Modeling of Grade Change Operations in Paper Plants

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ABSTRACT

In this work we developed the closed-loop model of a paper machine during grade change with the intention to provide a reliable dynamic model to be used in the model-based grade change control scheme. During the grade change, chemical and physical characteristics of paper process change with time. It is very difficult to represent these characteristics on-line by using physical process models. In this work, the wet circulation part and the drying section were considered as a single process and closed-loop identification technique was used to develop the grade change model. Comparison of the results of numerical simulations with plant operation data demonstrates the effectiveness of the model identified.

1. Introduction

A paper grade is typically specified with certain weight per unit area, moisture content, fiber type, chemical additives, color, surface appearance and a few other quality parameters. Grade change in a paper mill involves the changes of basis weight, moisture content level, fiber furnish, chemical additives, colorants additions and many others. Grade changes in paper plants are made by changing major process variables such as machine speed, stock flow and steam pressures at the same time to provide a fast transition in quality variables such as basis weight and moisture content. The paper made during the grade change is often out of quality criteria of both grades. This off-specification product is handled like a broke and this increases production costs.

The grade change is a very demanding operation. The objects of the grade change operation are to reduce the time taken in the grade change, to reduce the number of sheet breaks and to reduce variations in major process variables such as basis weight, moisture content and ash content. During the grade change, control systems implemented in the paper plant cannot meet the performance criteria. For this reason most of grade change operations have been executed manually by skilled operators. Enhancement of process performance during grade change has been a challenging problem. One of the most promising approach to achieve the required performance in the grade change is to employ a control technique based on the dynamic process model. But lack of a dependable multivariate model for the grade change has prohibited the use of advanced process control schemes such as model predictive control. In general, identification of a process model requires open-loop test for the process. Most of the identification techniques reported so far are based on the open-loop identification. Open-loop test may be possible during steady-state operation when single kind of paper is being produced. But introduction of arbitrary step or ramp inputs during grade change is almost impossible.

Dynamic modeling of paper plants during grade change has attracted attentions of a few researchers. Valisuo et al. [1] discussed requirements of grade change automation for paper and board machines. They adopted "mechanistic modeling" approach to develop a plant model by combining standard unit models from the model libraries details of which are not presented. Larsson and Gustafsson[2] used open-loop identification technique to develop dry line model during grade change. Murphy and Chen investigated problems of transition control during paper grade change. They obtained dynamic model by performing bump tests on key manipulated variables. By representing dynamic responses of the paper machine as well as transition patterns in terms of FOPDT(First-Order Plus Dead-Time) transfer functions, they determined profiles of key manipulated variables from simple algebraic manipulations. A partial least squares (PLS) regression method was employed to develop a multivariate model for grade change in a paperboard machine. [3] The PLS technique was combined with a physical model to develop a hybrid model of moisture in paper machine grade change. [4] The physical model for the drying process is based on the Stefan equation. But it is well known that dynamics of drying process are highly dependent on the heat transfer coefficients between web and air and between cylinder and web. Combination of more complicated drying model and other process models with empirical models is not a simple matter and the hybrid model has some limits to be used in model based control. Kuusisto et al.[5] developed SOPDT (Second-Order Plus Dead-Time) model to control grade change operations. In their model effects of machine speed change are not given in the form of SOPDT.

This paper is focused towards the closed-loop modeling of a paper machine during grade change with the intention to provide a reliable dynamic model to be used in the model-based grade change control scheme. During the grade change, chemical and physical characteristics of paper process change with time. It is very difficult to represent these characteristics on-line by using physical process models. In this work, the wet circulation part and the drying section were considered as a single process and closed-loop identification technique was used to develop the grade change model.

2. Materials & Methods

2.1 Closed-loop identification

The identification of plant models has traditionally been done in the open-loop mode as shown in Fig. 1. The desire to minimize the production of the off-spec paper product during an open-loop identification test and the unstable open-loop dynamics of certain systems have increased the need to develop methodologies suitable for the system identification.

Open-loop identification techniques are not directly applicable to closed-loop data due to correlation between process input (i.e., controller output) and unmeasured disturbances. Based on Prediction Error Method (PEM), several closed-loop identification methods have been presented by Forssell and Ljung:[6,7] Direct, Indirect, Joint Input-Output, and Two-Step Methods. Fig. 2 shows closed-loop identification.

However, these methods require a prior knowledge on the plant order and time delay. And, theoretically, the identifiability can be guaranteed under mild conditions. The newly developed, so-called the open-loop subspace identification method has been proven to be a better alternative to the traditional parametric methods. This is especially true for high-order multivariable systems, for which it is very difficult to find a useful parameterization among all possible candidates.

The subspace identification method has its origin in classical state-space realization theory developed in the 60's. It uses the powerful tools such as Singular Value Decomposition (SVD) and QR factorization. No nonlinear search is performed nor is a canonical parameterization used. There are many different algorithms in the subspace identification field, such as N4SID, MOESP and CVA. Recently, Ljung and McKelvey[7] investigated the subspace identification method which calculates the state-space model (Eq. [1]) from the closed-loop data.

$$x(t+1) = Ax(t) + Bu(t) + Ke(t)$$

[1]

$$y(t) = Cx(t) + Du(t) + e(t)$$

[2]

We can summarize the basic steps of the subspace identification as following (Overschee and De Moor, 1994):[8)]

1. Estimate states $x(k),\ k = 0,1,2,\mathrm{L}\ ,j-1$ from measured process inputs and outputs.
2. Estimate the system matrices (A, B, C, D, K) from the estimated states by the following procedure:
   i) Using LS method, estimate A, B, C and D and residual $\rho_1 = K\left[e(0)\ e(1)\ \mathrm{L}\ \ e(j-2)\right]$ and $\rho_2 = \left[e(0)\ e(1)\ \mathrm{L}\ \ e(j-2)\right]$ by

$$\begin{bmatrix} x(k+1) \\ y(k) \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} x(k) \\ u(k) \end{bmatrix} + \begin{bmatrix} Ke(k) \\ e(k) \end{bmatrix}$$

[3]

   ii) From the residual, estimate K by

$$K = \rho_1 \rho_2^T \left[\rho_2 \rho_2^T\right]^{-1}$$

[4]

In above steps, the state can be determined by using SVD. The future outputs are given by Eq. [5] with future inputs and noises being set to zero.

$$\begin{aligned} y(k+i) = &\sum_{m=1}^{na} CA^i H_m^y y(k-m) + \sum_{m=1}^{nb} CA^i H_m^u u(k-m) \\ &+ \sum_{m=1}^{i} CA^{i-m} Bu(k+m-1) + Du(k+i) \\ &+ \sum_{m=1}^{i} CA^{i-m} Ke(k+m-1) + e(k+i),\ i = 0,1,2,\mathrm{L}\ ,i-1 \end{aligned}$$

[5]

If the test data sets are gathered from open−loop tests, we can apply the LS method to Eq. [5]. The solutions are unbiased since the process inputs are uncorrelated with process noise terms. But, if the process input is a function of the process noise as in the closed−loop test, the solution for $CA^iH_m^y$, $CA^iH_m^u$, $CA^{i-m}B$ and D would be biased. For this reason, application of subspace identification methods for the closed−loop test gives biased estimation results regardless of the accuracy of the next steps. This is the main problem in the application of the subspace identification method for the closed−loop system.

We can assume $D=0$ since most processes have at least one delay between the process output and the process input. Then, Eq. [5] becomes

$$
\begin{aligned}
y(k+i) &= \sum_{m=1}^{na} CA^iH_m^y y(k-m) + \sum_{m=1}^{nb} CA^iH_m^u u(k-m) \\
&+ \sum_{m=1}^{i} CA^{i-m}Bu(k+m-1) \\
&+ \sum_{m=1}^{i} CA^{i-m}Ke(k+m-1) + e(k+i),\ i = 0,1,2,\mathrm{L}\ ,i-1
\end{aligned}
$$

[6]

If $i=0$, Eq. [6] becomes a high order ARX (Auto−Regressice with eXogeneous) input model as

$$
y(k) = \sum_{m=1}^{na} CH_m^y y(k-m) + \sum_{m=1}^{nb} CH_m^u u(k-m) + e(k)
$$

[7]

It should be noted that the process input $u(k-1)$ is a function of the past process outputs $y(k-m)$, $m=1,\ 2,\ \mathrm{L}\ ,\ na$ for usual feedback controllers and that the process inputs $u(k-m)$, $m=1,\ 2,\ \mathrm{L}\ ,\ nb$ are uncorrelated with $e(k)$. Therefore, if we apply LS method to the ARX model given by Eq. [7], we can obtain unbiased estimates of P_y, P_u for CH_m^y and CH_m^u.

$$\hat{y}(k)=\sum_{m=1}^{na}P_y y(k-m)+\sum_{m=1}^{nb}P_u u(k-m)$$

[8]

$$\begin{bmatrix} \hat{y}(k|k) & \hat{y}(k+1|k+1) & \cdots & \hat{y}(k+j-1|k+j-1) \\ \hat{y}(k+1|k) & \hat{y}(k+2|k+1) & \cdots & \hat{y}(k+j|k+j-1) \\ \hat{y}(k+2|k) & \hat{y}(k+3|k+1) & \cdots & \hat{y}(k+j+1|k+j-1) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{y}(k+i-1|k) & \hat{y}(k+i|k+1) & \cdots & \hat{y}(k+i+j-2|k+j-1) \end{bmatrix} = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} = U_1 \Sigma_1 V_1^T$$

[9]

The elements of the first column in Eq. [9] can easily be obtained from Eq. [8]. Subsequent steps for state estimation and the system matrix estimation are exactly the same with those of subspace identification methods. These methods do not require knowledge on the order and the time delay of the process. Fig. 3 shows closed-loop identification steps used in the present work.

3. Results & Discussion

The paper process consists of the wet end and the drying section. The wet end is a complex network that interconnects all the pulp preparation equipment and the forming section of the paper machine. The raw material from the stuff box with consistency of about 3% is fed into the wet end through the stock valve followed by physical and chemical dehydration at the wire section. White water is introduced into the white water silo and recycled as dilution water. The amount of the filler and the ash content of the broke in thick stock determine the ash content of the final product. The dehydrated web in the wet end is transported to the drying section. The moisture content of the web at the entrance of the drying section is approximately 55% regardless of paper grades. The drying section consists of the main dryer and the after dryer. More than 80% of the moisture contained in the web is evaporated in the main dryer. Starch is applied to the web in the size press followed by drying in the after dryer. In this work the paper process from the stuff box to the main dryer was modeled.

In the typical paper process as shown in Fig. 4, stock flow, steam pressure, clay flow and machine speed have different dynamics. The dynamic responses of these variables must be identified. Throughout the entire grade change operation, the changes to these variables have to be carefully manipulated in order to get a fast and smooth transition. The major controlled variables during the grade change are basis weight, ash content and moisture content. The relationship between the manipulated variables and the controlled variables can be represented in terms of transfer functions as

$$\text{Gp}: \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} & G_{13} & G_{14} \\ G_{21} & G_{22} & G_{23} & G_{24} \\ G_{31} & G_{32} & G_{33} & G_{34} \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ U_4 \end{bmatrix} \qquad [10]$$

where U_i are manipulated variables (U_1:stock flow, U_2: clay flow, U_3: steam pressure, U_4: machine speed) and Y_i are controlled variables (Y_1: basis weight at size press, Y_2 : ash content, Y_3 : moisture content at size press). G_{ij} are corresponding transfer functions to be identified by closed−loop identification. Ash content can also be affected not only by broke in thick flow but also by retention and mechanical properties. In this work, ash content in broke was assumed to be constant.

The state model (Eq. [3]) and the transfer function form Eq. [10] are interchangeable. The transfer function form Eq. [10] can be easily obtained form the state space form Eq. [3]. From the closed-loop identification we could get the state space model (Eq. [3]) with the matrices A, B, C and D given by

$$A =$$

$$\begin{bmatrix} 0.676 & 0.349 & -0.153 & -2.462 & -2.182 & 0.735 & -0.477 & -1.326 & 0.201 & -0.199 \\ -1.309 & 2.494 & -0.601 & -10.70 & -3.071 & -0.850 & -0.803 & -3.458 & 0.641 & -0.372 \\ 0.941 & -1.215 & 1.472 & 9.160 & 4.575 & -3.024 & 1.526 & 4.882 & -1.176 & 0.902 \\ -0.305 & 0.362 & -0.132 & -1.566 & -0.493 & -0.145 & -0.079 & -0.553 & 0.151 & -0.025 \\ -0.043 & 0.077 & -0.029 & -0.612 & 0.6193 & 0.449 & 0.164 & -0.017 & -0.098 & 0.035 \\ -0.318 & 0.358 & -0.108 & -2.318 & 0.066 & 0.193 & -0.523 & -0.131 & 0.146 & 0.064 \\ -0.027 & 0.071 & -0.021 & -0.491 & 0.052 & 0.398 & 0.542 & -0.111 & 0.434 & -0.060 \\ 0.179 & -0.203 & 0.024 & 1.140 & -0.029 & -0.006 & -0.046 & -0.143 & 0.162 & 0.023 \\ 0.437 & -0.511 & 0.161 & 3.481 & 0.593 & 0.311 & -0.526 & -0.215 & 0.584 & 0.220 \\ 0.420 & -0.519 & 0.174 & 3.604 & 0.577 & 0.241 & 0.102 & 0.272 & -0.462 & 0.354 \end{bmatrix}$$

$$B = \begin{bmatrix} -0.00515 & -0.01977 & 0.77550 & -0.01381 \\ -0.01938 & -0.05644 & 3.63000 & -0.05918 \\ -0.01642 & 0.03865 & -0.54360 & 0.05292 \\ -0.00295 & -0.00779 & 0.44291 & -0.01406 \\ 0.00713 & -0.00085 & -0.69900 & -0.00400 \\ -0.01250 & 0.00034 & 0.82260 & -0.01156 \\ 0.00565 & 0.00184 & -0.22270 & -0.00376 \\ 0.00723 & -0.01536 & 0.95470 & 0.00446 \\ 0.00613 & 0.00089 & 0.29520 & 0.01798 \\ 0.00109 & 0.00458 & 0.04471 & 0.01986 \end{bmatrix}$$

$$C = \begin{bmatrix} -1.742 & 0.390 & 0.118 & 2.347 & -2.043 & 1.614 & -0.316 & 0.125 & 0.037 & -0.141 \\ -0.304 & -0.088 & -0.159 & -0.141 & -0.419 & -0.070 & 0.064 & -0.355 & -0.106 & 0.132 \\ -0.207 & 0.189 & 0.002 & -2.854 & -0.934 & 0.275 & -0.256 & -0.822 & 0.159 & -0.186 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 5 and 6 show changes of manipulated variables and controlled variables respectively during grade change operations. In the plant operation, the sequence of grade changes based on the basis weight was 64➔49➔79➔102➔63➔100➔78.5 (g/m^2). The operation data for the sampling time 1~350 was used in the closed-loop identification. Values of manipulated variables (Fig. 5) at the same time period (1~350) were fed to the model identified and results obtained from the model were compared with the plant data (Fig. 6). From Fig. 7, we can see that the model tracks the plant satisfactorily.

Fig. 8 shows the results of the model prediction and measured controlled variables for the sequence of grade changes described before. The measured data for the sampling time 350~700 was used in the validation. Values of manipulated variables (Fig. 5) at the same time period (350~700) were fed to the model identified. The model obtained from the closed-loop identification is validated by comparing model predictions against the logged controlled variables during the sequence of grade changes in normal operations in Fig. 8. We can see that the model captures the typical dynamics of the plant.

4. Conclusions

The dynamic model of a paper machine during grade change was developed by using the closed-loop identification method with the intention to provide a reliable dynamic model to be used in the model-based grade change control scheme. During the grade change, chemical and physical characteristics of paper process change with time. It is very difficult to represent these characteristics on-line by using physical process models. In this work, the wet circulation part and the drying section were considered as a single process and closed-loop identification technique was used to develop the grade change model. Comparison of the results of numerical simulations with plant operation data demonstrates the effectiveness of the model identified. We can say that the present model be effectively used in the model-based control of grade change operations.

Literature Cited

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Table 1. Set point changes according to paper grades.

Paper grade	A	B	C	D	E	F	G
Basis weight (g/m^2)	64	49	78	102	63	100	78.5
Ash content (%)	7	7	17	17	9	17	14
Moisture content (%)	9	8	9	9	9	9	9

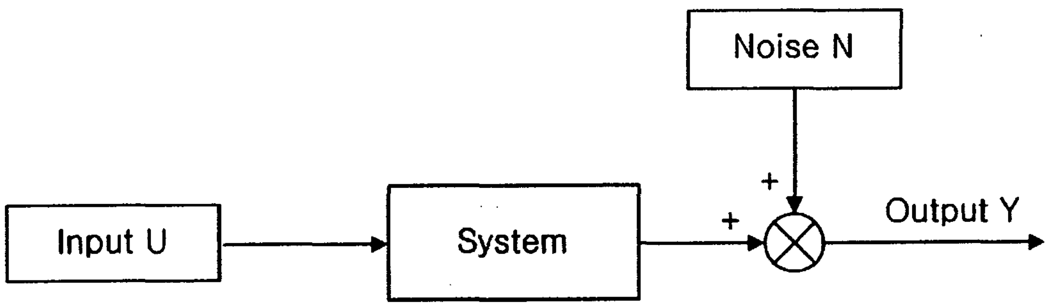

Fig. 1. Open-loop configuration.

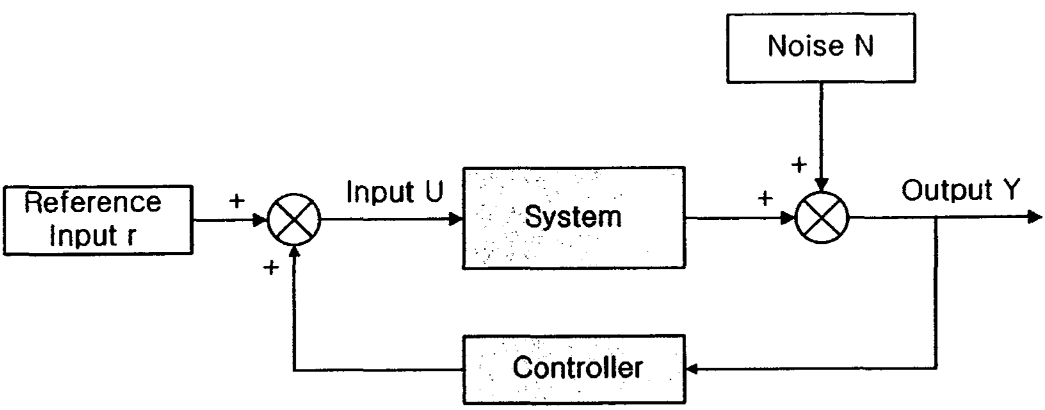

Fig. 2. Closed-loop configuration.

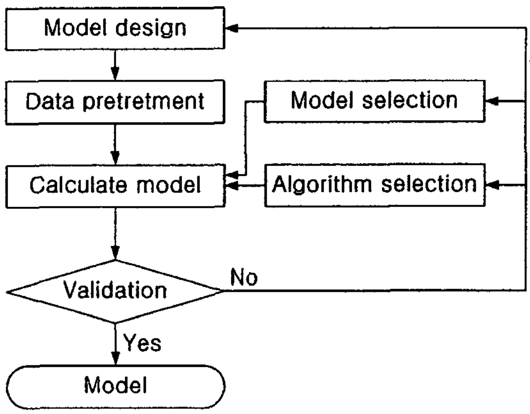

Fig. 3. Flow chart for the closed-loop identification.

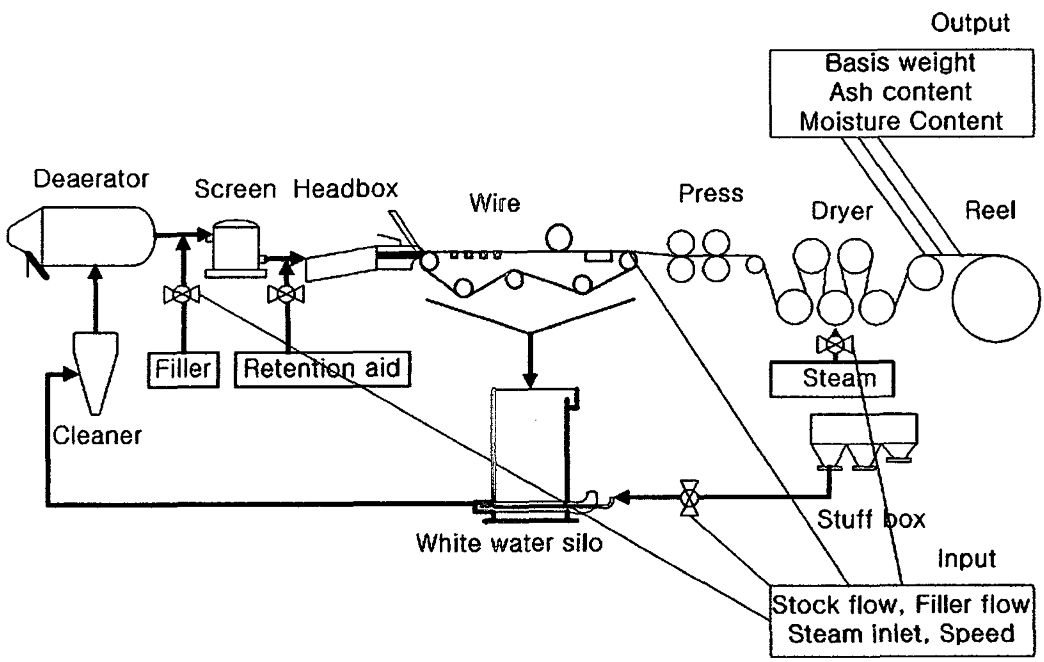

Fig. 4. Schematic diagram of paper machine.

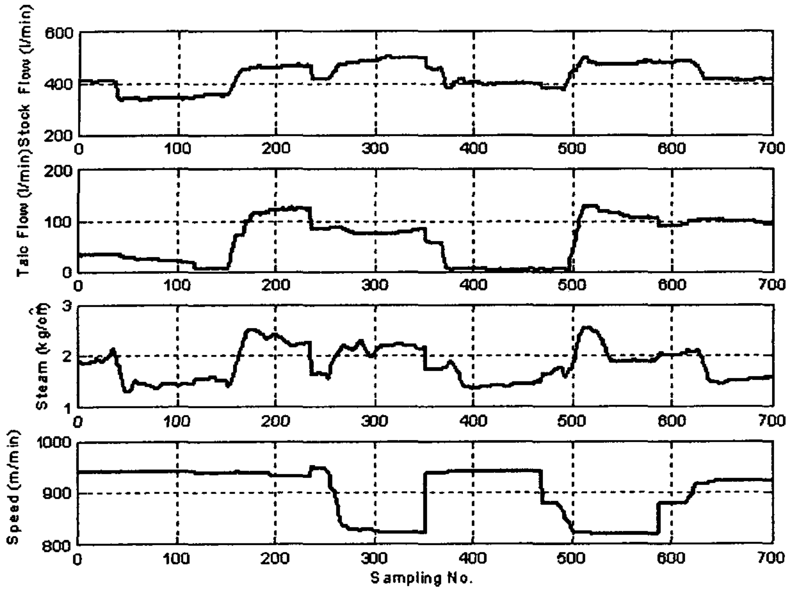

Fig. 5. Changes of manipulated variables

(basis weight : 64➔49➔79➔102➔63➔100➔78.5 g/m^2).

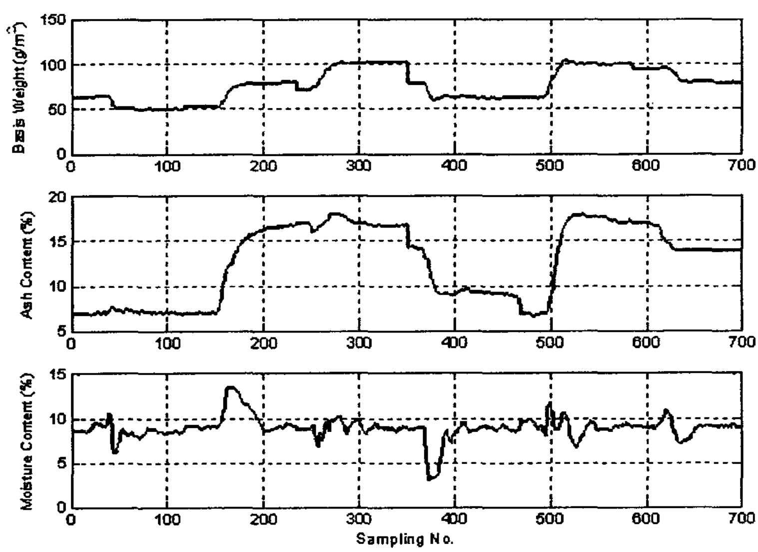

Fig. 6. Changes of controlled variables (64➔49➔79➔102➔63➔100➔78.5 g/m^2).

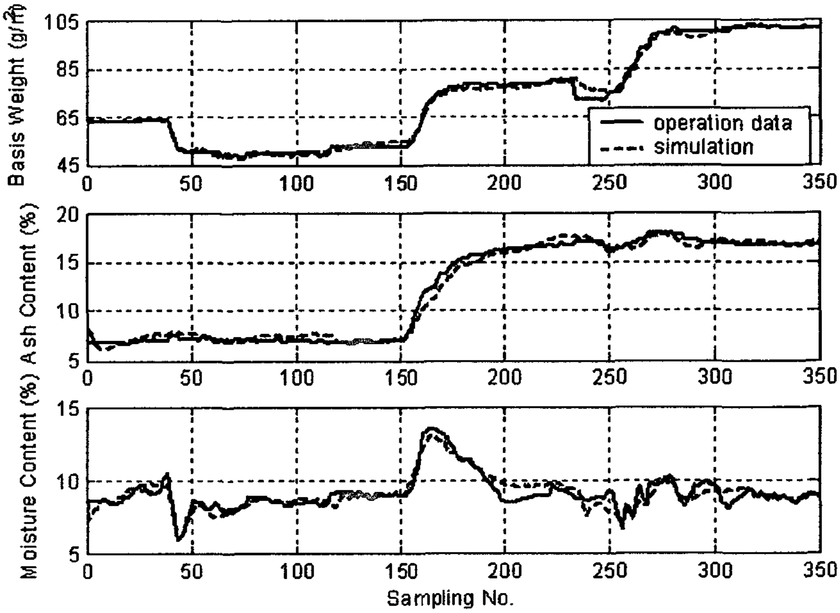

Fig. 7. Closed−loop identification.

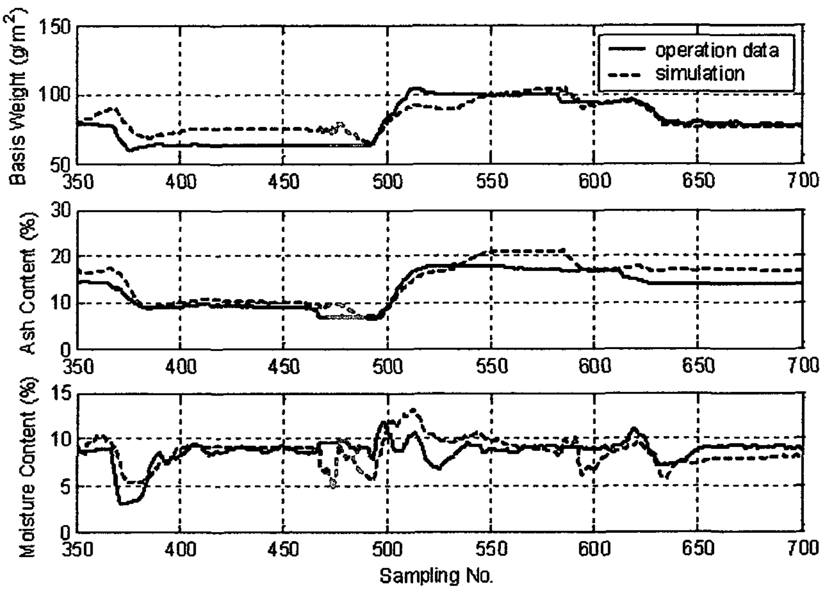

Fig. 8. Model predictions compared to measured variables.