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Power Plant Performance Assessment - Physical and Machine Learning Integration Through Multifidelity Modeling

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Abstract.*Energy conversion systems have assumed a crucial role in current society. In this context, the need for a more sustainable way of electricity production is evident. The integration of renewable energy sources, improving the conversion efficiency and controlling of power plant emissions is essential for energy transition. While a global energy transition is underway, further action is needed to reduce carbon emissions through smooth transactions from fossil fuels to clean energy. Power system optimization problems can be solved with the use of AI, which is becoming a key enabler of a complex, new and data-related energy industry, providing a key tool to increase operational performance and efficiency. The present paper proposes a multifidelity modeling approach to increase the efficiency of a 2x360MW coal-fired power plant located in Ceará, Brazil. The goal is to use multifidelity in order to ally the benefits of both the physical and machine learning modeling to increase accuracy. Multifidelity enable data associated with a high fidelity function that is costly to be evaluated or whose values are available at only a few points to be combined with another function of low-fidelity. The low-fidelity function is typically faster and can be evaluated at more points to form the set. A set of eleven experiments acquired on site is the high-fidelity data and an the low fidelity considers an Machine learning approach based on artificial neural networks (ANN). The low-fidelity model is used to generate samples globally over the range of the design parameters. The ANN considers operating data from 2018 to 2020. The proposed methodology aims safe and stable conditions to improve power plant performance during operation. The ANN results showed a relative deviation of around 6% while the multifidelity model decreased the relative deviation to around 1%. The increased model accuracy and ability to represent high-fidelity data are significant through multi-fidelity applications.*

Keywords: *Power generation, Performance Assessment, Multifidelity, Artificial Neural Networks*

1. INTRODUCTION

Energy conversion systems have assumed a crucial role in current society. Along with that, AI is becoming a key enabler of a complex, new and data-related energy industry, providing a key tool to increase operational performance and efficiency. The threat of climate change, fossil fuel depletion and the growing world energy demand ask for a more sustainable way of electricity production, eg, by using renewable energy sources, by improving the conversion efficiency and/or by controlling power plant emissions (Ahmad *et al.*, 2021; Stougie *et al.*, 2018).

There is a global consensus that our future energy supply should be cheap, clean, and safe. Efficient utilization of energy is one of the most effective ways to achieve the objective of carbon dioxide (CO2) reduction and can deliver benefits across the whole economy, with direct and indirect impacts on economic activity (Go *et al.*, 2020; IEA, 2019). AI technologies can help to achieve meaningful results to remain competitive extracting value from data and managing complex power systems. However, the effectiveness of these tools is based on the quality of both training and data sources.

A common issue encountered when applying machine learning to environmental sciences and engineering problems is the difficulty or cost required to obtain sufficient data for building robust models (Ahmad *et al.*, 2021).

There has been considerable growth in purely data-driven models. These models take advantage of data available to find functions that emulate the system's behavior. This approach does not follow the system physics, or any physical informed strategy, and they tend to be poor in extrapolations and require a large amount of data to find a satisfactory emulation function. In this context, multi-fidelity models are designed to augment the limited true observations available with cheaply-obtained approximations in a principled manner. These approach enable the integration of physical sources of information with purely data-driven models as different fidelity.

In such models, observations obtained from the true source are referred to as high-fidelity observations, whereas approximations are denoted as being low-fidelity. These low-fidelity observations are then systemically combined with the more accurate (but limited) observations in order to predict the high-fidelity output more effectively. Note than we can generally combine information from multiple lower fidelity sources, which can all be seen as auxiliary tasks in support of a single primary task. The usefulness of MF surrogates in the perspective of cost savings and accuracy improvement can be notice, for example, when it is not possible to afford enough HF simulations to build an acceptably accurate HF surrogate. But, an MF surrogate may offer superior accuracy at comparable cost (Giselle Fernández-Godino *et al.*, 2019).

This study aims to integrate physical and machine learning approach through multi-fidelity modeling in order to increase power plant performance. For this reason, it is proposed on field experiments as the high fidelity database and a simulation model using artificial neural networks as the low fidelity database. The paper contributes to the following questions: How AI and multifilidety can contribute to improving simulation models considering physics? How to use these models to improve power plant performance? And finally, what is the importance of system generation efficiency in the energy transition scenario?

The system under analysis is the steam generator of the PECEM power plant, a 2x360MW coal-fired power plant located in Ceará - Brazil. The proposed multifidelity modeling integrates physics and a machine learning approach to improve accuracy.

2. SYSTEM DESCRIPTION

The system under analysis is the steam generator of the PECEM power plant. The power plant is located near the ocean coast of the State of Ceará, Brazil, composed of three identical and independent power groups of 360MW. A schematic layout of the steam generator and its coupled coal mills is presented in Fig. 1.

The identical steam generators are equipped with heat exchangers such as super-heaters, reheaters, economizers and air heaters, arranged to efficiently absorb heat released by fuel combustion and deliver steam at rated temperature, pressure and capacity. These last parameters determine the steam generator configuration (Annaratone, 2008; The Babcock and Wilcox Company, 2015). Three independent mills feed one steam generator with dry pulverized coal as shown in 1.

3. METHODOLOGY

Figure 2 presents a flowchart of the proposed methodology.

3.1 Model representation and database selection

The model representation starts with a complex systems analyzes and database selection. It is divided into experimental data and system simulation. The experimental data includes in field experiments results and composes the high-fidelity (HF) database. The selected ML model for system simulation was Artificial Neural Networks (ANN) because of their ability to deal with complex problems. The ANN results formed the low-fidelity (LF) database. The metrics to evaluate the ANNs configuration performance were the Mean Absolute Error (MAE) and the Mean Squared Error (MSE).

The list of variables considered in the model is presented in Table 1. The set of variables are controllable parameters, which can be directly impacted by the actions of the unit control operator.

The operational range of each variable was defined with the assistance of the PECEM technical team, and limits were changed according to their experience and recommendations. It can be noticed that ranges are somehow limited but it always tried to reach the compromise of improving efficiency by respecting plant safety.

3.2 Multi fidelity Modeling

The low and high-fidelity databases were combined through multi-fidelity modeling. There are 11 in-field experiments and no option to perform new experiments due to power plant restrictions. In the perspective of cost savings and accuracy improvement, the solution is to perform low-fidelity simulation and build a multi-fidelity model. When the number of HF simulations is severely limited, there is an advantage of using the LF simulations (Giselle Fernández-Godino *et al.*, 2019)..

The present paper employed the Python toolkit Emukit, developed by (Paleyes *et al.*, 2021). The linear multi-fidelity

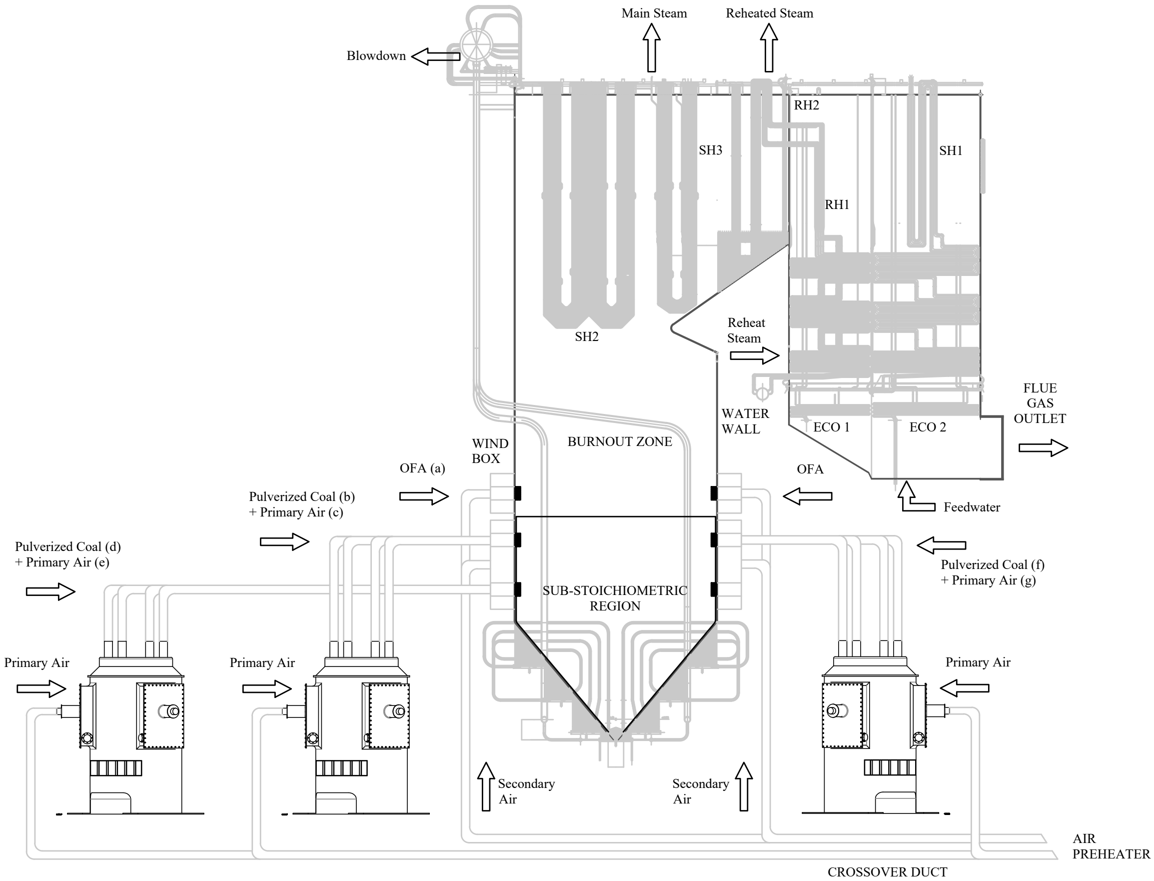

Figure 1. Steam generator schematic layout (UTE PECÉM, Brazil)

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

Factor	Lower Level	Upper Level	Description
P1 (kg/s)	24.0	28.0	Primary air flow
P2 (°C)	65	85	Pulverized coal outlet temperature
P3 (rpm)	90	100	Speed of the dynamic classifier
P4 (dimensionless)	0.80	0.95	Stoichiometry
P5 (%)	1.5	3.0	Excess O_2
P6 (mbar)	18	23	Secondary air crossover duct pressure
P7 (mbar)	70	85	Primary air crossover duct pressure

model proposed in (Kennedy and O'Hagan, 2000) is widely viewed as a reference point for all such models. In this model, the high-fidelity (true) function is modeled as a scaled sum of the low-fidelity function plus an error term according to Equation 1.

$$f_{\text{high}}(x) = f_{\text{err}}(x) + \rho\, f_{\text{low}}(x) \tag{1}$$

In this equation, $f_{\text{low}}(x)$ is taken to be a Gaussian process modeling the outputs of the lower fidelity function, while ρ is a scaling factor indicating the magnitude of the correlation to the high-fidelity data. Setting this to 0 implies that there is no correlation between observations at different fidelities. Meanwhile, $f_{\text{err}}(x)$ denotes yet another Gaussian process which models the bias term for the high-fidelity data. Note that $f_{\text{err}}(x)$ and $f_{\text{low}}(x)$ are assumed to be independent processes which are only related by the equation given above. This paper considered two fidelities, in the case of more fidelities the set-up can be generalized to cater for T fidelities as follows:

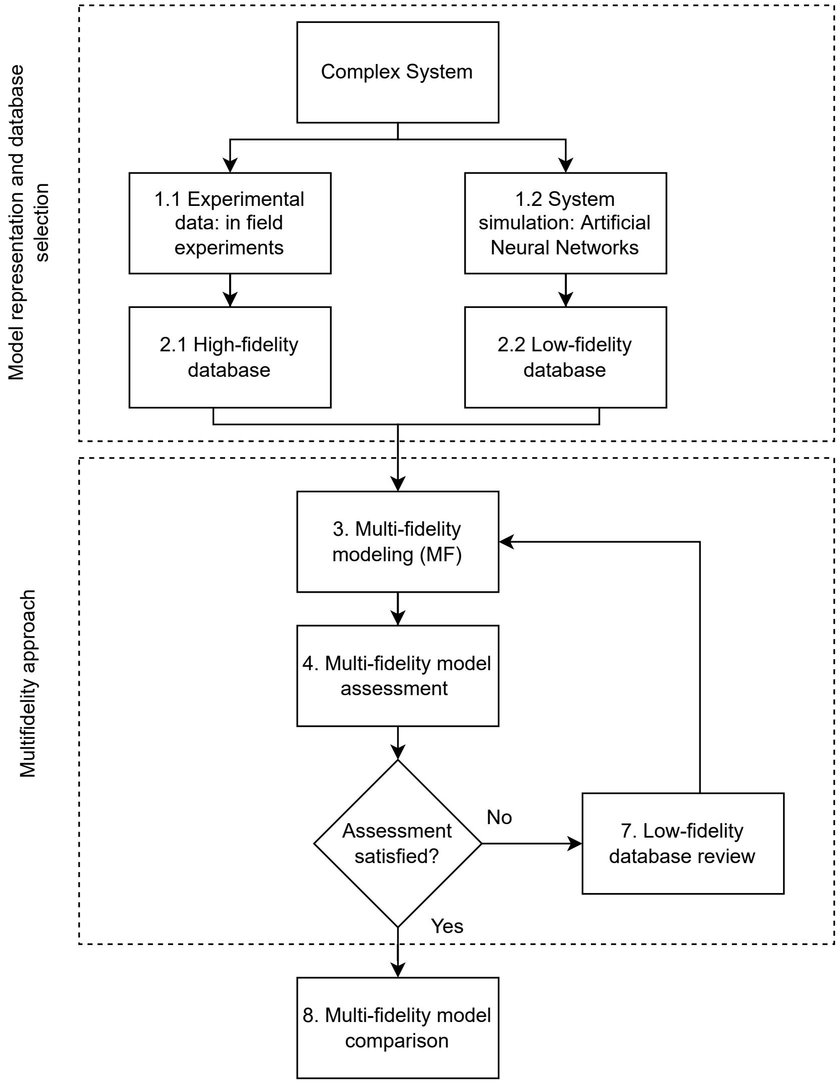

Figure 2. Methodology flowchart

$$f_t(x) = f_t(x) + \rho_{t-1}\, f_{t-1}(x), \quad t = 1, \ldots, T \tag{2}$$

If the training points are sorted such that the low and high-fidelity points are grouped together:

$$\begin{pmatrix} \mathbf{X}_{\text{low}} \\ \mathbf{X}_{\text{high}} \end{pmatrix} \tag{3}$$

It is possible to express the model as a single Gaussian process having the following prior.

$$\begin{bmatrix} f_{\text{low}}\,(h) \\ f_{\text{high}}\,(h) \end{bmatrix} \sim GP\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} k_{\text{low}} & \rho k_{\text{low}} \\ \rho k_{\text{low}} & \rho^2 k_{\text{low}} + k_{\text{err}} \end{bmatrix}\right) \tag{4}$$

The inputs to the models are expected to take the form of $ndarrays$ where the last column indicates the fidelity of the observed points.

Although only the input points, X, are augmented with the fidelity level, the observed outputs Y must also be converted to array form.

For example, a dataset consisting of 3 low-fidelity points and 2 high-fidelity points would be represented as follows, where the input is three-dimensional while the output is one-dimensional:

$$\mathbf{X} = \begin{pmatrix} x^0_{\text{low};0} & x^1_{\text{low};0} & x^2_{\text{low};0} & 0 \\ x^0_{\text{low};1} & x^1_{\text{low};1} & x^2_{\text{low};1} & 0 \\ x^0_{\text{low};2} & x^1_{\text{low};2} & x^2_{\text{low};2} & 0 \\ x^0_{\text{high};0} & x^1_{\text{high};0} & x^2_{\text{high};0} & 1 \\ x^0_{\text{high};1} & x^1_{\text{high};1} & x^2_{\text{high};1} & 1 \end{pmatrix} \quad \mathbf{Y} = \begin{pmatrix} y_{\text{low};0} \\ y_{\text{low};1} \\ y_{\text{low};2} \\ y_{\text{high};0} \\ y_{\text{high};1} \end{pmatrix} \tag{5}$$

It allows for a lot of flexibility for Gaussian processes that describe multiple correlated functions, like the 'multi-fidelity' model of Kennedy and O'Hagan (2000).

Fitting a standard GP model to the few high fidelity observations is unlikely to result in an acceptable fit, which is why we shall instead consider the linear multi-fidelity model.

3.3 Multi-fidelity model assessment

The high-fidelity database is a reference to verify the MF model. The amount of data to be left for training and testing varies according to the database size. One possible procedure is the Leave-one-out cross-validation (LOOCV) method, whenever the available database is small. Since only 11 experiments were available for the HF database, this was the procedure adopted in this paper.

3.4 Low-fidelity database review

After the MF model assessment, some low-fidelity points can be removed if they are not assisting the MF model predictions. If the model assessment is satisfied the last step is the multi-fidelity model comparison. If the model assessment is not satisfied, there is a new low-fidelity database review which can include a new database collection.

3.5 Multi-fidelity model comparison

The last step of the methodology includes the comparison between the experimental data, the ANN results and the MF results. The high-fidelity database is a reference to verify the results.

4. RESULTS AND DISCUSSION

Two sources of information were considered to analyze the steam generator of PECEM power plant: the historical data and experiments in-field. The historical data was acquired directly from the PECEM power plant Distributed Control System (DCS). Data processing identified the existence of special patterns, outliers, variation, and distribution. The input parameters were selected based on their controllability, which means they could be directly impacted by the actions of the unit control operator and were used for in field experiments and system simulation (see Table 1).

The complete in-field experiments results are presented in Table 2. The initial design matrix was proposed to the team in charge of conducting the experiments prior to its execution following a Design of Experiments approach. The eleven experiments shown in Table 2 are part of the initial design matrix which was not finalized.

The efficiency is plotted in the graph in Figure 3 to visualize the output variation during the experiments.

Table 2. High fidelity dabatase - in-field experiments at the PECEM power plant

Experiment Number	P1	P2	P3	P4	P5	P6	P7	Efficiency
01	26.0	65	90	0.88	2.3	23	78	84.19
02	24.0	75	100	0.88	2.3	18	70	84.37
03	26.0	75	100	0.80	3.0	23	78	84.02
04	26.0	75	100	0.80	3.0	18	78	82.89
05	26.0	75	100	0.88	2.3	21	78	83.90
06	24.0	75	110	0.88	3.0	21	78	83.61
07	26.0	65	100	0.88	3.0	21	85	83.19
08	28.0	75	100	0.88	2.3	23	85	83.76
09	26.0	85	100	0.88	3.0	21	85	82.92
10	24.0	75	100	0.88	2.3	18	85	82.82
11	24.0	85	100	0.95	2.3	21	78	83.71

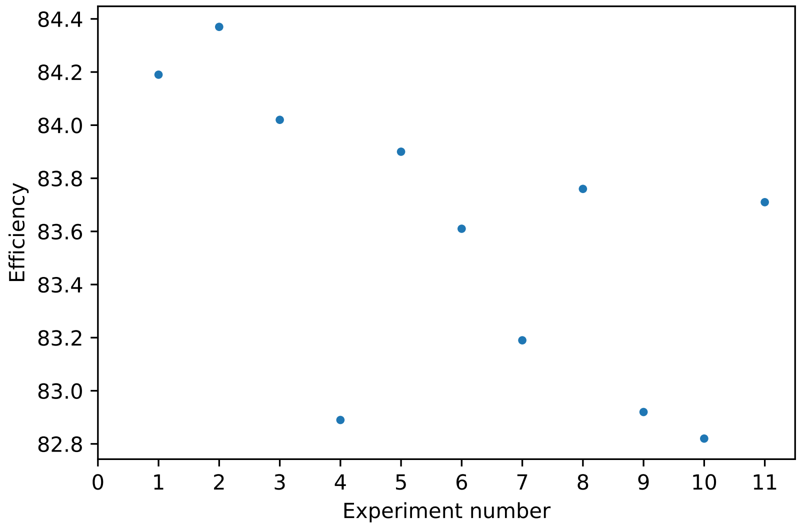

Figure 3. Steam generator efficiency of the real experiments at the PECEM power plant

The low fidelity database was build based on the representation of the system through ANNs. The historical data was randomized and divided into 70% for training and 30% for testing and validation (Burkov, 2019). Parameters were standardized with respect to their correspondent standard deviation. ANNs were built using the Keras programming interface (Chollet *et al.*, 2015) running on top of the Tensorflow machine learning library (Abadi *et al.*, 2015). The chosen topology for the ANN is presented in Figure 4, and detailed in Table 3.

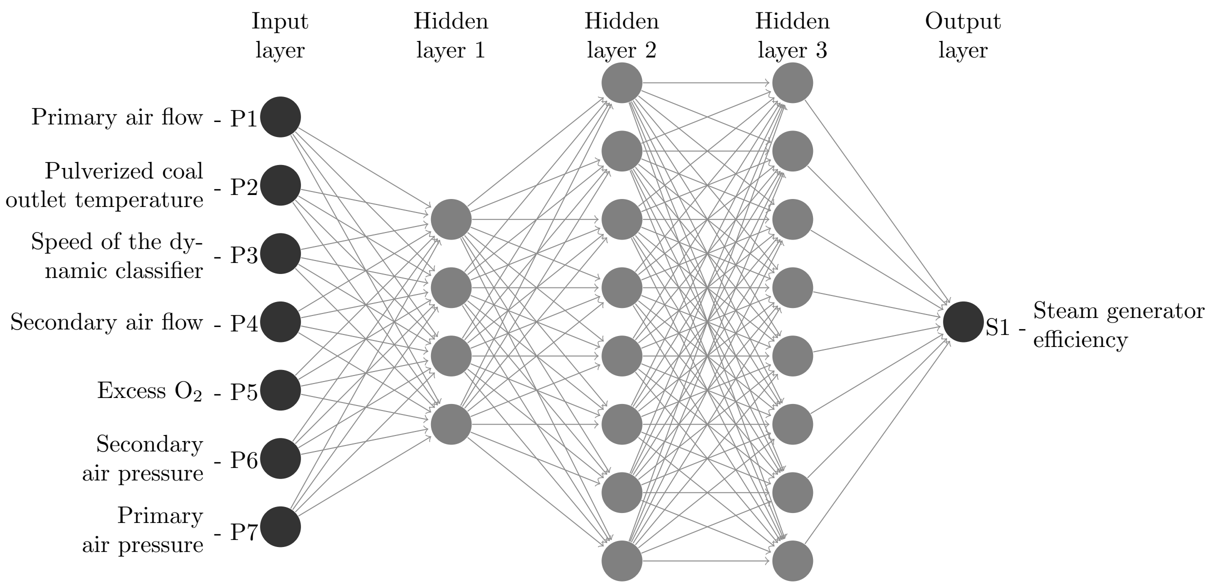

Figure 4. ANN steam generation subset model topology

Table 3. Chosen ANN - Backpropagation learning algorithm and Multi-Layer Perceptron network type for 200 epochs with a batch size of 256

Input layer	**Hidden neurons**	**Hidden layers**	**Activation function**	**Output layer**	**MAE training**	**MSE training**	**MAE testing**	**MSE testing**
7	4 - 8 - 8	3	tanh-tanh-relu	1	0.0130	0.0003	0.0135	0.0003

ANN generated both the low-fidelity database and the reproduction of the 11 in-field experiments for comparative analysis of results. The LF database was composed with 5% of ANN's training and testing data. They were randomly selected because it spans the entire project space, resulting in 146 data points.

Fitting a standard GP model to the few high fidelity observations is unlikely to result in an acceptable fit, which is why instead was considered the linear multi-fidelity model presented. A linear multi-fidelity model was fitted to the available low and high fidelity observations. An RBF kernel was used for both the bias and correlation components of the model.

The multi-fidelity model results were compared to the ANN results to represent the in-field experiments considered as the high-fidelity database (see Table 2). The results comparison is presented in Table 4.

Table 4. Results comparison of the ANN, Multi fidelity modeling and Experimental data

	ANN	**MF**	**In-field experiments**
Experiment 01	78.45	83.37	84.19
Experiment 02	78.32	83.24	84.37
Experiment 03	78.31	84.38	84.02
Experiment 04	78.28	83.69	82.89
Experiment 05	78.28	83.56	83.90
Experiment 06	78.24	83.53	83.61
Experiment 07	78.29	83.61	83.19
Experiment 08	78.29	83.44	83.76
Experiment 09	78.29	83.53	82.92
Experiment 10	78.33	82.98	82.82
Experiment 11	78.41	83.30	83.71

The ANN results showed a relative deviation around 6% while the multifidelity model decreased the relative deviation around 1%. The relative deviation was calculated by the ratio between the efficiency difference of the in-field experiments and the simulation model in relation to the in-field experiments efficiency. The increase in model accuracy and ability to represent the high-fidelity data is significant through the application of multi-fidelity.

5. CONCLUSIONS

The integration of physical models and machine learning was performed through the application of artificial neural networks and in-field data from a coal-fired power plant in operation. The in-field experiments account for 11, while the artificial neural network was built from a database of two years of operation. The steam generator was analyzed considering as the main output the efficiency based on seven controllable input parameters: the mills' primary air flow, pulverized coal outlet, the speed of the dynamic classifier, steam generator's secondary air flow, excess O2, and primary and secondary air pressures.

The 11 experiments collected do not constitute a sufficient database to represent the system and were considered as the high-fidelity database in the multi-fidelity model. The ANN modeled with seven inputs presents MAE and MSE of 0.0130 and 0.0003 for the training data set and MAE and MSE of 0.0135 and 0.0003 for the testing data set.

The result of the multi-fidelity model was compared with the ANN model to predict the steam generator efficiency. The ANN results showed a relative deviation around 6% while the multifidelity model decreased the relative deviation around 1%. The multi-fidelity model, when using the experimental data with the neural network, allowed a better representation of the system. The increase in model accuracy and ability to represent the high-fidelity data is significant through the application of multi-fidelity.

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