

Model Algorithmic Control of Grade Change Operations in Paper Mills

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Abstract—In this work, the Model Algorithmic Control (MAC) method is applied to control the grade change operations in paper mills. The neural network model for the grade change operations is identified first and the impulse model is extracted from the neural network model. Results of simulations for MAC control of grade change operations are compared with plant operation data. The major contribution of the present work is the application of MAC in the industrial plants based on the identification of neural network models. We can confirm that the proposed MAC method exhibits faster responses and less oscillatory behavior compared to the plant operation data in the grade change operations.

Key words: Grade Change Operation, Model Algorithmic Control, Impulse Model, Paper Mill

INTRODUCTION

The task of most control systems implemented in paper mills is to keep the process variables at a steady-state during the production of a single grade. However, during grade change operations, conventional PID control systems can hardly meet the performance criteria. For this reason most of the grade change operations are executed manually by skilled operators. Improvement of process performance during grade change operations is a challenging problem. Fast grade changes and highly skilled operators may be the only solution to this problem. Because of the lack of proper control tools to make the task of the operators easier, the process performance during grade change operations has not been satisfactory.

The model predictive control methods have found successful applications especially in the petrochemical industry. There have been many efforts to employ the model predictive control method in the operation of paper mills. But, because of the complexity and high nonlinearity of paper mills, an appropriate explicit plant model for the paper mill to be used in model predictive control schemes was hardly able to be identified. In this case, a model based on artificial neural networks can be an excellent candidate. Many researchers tried to find neural network models for paper production processes. The tensile strength of the paper web was identified by using neural networks [Borari et al., 1998]. Wang and Wan proposed a combination of the model predictive control method with the neural networks to control the cross directional profile of the basis weight [Wang and Wan, 2001]. Application of the general predictive control method to control the bone dry weight and the ash content of paper has been reported [Chow et al., 1994].

The key controlled variables in the grade change operations are the basis weight, the ash content and the moisture content of the paper being produced. As the manipulated variables it is common practice to choose the flow rate of the thick stock, the filler flow, the machine speed and the steam pressure. It is desired to control

all the three controlled variables simultaneously, but most of the control methods proposed so far have concentrated on the control of only one or two key variables. The PID control method presented by Tang and Shi focused on the basis weight [Tang and Shi, 2002]. A transition control scheme based on the process model was proposed by some researchers [Koglund and Brudin, 2000; Murphy and Chen, 1999]. The method tries to manipulate the steam pressure to make the moisture content follow the predetermined trajectory.

In the present study the Model Algorithmic Control (MAC) method is proposed to control the grade change operations in paper production plants. As the first step a neural network model for grade change operations is identified. In the actual plant operation, it is impossible to perform step or impulse tests. If the neural model could serve as the “actual” plant, we may be able to get a step or impulse model very easily. From the numerical simulations the neural model identified showed excellent agreement with the plant data, which justifies the use of the neural model as the “actual” plant. A multi-variable MAC scheme is proposed next to control all the key controlled variables (basis weight, the ash content and the moisture content) simultaneously followed by numerical simulations.

GRADE CHANGE OPERATIONS

A modern paper machine can be considered as a production line consisting of a stock preparation system, wire section, wet pressing, drying and coating units, as shown in Fig. 1. In stock preparation, different raw materials such as chemical pulp from pulp mills, mechanical pulp from chip refiners, chemicals and additives are mixed together. Pulps are usually refined in order to achieve the required product quality. After it is cleaned and diluted, pulp stock is fed into the white-water system in the wire section of the paper machine.

The white-water system consists of the headbox, wire and the circulated white-water that is a filtrate from the wire. White-water is used to dilute the stock to the desired consistency (0.3-1%) for the paper web forming process. The headbox spreads the stock flow

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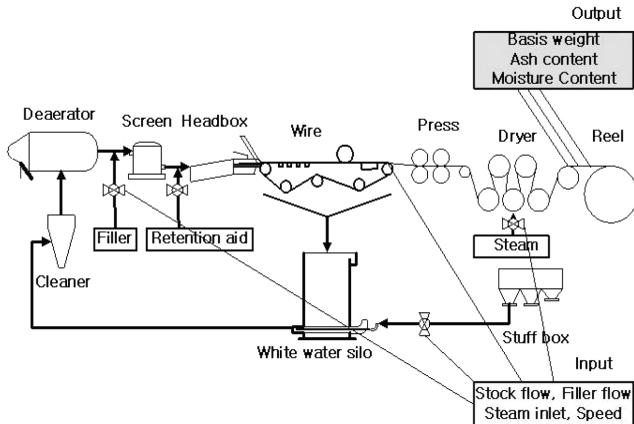


Fig. 1. Schematics of paper machine.

on the wire across the width of the machine and the paper web is formed. After that, water is removed first by wet pressing and then contact drying on steam-heated cylinders. Often, modern paper machines have on-machine coaters that apply pigment-coating color on the paper. Coating may be on both sides and even double or triple layered. In addition to these principal systems, there are several support systems such as for broke handling, chemical preparation and so on.

A grade change is a product quality change on a paper machine. In a big grade change, several inputs to the paper machine are changed, for example, proportioning of raw materials, refiner loads, stock flows, headbox settings, machine speed, lineal pressures in wet pressing, steam pressures and coating settings. So far, the most common way to execute a grade change is by ramping. An open-loop method such as ramping suits grade change well because there are no exact target values for the basis weight and moisture. It is satisfactory if the target values hit inside an acceptance range after the grade change. Most grade changes are basis weight transitions. The basis weights in a production schedule are run in a cycle. The cycle is optimized so that the basis weight changes are as small as possible. The ideal condition is that the allowed ranges of sequential grades overlap.

A typical grade change consists of a calculation of target values and a dynamic co-ordination of paper machine speed, pulp stock flow and steam. It is crucial to a successful grade change that the new target values are accurately known. Stock flow and machine speed together control both the production rate and basis weight. Drying is controlled by steam pressure, but often, only the last steam groups are used for control purposes. Because of long time constants and dead times in the drying process, the target values for steam pressures are the most important. Also raw material properties, the condition of the paper machine, basis weight, moisture and speed, all affect the drying rate. The machine tender usually gets the initial target values from the records of the previous runs.

MODEL ALGORITHMIC CONTROL (MAC) METHOD

Artificial neural networks are well known and widely used in modeling and control areas. Details on the neural networks can be

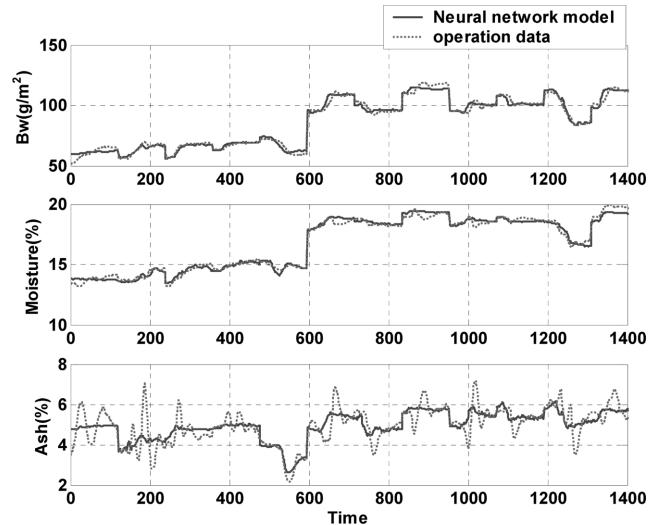


Fig. 2. Validation of the neural model (Company A).

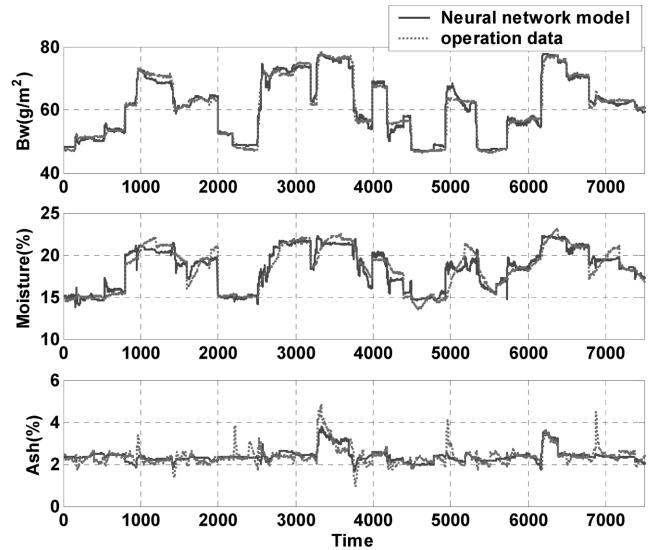


Fig. 3. Validation of the neural model (Company B).

found in numerous papers and books. The neural network designed in the present study consists of input and output layers with a hidden layer in-between. There are 4 and 3 neurons in the input and output layers, respectively. The hidden layer contains 25 neurons. Plant operation data were collected for more than 15 different grades of papers. Part of the operation data was used as a training set, and the remaining data set was employed in the validation of the neural model. Figs. 2 and 3 show the results of validations of the neural network model for paper companies A and B, respectively. Among the three output variables, the basis weight (BW) is by far the most important and major effort is taken to control BW first in the plant operation. As we can see in Fig. 2 and 3, results of the numerical validation simulations show excellent agreement with plant operation data. This justifies the use of the neural network model as the “actual” plant in the model predictive control scheme.

Model predictive control (MPC) is a basic concept or idea that can be implemented in many ways, depending on models used and

assumptions made. The exact models for the paper manufacturing processes can be found elsewhere [Yeo et al., 2004a, b]. The finite step and impulse models limit applications to open-loop stable processes and require many model coefficients to describe the response. It is now recognized that there are many advantages to using discrete state space models. State space models require fewer model parameters than step and impulse response models to describe process behavior. The step and impulse response models are all linear. For some processes where the process operating conditions are changed frequently, a single linear model may not describe the dynamic behavior of the process over a wide range of conditions. For paper production processes, the range of operating conditions is relatively small and no nonlinear chemical reactions are involved. This fact suggests the use of simple linear models (step or impulse response model). For the paper plants considered in the present study, it was found that the impulse model with the order of 17 fits the plant data very well compared to other types of models.

A multivariable impulse model can be expressed by

$$y_k(t) = \sum_{j=1}^{nu} \sum_{i=1}^n b_{k,j,i} u_j(t-i) \quad (k=1, \dots, ny) \quad (1)$$

The ARX (autoregressive with exogenous input) formulation of the impulse model is given by

$$A_0 Y(t) = B_1 U(t-1) + B_2 U(t-2) + \dots + B_n U(t-n)$$

$$A_0 = [100; 010; 001]$$

$$B_i = \begin{bmatrix} b_{1,1,i} & b_{1,2,i} & b_{1,3,i} & b_{1,4,i} \\ b_{2,1,i} & b_{2,2,i} & b_{2,3,i} & b_{2,4,i} \\ b_{3,1,i} & b_{3,2,i} & b_{3,3,i} & b_{3,4,i} \end{bmatrix}$$

$$U(t-i) = [u_{speed}(t-i) u_{stock}(t-i) u_{filter}(t-i) u_{steam}(t-i)]' \quad (2)$$

Matrices B_i contain impulse model parameters to be identified. A simple least-squares curve fitting method available from various computational tools such as MATLAB can be used in the identification. Figs. 4 and 5 show the results of validations of the impulse model for paper companies A and B, respectively. As we can see in Figs. 4 and 5, the impulse model tracks the plant confidently.

Predictions of outputs can be represented as

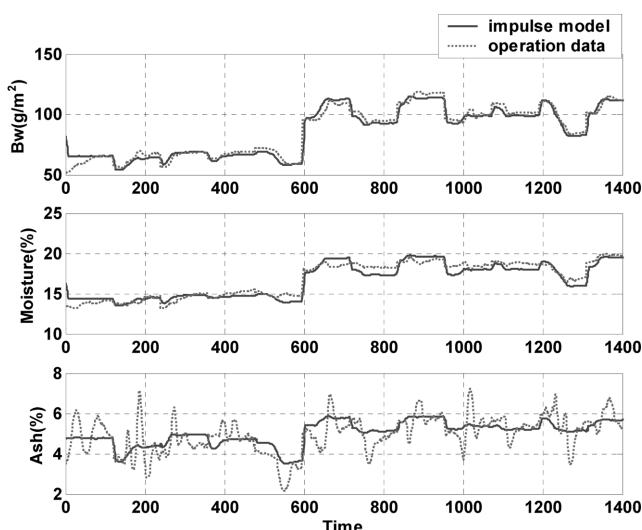


Fig. 4. Validation of the impulse model (Company A).

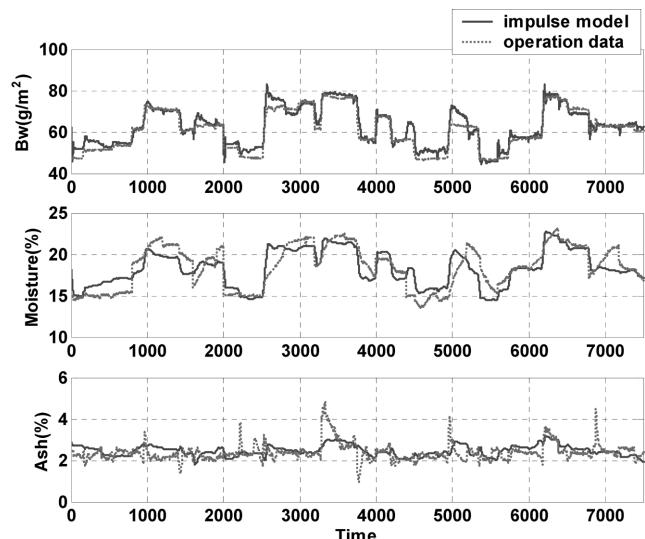


Fig. 5. Validation of the impulse model (Company B).

$$\hat{y}_k(t+l|t) = \sum_{j=1}^{nu} \sum_{i=1}^n b_{k,j,i} U_j(t+l-i) + \hat{n}_k(t+l|t) \quad (k=1, \dots, ny) \quad (j=1, \dots, nu) \quad (3)$$

$$\hat{y}_k(t+l|t) = \sum_{j=1}^{nu} \sum_{i=1}^l b_{k,j,i} U_j(t+l-i) + \sum_{j=1}^{nu} \sum_{i=l+1}^n b_{k,j,i} U_j(t+l-i) + \hat{n}_k(t+l|t) \quad (k=1, \dots, ny) \quad (4)$$

If the future noise is assumed to be kept as the present noise, we have

$$\hat{n}_k(t+l|t) = \hat{n}_k(t|t) = y_k(t) - \sum_{j=1}^{nu} \sum_{i=1}^n b_{k,j,i} U_j(t-i) \quad (k=1, \dots, ny) \quad (5)$$

At first, we assumed that the measured output $y_k(t)$ is equal to the value computed from the model, $\sum_{j=1}^{nu} \sum_{i=1}^n b_{k,j,i} U_j(t-i)$. The desired output trajectory can be defined as

$$\omega_k(t+l) = \alpha \cdot \omega_k(t+l-1) + (1-\alpha) \cdot \gamma(t+l) \quad (6)$$

The predicted outputs can be written as

$$Y = H_p U_p + H_{mi} U_{mi} + n = H_p U_p + f \quad (7)$$

The combination of a linear model and a quadratic objective function leads to an analytical solution for the control moves as given by

$$U_p = (H_p^T H_p + Q + \lambda \cdot I)^{-1} \cdot H_p^T \cdot (\omega - f) \quad (8)$$

In practice, constraints on manipulated inputs can be very important. If the analytical solution results in an infeasible control action, then obviously the control moves must be truncated at the maximum or minimum values. Since the resulting truncated solutions may not be optimal if the control horizon is greater than 1, it is important to use a constrained optimization formulation for these problems. Fortunately, MAC is easily formulated to explicitly handle constraints by using quadratic programming.

RESULTS AND DISCUSSION

In steady-state operation, an appropriate control method can be

used to stabilize process operations and especially to stabilize the short circulation. This will mean stable retentions. However, the control task is very different during grade change operations. The primary objective is to minimize the grade change time. This leads also to short control horizon and larger allowed control actions, because before a grade change time MAC should already be running the process towards a new grade. Yet, as well, it is necessary to keep product quality at accepted grade specifications as long as the old grade run is continuing. Prevention of web break is by far the most important target during the grade change operation. At the end of the grade change, the process should meet the limits of the new grade as soon as possible and not overshoot outside quality limits. But, in actual operations, overshoot less than $\pm 5\%$ of the grade change span is usually allowed. The optimization horizon and the number of actions in the calculated sequence must be extended towards the end of the grade change.

In most grade change operations, changes of concurrent machine speed are also included. Moisture content is usually a challenging variable for automatic grade changes. Water content after the press section would be dependent upon many variables including machine speed, paper basis weight and ash content. The paper web inside a drying section during grade change will have special conditions. There will be different basis weight in each drying section. Also, a piece of paper web will have different speed in each drying section compared to pieces in other drying sections. If we increase the web speed, we will decrease drying time in the drying section at the same time. This fact implies that we must correspondingly increase drying power. The drying process itself is also dependent upon heat production at the heated drying cylinders and water evaporation conditions in the hood.

In the beginning of each grade change it is important to have a good predictive model to adjust manipulated variables, almost according to a traditional open-loop grade change program. At the end of grade change, we must smoothly move towards steady-state MAC operation by extending the prediction horizon and decreasing the amount of control movement allowed during each optimization cycle.

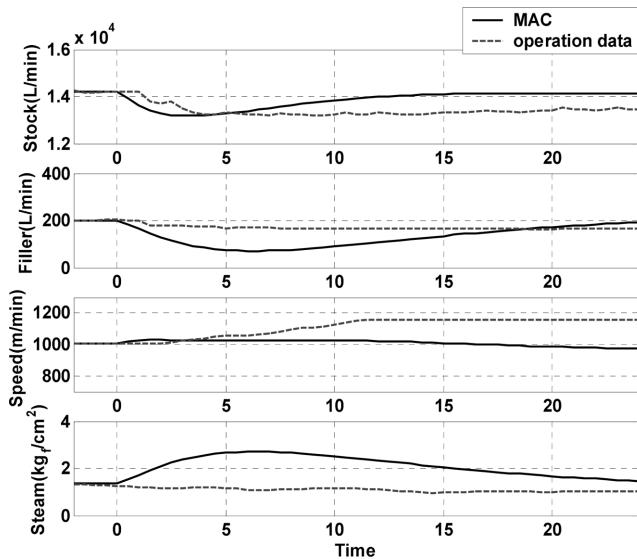


Fig. 6. MAC input trend for $110 \text{ g/m}^2 \rightarrow 84 \text{ g/m}^2$ (Company A).

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The performance of the proposed control scheme was evaluated by using numerical simulations. Grade change operation data were collected for plant A and plant B. For plant A, the prediction horizon was set to 16 and the input suppression parameter was set to 17. After some trials, the suitable weights for the outputs (Q_o) and the inputs (R) were found to be [3 1 1] and [0.1 0.1 0.2 0.1], respectively. The parameter in the desired output trajectory (α) was set to 0.85. For plant B, the same values as for plant A were used for the prediction horizon and the input suppression parameter. The suitable weights for the outputs (Q_o) and the inputs (R) were found to be [3 3 1] and [0.1 0.1 0.2 0.1], respectively. The parameter in the desired output trajectory (α) was set to 0.9. The sampling time was 30 sec (0.5 min).

Figs. 6 and 7 show results of numerical simulations for the grade change of $110 \rightarrow 84 \text{ g/m}^2$ in plant A. It is normal practice to express a grade change operation in terms of the basis weight (BW)

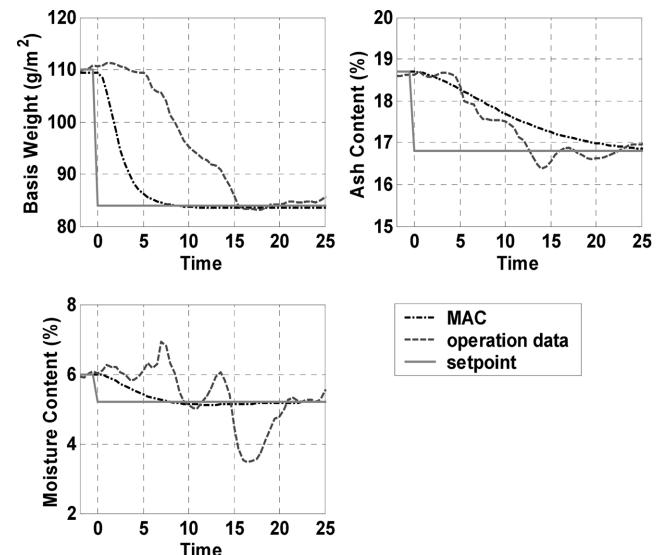


Fig. 7. MAC output trend for $110 \text{ g/m}^2 \rightarrow 84 \text{ g/m}^2$ (Company A).

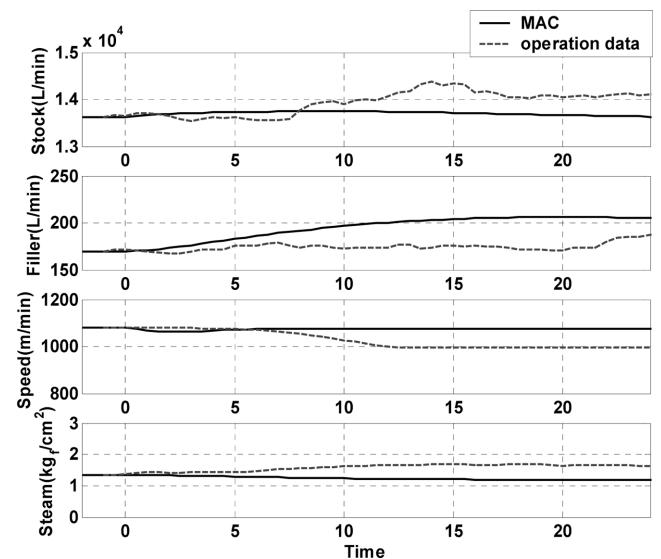


Fig. 8. Input trend for $96 \text{ g/m}^2 \rightarrow 110 \text{ g/m}^2$ (Company A).

because BW is the most important output variable. Fig. 6 shows the optimal input trend obtained from MAC compared to the plant operation data. We cannot say which one is “better,” but the primary concern is to avoid unnecessary oscillations or perturbations in the inputs. Fig. 7 shows the output trend. In Fig. 7, the MAC line was obtained by applying the optimal inputs from MAC to the “plant.” As described before, the “plant” is the neural network model for the plant and the accuracy of the neural model is depicted in Figs. 2 and 3. It is obvious that the grade change time was reduced up to 50% (approximately from 15 min to 7 min) and that oscillations were suppressed enough. This fact makes the application of the MAC scheme in the plant operation promising. Figs. 8 and 9 show similar results for a grade change of $96 \rightarrow 110 \text{ g/m}^2$ in the plant A. Again, the grade change time was reduced more than 50% and the trends obtained by MAC show smooth behavior without overshoots.

Figs. 10 and 11 show results of numerical simulations for a grade change of $57.5 \rightarrow 73 \text{ g/m}^2$ in plant B. As in the case of plant A, we can see that a decrease in the grade change time and smooth

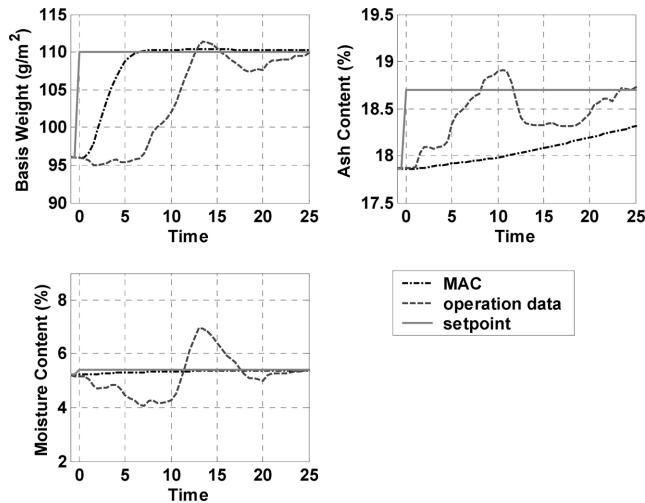


Fig. 9. Output trend for $96 \text{ g/m}^2 \rightarrow 110 \text{ g/m}^2$ (Company A).

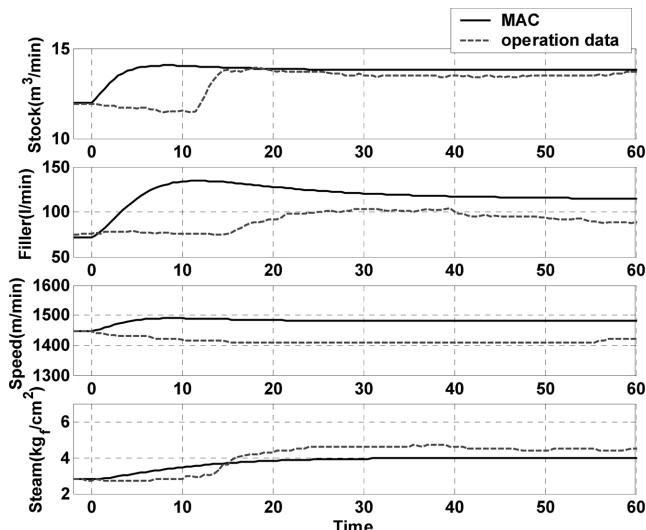


Fig. 10. Input trend at $57.5 \text{ g/m}^2 \rightarrow 73 \text{ g/m}^2$ (Company B).

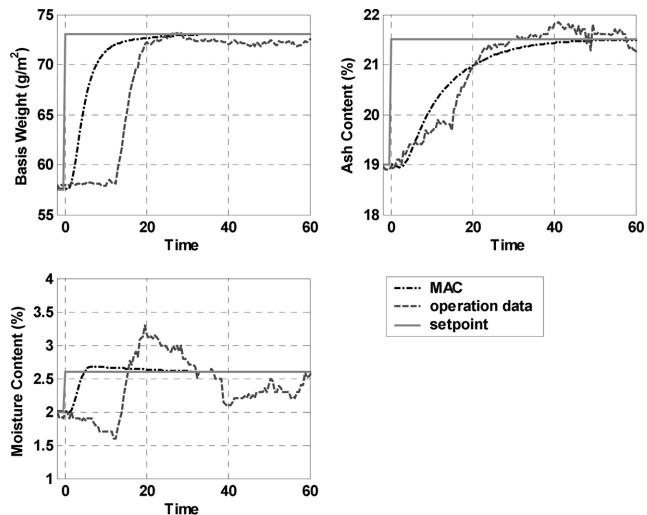


Fig. 11. Output trend at $57.5 \text{ g/m}^2 \rightarrow 73 \text{ g/m}^2$ (Company B).

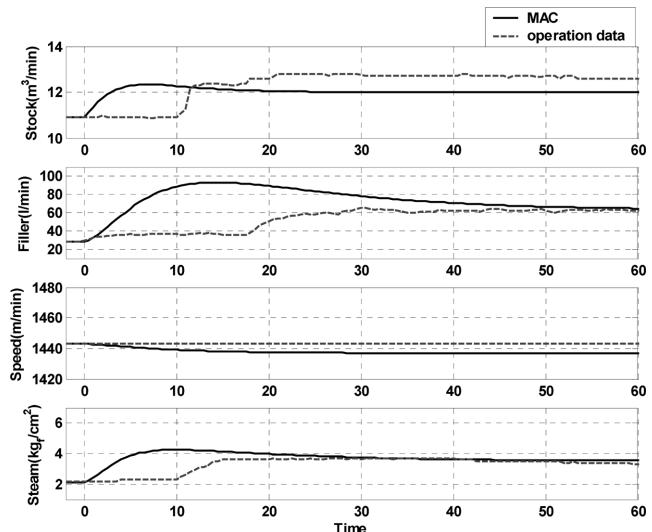


Fig. 12. Input trend for $47.5 \text{ g/m}^2 \rightarrow 57 \text{ g/m}^2$ (Company B).

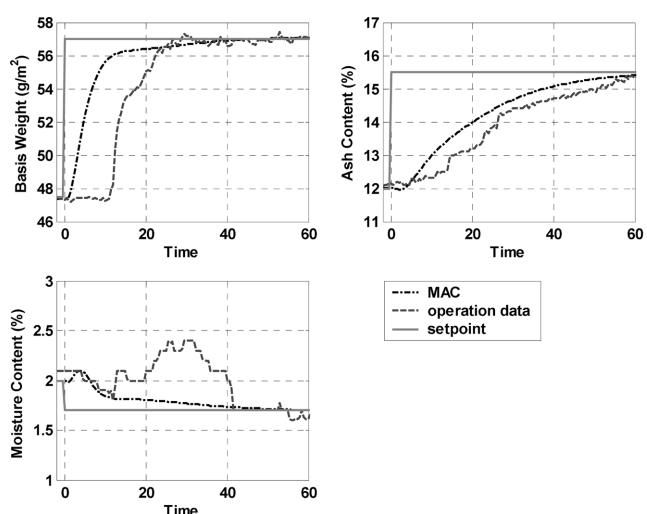


Fig. 13. Output trend for $47.5 \text{ g/m}^2 \rightarrow 57 \text{ g/m}^2$ (Company B).

trends are successfully achieved by MAC. Figs. 12 and 13 show similar results for a grade change of $47.5 \rightarrow 57$ (g/m²) in plant B. Again, the grade change time was greatly reduced and the trends obtained by MAC show smooth behavior without perturbations.

CONCLUSIONS

The most challenging issue for automatic grade change operation is the reduction of grade change time without web break. This leads to a short control horizon and larger allowed control actions, because before a grade change time the model predictive control method being used should already be running the process towards a new grade. The Model Algorithmic Control scheme based on the impulse plant model was found to achieve the expected primary control objectives: reduction in the grade change time and suppression of input/output trends. The neural network model for the grade change operations were developed first. From the numerical simulations the neural network model was found to track the plants closely. Thus, the neural model acted as the real plant in the control simulations. The MAC proposed in the present study showed desired performance: the grade change time was decreased more than 50% and the input/output trends showed smooth behavior without severe oscillations.

NOMENCLATURE

A_0	: unit matrix
B_i	: impulse parameter matrix
$b_{i,j,k}$: impulse parameter element in B_i matrix
H_{pl}, H_{mi}	: dynamic matrix
Q_o	: output weighting
R	: input weighting
t	: time
U_{pl}	: future input
U_{mi}	: past input
u_{speed}	: speed [m/min]
u_{stock}	: thick stock [L/min], [m ³ /min]
u_{filler}	: filler flow [L/min]
u_{steam}	: steam pressure [kg/cm ²]
\hat{n}_k	: noise
w	: desired output trajectory

y_k	: measured output
\hat{y}_k	: predictive output

Greek Letters

α	: parameter in desired output trajectory
γ	: setpoint

REFERENCES

Borari, M., Wang, H. and Roberts, J. C., "Dynamic Modeling of a Paper Making Process Based on Bilinear System Modeling and Genetic Neural Networks," *UKACC International Conference on Control September*, **455**, 1277 (1998).

Chow, C., Kuznetsov, A. and Clarke, D., "Application of Multivariable Generalized Predictive Control to the Simulink Model of a Paper Machine," *Proceedings of the Third IEEE Conference on*, **3**, 1675 (1994).

Hornik, K., Stinchcombe, M. and White, H., "Multilayer Feedforward Networks are Universal Approximators," *Neural Network: The Official Journal of the International Neural Network Society*, **2**, 359 (1989).

Kuusisto, R., Kosonen, M., Shakespeare, J. and Huhtelin, T., "Multivariable Control of Paper Machine Grade Changes," *Pulp & Paper Canada*, **103**, 28 (2002).

Murphy, T. F. and Chen, S. C., "Transition Control of Paper-making Processes: Paper Grade Change," *Control Applications, 1999. Proceedings of the 1999 IEEE International Conference on Control Applications*, **2**, 1278 (1999).

Skoglund, A. and Brundin, A., "A Multivariate Process Model for Grade Change in a Paperboard Machine," *Nordic Pulp & Paper Research Journal*, **15**, 183 (2002).

Tang, W. and Shi, S. J., "Autotuning PID Control for Large Time-delay Processes and its Application to Paper Basis Weight Control," *Industrial & Engineering Chemistry Research*, **41**, 4318 (2002).

Wang, L. and Wan, F., "Structured Neural Networks for Constrained Model Predictive Control," *Automatica*, **37**, 1235 (2001).

Yeo, Y. K., Hwang, K. S., Yi, S. C. and Kang, H., "Modeling of the Drying Process in Paper Plants," *Korean J. Chem. Eng.*, **21**, 761 (2004a).

Yeo, Y. K., Yi, S. C., Ryu, C. Y. and Kang, H., "Modeling and Simulation of Wet-end White Water System in the Paper Mill," *Korean J. Chem. Eng.*, **21**, 358 (2004b).