A grey-box Neural Network Composite Model for an Industrial Heating Furnace

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Abstract

Industrial furnaces consume large amounts of energy and their operating points have a major influence on the quality of the final product. Designing a tool that analyzes the combustion process, fluid mechanics and heat transfer and assists the energy audit work is then of the most importance.

This work proposes a hybrid composite model for such a tool, having, as its base, two white-box models, namely a detailed Computational Fluid Dynamics (CFD) model and a simplified Reduced-Order (RO) model, plus a black-box model developed using Artificial Neural Networks. The preliminary results presented in this paper show that this composite model is able to improve the accuracy of the RO model without having the high computational load of the CFD model.

1 Introduction

Industrial furnaces are important heating equipment. They have a major influence on the quality of the final product and consume large amounts of energy. The objective of this work is to develop a tool that analyzes the combustion process, fluid mechanics and heat transfer and assists the work done by energy auditors in the data analysis and the definition of measures for improving energy efficiency. This tool should have a high degree of accuracy without a high computational cost and be able to be applied to a variety of furnace geometries.

This paper presents a preliminary work carried out under the "Audit Furnace" project and is part of the prototype development of such a tool. Primarily, two physics based models were built up for a specific billet heating furnace [2]: a detailed Computational Fluid Dynamics (CFD) model and a simplified Reduced-Order (RO) model. These two white-box models constitute the base to build a black-box model developed using Machine Learning (ML) techniques. The main goal of such a hybrid model is to further improve the accuracy of the RO model without the computational cost of the CDF one. Since the acquisition of sufficient furnace functioning points was not possible, the data generated by a validated CFD model was used as ground truth to train the ML model.

This work, which uses Artificial Neural Networks as the ML technique, follows the one presented in [4].

2 White-box models

Large industrial process heating furnaces are complex systems designed to deliver heat to loads for many distinct processes. They are critical for the final product quality and should run efficiently so that energy usage and operation costs are kept the lowest possible.

Computational Fluid Dynamics model. Although using CFD models to simulate furnaces is the approach that provides the most detailed information, it includes complex tasks, such as constructing a spatial discretization grid, and the computational cost is large. Additionally, due to the diversity of processes and raw materials processed, the types of furnaces are numerous. Therefore, there is no universal model and the CFD models must be adapted to each furnace to closely represent the physical and chemical phenomena that take place.

The CFD model implemented aims at modelling an industrial furnace that heats metal billets using liquefied propane gas as fuel. Its description can be found in [2]. The 3-D, steady, differential, ensemble averaged transport equations of mass, momentum, energy, and mass of chemical species were numerically solved using the commercial software Fluent v19.0 [1] and the model was validated against experimental data [3].

Since the CFD simulations of the complete furnace took too much time (around 300 h each), the model presented in this paper was developed to simulate only one furnace section.

Reduced Order model. Reduced Order models do not consider all the details and complexity of the physical phenomena involved, but keep an acceptable accuracy regarding the overall energy and mass balances. They are based on physical principles and laws and constitute simplified models usually with extremely light computational load when compared with CFD models. This gives them much faster response times, these models being, also, more simple to build, at the expense of a decrease in the accuracy. In this work, the developed RO model is based on the division of the furnace into a relatively small number of zones and on solving energy and mass balances for each of these zones.

3 Grey-box model

The proposed model gets data from the CFD and RO models and uses a Machine Learning approach to further increase RO model accuracy, making the new model closer to the CFD one. Thus, the approach can be seen as a composite model of black-box and white-box models, consisting of the RO generated output along with an adjustment generated by the ML model. This grey-box composite model aims at being a trade-off between the high complexity/more accurate CFD model and the much simpler/less accurate RO model. Figure 1 presents this grey-box model composed by the RO and ML models along with the CFD and RO only models.

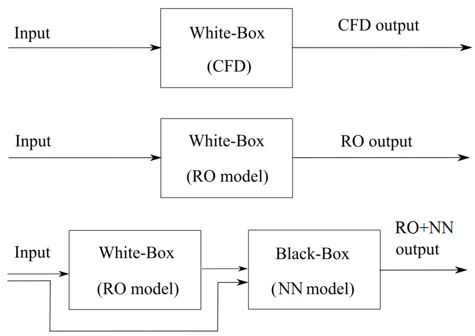

Figure 1: CFD, RO and grey-box (composed by the RO and ML) models.

The training phase of ML approaches should have a large amount of data and this data must be representative of all relevant situations of the system. As such, it should include a diversity of operating regimes, as well as, furnace characteristics. As already mentioned, we propose to use the data generated by the detailed CFD model for training, aiming to overcome the difficulty of obtaining real data from industrial furnaces covering all the relevant situations (operation regimes and furnaces characteristics). We are aware that the number of CFD simulations used could still not be enough to develop an accurate and sound model.

The ML model. Artificial Neural Networks (ANN) is a ML algorithm inspired by the human brain. It can be used in classification or regression problems and can be very memory and CPU intensive because of matrix multiplications and storage of weights, especially in deep neural networks where there are more than one hidden layer.

A grid search algorithm was used to find the best combination of the ANN hyper-parameters. One hidden layer was established to lighten the computational load and the considered range for the parameters was: *neurons*={3,5,7,9}, *epochs*={100,150,200}, *batch size*={5,10,20} *activation function*={"elu","relu"}, and *optimizer*={"sgd","adam"}.

Using 80% of the dataset and a 10 fold cross-validation procedure, the optimal combination of hyper-parameters (for both architectures) was found to be 9 *neurons*, 200 *epochs*, *batch size*=5, "relu" *activation function* and "adam" *optimizer*.

4 Experiments and Results

Dataset. As previously mentioned, the data used to build the ML model was generated by the validated CFD model for one section of a specific furnace used in the metal industry.

The exhaust combustion gas temperature downstream, named *TGO*, is one of the ten chosen continuous variables generated by the CFD model; This variable is considered the dependent variable of the ML model (output variable), while the other eight variables behave as input of the model. These variables are also available to be used by the RO model. Besides these CFD variables, the ML approach also uses variables generated by the RO model. Thus, the generated dataset includes thirteen continuous variables used as input plus one variable to be predicted. Since variables have different scales, all were normalized to the interval $[0,1]$. The input variables are presented in Table 1.

Name	Meaning	Source
SurplusAir	Excess air	CFD
T_IN	Temperature at burner inlets	CFD
M1_IN	Mass flow rate at burner inlets	CFD
T_ WG_UP	Flue gas temperature	CFD
M1_WG_UP	Flue gas mass flow rate	CFD
T_BILL	Billet inlet temperature	CFD
DTB	Variation of billet temperature	CFD
M1_WG	Combustion gas mass flow rate	CFD
FUEL_V	Flow rate of fuel in the burners	RO
AIR_V	Flow rate of air in the burners	RO
M_BILL	Billet mass flow rate	RO
TGI	Combustion gas inlet temperature	RO
TBO	Billet output temperature	RO

Table 1: Continuous variables used as input for the ML model.

Other variables generated by the CFD and RO models were also considered but discarded after analysing their interdependence.

A total of 100 pairs input-output (that correspond to different furnace working settings) were generated by the CFD and the input values of the RO model were adjusted to the CFD inputs in order for both outputs to be comparable.

Experiments. The proposed method was tested according to two different architectures: (a) *RO+NN*, where the estimated exhaust combustion gas temperature from the RO model is added to the NN output; (b) *RO2NN*, where the estimated exhaust combustion gas temperature from the RO model is used as an input variable to the NN.

In the first proposed architecture, *RO+NN*, the ANN aims at predicting the difference between the RO model output and the CFD output (the RO model prediction error). This difference enables the adjustment of the RO model output to a value closer to the CFD output. In the second case, *RO2NN*, the ANN receives as input, the estimated exhaust combustion gas temperature (TGO) from the RO model, besides the remaining fourteen attributes, and directly aims at predicting the TGO value given by the CFD model.

Results. To evaluate the ANN prediction power two measures were used: the root mean square error (RMSE) and the mean absolute percentage error (MAPE). Table 2 presents the results obtained for both evaluation measures[1] and proposed architectures; the first column presents the results given by the RO model. As can be seen, when compared to the RO model, a grey-box model (for any of the proposed architectures) significantly reduces the error to less than one third in both mesasures. On the other hand, the errors obtained with both *RO+NN* and RO2NN architectures are similar.

Measures	RO model	RO+NN	RO2NN
RMSE	144.73	41.55	41.23
MAPE (%)	12.24	3.77	3.23

Table 2: RMSE and MAPE results of the different models.

[1] Note that while *MSE* and *RMSE* are calculated over absolute differences, *MAPE* is a normalized measure.

Figure 2 presents, for each test example, the *RO2NN* model data points: the difference of the TGO predicted value to the actual one (the CFD output). For the 20 points (with TGO values varying between around 750 and 1050 K), 4 have a difference higher than 50, and 12 have a difference less than 25.

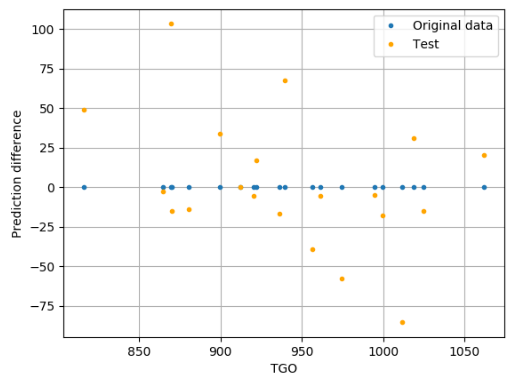

Figure 2: *RO2NN* TGO predicted values vs. actual ones for the test set.

The *RO+NN* model presents similar results (8 points with a difference less than 25). Given the similarity, it is difficult to argue which architecture is better able to predict values closer to the real ones. New findings should emerge with a bigger dataset.

5 Conclusions and Future Work

Although the presented work is still a work in progress and being aware that the amount of data used to build the model is not enough, these experiments seem to demonstrate the effectiveness of the approach. The results show that the proposed ML approach based on ANN is adequate to help on the mathematical models built for energy audits. It also demonstrates that physically based RO models complemented with black-box models can generate a composite model with increased accuracy while keeping a low computational running load.

We should also note that this strategy with CFD generated data helps to overcome the difficulty of obtaining rich experimental data from industrial furnaces.

In order to support these conclusions, we intend, as future work, to test this approach using more CFD simulations and other furnaces. These will increase and enrich the dataset and enable the development of more accurate models applicable also to different furnaces. Also, we intend to apply genetic algorithms to better fine tune the ANN hyper parameters. Moreover, the proposed model will be incorporated into a computer tool that will allow a rapid analysis of furnaces in the scope of energy audits.

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