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Estimation of basis weight, ash content and moisture content in papermaking plants: A comparative study

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Abstract−The papermaking process is a typical nonlinear process with multiple input-output variables, so it is difficult to construct an accurate model for the process. Data-based modeling techniques may be used to establish a reliable paper plant model. In particular, the LSSVM (least-squares support vector machine) can be used to create a high-performance papermaking process model based on operation data. In this paper, we present a paper plant model that can predict three key output variables (basis weight, ash content, moisture content) with four input variables (stock flow, filler flow, speed, steam pressure) using LSSVM. The proposed LSSVM model is compared with other data-based models (the ANN (artificial neural network) model and the state-space model). The LSSVM model turned out to exhibit better estimation performance compared to others.

Keywords: Basis Weight, Ash Content, Moisture Content, LSSVM, ANN, State-space Model

INTRODUCTION

Construction and application of a paper plant model in the operation of papermaking plant are very complicated processes that involve the multivariable control problem to produce uniform sheets with desired specifications. In the papermaking process, various utilities being used are attached to each other in cascade structure to improve the paper property. In particular, the wet-end part consists of a combination of complex facilities such as wire, pressure and dryer. Use of a vast amount of water adds difficulties and complications in the operation of a paper plant. In the papermaking process, most of the used water is recycled, which makes the system more complicated. As a result, difficulties will certainly arise during the establishment of accurate models. To increase the quality of the paper products, it is necessary to develop and to use nonlinear dynamic models for papermaking process.

There have been many attempts to develop a model and to devise a control strategy for the papermaking process. Bo and Mardon [1,2] regarded the wet-end as a simple tank structure and built a dynamic model to simulate it. Fu and Dumont [3] proposed a general predictive control based on black box models with 2-input (stock flow, filler flow) and 2-output (dry weight, ash weight). Kuusisto and Kosonen [4] represented the papermaking process as 3-input (thick stock, filler flow, steam pressure) and 3-output (basis weight, ash content, moisture content) models. Kim et al. [5] constructed the paper grade-change process model using closed-loop process recognition method and implemented model predictive control for the process. Yeo et al. [6,7] presented models for the wet-end and the drying parts in the papermaking process. Khanduja et al. [8] carried out the mathematical modeling and optimization for the papermaking process using genetic algorithm. Edwards [9] developed the artificial neural network (ANN) model to encapsulate the papermaking process. It showed that the data-based model is accurate enough to be useful in a specific case. Wang and Oyebande [10] applied the improved neural network modeling scheme to the papermaking process. They found that the B-spline ANN could be efficiently used to predict the wet-end part.

In this work, we consider the data-based modeling of papermaking process based on operation data obtained from the actual paper plants. The LSSVM (least-squares support vector machine) method being used in this work is a powerful modeling tool developed by Suykens [11] who applied least-squares theory to SVM. Complex secondary programming problems can be solved using the linear Karush-Kuhn-Tucker (KKT) method. In this work, the papermaking process is considered as a MIMO (multi-input multi-output) system consisting of four input variables (stock flow, filler flow, speed, steam pressure) and three output variables (basis weight, ash content, moisture content). The ANN model has been widely used to construct the papermaking black-box model [9,10]. Thus, for the purpose of comparison, we chose the ANN and the state-space model as described in the revised manuscript. The state-space model was chosen because it has been commonly used to represent MIMO processes. The estimation performance of the proposed LSSVM model is compared with that of the ANN and the state-space models.

PROCESS DESCRIPTION

In general, a paper plant process largely is divided into a stock preparation and a papermaking process. The entire process is shown in Fig. 1. The stock preparation is the process of making stock of the pulp from the feed. In the process of stock preparation, the chips from storage are fed into a stuff box to produce the pulp which is passed through various facilities including knotter, decker, opener

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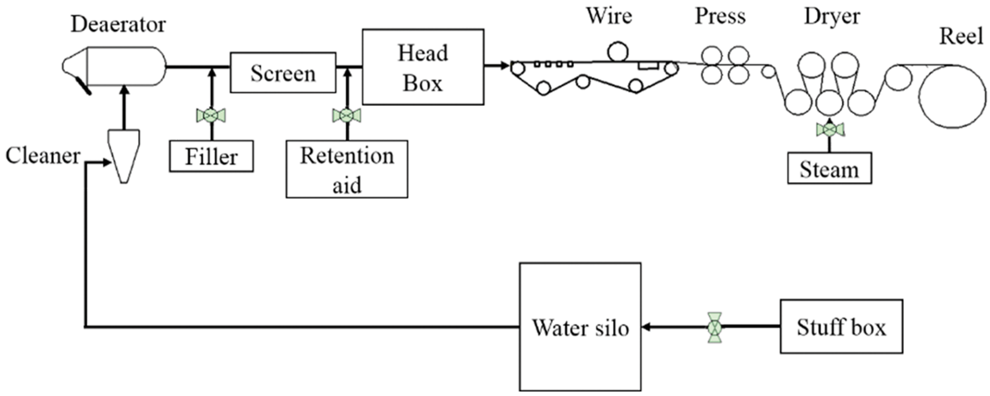

Fig. 1. Schematic diagram of a papermaking process.

and washing. The washed pulp, after bleaching, becomes chlorine-free white pulp, which is fed into the cleaner and screen to separate out oversize and odd shaped particles. After that, the stock of the pulp is mixed with the filler and the retention aid to adjust the paper properties and is stored in the head box.

The papermaking process consists of wet-end part and dry-end part. First, the stock is delivered to the wire part of the paper machine. The stock is pumped into the head box at a constant rate to keep the head of stock constant. The consistency of the stock at this point is about 4%. In the wire part, the stock, which has a consistency of about 1%, flows onto the wire of the paper machine at a controlled rate. In this section, the pulp is spread out evenly so that part of the water can be removed. The wire also passes over a series of table rolls, which aid the formation of the sheet. The wire passes the dandy roll, which helps to improve the closeness of formation of the sheet and to form water marks. This is followed by the couch interconnected to the vacuum pump in order for water and air to be drawn from and through the formed sheet into the couch. The wet web which passes through the wire is transferred to the first press by a transfer roll from the couch. At this stage, the web contains 70-80% of water and 20-30% of paper solids and is just strong enough to support its own weight. In the press section, the water is removed by mechanical means rather than by evaporation. After passing the press section, the web is sent to the drying section. The purpose is again to remove the rest of the water by evaporation. This is performed by pressing the web against the surface of a number of drying cylinders which are hollow, internally steam heated, cast iron cylinders. After the last drying cylinder, the web usually contains 3-4% of moisture [12].

In this work, we selected stock flow, filler flow, speed, and steam pressure as the input variables for the papermaking model. These four variables are the key variables that determine the quality of paper produced by the paper plant. The stock flow and the speed of the paper web from the wire determine the speed of the stock preparation and papermaking processes, respectively. The filler introduced in the stock preparation determines the basic properties of the paper, and the steam pressure in the dryer determines the moisture content of the paper. The basis weight, ash content, and moisture content of the paper are selected as the output variables. These three variables represent the properties and value of the paper product.

MODELING OF PAPER PLANT

1. ANN (Artificial Neural Network) Model

The artificial neural network (ANN) can be considered as a kind of nonlinear mapping process of two different subspaces [13]. Theoretically, a three-layer feedforward network can estimate any continuous functions after training [14]. The sigmoid function is widely used as the activation function for the network nodes. When the ANN model is used, the set of inputs to the hidden layer, $\{S_j\}$, is computed after the sample $A_k=(a_1^k, a_2^k, \cdots, a_n^k)$ is supplied to the input layer, and the output vector from the hidden layer, $\{B_j\}$, is obtained through the sigmoid function, σ:

$$B_j = \sigma(S_j) = \sigma\left(\sum_{i=1}^{N} W_{ij} \cdot a_j - \theta_j\right) \quad (1)$$

where W_{ij} is the connection weight of the jth input layer to the ith hidden layer, a_j is the input vector to the internal recurrent neural network model, θ_j is the output layer threshold and N represents the number of neurons used in the hidden layer. Next, the input vector to the output layer $\{L_t\}$ is computed, followed by computation of the output vector of the output layer $\{C_i^k\}$ through the sigmoid function, σ:

$$C_t^k = \sigma(L_t) = \sigma\left(\sum_{j=1}^{p} V_{jt} \cdot b_j - \gamma_t\right) \quad (2)$$

where V_{jt} is the connection weight of the tth hidden layer to the jth output layer, b_j is the output vector of the hidden layer, γ_t is the threshold of the output layer and p denotes the number of neurons used in the output layer. The gradient drop law is used to backward compute the error of the network node, and the backward propagation of the accumulated error is employed to update the connection weights of the network. This procedure is repeated constantly. The root mean square error in the constructed network, E, is given by

$$E = \sum_{k=1}^{m}\sum_{t=1}^{q}\sqrt{(y_t^k - C_t^k)^2} \quad (3)$$

where y_t^k represents the expected output vector from the ANN model. The output vector from the ANN including the bias node can be expressed as follows:

$$Y(k)=\sum_{j=1}^{p} WO_j \cdot \sigma(S_j(k))+WO_{bias} \tag{4}$$

$$S_j(k)=\sum_{i=1}^{p} WR_{ij} \cdot \sigma(S_j(k-1))+\sum_{i=1}^{n} WI_{ij} \cdot I_{ij}(k)+WI_{j,\,bias} \tag{5}$$

where WI, WR and WO are the weight coefficient matrices connecting the input layer to the intermediate hidden layer, from the feedback layer to the hidden layer backwardly, and from the hidden layer to the final output layer, respectively, I denotes the input vector for the bias node, and WI_{bias} and WO_{bias} are the weight coefficients of connecting the first bias node 1 to the intermediate hidden layer and the second bias node 2 to the final output layer, respectively.

In this work, the ANN model contains single hidden layer with the number of input layer nodes equal to that of input data. The number of nodes in the hidden and output layer is set to 3 and 3, respectively, and the sigmoid function is used as the activation function. The ANN model is trained with available data from the paper plant. After training, the remaining data not used in the training are employed in the validation of the model.

2. State-space Model

The state-space model aims at determining a black-box model with p inputs and q outputs in the following form:

$$\begin{aligned}\mathbf{X'}&=\mathbf{AX}+\mathbf{BU}\\ \mathbf{Y}&=\mathbf{CX}+\mathbf{DU}\end{aligned} \tag{6}$$

where $\mathbf{u}(k)$ is the input vector, $\mathbf{y}(k)$ is the output vector and $\mathbf{x}(k)$ is the state vector with finite dimension. The matrices A, B, C and D, which are unknown system matrices, have suitable dimensions. Furthermore, it is assumed that the model representation is minimal: the system is completely reachable and observable.

In a paper plant, the state-space model given below includes four inputs (stock flow, filler flow, speed, steam pressure) and three outputs (basis weight, ash content, moisture content).

$$X'=\begin{bmatrix} C_1' \\ C_2' \\ C_3' \end{bmatrix}=\mathbf{A}\begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix}+\mathbf{B}\begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \\ V_5 \end{bmatrix}$$
$$\mathbf{Y}=\mathbf{C}\begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix}+\mathbf{D}\begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \\ V_5 \end{bmatrix} \tag{7}$$

$$\mathbf{Y}=\begin{bmatrix} G_{11} & G_{12} & G_{13} & G_{14} \\ G_{21} & G_{22} & G_{23} & G_{24} \\ G_{31} & G_{32} & G_{33} & G_{34} \end{bmatrix}=\mathbf{GU} \tag{8}$$

3. LSSVM Model

SVM was initially used in the classification of data as well as approximation of nonlinear functions, and further investigated by many researchers [15]. The SVM for regression is formulated to solve a convex optimization problem usually known as quadratic programming (QP). However, the SVM has a drawback in its higher computational load due to the computation of constrained optimization problem. This drawback can be overcome by the introduction of a least-squares SVM (LSSVM). In LSSVM [16,17], the inequality constraints are transformed into equality constraints and the objective function consists of a sum of squared error (SSE) as in the training of typical neural networks. With this reformulation, the calculation procedure becomes very simple and the whole problem is greatly simplified in such a way that the solution is obtained as a linear system. Iterative methods including the conjugate gradient algorithm can be effectively used to solve the linear system.

LSSVM has enjoyed successful applications in many areas on nonlinear modeling due to its good generalization feature and lower computational burden. Given a certain individual learning subset L_k(k=1, …, T) which consists of data samples $\{x_i, y_i\}_{i=1}^{n}$, the LSSVM regression model is transformed into an optimization programming as follows:

$$\min J(\omega, \xi)=\frac{1}{2}\omega^T\omega+\frac{1}{2}\gamma\sum_{i=1}^{n}\xi_i^2 \tag{9}$$
Subject to $y_i=\omega^T \varphi(x_i)+b+\xi_i$, i=1, …, n

where φ denotes a nonlinear function which maps the input data into a higher dimensional subspace, b is the bias, ω is the weight vector, $\xi=[\xi_1, \dots, \xi_n]^T$ is the error variable vector, and γ is the penalty factor. If data are noisy, smaller γ is used to prevent overfitting. The well-known Lagrange function and Karush-Kuhn-Tucker conditions are employed in the solution of the optimization problem. The resultant LSSVM model for function estimation can be represented as follows:

$$y(x)=\sum_{i=1}^{n}\alpha_i K(x, x_i)+b \tag{10}$$

where $\alpha=[\alpha_1, \dots, \alpha_n]^T$ is the Lagrange multiplier vector, K is the kernel function used to substitute the mapping procedure and to avoid calculating the function φ. Usually, the kernel K is a symmetric function satisfying Mercer's theorem. In this work, the Gaussian radial basis function shown below is employed as the kernel function:

$$K(x, x_i)=\exp(-\|x-x_i\|^2/\sigma^2) \tag{11}$$

where σ is a tuning kernel parameter.

To establish a reliable LSSVM model for the paper plant process, a large amount of operation data set is used to train the model. The input data are scaled to be positioned within the range of [0 1] and the Gaussian radial basis function given by Eq. (11) is used. The values of the penalty factor, γ, and the tuning kernel parameter, σ, should be specified by the operator. In this work, γ is set to 1.7 and σ is set to 2.9.

RESULTS AND DISCUSSION

The papermaking models proposed in this work include four input variables and three output variables. Two plant (plant A, plant B) data sets were used to create models. Each plant data set consists of up-step and down-step response of the basis weight. Up-step and down-step occur in the paper grade-change operations. The four sets of simulation results were employed in the comparison of the performance of the papermaking models.

1. Grade-change Operation in the Plant A

In plant A, the first data set contains 585 data points to take into account of up-step response of the basis weight. The basis weight increases from 52 g/m^2 to 79 g/m^2. The second data set contains 585 data points for down-step response of the basis weight. The basis weight decreases from 64 g/m^2 to 49 g/m^2. The up-step model is labelled Case 1 and the down-step model is labelled Case 2 in this work. Fig. 2 shows the training results of each model for the three output variables. In Fig. 2, "Operation" means the operation data of the paper plant, "LSSVM" means the prediction results obtained from LSSVM model, "ANN" represents the prediction results obtained from the ANN model and "SS" denotes the prediction results computed using the state-space model. Table 1 shows values of the root-mean square error (RMSE) for training models, and Table 2 shows the average relative errors. We can see that all models show good accuracy. Although the ANN model for the basis weight has large modeling errors, it tracks the operation data well.

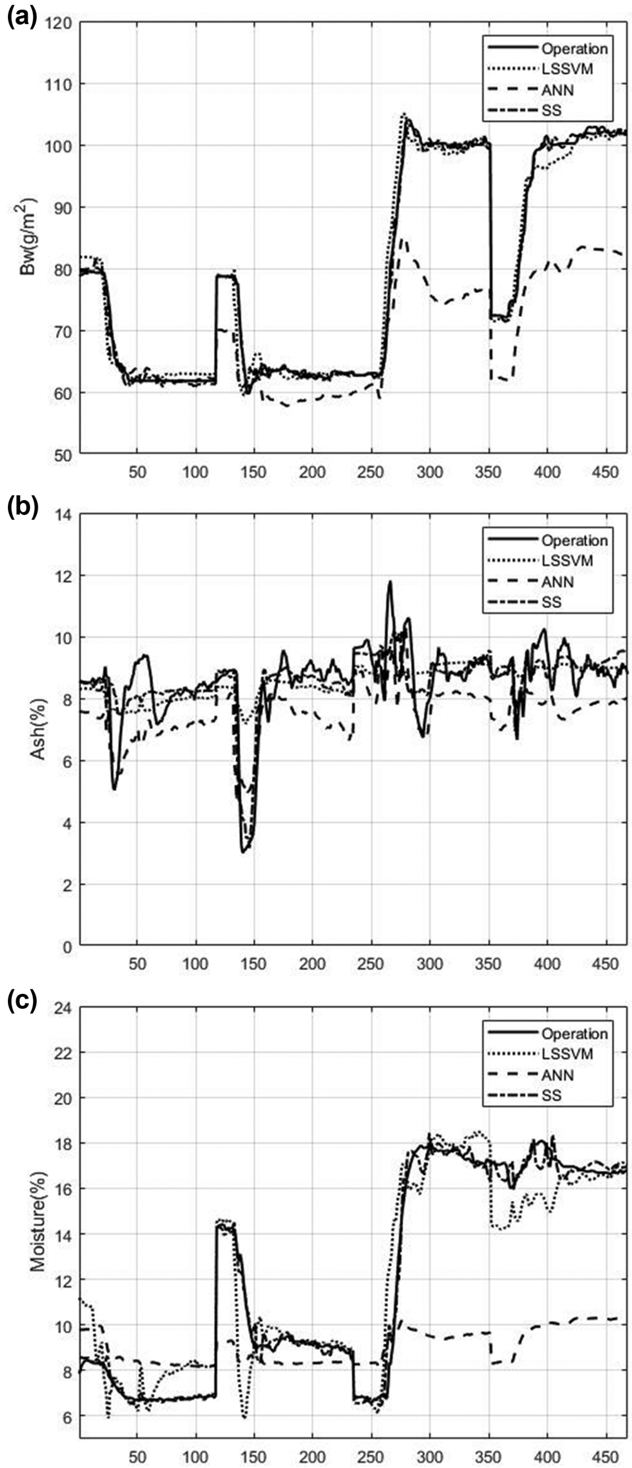

Fig. 2. Training results by using LSSVM, ANN, state-space model for Case 1: (a) Basis weight, (b) ash content, (c) moisture content.

In the models based on Case 1, 468 data points of the 585 data are used in the model training and the remaining 117 data points are used in validation. Fig. 3 shows the prediction results of each model for the three output variables. Table 3 shows values of the root-mean square error (RMSE) for each model and Table 4 shows the average of the relative error values. When comparing the errors for each output variable, the basis weight from the state-space model is smaller compared to other models, but LSSVM model shows overall best estimation results for the ash content and moisture content.

Table 1. RMSE values of paper plant training models for Case 1

	LSSVM	ANN	State-space model
Basis weight	0.9145	10.2283	2.5563
Ash content	0.7127	4.2593	1.0204
Moisture content	0.5161	5.0259	1.5366

Table 2. The average of the relative error values of paper plant training models for Case 1

	LSSVM	ANN	State-space model
Basis weight	0.8098	10.8339	2.0512
Ash content	0.6746	4.4658	0.9308
Moisture content	0.4418	4.5834	1.3537

Table 3. RMSE values of paper plant models for Case 1

	LSSVM	ANN	State-space model
Basis weight	3.204	4.9347	2.7281
Ash content	2.1565	2.5600	2.2896
Moisture content	2.4898	6.0804	3.4521

Table 4. The average of the relative error values of paper plant models for Case 1

	LSSVM	ANN	State-space model
Basis weight	6.5907	7.9077	3.0987
Ash content	2.1443	3.3700	2.5143
Moisture content	2.8989	5.6345	1.3909

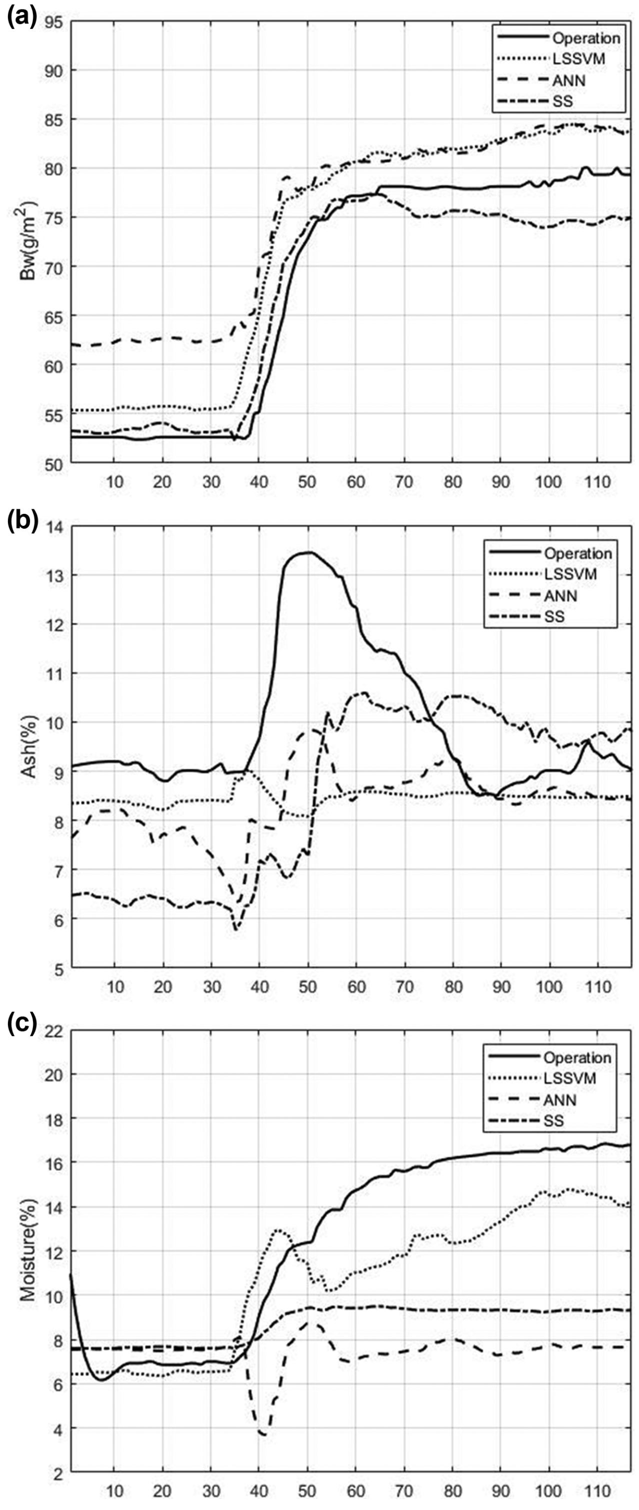

Fig. 3. Simulation results by using LSSVM, ANN, state-space model for Case 1: (a) Basis weight, (b) ash content, (c) moisture content.

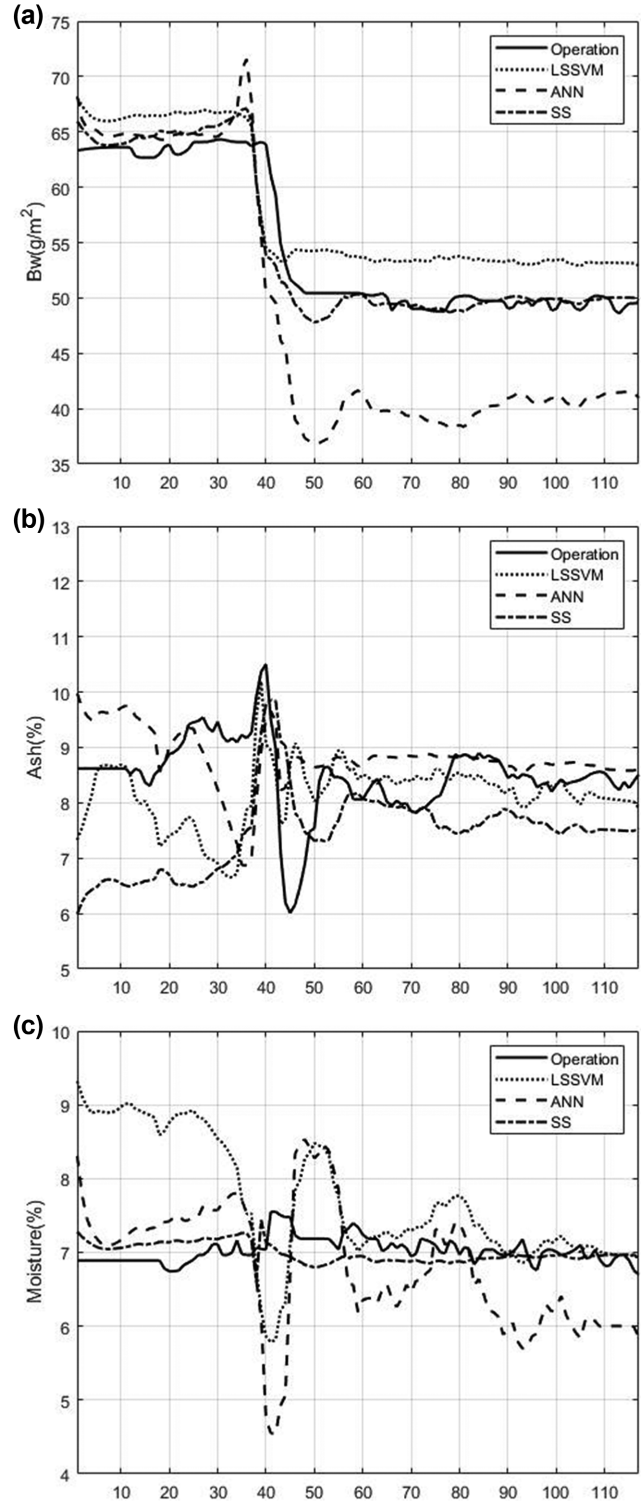

Fig. 4. Simulation results by using LSSVM, ANN, state-space model for Case 2: (a) Basis weight, (b) ash content, (c) moisture content.

We can see the good tracking performance in the basis weight of the LSSVM and state-space model.

The basis weight has the largest modeling error among the three variables in all models. However, we can see that all models track the operation data well. The results of each model follow the similar increasing pattern. We can see that the basis weight can be estimated satisfactorily by using all proposed models. For ash content and moisture content, while each model produces small error, the models could not track the operation data in the range where the operation data changes greatly.

In the models based on Case 2, 468 data points of the 585 data are used in the model training and the remaining 117 data points are used in validation. Fig. 4 shows the prediction results of each model for the three output variables. Table 5 shows RMSE values of each model and Table 6 shows the average of the relative error values. When comparing the errors for each output variable, the basis weight from the state-space model is smaller compared to other models, but LSSVM model shows overall best estimation results for the ash content and moisture content. There is little difference in the estimation of ash content between the LSSVM and state-space model.

The basis weight has the largest modeling error among the three variables in all models. However, we can see that the LSSVM and state-space models track the operation data well. The results of each model follow the similar decreasing pattern. We can see that the basis weight can be estimated satisfactorily. For ash content and moisture content, each model produces relatively small error.

2. Grade-change Operation in the Plant B

In plant B, the first data set contains 2200 data points to take into account of up-step response of the basis weight. The basis weight increases from 105 g/m^2 to 112 g/m^2. The second data set contains 2200 data points for down-step response of the basis weight. The basis weight decreases from 120 g/m^2 to 112 g/m^2. The up-step model is labelled Case 3 and the down-step model is labelled Case 4 in this work. Fig. 5 shows the training results of each model for the three output variables. Table 7 shows the RMSE values of training model and Table 8 shows the average relative errors. Again, we can see that all models show good accuracy. Although the ANN model for the basis weight exhibits relatively large modeling errors, it follows the trend of operation data well.

Table 5. RMSE values of paper plant models for Case 2

	LSSVM	ANN	State-space model
Basis weight	3.6925	8.3053	1.9512
Ash content	0.8202	2.5648	1.4927
Moisture content	1.1491	2.3256	2.2481

Table 6. The average of the relative error values of paper plant models for Case 2

	LSSVM	ANN	State-space model
Basis weight	6.6101	14.1201	2.1327
Ash content	1.0481	4.4974	2.1616
Moisture content	1.4281	3.1749	2.3831

Table 7. RMSE values of paper plant training models for Case 2

	LSSVM	ANN	State-space model
Basis weight	1.5816	17.0247	1.2235
Ash content	0.2580	0.8964	0.3222
Moisture content	0.3341	2.3516	0.3825

Table 8. The average of the relative error values of paper plant training models for Case 2

	LSSVM	ANN	State-space model
Basis weight	1.4826	17.7613	1.1212
Ash content	0.2625	0.9898	0.3157
Moisture content	0.2820	2.0302	0.3226

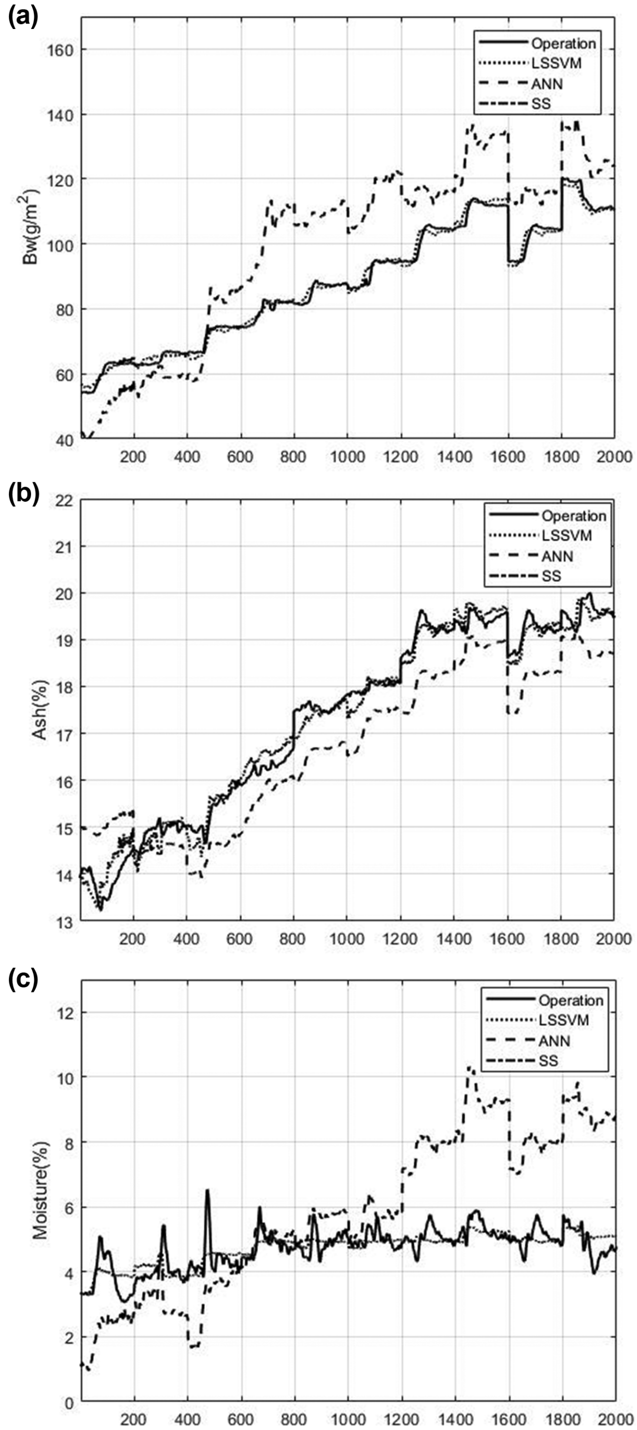

Fig. 5. Training results by using LSSVM, ANN, state-space model for Case 2: (a) Basis weight, (b) ash content, (c) moisture content.

In the models based on Case 3, 2000 data points of the 2200 data are used in the model training and the remaining 200 data points are used in validation. Fig. 6 shows the prediction results of each model for the three output variables. Table 9 shows the RMSE values of each model and Table 10 shows the average of the relative error values. When comparing the errors for each output variable, the ash content from the ANN model is smaller compared to other models, but LSSVM model shows overall best estimation results for the basis weight and moisture content.

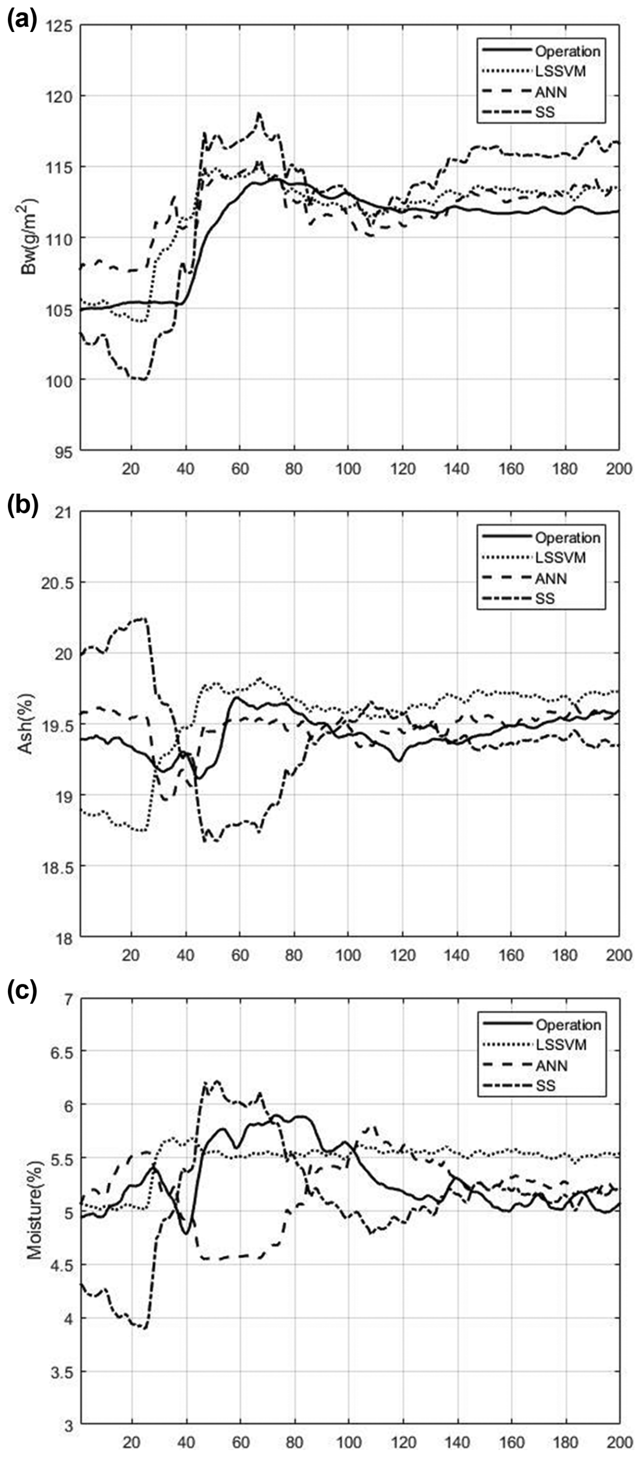

Fig. 6. Simulation results by using LSSVM, ANN, state-space model for Case 3: (a) Basis weight, (b) ash content, (c) moisture content.

The basis weight has the largest modeling error among the three variables in all models. However, we can see that all models track the operation data well. In Case 3, the operation data is increased from 105 g/m^2 to 112 g/m^2 and the results of each model follow a similar increasing pattern. We can see that the basis weight can be estimated satisfactorily by using all proposed models. For ash content the models, except the state-space model, follow the trend of operation data well. For moisture content, all models do not seem to track the trend of operation data on Fig. 6. However, the moisture content has the smallest error among all models.

In the models based on Case 4, 2000 data points of the 2200 data are used in the model training and the remaining 200 data points are used in validation. Fig. 7 shows the prediction results of each model for the three output variables. Table 11 shows the RMSE values of each model and Table 12 shows the average of the relative error values. When comparing the errors for each output variable, the ash content and the moisture content from the ANN model are smaller compared to other models. The LSSVM model shows better estimation results for the basis weight.

The basis weight has the largest error among the three variables in all models. However, all models track the operation data well. In Case 4, the operation data is decreased from 120 g/m^2 to 112 g/

Table 9. RMSE values of paper plant models for Case 3

	LSSVM	ANN	State-space model
Basis weight	1.8864	3.1395	2.8765
Ash content	0.8160	0.4684	0.6573
Moisture content	0.3446	0.3841	0.6955

Table 10. The average of the relative error values of paper plant models for Case 3

	LSSVM	ANN	State-space model
Basis weight	1.2700	2.5684	2.0342
Ash content	0.6738	0.4073	0.5408
Moisture content	0.2756	0.2995	0.5416

Table 11. RMSE values of paper plant models for Case 4

	LSSVM	ANN	State-space model
Basis weight	2.8932	6.2132	4.1586
Ash content	0.6632	0.2906	1.0537
Moisture content	0.7042	0.6414	1.3356

Table 12. The average of the relative error values of paper plant models for Case 4

	LSSVM	ANN	State-space model
Basis weight	2.3227	4.6453	3.0648
Ash content	0.4417	0.1917	0.8993
Moisture content	0.5565	0.5076	1.1475

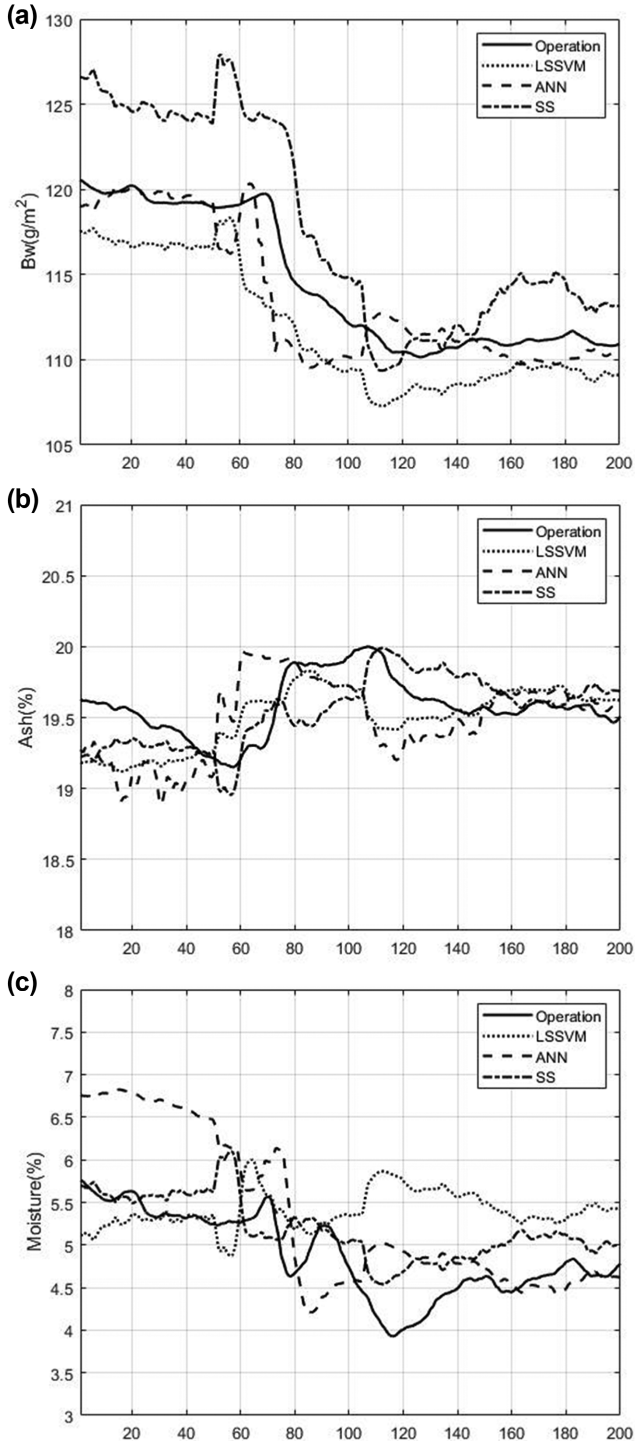

Fig. 7. Simulation results by using LSSVM, ANN, state-space model for Case 4: (a) Basis weight, (b) ash content, (c) moisture content.

m^2 and the results of each model follow a similar decreasing pattern. For ash content, all models follow the trend of operation data well. For moisture content, the operation data increase and decrease frequently, but all models do not seem to track the trend of operation data satisfactorily.

In the plant A, each model shows relatively large modeling errors in up-step compared to those in down-step. The up-step difference is 27 g/m^2 and down-step difference is 15 g/m^2. Although the trend of the operation data is well tracked, the model cannot keep up with its gain as expected. In the plant B, the up-step difference is 7 g/m^2 and down-step difference is 8 g/m^2. We can see similar magnitude of error values in both cases. When Case 1 and 2 are compared with each other, the error in Case 2 exhibits overall smaller errors compared to Case 1. In Case 2, the amount of data used in the training process is three-times larger than that used in Case 1.

CONCLUSION

Four inputs and three outputs were chosen to construct a model for a papermaking plant. The LSSVM, ANN, and state-space modeling techniques were applied to build a model representing the characteristics of the papermaking process. The models were used to compare predictions using two papermaking plant data sets. In plant A, each model simulated the trend of basis weight best. The error value was the smallest in the moisture content, but it did not simulate the trend of operation data well. The basis weight for up-step and down-step data had the smaller error in the state-space model, but the LSSVM had a smaller error for the remaining variables. In plant B, each model simulated the trend of moisture content well, and the error value was the smallest. The ash content for up-step and down-step data had a smaller error for the ANN model, but LSSVM had a smaller error for the remaining variables. Although the LSSVM model did not show the best results for all output variables, the overall results showed that the LSSVM model exhibited good performance for predicting three output values of the papermaking process.

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