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ESTIMATING FLUE-GAS DISTRIBUTION IN ANODE BAKING FURNACES EMPLOYING AN ARTIFICIAL NEURAL NETWORK-BASED METHOD

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ABSTRACT

2GJ of energy is required to bake one ton of carbon anodes which are heat-treated in the anode baking furnaces. Computational fluid dynamic (CFD) modeling is useful in conducting coupled transient heat transfer, turbulent fluid flow, and combustion simulations. However, due to the huge temporal and spatial domains, it is difficult and expensive computationally to use CFD models for the evaluation of the overall furnace operation. As a part of quality control in most of the modern aluminum smelters, large flue-gas and anode temperature measurements are available. The present study applies an artificial neural network-based method to better exploit these large datasets and gain new physical insight in a cost-effective manner. A shallow neural network is considered consisting of an input layer, a hidden layer, and an output layer. The data is divided into a training set (70%) and a validation set (30%), to avoid overfitting of the data. It is remarked that there is a good agreement between the fitted data and targeted values for both the validation set as well as the training set. For the case study, 147 epochs are required to reach the best validation performance, which is 84.9. The error between predicted and target values are mostly between ±20°C, which indicates a high accuracy in the prediction level. The neural network-based model can be effectively integrated into the anode baking process models to estimate anode baking uniformity more precisely. The methodology presented in the current research can be extended to simulate the entire anode baking process, preheating, firing and cooling sections, cost-effectively.

Keywords: Anode baking furnace, artificial neural network, anode baking, flue-wall.

1. INTRODUCTION

Green (unbaked) anodes should be baked (heat-treated) to obtain desired mechanical, thermal, and electrical properties that make them suitable to be used as anodes in the aluminum production. In the overall anode manufacturing process, baking contributes to ~ 44 % of the total processing cost. Anode baking is the most crucial step in the carbon anode production.

		1st Replicate					
		Flue -3 (A hole)-Downstream			Flue -3 (C hole)-Upstream		
		Top	Middle	Bottom	Top	Middle	Bottom
Number	Section	DS3	DS2	DS1	US3	US2	US1
1	PH-1	0.080466472	0.098542274	0.115306122	0.140015	0.108965	0.14154519
2		0.076676385	0.101822157	0.112609329	0.14898	0.112536	0.142419825
3		0.075218659	0.103498542	0.112026239	0.152332	0.114796	0.143148688

2nd Replicate							
Flue -4 (A hole)-Downstream			Flue -4 (C hole)-Upstream				
Top	Middle	Bottom	Top	Middle	Bottom		
DS3	DS2	DS1	US3	US2	US1	Section	Number
0.075073	0.101093	0.126020408	0.1469388	0.113192	0.172157434	PH-1	1
0.078207	0.113703	0.137973761	0.1632653	0.12981	0.188921283		2
0.080831	0.121574	0.145189504	0.1667638	0.138848	0.197376093		3

Fig 1 Flue-gas experimental measurements in flow downstream and upstream for two flue-walls

As shown in Fig 1, flue-gas experimental measurements are done in flow downstream and upstream for the flue-walls on the two sides of the anodes (pit). As depicted in Fig 2, during firing sections, due to pulse combustion features, the uniformity in gas temperature is significantly low. This non-uniformity in gas temperature results in non-homogenous baking of the anodes. In the literature [1-3], the average gas temperature is considered, which can be highly

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erroneous and does not provide insight into the degree of non-uniformity.

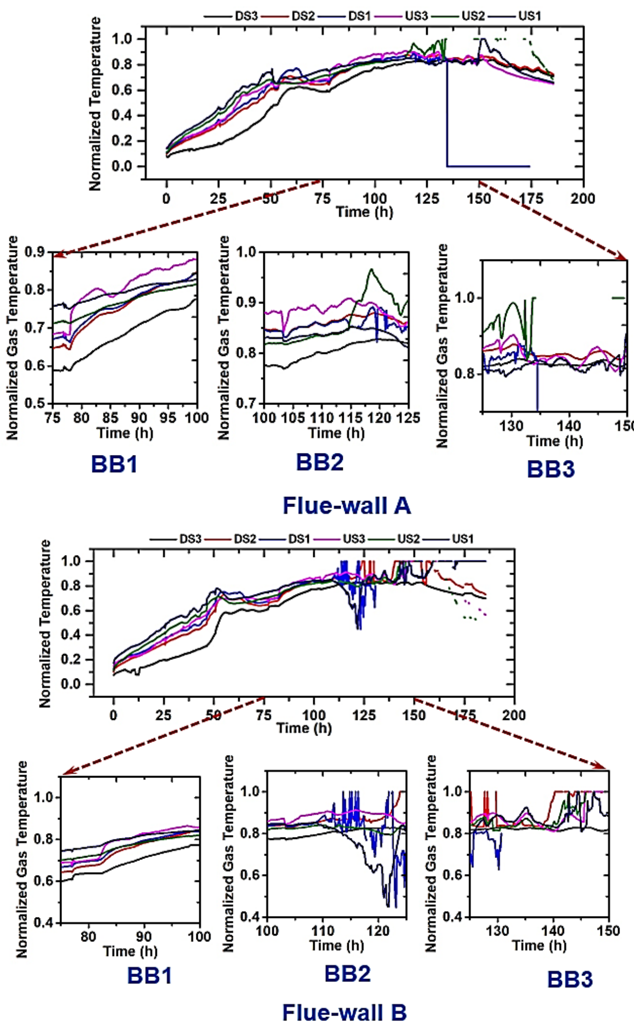

Fig 2 Flue-gas experimental measurements in flow downstream and upstream for two flue-walls

Anode baking CFD modeling is useful in conducting coupled transient heat transfer, turbulent fluid flow, and combustion simulations for the anode baking furnace [4-13]. However, due to the huge temporal and spatial domains, it is difficult and expensive computationally, to use CFD models for the evaluation of the overall furnace operation. As a part of quality control in most of the modern aluminum smelters, large flue-gas and anode temperature measurements are available. The present study applies a neural network-based method, to better exploit large datasets and gain new physical insight by making use of the unprecedented detail of these data to construct reliable models cost-effectively.

2. NETWORK STRUCTURE

As shown in Fig 3, the large data sets available can be used to develop data-driven models. In the neural network-based models, the learning rules are applied, which can be supervised or unsupervised. In the present study, supervised learning is adopted.

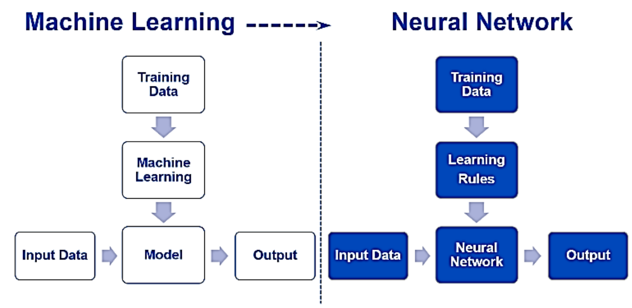

Fig 3 Flow chart for machine learning and neural network-based models

Fig 4 shows the structure of a shallow neural network consisting of input, hidden, and output layers.

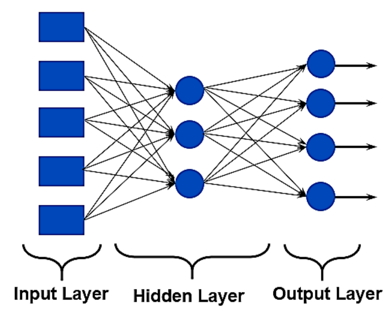

Fig 4 Input, hidden and output layers for a shallow neural network

As summarized in Table 1, activation functions are used to determine the behavior of different input and to predict the output.

Table 1 Different activation functions

Activation Function	Description
$f(x)=\begin{cases}1\ if \sum_{i=1}^{n} x_i w_i > 0 \\ 0\ if \sum_{i=1}^{n} x_i w_i \le 0\end{cases}$	Step function: The activation function only responds to the sign of the weighted input sum defined by Eq. 1.
$f(x)=\begin{cases}k\sum_{i=1}^{n} x_i w_i & if \sum_{i=1}^{n} x_i w_i < MAX \\ MAX & otherwise\end{cases}$	Saturation function: The activation value corresponds to the value of the weighted sum defined by Eq. 1, where k is a constant only if this sum does not exceed a pre-defined MAX value.
$f(x)=\frac{1}{1+e^{-x}}$	Sigmoid function: An *S-shaped* function, it provides a graded, non-linear response. The saturation levels range from 0 to 1.
$f(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$	Hyperbolic tangent function. An *S-shaped* function, it provides a graded, non-linear response. The saturation levels range from -1 to 1.

Fig 5 depicts the structure of a shallow neural network consisting of input, hidden and output layers with the activation function included.

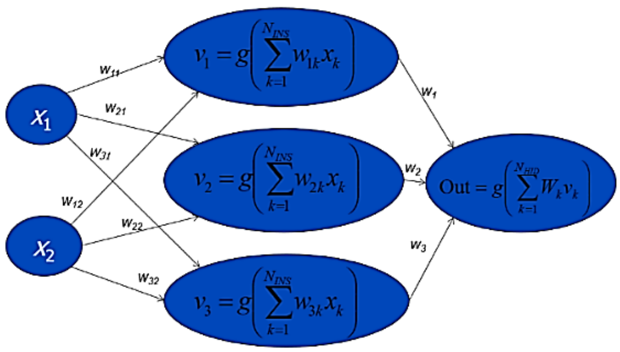

Fig 5 Input, hidden and output layers for a shallow neural network including an activation function

As sensitivity study is conducted and the sigmoid function is selected as the activation function.

3. RESULTS AND DISCUSSIONS

Fig 6 shows the regression results for training data, validation set, test set, and overall sets. The data is divided into a training set (70%) and validation set (30%) to avoid overfitting of the data. It can be seen that there is a good agreement between the fitted data and targeted values for both the validation set as well as the training data sets.

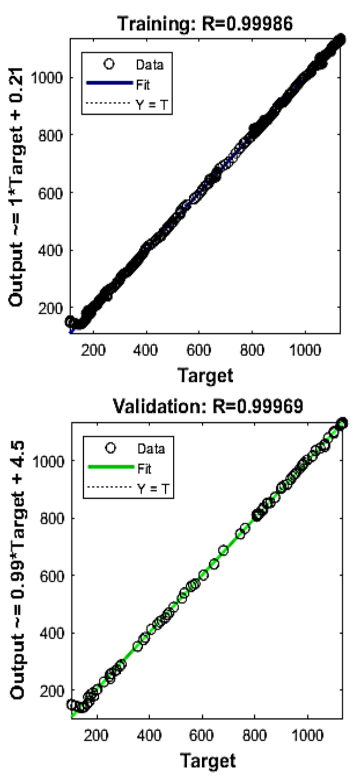

Fig 6 The regression results for the training data and validation sets

As shown in Fig 7, 147 epochs or iterations are required to reach the best validation performance, which is 84.9.

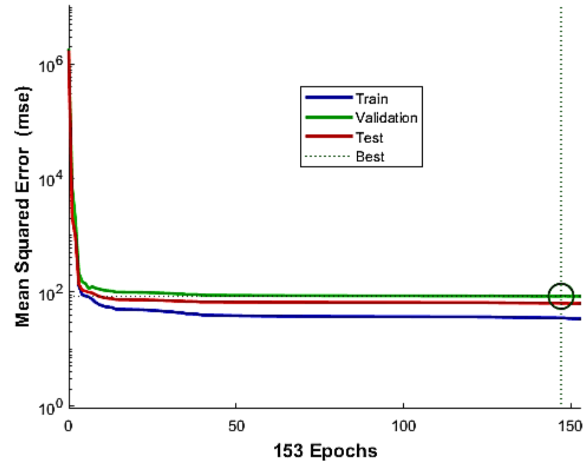

Fig 7 Best validation performance

Fig 8 shows the Error values between output and target values for different sets. It can be seen that the error values are mostly between -20 to 20 °C, which indicates a high accuracy in the prediction level.

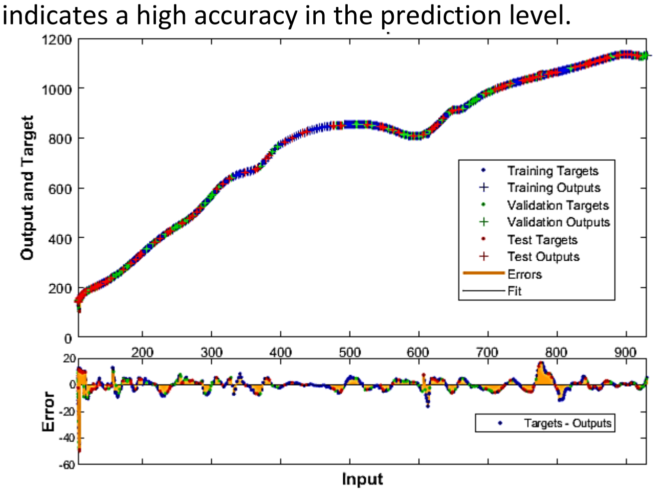

Fig 8 Error-values between output and target values for different sets

Using the established model, the relation between the average gas temperature and different temperature measurements in the flow upstream and downstream can be estimated. The established models can be effectively integrated into the other physics-based models. Thus, Artificial neural network (ANN) can be considered as a useful tool to simulate the entire anode baking process, preheating, firing and cooling sections, cost-effectively. Future studies are required to investigate more thoroughly the application of ANN in anode baking process modeling and optimization.

4. CONCLUSIONS

In the present research, a neural network-based model is employed to exploit large datasets of experimental measurements and gain new physical insight cost-effectively. Using the established model, the relation between the average gas temperature and different temperature measurements in the flow upstream and downstream can be estimated. A shallow neural network is considered consisting of an input layer, a hidden layer, and an output layer. The data is divided into a training set (70%) and a validation set (30%) to avoid overfitting of the data. It is remarked that there is a good agreement between the fitted data and targeted values for both the validation set as well as the training data set. The error between predicted and target values are mostly between $\pm 20°C$, which indicates a high accuracy in the prediction level. The neural network-based model can be effectively integrated into the anode baking process models to estimate anode baking uniformity more precisely. The methodology presented in the current research can be extended to simulate the entire anode baking process, preheating, firing and cooling sections, cost-effectively.

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