stated that for this application, a Recurrent Neural Network is more stable and reliable when it comes to the prediction of the steam generator's efficiency, which means that the existence of recurrent connections in this structure allows the current conditions to be a direct result of past ones and that has a positive influence in the model performance.

5. CONCLUSIONS

The evaluation of different ANNs was performed in this work to predict the efficiency of the steam generator of a coal-fired power plant in Ceará, Brazil. This is a complex and dynamic system with many inputs and time dependencies involved. For this purpose, an FFNN and an RNN were used to predict the system's efficiency and the comparison of these models was made by the evaluation of the MAE and RMSE metrics.

In this evaluation, the Recurrent Neural Network showed to be the most suitable model to predict the steam generator's efficiency over a time horizon, with results for MAE and RMSE of 0,0539 and 0,0662 respectively, in comparison to the Feedforward Neural Network, with values of 0,0680 and 0,1026. These results indicate that the differences in the structure of the neural networks affects the model performance, in this case, the impact can be attributed to the recurrent connections in the RNN. Therefore, the proposed study restates the importance of identifying appropriate models to represent dynamic and complex systems to improve its controllability and performance.

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