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Online prediction of biomass moisture content in a fluidized bed dryer using electrostatic sensor arrays and the Random Forest method

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Abstract

The inherent moisture content in biomass needs to be dried before it is used for energy production. Fluidized bed dryers (FBD) are widely applied in drying biomass and the moisture content should be monitored continuously to maximise the efficiency of the drying process. In this paper, the moisture content of biomass in a FBD is predicted using electrostatic sensor arrays and a random forest (RF) based ensemble learning method. The features of electrostatic signals in the time and frequency domains, correlation velocity and the outlet temperature and humidity of exhaust air are chosen to be the input of the RF model. Model training is accomplished using the data taken from a lab-scale experimental platform and the hyper-parameters of the RF model are tuned based on the Bayesian optimization algorithm. Finally, comparisons between the online predicted and sampled values of biomass moisture content are conducted. The maximum relative error between the online predicted and reference values is less than 13%, indicating that the RF model provides a viable solution to the online monitoring of the fluidized bed drying process.

Keywords: Biomass; moisture content; fluidized bed dryer; electrostatic sensor; soft computing; Random Forest

1. Introduction

The threat of global warming requires the reduce of fossil fuel in the energy production due to the greenhouse gas (GHG) and pollutant emissions. Biomass, as a renewable and carbon-neutral energy source, has attracted the attention in the nations around the world [1]. Biomass fuels are mainly composed of carbon, hydrogen, oxygen, nitrogen and other elements. They are widely used for environment friendly energy production through different conversion processes such as biomass co-firing with coal [2, 3] and biomass gasification [4-6]. The inherent moisture content in biomass decreases its heating value and it needs to be dried before it is used for energy production [7]. Drying is an energy intensive process and a significant amount of energy is consumed for drying of biomass. Various dryers are used for drying of biomass. Among them, fluidized bed dryers (FBD) have more advantageous features than others for drying solid material in granular and powder form, such as handling a large amount of particles and uniformly dried products. In addition, the moisture content of biomass should not exceed the optimum value for the efficiency of the drying process. For example, the optimum moisture content of woody biomass is between 10 and 15 wt% for combustion [7]. As a result, it is necessary to predict the moisture content of biomass in an online continuous manner in order to control and optimize the FBD based drying process.

Different types of methods are available for monitoring the operation conditions of the FBDs, including acoustic emission [8], electrical capacitance tomography (ECT) [9, 10], microwave resonance [11] and triboelectric probes [12]. Aghbashlo et al. presented a review on the techniques to monitor and control the fluidization quality in the FBDs [13]. The features of each technique for moisture content and flow behavior measurement were explained. However, considering the industrial application, some limitations are present in each method. For example, the signals from acoustic emission sensors are prone to be polluted by the noise, ECT and microwave resonance methods need sophisticated instruments and triboelectric probes are intrusive to the drying process. As a result, new methods are required for reliable operations of the drying process.

In addition to the direct measurement methods mentioned above, indirect measurement methods using soft computing are also widely applied to monitor the process industry. Soft computing or soft sensors build inferential models that use online available sensors (e.g. temperature, pressure, flow rate, etc.) to predict the variables which cannot be automatically measured or can only be measured at high cost or with long delays (e.g. laboratory analysis) [14]. Kadlec et al. reviewed soft sensor development methodology, soft sensor applications and data driven methods for soft computing [15]. Chavan et al. developed data-driven models using the coal properties and gasification process parameters to predict the flow rate and heating value of the product gas [16]. Considering the complicated heat and mass transfer in the drying process, it is difficult to build theoretical models, while soft computing methods, such as artificial neural networks (ANNs) and support vector machines (SVMs) provide solutions to the above

problems [17]. Topuz used the ANN method to predict the drying characteristics of agricultural products such as hazelnut, bean and chickpea. The results showed fairly good agreement between the predicted results by ANN and the measured data taken under the same conditions [18]. Adaptive-network-based fuzzy inference system (ANFIS) was applied to predict the coal moisture content during the drying process. The ANFIS network can achieve satisfying results with acceptable deviations [19]. Exergy and energy analysis of fluidized bed dryer for potato cubes were carried out using the application of ANN. The results revealed that energy utilization, efficiency, and utilization ratio can be investigated by the model created by ANN [20]. However, some algorithms used in soft computing, such as decision tree (DT) and ANN, are suspected to be unreliable because of their instability issues, which result in suboptimal performance and lack of robustness. As a result, new learning algorithms are needed to develop reliable and robust soft computing models.

Electrification is inevitable in the fluidization process due to the contact and frictions between particles and the collisions between the particles and the wall. The charging characteristics of solid particles depend on many factors, such as particle properties (size, work function and moisture content), environmental parameters (temperature and humidity) and flow hydrodynamics (gas velocity and solids concentration) [21]. The moisture content of solid particles affects the charge generation and dissipation processes and hence the charge-to-mass ratio. As a result, the charging characteristics of solid particles can be used to predict the moisture content. As a non-intrusive method, electrostatic sensor arrays have been widely used to monitor the charging characteristics and flow parameters of solid particles in fluidized beds [22-24]. Recently, the effects of moisture content on the mass flow measurement of pneumatically conveyed particles using electrostatic sensors were investigated [25]. In addition, electrostatic sensor arrays have been applied to measure the moisture content of solid particles in a FBD [26]. However, it is difficult to theoretically build a model between the charging characteristics and the moisture content. Apart from moisture content, the charging characteristics of solid particles depend significantly on particle velocity and the measurement accuracy of moisture content is different under different particle velocities. Due to the advantages of low cost, high sensitivity and robust performance, electrostatic sensor arrays are adopted in this study to monitor the FBD process. In addition, a soft computing model is selected to overcome the limitations of the theoretical and empirical models. Ensemble learning method can overcome the instability issues in the individual models and generally has better prediction performance. As a result, electrostatic sensor arrays are combined with a Random Forest (RF) based ensemble learning method to predict the moisture content of biomass. The steps regarding to the model training and hyper-parameter optimization are given in detail and the online prediction results of the RF model are compared with the moisture content of sampled particles in order to verify the accuracy of the prediction method.

2. Methodology

2.1. Overall strategy

Fig. 1 shows the overall strategy for measuring moisture content of biomass using the RF method. Firstly, the electrostatic signals from the sensor arrays and the time series of the outlet air temperature and humidity are collected during the fluidized bed drying process. Secondly, the features of the electrostatic signals in the time and frequency domains are calculated and the signal features, correlation velocity and outlet air temperature and humidity are chosen to be the input of the RF model. By optimizing the hyper-parameters of the model, the moisture content of biomass can be predicted by aggregating the results from a group of decision trees.

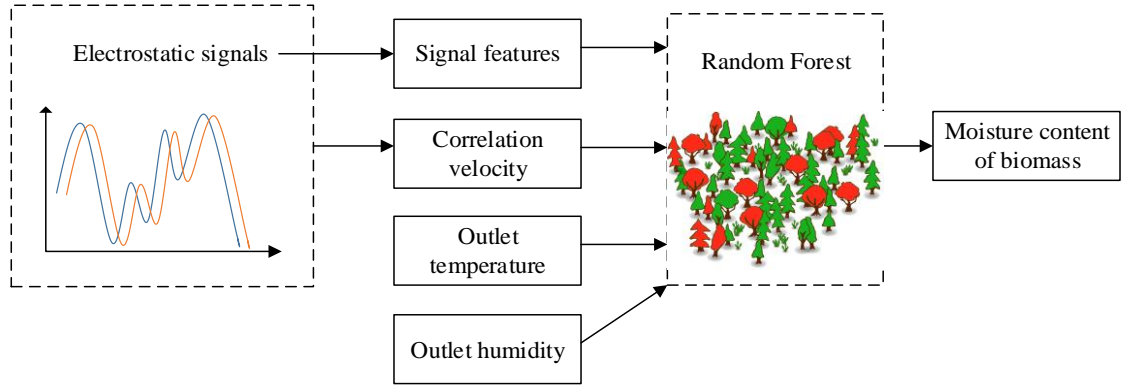


Fig. 1. Overall strategy for predicting moisture content of biomass

2.2. Electrostatic sensing

With the fluidization of wet biomass, charges are induced on the metal electrodes of the sensor arrays by the particles and they are further transformed, filtered and amplified by a signal conditioning unit to obtain the electrostatic signals [22]. He et al. [27] proposed an empirical relationship between the induced electrostatic current, the particle charge-to-mass ratio and the bubble rise velocity:

$$I_{ind} = -0.17q_m u_b^{1.1} \quad (1)$$

where I_{ind} represents the induced electrostatic current, q_m the particle charge-to-mass ratio and u_b the bubble rise velocity. The moisture content affects the particle charge-to-mass ratio and hence the generated electrostatic signal.

The electrostatic sensor arrays are installed on the bed wall, as illustrated in Fig. 2. In order to investigate the electrostatic characteristics in different parts of the FBD, four sets of arc-shaped electrodes are included, which are labeled as A, B, C and D, respectively. Three identical electrodes are included in each set and the signals from each two electrodes are cross-correlated and weighted to derive the particle velocity. Since the inner diameter of the model FBD used in this study is 180 mm, the distance between two adjacent electrodes is set to 20 mm and the ratio between the distance and the diameter of the bed is less than 12%, which maintains good similarity between the

signals from adjacent electrodes [22]. In addition, the electrodes in the sensor arrays are made of copper and tightly wrapped around the outer surface of the bed. According to the spatial filtering effect, the wider the electrode, the narrower the bandwidth of the signal [22]. In consideration of the amplitude and bandwidth of the signal, the width of the electrode is set to 6 mm. The central angle is set to 60 degree for localized sensitivity of the electrode. With the application of the sensor arrays, the electrostatic signals as well as the correlation velocities of the solid particles in different parts of the FBD are obtained [22-26].

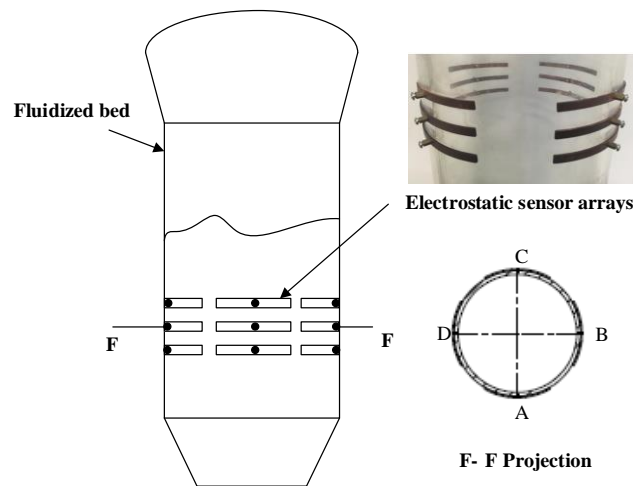


Fig. 2. Electrostatic sensor arrays

2.3. RF based ensemble learning model

2.3.1. RF method

RF is a bagging-based ensemble learning method, which was introduced in 2001 by Breiman [28]. It is a combination of many decision trees that are created using the bootstrapping technique from training samples, and a random subset of the features is given to the tree at each node in order to limit the choices that the decision tree can make. The prediction of the random forest is obtained by the majority vote for classification or the mean response for regression over the predictions of the individual trees. The structure of the RF algorithm is given in Fig. 3. The basic methodology for generating RF can be described as follows: for each of the N trees, firstly, a new bootstrap sample of the training set is created and this bootstrap sample is used to train a decision tree. Then at each node of the decision tree, a set of features is randomly selected and the information gain (or Gini impurity) is computed only on that set of features in order to select the optimal one. At last, the above steps are repeated until the tree is complete. As shown in Fig. 3, the final prediction of the model is obtained by averaging the response from all the trees. It is proved that the RF model has high prediction accuracy, features a high tolerance for outliers and noise data, and is not prone to overfitting [28]. Due to the above advantages, the RF model has been widely applied in nonlinear regression problems, such as estimation of coal properties [29, 30], solar radiation prediction [31] and coal spontaneous combustion prediction [32].

Moisture content of biomass exhibits nonlinear variations during the drying process and it is also affected by various operational and environmental parameters. As a result, random forest based ensemble learning method is adopted to develop reliable soft computing models.

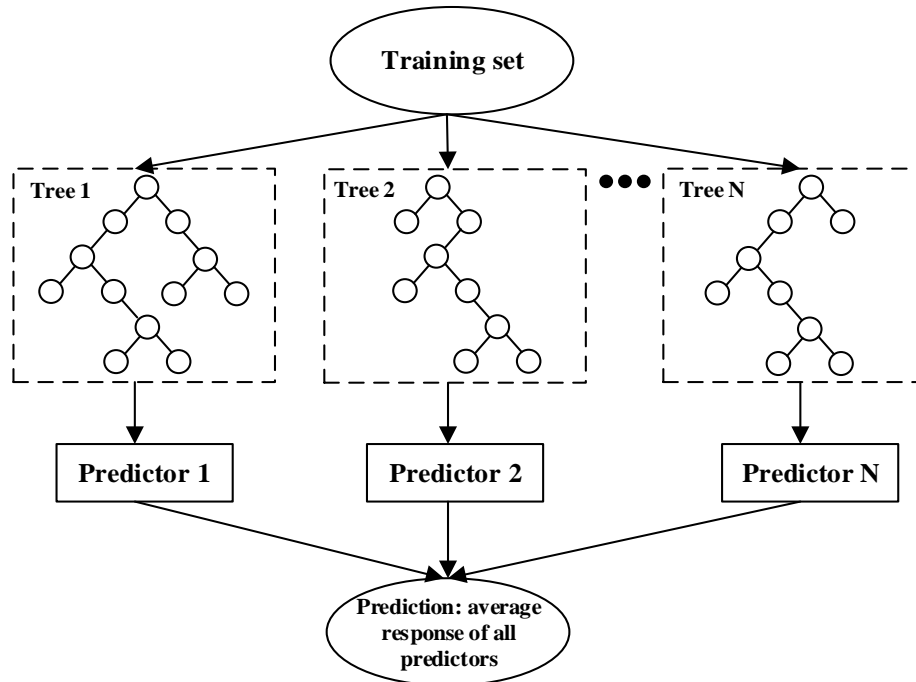


Fig. 3. Structure of the RF algorithm

2.3.2. Bayesian hyper-parameter optimization

Every machine learning algorithm or prediction system has its own set of parameters that must be adjusted to obtain an optimal performance. Bayesian optimization (BO) has emerged as a practical tool for high-quality parameter selection in prediction systems. BO method provides efficient alternatives to the grid or random search of the parameter space [33, 34]. In addition, BO method is very useful for optimizing black-box objective functions that lack an analytical expression, which is difficult to evaluate. BO method internally maintains a Gaussian process model of the objective function and uses objective function evaluations to train the model. One innovation in BO method is the use of an acquisition function, which is used to determine the next point to evaluate. The acquisition function can balance sampling at points that have low modeled objective functions and explore areas that have not yet been modeled well. The flowchart of the BO algorithm is given in Fig. 4. The Gaussian model is iteratively updated until the optimal values of the parameters are found. As suggested by the developer of the algorithm [35], the number of iterations is set to 30. BO is an effective optimization method and it is widely used in structure design [36] and hyper-parameter tuning in machine learning [37, 38]. Due to the above features, BO algorithm is applied to optimize the hyper-parameters of the RF model in this paper.

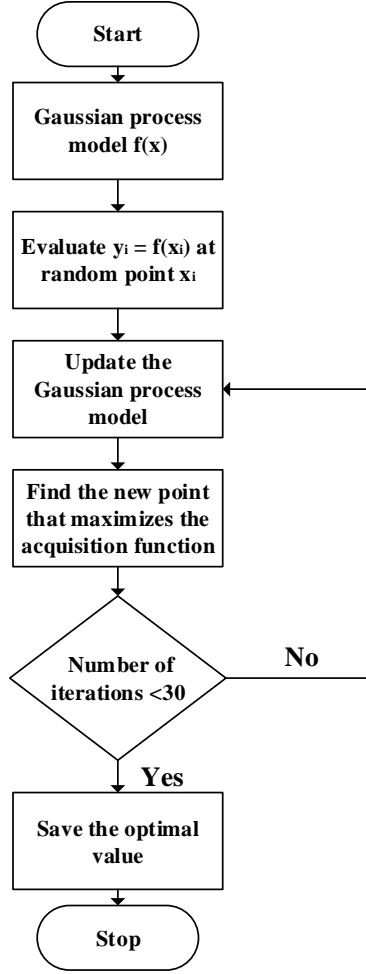


Fig. 4. Flowchart of BO algorithm

2.3.3. Input variables

A set of 12 variables is selected to be the input of the RF model, which are listed in Table 1. The outlet temperature and humidity are obtained by averaging the air temperature and relative humidity readings from the sensor. The six time-domain features of the electrostatic signals are the average from the 12 electrodes in the sensor arrays, which represent the electrostatic characteristics of biomass in the FBD. The equations to calculate the three frequency-domain features are given as follows [39]:

$$F = \frac{\sum_{i=1}^J p_i f_i}{\sum_{i=1}^J p_i} \quad (2)$$

$$d_i = \frac{p_i}{\sum_{i=1}^J p_i} \quad (3)$$

$$E = -\sum_{i=1}^n d_i \cdot \log d_i \quad (4)$$

$$SF = \frac{1}{p} \sqrt{\frac{1}{J-1} \sum_{i=1}^J (p_i - \bar{p})^2} \quad (5)$$

where f_i is the j -th discrete frequency, p_i is the power density of the j -th frequency component and J is the number of discrete frequencies, F is the average fluctuation of the signal, d_i is the probability density function, E and SF are the entropy and shape factor of the power spectral. In addition, the correlation velocity is obtained by averaging the weighted average velocities from the four sets of the electrodes in order to represent solids flow behaviors in the FBD.

Table 1

Input variables

ID	Abbreviation	Variable name	Source
x1	T	Outlet temperature	Temperature and humidity sensor
x2	RH	Outlet humidity	Temperature and humidity sensor
x3	DC	DC component	Electrostatic sensor arrays
x4	AC	AC component	Electrostatic sensor arrays
x5	NUM	Number of zero crossing points	Electrostatic sensor arrays
x6	STD	Standard deviation	Electrostatic sensor arrays
x7	SKE	Skewness	Electrostatic sensor arrays
x8	KUR	Kurtosis	Electrostatic sensor arrays
x9	AF	Average fluctuation frequency	Electrostatic sensor arrays
x10	EN	Entropy of the power spectral	Electrostatic sensor arrays
x11	SF	Shape factor of the power spectral	Electrostatic sensor arrays
x12	VC	Correlation velocity	Electrostatic sensor arrays

2.3.4. Input variable selection

In soft computing models, in cases that some of the input features are not contributing to the output, the performance of the model will deteriorate and the computation time will increase. In RF method, selection of the input variable can be accomplished by calculating the variable importance. It is measured using data permutation to evaluate the impact of each variable on the overall prediction performance of the model. The decrease of prediction accuracy resulting from randomly permuting the values of a variable is considered as the variable importance. The higher the drop in prediction accuracy, the more important a variable is, and vice versa. The importance of each variable reveals their relationship with the output. In addition, RF measures the variable importance of each variable by considering the impact of each variable as well as its multivariate interactions with other variables. Variable importance can be used to select the most important variables in the RF model, which helps users in targeting the most influential factors and understanding the relationships between input and output variables.

3. Experimental results and discussion

Experimental investigations were conducted in a lab-scale FBD, the detail of which was given in reference [26]. Electrostatic sensor arrays were installed on the wall of the FBD to collect the electrostatic signals in the bed and a temperature and humidity sensor (Model HMP110, Vaisala) was installed at the outlet of the bed to obtain the temperature and humidity of the exhaust air. The biomass properties and experimental conditions are listed in Table 2. A total of 9 groups of experiments was conducted in the FBD and the biomass used in this paper was corn particles. The corn particles were prepared to a desirable moisture content and nearly 8 kg of wet particles were used in the experiments, which formed a static bed height of 415 mm. Since the distance between the sensor arrays and the distributor was 200 mm, the electrostatic signals in the bubbling fluidized region of the FBD were thus acquired. During the experiments, the heated air generated by a blower and a furnace was used to dry the biomass under the bubbling fluidization condition and the corn particles were sampled from a sampling port (170 mm above the sensor arrays) every 5 minutes after the start of drying. Meanwhile, the signals from the temperature and humidity sensor and the electrostatic sensor arrays were recorded simultaneously for 60 seconds using a data acquisition device (Model USB-6363, National Instruments). The moisture content of the sampled particles was measured using a Halogen Moisture Analyzer (Model HE83, METTLER TOLEDO). All the signals and moisture content of corn particles during the drying process under different inlet air velocities and air temperatures were used as the data for the training and validation of the RF model.

Table 2
Biomass properties and experimental conditions

Biomass	Corn particles
Particle size range (mm)	1 - 1.8
True particle density (g/cm ³)	1.1
Inlet air flow rate (m ³ /h)	25, 30, 35
Inlet air temperature (°C)	45, 60, 75
Inlet air humidity	4% - 7%

Typical time series of solids moisture content, relative humidity and temperature of the exhaust air are given in Fig. 5. With the progress of drying, the relative humidity of the exhaust air decreases with less evaporation of moisture on the particles and the temperature of the air increases with the variation of moisture content. In addition, the electrostatic signals from set A electrodes of the sensor arrays are shown in Fig. 6, where the labels of A-1, A-2 and A-3 represent the electrodes from low to high positions. At the beginning of drying (Fig. 6 (a)), the electrostatic signals are weak because of the high moisture content and the immobility of the particles due to the channeling effect in the FBD. The channeling effect disappeared and smooth fluidization are found with the progress of drying. As a result, the moisture content is lower and the electrostatic signals become stronger (Fig. 6 (b) and (c)). However, the amplitudes of the electrostatic signals show less variations after 110 min drying (Fig. 6 (d)), which shows that only the amplitudes of the signals cannot discriminate the change of the moisture

content. As a result, the features of the electrostatic signals in the time and frequency domains are applied to extract more information from the signals, which are applied to predict the variations of the moisture content in the FBD. However, due to the complex flow dynamics in the FBD, the electrostatic characteristics of the solid particles are influenced not only by the moisture content but also by the solids velocity [26]. As a result, the correlation velocity from the sensor arrays, which represents the solids flow behavior in the FBD, is also selected to be the input of the soft computing model.

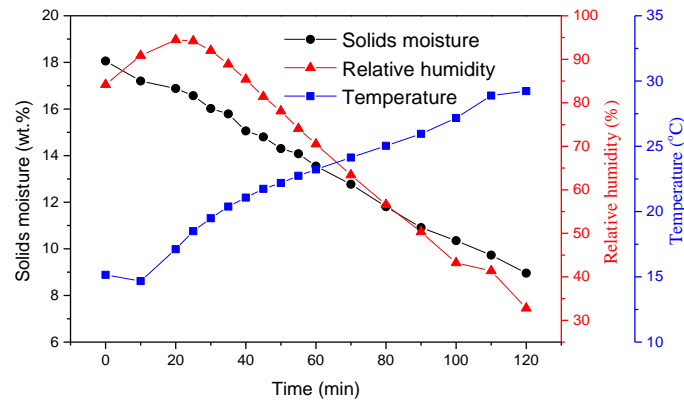


Fig. 5. Typical time series of moisture content, relative humidity and temperature of the exhaust air during the drying process

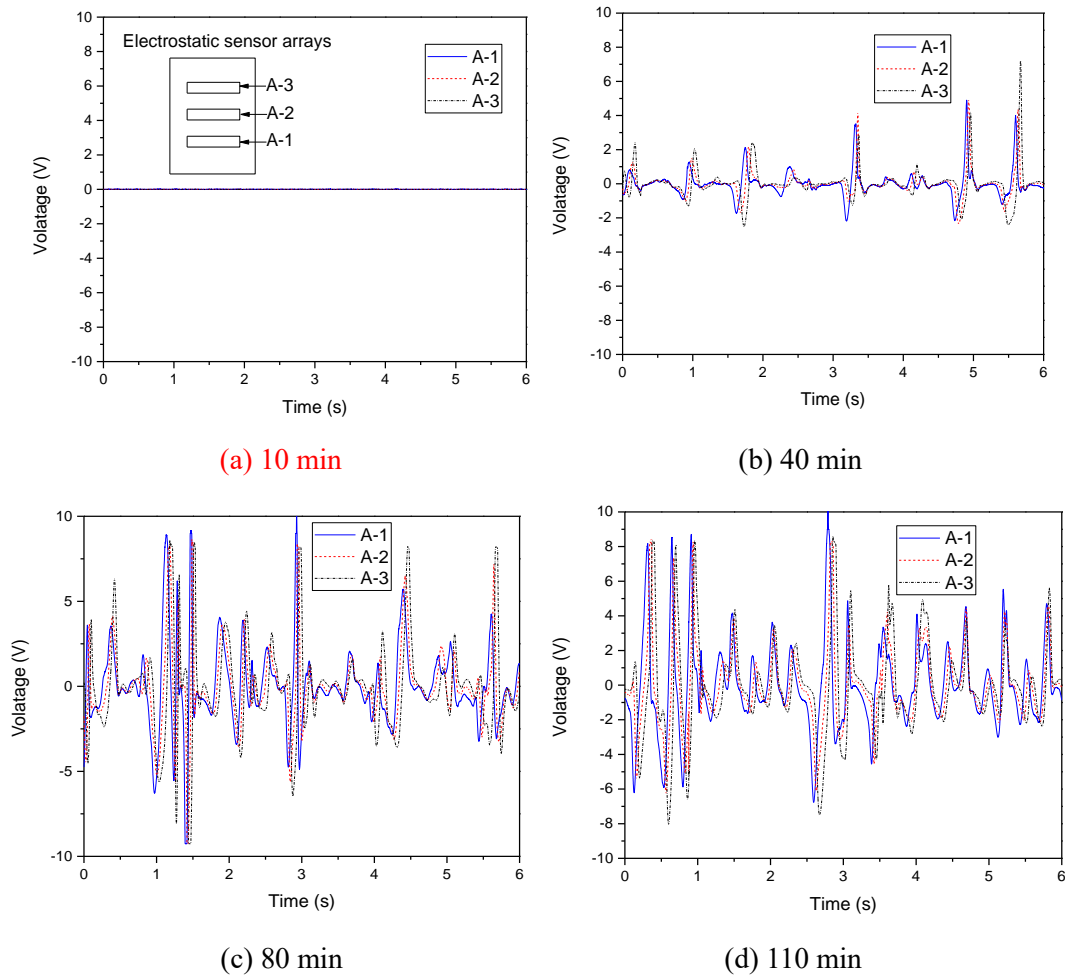


Fig. 6 Typical electrostatic signals from electrodes A-1, A-2 and A-3

3.1. Calculation of variable importance

The variable importance is calculated as the first step to build the RF based soft computing model. In the calculation, all the data from the experimental investigations are used and the number of trees is 250, the minimum number of observations per tree leaf is set to 5 and the number of variables to select at random for each decision split is one third of the number of variables, as suggested by the developer of the algorithm [40]. In addition, around one-third of the data are left out during the bootstrap sampling during the generation of RF, which is called “out of bag” data. The out of bag data are used to estimate the variable importance. As shown in Fig. 7, it is clear that all the input variables are contributing to the moisture content prediction with different importance. It is found that outlet temperature and humidity are the two most important variables to estimate the moisture content of biomass. These two parameters are often applied in a first-principle model to predict the moisture content of particles in the FBD based on the heat and mass balance [41]. The skewness of the electrostatic signals has the third importance, which represents the asymmetry of the data around the mean value. In order to keep the asymmetry of the data around the mean value, the signal conditioning circuits of the sensor arrays are powered from a bipolar power source. In addition, the solids velocity influences the rate of moisture evaporation and hence the electrostatic characteristics in the FBD. As a result, the correlation velocity from the sensor arrays is also an important variable to predict the moisture content of biomass. Finally, there is no input variables with zero importance and it means that none of the variables has to be removed.

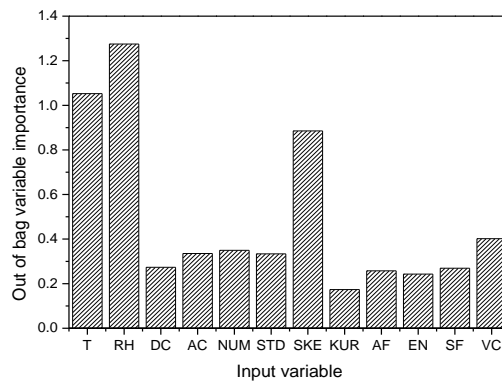


Fig. 7. Variable importance of input features (the name of each variable is given in Table 1)

3.2. Model training and hyper-parameter optimization

During the training and hyper-parameter optimization of the RF model, 9 groups of experimental data are divided. 2 groups of data (23 samples) are randomly selected to be the validation set and the remaining 7 groups of data (94 samples) are used as the training set. Three hyper-parameters of the RF model have to be optimized, which are

the number of trees (numTR), the minimum number of observations per tree leaf (minLS) and the number of variables to select at random for each decision split (numPTS). Although more trees are better based on the principle of bagging, in practice the error sometimes reaches a minimum before increasing the number of trees [42]. As a result, numTR is an important parameter to be optimized. The minLS presents the complexity of the trees in the forest. Deep trees tend to over-fit, but shallow trees tend to underfit. In addition, numPTS is another parameter to be determined in order to improve the prediction performance of the RF model. In the hyper-parameter optimization, numTR is changed from 100 to 500 and the corresponding optimized values of minLS and numPTS under each numTR are calculated using the BO algorithm. In addition, in order to evaluate the performance of the models with different parameters, the statistical measures of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are applied,

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - S_i)^2}{n}} \quad (6)$$

$$MAE = \frac{\sum_{i=1}^n |P_i - S_i|}{n} \quad (7)$$

where P_i and S_i are the predicted and sampled values of biomass moisture content, respectively. It is found that the predicted errors of RMSE and MAE reach the minimum values when numTR is 200, as given in Fig. 8. The corresponding minLS and numPTS obtained from the BO algorithm is 1 and 8, respectively. The prediction performance and relative error of the validation data set after hyper-parameter optimization are shown in Fig. 9. The predicted results closely follow the changes of the moisture content from the sampled particles and the maximum relative error between the predicted and sampled values is less 8%, which shows satisfying training results of the RF-BO model.

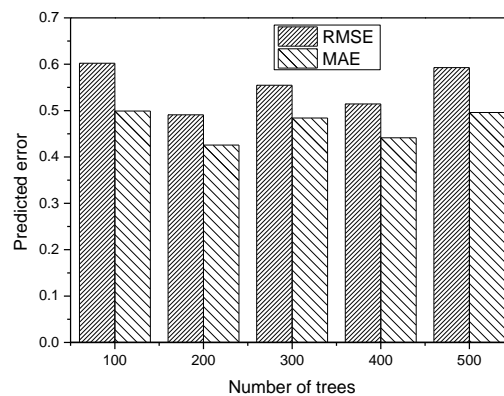
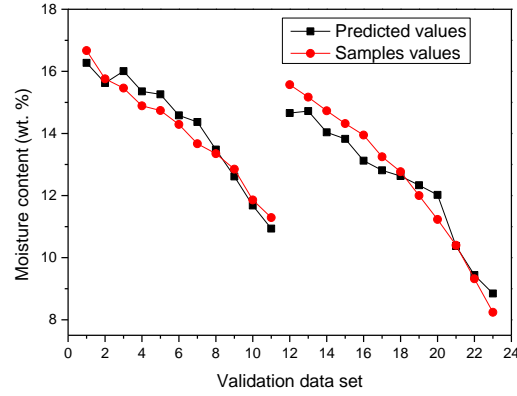
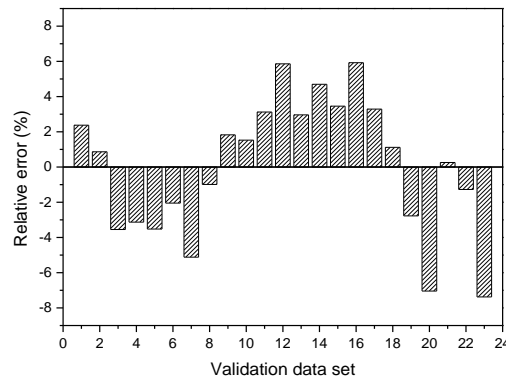


Fig. 8. Predicted errors under different numbers of trees



(a) Prediction results



(b) Relative errors

Fig. 9. Prediction performance and relative errors of the validation data set after hyper-parameter optimization

3.3 Comparison with other machine learning models

In order to verify the performance of the proposed RF-BO model, comparison with other machine learning models are conducted. The algorithms of decision tree regression (DTR), support vector regression (SVR) and RF with default values (RF-DEF) are selected. DTR builds one regression tree and this model is selected to show the necessity of ensemble steps in the RF algorithm. SVR is widely applied in soft computing and it can approximate any nonlinear relationships between the input and output variables. In addition, RF-DEF is chosen to verify the performance of the hyper-parameter optimization. During the calculation, the minLS value of the DTR model is determined by the cross-validation, which is set to 5 in the model. The SVR model is trained using a Gaussian kernel function with an automatic kernel scale. The numTR, minLS and numPTS values of the RF-DEF model are set to the default values, which are 250, 5 and 4, respectively. The predictions of different models are carried out on a personal computer (PC, Intel Core i5 2.50 GHz with 8 GB of RAM). The RMSE, MAE, the time taken for training and prediction of the four models are listed in Table 3. DTR model has the largest prediction error due to instability issues relating to the algorithm. SVR model predict more accurately than the DTR model, but its performance is significantly affected by the hyper-parameters of the model. By comparing the results

from RF-DEF and RF-BO models, the necessity of hyper-parameter optimization in building RF models is proved. Considering the time consumption, DVR and SVR have only one model and less time are needed in the training and prediction steps. Since the time constant of the drying process is large, it is unnecessary for the online prediction model to have a very fast response. Although the prediction time of the RF-BO model is nearly 50 ms, it is fast enough for online monitoring of biomass moisture content in the FBD. Finally, it can be concluded that the prediction performance of the RF-BO model is superior than the other three models and the time consumption can also meet the requirement for the dynamic measurement of the moisture content.

Table 3

Predicted errors and calculation time of different models

Model	DVR	SVR	RF-DEF	RF-BO
RMSE	1.07	0.80	0.74	0.49
MAE	0.84	0.69	0.56	0.43
Training time (s)	5.55×10^{-3}	2.60×10^{-2}	0.39	0.44
Prediction time (ms)	0.60	0.82	53.44	46.18

4. Online prediction of biomass moisture content

Online prediction of moisture content in the FBD was conducted to further verify the performance of the RF-BO model. The experimental setup for the online prediction is shown in Fig. 10. The air flow rate and temperature during the drying process were 30 m³/h and 85 °C, respectively, which was out of the range of the training data. The electrostatic signals and the time series of the outlet temperature and humidity were sampled by a data acquisition device. With the help of the data acquisition toolbox in Matlab, all the signals from the data acquisition device were stored on the computer. In addition, online prediction of the moisture content was also implemented in Matlab. Firstly, the input features were calculated, then they were fed into the RF-BO model and the predicted moisture content of biomass was finally displayed in the graphical user interface of the PC. At the same time, the moisture content of the sampled particles was obtained by the Halogen Moisture Analyzer. The comparisons between the online predicted values and the sampled values of biomass moisture content are shown in Fig. 11. Since it took nearly 5 minutes to obtain the moisture content of sampled particles, the online prediction was conducted every 5 minutes and only one result was calculated, thus it is not possible to give the repeatability of online prediction. However, the random forest is a type of ensemble learning method. As a result, it can overcome the instability issues relating to other machine learning algorithms and give stable online prediction results. The online prediction results follow the trend of the sampled results and the maximum relative error between them is less than 13%. Although the online prediction errors are larger than those from the validation data set, it is proved that the proposed model can be used for online prediction of biomass moisture content.

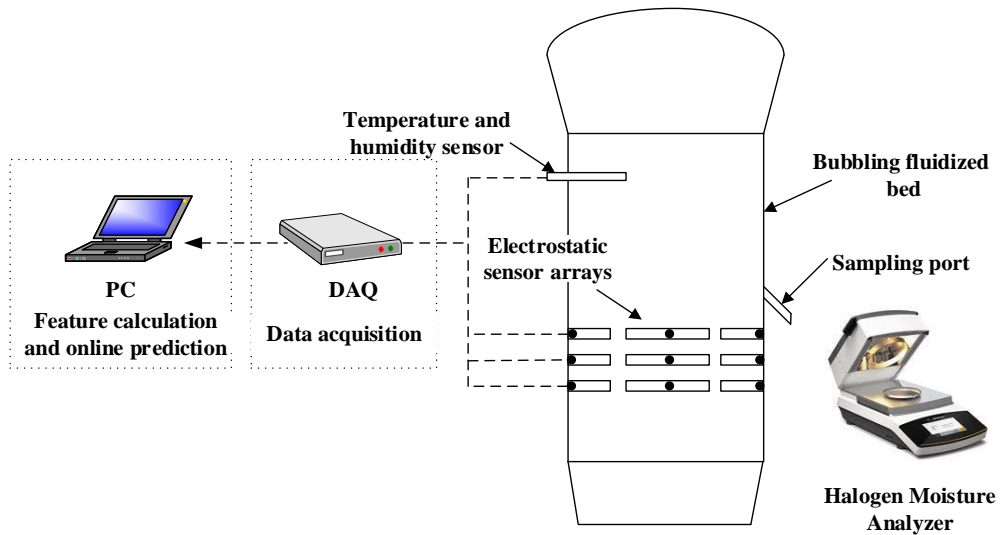
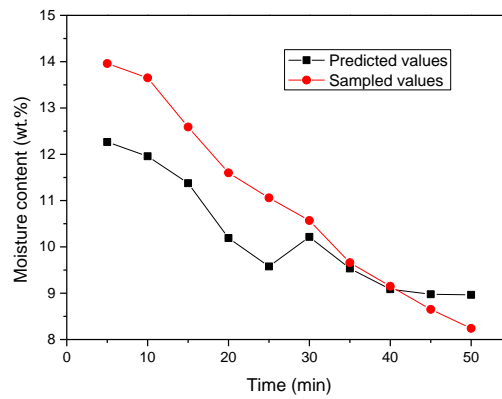
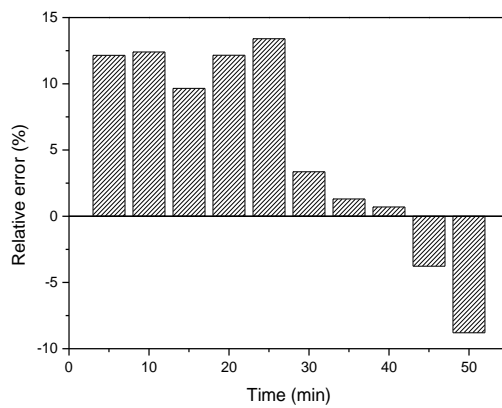


Fig. 10. Experimental setup for online prediction of moisture content



(a) Online prediction results



(b) Relative errors

Fig. 11. Online prediction performance and relative errors of the RF-BO model

5. Conclusions

In this paper, online prediction of biomass moisture content in a FBD has been conducted using electrostatic sensor arrays and a RF-BO based soft computing model. The following points can be concluded:

- (1) The features of the electrostatic signals in the time and frequency domains, correlation velocity and outlet temperature and humidity are selected as the inputs of the model. Based on the calculated variable importance, the relationships between the input and output variables are investigated and the main factors for the prediction of biomass moisture content are found.
- (2) The hyper-parameters in the RF model have been tuned based on the BO algorithm and the optimal values of the parameters are obtained and the maximum relative error of the prediction results from the validation data set is less than 8%.
- (3) Although the proposed RF-BO model takes longer time, the prediction performance is much better than the models of DTR, SVR and RF-DEF and the RF-BO model can satisfy the time requirements for online prediction.
- (4) Online prediction performance of the moisture content is verified in a lab-scale FBD and the operational condition is out of the range of the training data. The maximum relative error between online predicted and reference values is less than 13%. Although it is higher than the result from validation data set (8%), the proposed model can still be used to online estimate the moisture content of biomass.
- (5) With the knowledge of biomass moisture content in the FBD, the drying process can be controlled and optimized under variable operating conditions.

Acknowledgements

The authors would like to acknowledge the financial support of Beijing Natural Science Foundation (No.3162031) and Fundamental Research Funds for the Central Universities (No. 2017044).

Reference

- [1] Garcia R, Pizarro C, Lavin AG, Bueno JL. Biomass sources for thermal conversion. Techno-economical overview. *Fuel* 2017; 195: 182-9.
- [2] De S, Assadi M. Impact of cofiring biomass with coal in power plants - a techno-economic assessment. *Biomass Bioenerg* 2009; 33: 283-93.
- [3] Basu P, Butler J, Leon MA. Biomass co-firing options on the emission reduction and electricity generation costs in coal-fired power plants. *Renew Energ* 2011; 36: 282-8.
- [4] Kirkels AF, Verbong GPJ. Biomass gasification: Still promising? A 30-year global overview. *Renew Sust Energ Rev* 2011; 15: 171-81.
- [5] Ruiz JA, Juarez MC, Morales MP, Munoz P, Mendivil MA. Biomass gasification for electricity generation: review of current technology barriers. *Renew Sust Energ Rev* 2013; 18: 174-83.
- [6] Heidenreich S, Foscolo PU. New concepts in biomass gasification. *Prog Energ Combust* 2015; 46: 72-95.
- [7] Verma M, Loha C, Sinha AN, Chatterjee PK. Drying of biomass for utilising in co-firing with coal and its impact on environment - a review. *Renew Sust Energ Rev* 2017; 71: 732-41.
- [8] Ihunegbo FN, Ratnayake C, Halstensen M. Acoustic chemometrics for on-line

monitoring and end-point determination of fluidised bed drying. *Powder Technol* 2013; 247: 69-75.

[9] Wang HG, Senior PR, Mann R, Yang WQ. Online measurement and control of solids moisture in fluidised bed dryers. *Chem Eng Sci* 2009; 64: 2893-2902.

[10] Rimpilainen V, Heikkinen LM, Vauhkonen M. Moisture distribution and hydrodynamics of wet granules during fluidized-bed drying characterized with volumetric electrical capacitance tomography. *Chem Eng Sci* 2012;75: 220-234.

[11] Chen L, Xie YH, Lin CH, Du S. Experimental research on granule moisture measurement by microwave resonance technology in a fluidized bed dryer. *Key Eng Mater* 2013; 544: 466-470.

[12] Portoghese F, Berruti F, Briens C. Continuous on-line measurement of solid moisture content during fluidized bed drying using triboelectric probes. *Powder Technol* 2008; 181: 169-177.

[13] Aghbashlo M, Sotudeh-Gharebagh R, Zarghami R, Mujumdar AS, Mostoufi N. Measurement techniques to monitor and control fluidization quality in fluidized bed dryers: a review. *Dry Technol* 2014; 32: 1005-1051.

[14] Souza FAA, Araujo R, Mendes J. Review of soft sensor methods for regression applications. *Chemometr Intell Lab* 2016; 152: 69-79.

[15] Kadlec P, Gabrys B, Strandt S. Data-driven soft sensors in the process industry. *Comput Chem Eng* 2009; 33: 795-814.

[16] Chavan PD, Sharma T, Mall BK, Rajurkar BD, Tambe SS, Sharma BK, Kulkarni BD. Development of data-driven models for fluidized-bed coal gasification process. *Fuel* 2012; 93: 44-51.

[17] Aghbashlo M, Hosseinpour S, Mujumdar AS. Application of artificial neural networks (ANNs) in drying technology: a comprehensive review. *Dry Technol* 2015; 33: 1397-1462.

[18] Topuz A. Predicting moisture content of agricultural products using artificial neural networks. *Adv Eng Softw* 2010; 41: 464-470.

[19] Pusat S, Akkoyunlu MT, Pekel E, Akkoyunlu MC, Ozkan C, Kara SS. Estimation of coal moisture content in convective drying process using ANFIS. *Fuel Process Technol* 2016; 147: 12-17.

[20] Azadbakht M, Aghili H, Ziaratban A, Torshizi MV. Application of artificial neural network method to exergy and energy analyses of fluidized bed dryer for potato cubes. *Energy* 2017; 120: 947-958.

[21] Fotovat F, Bi XT, Grace JR. Electrostatics in gas-solid fluidized beds: A review. *Chem Eng Sci* 2017; 173: 303-334.

[22] Zhang WB, Yan Y, Yang YR, Wang JD. Measurement of flow characteristics in a bubbling fluidized bed using electrostatic sensor arrays. *IEEE Trans Instrum Meas* 2016; 65(3): 703-712.

[23] Yang Y, Zhang Q, Zi C, Huang ZL, Zhang, WB, and Liao ZW, Wang JD, Yang YR, Yan Y, Han GD. Monitoring of particle motions in gas-solid fluidized beds by electrostatic sensors. *Power Technol* 2016; 308: 461-471.

[24] Shi Q, Zhang Q, Han GD, Zhang WB, Wang JD, Huang ZL, Yang Y, Yang YR, Wu WQ, Yan Y. Simultaneous measurement of electrostatic charge and its effect on particle

motions by electrostatic sensors array in gas-solid fluidized beds. *Power Technol* 2017; 312: 29-37.

[25] Qian XC, Shi DP, Yan Y, Zhang WB, Li GG, Effects of moisture content on electrostatic sensing based mass flow measurement of pneumatically conveyed particles, *Power Technol* 2017; 311: 579-588.

[26] Zhang WB, Cheng XF, Hu YH, Yan Y. Measurement of moisture content in a fluidized bed dryer using an electrostatic sensor array, *Power Technol* 2018; 325: 49-57.

[27] He C, Bi XT, Grace JR. Simultaneous measurements of particle charge density and bubble properties in gas-solid fluidized beds by dual-tip electrostatic probes, *Chem Eng Sci* 2015; 123: 11–21.

[28] Breiman L. Random Forests, *Mach Learn* 2001; 45: 5-32.

[29] Matin SS, Chelgani SC. Estimation of coal gross calorific value based on various analyses by random forest method, *Fuel* 2016; 177: 274-278.

[30] Chelgani SC, Matin SS, Hower JC. Explaining relationships between coke quality index and coal properties by Random Forest method, *Fuel* 2016; 182: 754-760.

[31] Ibrahim IA, Khatib T. A novel hybrid model for hourly global solar radiation prediction using random forests technique and firefly algorithm, *Energ Convers Manage* 2017; 138: 413-425.

[32] Lei CK, Deng J, Cao K, Ma L, Xiao Y, Ren LF. A random forest approach for predicting coal spontaneous combustion, *Fuel* 2018; 223: 63-73.

[33] Snoek J, Larochelle H, Adams RP. Practical Bayesian optimization of machine learning algorithms, *Adv neural Information Process Syst* 2012.

[34] Shahriari B, Swersky K, Wang ZY, Adams RP, de Freitas N. Taking the human out of the loop: a review of bayesian optimization, *Proc IEEE* 2016; 104: 148-175.

[35] Bayesian Optimization Algorithm. Mathworks; 2018. <<https://ww2.mathworks.cn/help/stats/bayesian-optimization-algorithm.html>> [accessed October 27, 2018].

[36] Lisicki M, Lubitz W, Taylor GW. Optimal design and operation of Archimedes screw turbines using Bayesian optimization, *Appl Energ* 2016; 183: 1404-1417.

[37] Xia YF, Liu CZ, Li YY, Liu, NN. A boosted decision tree approach using Bayesian hyper-parameter optimization for credit scoring, *Expert Syst Appl* 2017; 78: 225-241.

[38] Cornejo-Bueno L, Garrido-Merchan EC, Hernandez-Lobato D, Salcedo-Sanz S. Bayesian optimization of a hybrid system for robust ocean wave features prediction, *Neurocomputing* 2018; 275: 818-828.

[39] Yan Y, Xu LJ, Lee P, Mass flow measurement of fine particles in a pneumatic suspension using electrostatic sensing and neural network techniques, *IEEE Trans Instrum Meas* 2006; 55(6): 2330-2334.

[40] MATLAB. TreeBagger. Mathworks; 2018. <<http://www.mathworks.com/help/stats/treebagger.html>> [accessed August 28, 2018].

[41] Pla DL, Kamyar R, Hashemian N, Mehdizadeh H, Moshgbar M, Moisture soft sensor for batch fluid bed dryers: a practical approach, *Power Technol* 2018; 326: 69-77.

[42] Probst P, Boulesteix AL, To tune or not to tune the number of trees in random forest, *J Mach Learn Res* 2018; 18: 181.