Performance Modelling of the Regenerative Blower for Air Supply of SOFC System with Random Forest and Bayesian Optimization

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Abstract

Air starvation is a serious hazard during the operation of a solid oxide fuel cell (SOFC) system. So, an accurate performance model of the air supply system is needed for the control of air flow rate and the reduction of air starvation. The performance modelling of a regenerative blower, which is used for the air supply of a 5 kW SOFC system during power generation, is proposed based on the methods of random forest (RF) and Bayesian Optimization (BO). The performance model is first built through the RF method. The BO algorithm is then used to adjust the hyper-parameters of the model. The developed model can predict the outlet air flow rate through the operation data of regenerative blower, i.e. the rotation speed of impeller, the inlet and outlet pressure, humidity and temperature, without specific geometrical parameters. A series of operation data obtained from an experimental test rig are adopted to train and validate the presented method. Finally, the prediction performance of the developed algorithm is compared with different machine learning methods, such as decision tree regression, deep neural network. Results show that the proposed method can predict the outlet air flow rate under different working conditions with minimum prediction errors within 3.5% and acceptable computational cost. Therefore, the developed algorithm is promising for performance modelling of the blower, which can be used to predict the outlet flow rate and control the air supply system at SOFC in our next research.

1 Introduction

Due to the increasingly serious greenhouse gas emission, clean coal technology has attracted great attention. The solid oxide fuel cell (SOFC) system, a high efficiency energy conversion system mainly composing of SOFC stacks, fuel and air supply system, heat and water management system, has been considered as a promising technology to combine with coal gasification to reduce the emission of greenhouse gas (Grasham et al. 2019; Choudhury et al. 2013). Coal gasification integrating SOFC will play an important role on coal industry in future (Guo et al. 2007; Krüger 2019; Chen et al. 2015), such as clean coal technology, coal-fired power generation with carbon dioxide capture and multiple cogeneration system. However, oxygen starvation may occur during power generation due to imprecise model and control of blower or compressor in the air supply system, which will lead to the degradation of cell performance, damage of electrode and electrolyte and even the whole system. Therefore, an accuracy and rapid modelling method is essential to control the air supply and SOFC system based on the structure of model predictive control and maintain the reliability, quality and efficiency of power generation of a SOFC system (Mayne 2014).

The behavior and prevention of oxygen starvation, a serious hazard condition that will significantly influence the efficiency, durability and safety of fuel cell, has been studied and reported by many researchers (Liu et al. 2006; Gerard et al. 2010; Taniguchi et al. 2008; Vahidi et al. 2004). Fuel, such as hydrogen, methane and syngas, is electrochemically combined with oxygen to produce electrical energy and heat in fuel cell with the presence of electrolyte and electrode. The electrode half reaction and overall reaction follow the given flux stoichiometry according to electrochemical equations, which means that the fluxes of reactants should be high enough to maintain the balance of reaction (Yu et al. 2011). While

the fluxes of fuel or oxygen are insufficient for the electrochemical reaction, the fuel cell performance will decrease sharply, which is called starvation vividly. There are probably many reasons contributing to this phenomenon, such as uneven flux distributions in flow field and between cells due to poor design and assembly of cell and stack, flow channel blockage due to poor water and heat management, low dynamic response of air supply due to poor control of blower or compressor (Liu et al. 2006; Gerard et al. 2010). The control of blower or compressor is a better way to reduce the oxygen starvation except for the optimization of single cell and stacks design. Voltage, current and power are the key parameters of a SOFC system, which are often used as control parameters for sub-systems, such as the flow rates and pressures of air and fuel, temperature of SOFC stacks and water management. However, Gu et al. (2012) found that flow rate oscillation may occur when the output current of fuel cell stacks is used as feedback reference to control the flow rate of the blower. Although either fuel starvation or oxygen starvation could happen in fuel cell, the latter in cathode impact current density of all fuel cells while the former in anode only influences the starved region (Liu et al. 2006). Furthermore, oxygen starvation even will accelerate the emphasized the degradation of electrolyte and dissolution of cathode (Gerard et al. 2010; Taniguchi et al. 2008). In summary, the performance modelling of air supply system is significantly needed for the optimal control of SOFC system.

Modelling of the SOFC system includes the modelling of fuel cell stacks and auxiliary devices, such as the blower or compressor, heat exchanger, heater, humidifier. In the past, when the SOFC system is designed and simulated, the flow rate and pressure of air are referenced from characteristic map or assumed to be ideal dynamic response or modelled simply by a nonlinear polynomial function (Zhang et al. 2015; Hong et al. 2012). However, many types of blowers or compressors can supply air to SOFC stacks, such as scroll, lobe, screw and centrifugal blowers or compressors (Tamminen et al. 2014). The performance characteristics of each kind of blowers or compressors are different, even the same kind are not similar due to manufacturing factors and environmental factors. Although many studies on blower modelling have been done, such as those methods based on theoretical analysis (Yoo et al. 2005), numerical modelling (Badami and Mura 2010) and experimental investigation (Badami and Mura 2012), more research is still needed to improve the models in order to predict the behaviors of the blower in a fuel cell system more accurately.

In recent years, there has been a great achievement in the modelling of air supply system in fuel cell system. Zhang et al. (2017) used a one-dimensional dynamic simulation model of air supply system established in the simulation environment to analyse the performance of a fuel cell air supply system. Zhao et al. (2017) presented a semi-physical centrifugal compressor model using state-space equations and interior-point method, which have good agreement with the experimental data. Hering et al. (2018) designed and implemented several approaches for the characteristic map modelling of the blower in a 10 kW SOFC system based on the blower laws of similitude and different regression models. In summary, most of the researches above mentioned focus on the proton exchange membrane fuel cell system in automotive applications and few literatures of air supply system in SOFC system can be found. Due to errors of theoretical model and variation of operating circumstance, the working characteristics of the centrifugal blower manufactured based on theoretical calculation or numerical simulation will change

when it is integrated into a SOFC system for air supply. On the other hand, it is difficult to obtain the specific geometry parameters of a blower for operators. Nowadays, machine learning based methods driven by a great amount of experimental data have been widely used in industry, such as wake modelling of wind turbine (Ti et al. 2020), characteristic analysis of axial compressor (Wu et al. 2019; Wu and Li 2012), fault diagnosis and modelling of SOFC system (Costamagna et al. 2016; Razbani and Assadi 2014). Thus, the performance model driven by experimental data is a better and necessary method to predict and control the air flow rate supplied to fuel cell stacks more accurately.

In this study, we propose a method to build the performance model of a regenerative blower, which can be used to predict the outlet air flow rate, based on a widely used machine learning method, random forest (RF), and Bayesian Optimization (BO). The rest of the paper is organized as follows. Section 2 describes the performance modelling method through the RF and BO (RF-BO). In Section 3, experimental results of the outlet air flow rate prediction are shown under the developed model using the collected data from an experimental test rig, which emulates the air supply system with the regenerative blower at a 5 kW SOFC power generation system. We also compare the prediction performance of the outlet air flow rate among the proposed method, decision tree regression, and deep neural network in Section 4. The conclusions are drawn in Section 5.

2 Methodology

2.1 RF modelling of blower performance

2.1.1 Principle of RF algorithm

Based on bagging and bootstrapping theory, Breiman (2001) proposed RF method by improved decision tree algorithm and its training procedure. Several of independent decision trees, typically called Classification and Regression Tree (CART), are ensemble in RF to enhance the prediction performance by combining the prediction results of weak learners. Fig. 2 shows the structure and basic construction procedure of the RF algorithm. Set X as the input vector consisting of m features with $X = \{x_1, x_2, \dots, x_m\}$, and Y as the output scalar. The training data set, S_n , containing n samples can be given as follows: (see Equation 1 in the Supplementary Files)

As shown in Fig. 2, for a RF model containing q decision trees, a series of new data set sampled from the original training data set S_n based on bootstrapping technique, i.e. sampling with replacement, is created to train each of the q decision trees, which consisting of numbers of decision nodes and leaf nodes. The new bootstrap data set reduce the correlation between each of the q trees. In addition, a new feature set sampling without replacement from the original m features will be chosen at each decision node to increase the generalization ability further. When a decision tree is constructed, splitting of samples started from root decision node will repeat until the node has a required number of samples and this node become leaf node. The criterion to choose the optimal feature and its value is the mean square error (MSE). Finally, a forest consisting of q different decision trees due to the bootstrap sample data set and

random subset of features are complete. When the construction of every decision tree is completed, the RF model provide the final prediction value using the average value for regression over the predictions of the individual trees. Many researchers have applied the RF method to solve the nonlinear regression missions which are difficult to calculate analytically and mathematically, such as characteristics analysis of a heavy-duty gas turbine axial compressor (Wu et al. 2019), capacity estimation of lithium-ion battery (Li et al. 2018) and prediction of moisture content of biomass (Zhang et al. 2019). The performance of regenerative blower is seriously influenced by the complex structure and different operation and environment parameters. Therefore, RF method is used to build accurate prediction model for the outlet flow rate of the regenerative blower in our case.

2.1.2 Feature importance evaluation

The operation and environment factors, i.e. rotation speed of impeller, inlet and outlet pressure, humidity and temperature, are adopted as input features for the random forest model. The feature importance is a useful tool to investigate the relationship between input features and output target and each feature impact on prediction accuracy in the RF method. It can be defined as decreasing prediction accuracy from randomly permuting values of a feature (Zhang et al. 2019). A high drop of prediction accuracy indicates that feature owns large contribution to the output target. Furthermore, the feature with a zero feature importance can be removed in the RF model as it has no contribution to the output target.

2.2 Bayesian hyper-parameter optimization

RF method needs to tune several hyper-parameters to acquire optimal prediction accuracy. BO method, a practical tool for high-quality hyper-parameter tuning, can provide efficient alternatives to the grid or random search of hyper-parameters domain (Snoek et al. 2012). The relationship between a group of hyper-parameters and the prediction accuracy over a determined training data set, lacking an analytical expression, is considered as black-box function. This method assumes that the output of the black-box function obey Gaussian process model and uses the observation set consisting of a group of hyper-parameters and its corresponding prediction accuracy values to train the model. Furthermore, acquisition function is used to choose hyper-parameter from domain to evaluate in BO method. Fig. 3 shows the procedure of the BO algorithm. After the determination of the hyper-parameter domain, several points are randomly selected to initialize the Gaussian process model and then many points are iteratively selected to update the Gaussian process model using the acquisition function. Optimization ceases as the iteration reaching the maximum times and the optimal values are obtained for hyper-parameters. The numbers of the initial random points and the total iteration times are set to 5 and 30 respectively according to the reference (Snoek et al. 2012)..

3 Experimental Results

3.1 Test rig design

A 5KW SOFC system mainly includes fuel and air supply system, and heat and water management system, as shown in Fig. 4. The regenerative blower is considered as the air source following references (Badami and Mura 2010; Badami and Mura 2012), whose structure is shown in Fig. 5.

The performance model of the blower with specific geometry can be affected by the environmental factors, such as the pressure, humidity and temperature (Wu and Li 2012). So, the operation data of the inlet and outlet pressure, humidity and temperature, and rotation speed of impeller need to collect for the performance modelling of the blower in this study.

To investigate the performance of the regenerative blower in the SOFC system and acquire the data set used for training and validating the RF model, a test rig has been built as shown in Figs. 6 and 7. Several off-the-shelf sensors are installed on the test rig to obtain these parameters. The detail of parameters and their sources are listed in Table 1. As shown in Fig. 6, pressure sensors (HH316), and temperature-humidity sensors (TH10S-B) are installed at both the inlet and outlet of blower. The rotation speed of blower is controlled by a variable-frequency drive (VFD007M23A) with a range of 0-80 Hz. A vortex flowmeter (Focvor4102-01) is used for the measurement of outlet volume flow rate. Furthermore, the variation of blower load is simulated by the adjustment of the cross-sectional area at the outlet pipe with a ball valve. The outputs of all sensors are transmitted to a data acquisition circuit for the temporary storage using RS-485 bus and can be accessed by the host computer based on the Modbus communication protocol. With the help of the data acquisition toolbox in LabView, all signals from the data acquisition device are stored in the computer.

Table 1 Input features

ID	abbreviation	Feature name	Source
1	TI	Inlet temperature	Temperature and humidity sensor
2	RHI	Inlet humidity	Temperature and humidity sensor
3	TO	Outlet temperature	Temperature and humidity sensor
4	RHO	Outlet humidity	Temperature and humidity sensor
5	PI	Inlet pressure	Pressure sensor
6	PO	Outlet pressure	Pressure sensor
7	RPM	Rotation speed	Variable frequency drive

In order to collect operation data of the blower for training and validating the RF model, a series of experimental investigations are conducted in the proposed test rig. Thirteen experimental conditions are chosen, from 1200 rpm to 4800 rpm with an interval of 300 rpm. Thirteen groups of experiments are conducted in the designed test rig and the collected data are shown in Fig. 8.

3.3 RF Model training and hyper-parameters optimization

It is important to select the input feature through calculating the feature importance before building the performance model of the blower with RF model and optimizing the hyper-parameters. According to the reference (Breiman 2001), the number of trees is set as 250, the minimum number of samples of leaf node is set as 5 and the number of features selected randomly for each decision node is 1/3 of the total number of input features. During the generation of RF with all collected experimental data, which is called “out of bag” data, are left out when bootstrap technique is applied. The feature importance is estimated with the out of bag data. As shown in Fig. 9, all input features contribute to the performance estimation with different importance. The inlet pressure, inlet humidity, and the rotation speed of the impeller are found as the most important features to estimate the outlet air flow rate. The scores of outlet pressure, humidity and temperature are very close and own the same importance. So, there are no input feature with zero importance and none of the feature need to be removed in our case.

During the training and hyper-parameter optimization of the RF model, 13 groups of experimental data are divided. Groups 1, 7 and 13, about 25% of total data (107 samples), are selected as the validation set and the remaining 10 groups, about 75% of total data (328 samples), are used as the training set. The RF model needs to optimize five hyper-parameters, i.e. the number of trees (numTR), the minimum number of samples of leaf node (minLS), the minimum number of samples of decision node (minDS), the number of features selected randomly for each decision node (numFTS) and the maximum depth of trees (maxDT). In our case, numTR is set from 10 to 1500 (Breiman 2001) and the corresponding optimized values of minLS, minDS and numFTS, maxDT under each numTR are calculated through BO algorithm. The value of optimal numTR, min LS, minDS, numFTS and maxDT can be obtained as 350, 1, 2, 7 and 15, respectively. In order to evaluate the prediction performance of the developed method, the statistical tools of Maximum Absolute Relative Error (MARE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are applied:(see Equations 2-4 in the Supplementary Files)

where y_i and $\hat{y}_i$ are the predicted and sampled values of flow rate, respectively. The predicted results with the optimized RF model have a good agreement with experimental data and the MAE, RMSE and MARE between the prediction and experimental values are illustrated in Fig. 10.

3.4 Validation of the RF-BO method

Three groups of experimental data (groups 1, 7 and 13) are used to validate the performance of the RF-BO model. As shown in Fig. 8, groups 1 and 13 are out of the range of the training data while group 7 is in the middle of the training data set. The comparisons between the predicted values and the experimental values of outlet flow rate are shown in Fig. 11. The predicted MAE, RMSE and MARE of the validation

data are shown in Fig. 12. The proposed model can predict outlet air flow rate with good performance, whose MARE is within 3.5%, based on the results shown in Figs. 11 and 12.

4 Comparisons With Other Machine Learning Methods

Comparisons are conducted with three machine learning methods, such as Classification and Regression Tree (CART), deep neural network (DNN) and RF with default hyper-parameters (RF-DEF), to verify the prediction performance of the proposed RF-BO method. CART (Breiman et al. 1984) builds one regression tree model and is used to show the benefit of ensemble steps in the RF algorithm. DNN approximates the nonlinearity between input and output features. During the comparison, the value of minLS in the CART model is determined by cross validation, which is set to 5. The DNN model (Glorot and Yoshua 2010) has 100 hidden layers activated by the rectified linear unit function and is solved by a stochastic gradient-based optimizer. The values of numTR, minDS, minLS and numFTS in the RF-DEF model are set to the default values, i.e. 100, 2, 1 and 7, respectively. A Laptop (Intel Core i7 2.5 GHz CPU and 12GB RAM) is used for the prediction of different models. The MARE, MAE, RMSE and computation time are used to evaluate the performance of prediction at each model.

DNN model shows the largest prediction errors (Table 2) even 100 hidden layers have been applied to fit the relationships between the outlet flow rate and input features. The DNN model also spends the longest time due to complicated structure and numerous computations for the solution of the weight parameter at each neuron. The performance of CART model is better than DNN model, but its prediction errors are larger than both RF-BO and RF-DEF models due to limitation in the generalization ability of a single tree. Finally, it shows that the RF-BO method has the minimum prediction errors comparing with other three methods. So, it is necessary to optimize the hyper-parameters in the RF model. The computation time of the developed method can also be accepted, since the control response time of outlet air flow rate is within two seconds in our test rig.

Table 2 Predicted errors and calculation time of different models on the validation set

Model	MARE (%)	MAE (m ³ /h)	RMSE (m ³ /h)	Training time (s)	Computation time (ms)
CART	15.55	1.11	1.63	0.068	81
DNN	20.86	1.05	1.42	0.64	73
RF-DEF	8.27	0.81	1.01	0.393	199
RF-BO	3.50	0.43	0.54	0.829	427

5 Conclusions

The RF-BO method is capable of building the performance model for the regenerative blower in a 5 kW SOFC power generation system using the dynamic parameters of the blower, including the rotation speed of impeller, the inlet and outlet pressure, humidity and temperature. The designed and implemented experimental test rig can provide operation data of the blower for the training and validating the RF-BO model. The relationships between the characteristic features and the outlet air flow rate are investigated and the main factors are found through the calculated variable importance. With the help of BO algorithm, the well-tuned RF model can accurately predict the outlet air flow rate under different rotation speeds of the blower successfully with the maximum absolute relative error (3.5%). Furthermore, the comparisons with other machine learning methods indicate that the proposed algorithm owns the best prediction accuracy at acceptable computation time without any data pre-processing procedures. Therefore, the proposed method is suitable for the prediction of outlet air flow rate, and promising for the control of air supply system at the SOFC system for the prevention of air starvation.

Declarations

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Declaration of interests

The authors declare that they have no known conflict of interests.

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Figures

Figure 1

Overall strategy of the performance modelling for regenerative blower

Figure 2

Structure of the RF algorithm

Figure 3

Flowchart of the BO algorithm

Figure 4

Diagram of the 5 kW SOFC system

Figure 5

Schematic principle of the regenerative blower

Figure 6

Diagram of the regenerative blower performance test rig

Figure 7

Implementation and installation of the regenerative blower performance test rig

Figure 8

Performance map of the blower

Figure 9

Feature importance of input features (the name of each feature is given in Table 1)

Figure 10

Predicted errors of the training data set

(a) Group 1

(b) Group 7

(c) Group 13

Figure 11

Prediction performance of the validation data set (groups 1, 7 and 13) using RF model after hyper-parameter optimization

Figure 12

Predicted MAE, RMSE and MARE of the validation data set (groups 1, 7 and 13)

Supplementary Files

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- [Equations.pdf](#)