TIME SERIES ANALYSIS AND CONTROL OF A DRY KILN

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(Received January 2004)

ABSTRACT

This paper presents an application of Engineering Process Control (EPC) techniques, specifically, time series control techniques, to reduce the variability in the drying rate of lumber in commercial dry kilns. The main research objective of this paper is to evaluate the optimality of the drying schedules used in industry by comparing with various feedback control strategies available in the statistical literature. The analysis of the drying process is done by building a single-input-single-output (SISO) Box-Jenkins transfer function model and deriving feedback control strategies based on such a model. The comparisons of the simulations of the drying process, both using kiln schedule-control and the suggested feedback control, show significant reduction in drying rate variability and drying time if the feedback control methods are adopted.

Keywords: Kiln control, wood drying process, statistical process control.

INTRODUCTION

In the conversion of logs to lumber, more time and energy are incurred in drying than in any other processing step (Simpson 1991). Some of the various factors that affect the drying rate in wood are wood species, relative humidity (RH), dry bulb temperature (T_{db}) of surroundings, lumber thickness, air velocity and circulation, and moisture content gradient. The optimum way for drying any wood species should be the one that dries wood in a minimum amount of time and energy while keeping the number of drying defects within the acceptable limits.

Conventional steam drying technology is the most popular way for drying hardwoods in the United States. Process improvements in wood drying, such as faster drying rates without increasing drying-induced defects, are of primary importance to the hardwood processing industry. The primary objective of kiln-drying hardwoods is to provide hardwood lumber dried as quickly as possible with a minimum of drying-induced defects.

DYNAMIC MODELLING BASED ON TIME-SERIES DATA

Many dynamic processes can be represented in terms of the values of an input or controllable factor and an output or measured quality characteristic (Fig. 1). Dynamic modeling using the

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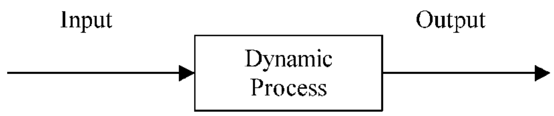

FIG. 1. Graphic representation of a dynamic process, Adapted from del Castillo (2002).

time-series method offers an opportunity for improving the kiln-drying process for hardwoods.

In dynamic modeling, the levels of the input directly affect the output of the system or the process. Usually, due to inertial elements in the process, changes in the input will not immediately affect the output, but may influence the output after some delay in time. Also, since the model is dynamic, there may also be some influence of other factors in the process that are not used as an input factor. Those unwanted influences are modeled as a disturbance or random noise. Thus, in many industrial processes, the output is driven by the input in the presence of random noise.

This section reviews various methods that may be used to represent the system behavior in terms of a statistical model. The main purpose of building these statistical models is to gain a better understanding of the process and to use this understanding to intelligently manipulate the input factor for the control of the system. In terms of a block diagram, any process with noise and input can be represented as shown in Fig. 2.

The subscript t denotes the time of measurement of any parameter. From now on, Y_t is used to denote quality characteristic or the measured response, X_t denotes the input or controllable factor, and errors are represented by ε's.

A transfer function (TF) model is used to describe the dynamic process relation between controllable factors and quality characteristics. There are many ways by which a transfer function model can be represented. One way is to represent it as a linear combination of past values of the input factor. This is called the impulse response transfer function and is given by:

$$Y_t = (\nu_0 + \nu_1\mathcal{B} + \nu_2\mathcal{B}^2 + \ldots)X_t = H(\mathcal{B})X_t \qquad (1)$$

where $\mathcal{B}$ = back shift operator, which can be defined as $\mathcal{B}(L_t) = L_{t-1}$ for any time series L. The letter H is therefore a polynomial in $\mathcal{B}$, possibly of infinite order, and the ν_i are the weights that measure the effect or influence of past values of the control factor on the response Y. This form of a TF model is useful for model identification purposes. A detailed description of back-shift operators and time series modeling can be found in references del Castillo (2002) and Box et al (1994). In the control engineering literature, transfer functions are also represented by Box-Jenkins transfer function models, which have fewer parameters to estimate. The Box-Jenkins transfer function with noise model in general form is given as:

$$Y_t = \frac{B_s(\mathcal{B})}{A_r(\mathcal{B})}\mathcal{B}^k X_t + \frac{C(\mathcal{B})}{D(\mathcal{B})}\varepsilon_t \qquad (2)$$

where $B_s(\mathcal{B}) = b_0 - b_1\mathcal{B} - b_2\mathcal{B}^2 \ldots - b_s\mathcal{B}^s$ is called the numerator dynamics polynomial,

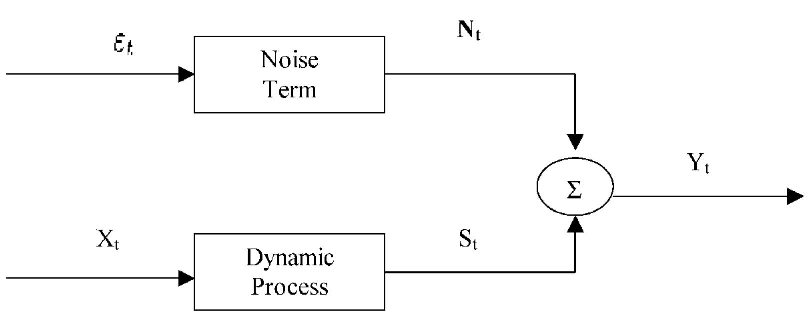

FIG. 2. Graphic representation of the components of a transfer function with noise, Adapted from del Castillo (2002). ε_t = White noise, X_t = Input (controllable factor), S_t = Signal or response of process in the absence of noise, N_t = Noise, Y_t = Output (Quality Characteristic) in the presence of noise, $Y_t = S_t + N_t$.

$A_r(\mathcal{B}) = 1 - a_1\mathcal{B} - a_2\mathcal{B}^2 - a_3\mathcal{B}^3 \ldots - a_r\mathcal{B}^r$ is called the denominator dynamics polynomial, and k is the process lag or input-output delay.

This model is frequently called a (r, s, k) Box-Jenkins transfer function model. The second term of the model is the noise model. This form of a TF model is useful for parameter estimation.

A third way of writing this model, useful in deriving optimal feedback controllers, is in the so-called ARMAX (AutoRegressive-Moving Average eXogeneous variable) form:

$$A'(\mathcal{B})Y_t = B'(\mathcal{B})\mathcal{B}^k X_t + C'(\mathcal{B})\varepsilon_t \qquad (3)$$

The sample cross-correlations between the input and output reveal the relationship of interest from which the weights v_i in Eq. (1) may be identified. The sample cross-correlations are proportional to estimates of the impulse response weights. Thus, the pattern in the sample cross-correlation function is compared with impulse response weights that indicate a tentative transfer function model. More details about impulse response weights and their use to identify (r, s, k) in a Box-Jenkins model are in the appendix and in del Castillo (2002) and Box et al. (1994).

FEEDBACK CONTROL OF A TRANSFER FUNCTION MODEL

The main purpose of any control strategy is to keep the output or quality characteristic as close as possible to the target in a dynamic system in the presence of noise. The transfer function is used to develop the control algorithms to determine how the input factor should be adjusted in a given time interval, so that the output is as near the desired target as possible. These algorithms or rules are also called controllers. A common objective for these controllers is to minimize the mean square error in the output. In the control engineering literature, the feedback principle has been defined as:

- If the response is lower than the target, increase the controllable factor.
- If the response is higher than the target, decrease the controllable factor.

This type of feedback is also called the negative feedback principle as the input is adjusted in the opposite direction of the measured output. A block diagram for any process with feedback control can be represented as shown in Fig. 3.

Minimum mean square error (MMSE) Control and Generalized Minimum Variance (GMV) control strategies are two frequent objectives that can be used to control a dynamic process represented by transfer functions. MMSE control tries to achieve the minimum possible variation in the quality characteristic, without regard for the variation in the changes in the controllable factor. (A GMV controller attempts to balance these two variabilities, see below). Let Y_t be the deviation from target. To obtain the MMSE controller, we need to minimize the equation:

$$\text{MSE}(Y_t) = E[Y_t^2] = \text{Var}(Y_t) + (E[Y_t])^2 \qquad (4)$$

The MMSE control law is obtained by minimizing (4) and is given by:

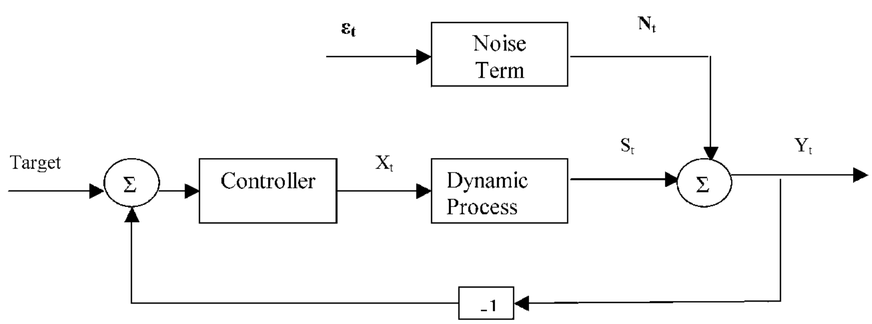

FIG. 3. Graphic representation of a process with feedback control, Adapted from del Castillo (2002).

$$X_t = \frac{-G(\mathcal{B})}{B'(\mathcal{B})F(\mathcal{B})} Y_t. \quad (5)$$

The coefficients of the $G(\mathcal{B})$ and $F(\mathcal{B})$ polynomials are obtained by equating coefficients of like powers of $\mathcal{B}$ in the so-called Diophantine identity (del Castillo 2002):

$$C' = A'F + \mathcal{B}^k G \quad (6)$$

where $G(\mathcal{B}) = g_0 + g_1\mathcal{B} + \ldots + g_{n-1}\mathcal{B}^{n-1}$ is of order (n − 1), n = max($n_{A'}$, $n_{B'}$, $n_{C'}$), and $F(\mathcal{B}) = 1 + f_1\mathcal{B} + \ldots + f_{k-1}\mathcal{B}^{k-1}$ is of order (k − 1).

Because this method disregards the variation in the input factor, this control strategy is unsuitable for many practical applications. However, it is relatively easy to modify this equation to achieve the controlled variation in the input factors. While applying MMSE control, controllable factor adjustments may be very large and variable, making it impractical to use, because large variability in the input is not desirable in many industrial applications. To obviate this difficulty, Clarke and Gawthrop's GMV controller (Clarke and Gawthrop 1975), which constrains the variation in the controllable factor, can be used. To obtain the GMV controller, instead of minimizing (4), the following equation is minimized, which tries to achieve a balance between output and input variability:

$$J = E[Y_t^2 + \lambda X_{t-k}^2] \quad (7)$$

The GMV Control Law obtained by minimizing (7) can be shown to equal:

$$X_t = \frac{-G(\mathcal{B})}{B'(\mathcal{B})F(\mathcal{B}) + \lambda/b_0 C'(\mathcal{B})} Y_t \quad (8)$$

where λ is a tuning constant, varied between 0 and 1 and chosen by user. As λ increases, the variance in X decreases and the variance in Y increases. However, increase in variance in Y is nominal as compared to decrease in variance of X. When λ is equal to zero, the GMV controller is identical to the MMSE controller described by (5). For more details about Box-Jenkins models and control strategies please refer to the Appendix, del Castillo (2002), and Box et al. (1994).

INDUSTRIAL DATA FOR SINGLE-INPUT-SINGLE-OUTPUT (SISO) MODELING

Modeling a transfer function provides an understanding of the dynamical relationship between input factors and output quality characteristic. This is the same as understanding the relationships inside the "black box" of the process. From the control point of view, the main goal is to bring the process to a target by adjusting the input factors. The main assumption is that the input factor is in the control of the operator and the process is bounded-input-bounded-output (BIBO) stable.

Actual drying data were provided by a hardwood sawmill. The kiln operator used electric resistance probes to monitor the moisture content across the kiln charge. The kiln schedule used was modified from the conventional schedule and was designed to dry "white" hard maple (*Acer saccharum*).

White hard maple demands a premium paid from kitchen cabinet and furniture manufacturers. As such, drying rates are carefully monitored and controlled in order to produce a white rather than an off-white color in the hard maple lumber.

The drying dataset was for the complete kiln run from green (above 30% moisture content) to the final desired moisture content (MC) of 8%. Electronic resistance probes are more accurate below 30% MC, and the first dry bulb change in the kiln schedule is at 30% MC. Hence, the modeling of the transfer function is focused on the drying data below 30% MC. Using the drying data provided, the time series data were collected every 2 h, 45 min for a hard maple kiln charge. The specific time interval used was due to the data collection methodology of the company providing the data for this study. Any time interval should work as well for this technique, but the control engineer should be aware of the drying response rate relative to set point changes to determine the desired interval. A total of 95 observations were collected while drying maple from average moisture content of 63% to 7.2%. For modeling of the drying process, a target of −4.5% decrease in moisture content per day

(0.515% per time interval) was used. This drying rate target for hard maple is the drying rate target used by the sawmill providing the drying data, to produce their premium white hard maple lumber.

Figure 4 shows the moisture removal rate versus each time interval for the drying process below MC of <30%.

For these data, the average moisture removal rate (MRR) is 0.403% for every time interval. As seen in the graph, in some of the time intervals, instead of losing moisture, the average readings from the sensors indicate a positive difference in moisture removal rate. Also, during some of the time intervals, the drying process appears to be too fast, indicated by average moisture losses as much as 2.25% per interval. However, when a linear trend line is fitted to the graph, it shows that the drying rate decreases towards the end of process. It is evident from the graph that the drying process varies from the target of 0.515% per time interval.

For the purpose of SISO modeling, we denote the adjustment in kiln EMC as X_t and the moisture content deviation from target as Y_t. The SAS system (PROC ARIMA) was utilized to fit the models. Only partial SAS output is shown here. The cross-correlation function between X_t and Y_t is shown in Fig. 5.

As shown in the graph, the first significant cross-correlation is at lag = 1. This indicates that the input-output lag k is equal to one period. Since the decay is not sinusoidal (del Castillo 2002; Box et al. (1994)), a tentative value of r = 1 is hypothesized. Also, since the decay starts at lag 3, s is chosen to be 2 because there are two weights at lag 1 and 2 that do not follow any pattern. So, the initial transfer function was identified to be $(r, s, k) = (1, 2, 1)$.

To identify the noise model, we need to look at the sample autocorrelation function (SACF) and the sample partial autocorrelation function (SPACF) of the residuals of the preliminary transfer function (TF) model shown in Fig. 6.

After fitting various noise models iteratively, the tentative noise model that provided the best overall model fit was identified to be (p, d, q) = ([4], 0, 2). The value in [ ] represents that only the fourth power of autoregressive part was significant enough to be included in the model. Figure 7 shows the parameter estimates and polynomials of the complete transfer function model.

Thus, the fitted SISO model is

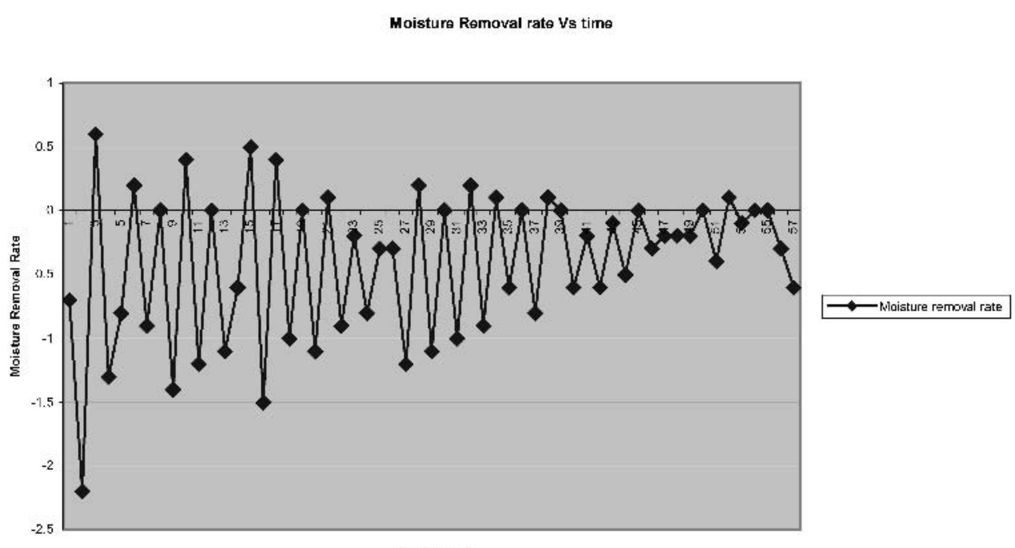

FIG. 4. Moisture removal rate vs time interval.

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Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
  0   0.043293      0.09279      |                 .   |**   .             |
  1   0.085953      0.18422      |                 .   |****.              |
  2   0.041413      0.08876      |                 .   |**   .             |
  3   0.109796      0.23532      |                 .   |*****              |
  4   0.079266      0.16989      |                 .   |***  .             |
  5   0.102827      0.22039      |                 .   |****.              |
  6   0.019162      0.04107      |                 .   |*    .             |
  7   0.054570      0.11696      |                 .   |**   .             |
  8   0.042166      0.09037      |                 .   |**   .             |
  9   0.029595      0.06343      |                 .   |*    .             |
 10   0.027237      0.05838      |                 .   |*    .             |
 11   0.042911      0.09197      |                 .   |**   .             |
 12   0.033522      0.07185      |                 .   |*    .             |
 13   0.026958      0.05778      |                 .   |*    .             |
 14   0.015930      0.03414      |                 .   |*    .             |
 15   0.021421      0.04591      |                 .   |*    .             |
 16   0.019573      0.04195      |                 .   |*    .             |
 17   0.0033589     0.00720      |                 .   |     .             |
 18   0.021769      0.04666      |                 .   |*    .             |
 19   0.010189      0.02184      |                 .   |     .             |
 20   0.0067754     0.01452      |                 .   |     .             |
```

FIG. 5. Cross-correlation between X_t and Y_t.

$$Y_t = \frac{0.03113 + 0.16128\mathscr{B}^2}{1 - 0.66029\mathscr{B}} X_{t-1} + \frac{1 - 0.6096\mathscr{B} + 0.456\mathscr{B}^2}{1 - 0.3439\mathscr{B}^4} \varepsilon_t \qquad (9)$$

where Y_t = deviations from target, X_t = change in EMC and $\varepsilon_t \sim (0, 0.3544^2)$.

The key diagnostics are shown in Fig. 8 to check the adequacy of the fitted model. The autocorrelation plot of residuals shows no structure and thus all the autocorrelation present in the data is explained by the model. Also, the cross-correlation check of residuals with the X's shows no evidence of model inadequacy. This leads to the conclusion that the model is appropriate.

FEEDBACK CONTROL RULES

The design of the optimal feedback controllers for the single-input-single-output model was shown in Eq. (9). For finding the optimal controller, we need to transform the Box-Jenkins model Eq. (9) into ARMAX form Eq. (3). Thus, the A, B, and C polynomials of the ARMAX form are given by the equations:

$$A(\mathscr{B}) = (1 - 0.66029\mathscr{B})(1 - 0.3439\mathscr{B}^4)$$

$$B(\mathscr{B}) = (0.03113 + 0.16129\mathscr{B}^2)(1 - 0.3439\mathscr{B}^4)$$

$$C(\mathscr{B}) = (1 - 0.6096\mathscr{B} + 0.456\mathscr{B}^2)(1 - 0.66029\mathscr{B})$$

In this case, we have k = 1, so $F(\mathscr{B})$ is of the order (k − 1) = 0 and $G(\mathscr{B})$ is of order (n − 1) where n = max(n_A, n_B, n_C) = 5. The Diophantine identity (6) for this case is:

$$(1 - 0.6096\mathscr{B} + 0.456\mathscr{B}^2)(1 - 0.66029\mathscr{B}) = [(1 - 0.66029\mathscr{B})(1 - 0.3439\mathscr{B}^4)] + \mathscr{B}(g_0 + g_1\mathscr{B} + g_2\mathscr{B}^2 \ldots + g_5\mathscr{B}^5) \qquad (10)$$

After simplifying and equating the same powers of $\mathscr{B}$ of (10), the $G(\mathscr{B})$ polynomial was calculated to be:

$$G(\mathscr{B}) = 0.61 + 0.86\mathscr{B} - 0.3\mathscr{B}^2 + 0.344\mathscr{B}^3 - 0.23\mathscr{B}^4$$

```
                     Autocorrelation Plot of Residuals

Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 0     0.244206        1.00000      |                    |********************|
 1    -0.157423        -.64463      |       *************|  .                 |
 2     0.142302        0.58271      |             .      |************        |
 3    -0.077264        -.31639      |            . ******|       .            |
 4     0.075343        0.30852      |            .       |****** .            |
 5    -0.0050405       -.02064      |           .        |        .           |
 6    -0.010671        -.04370      |           .       *|        .           |
 7     0.063080        0.25831      |           .        |*****   .           |
 8    -0.066431        -.27203      |           .   *****|        .           |
 9     0.109497        0.44838      |           .        |*********           |
10    -0.093824        -.38420      |          . ********|         .          |
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                     Partial Autocorrelations

Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1      -0.64463     |       *************|    .               |
  2       0.28602     |               .    |******              |
  3       0.25377     |               .    |*****               |
  4       0.13703     |               .    |*** .               |
  5       0.32960     |               .    |*******             |
  6      -0.09022     |               .  **|    .               |
  7       0.13407     |               .    |*** .               |
  8      -0.09085     |               .  **|    .               |
  9       0.16613     |               .    |*** .               |
 10       0.02573     |               .    |*   .               |
```

FIG. 6. SACF and PACF of the preliminary transfer function model.

After putting the various polynomials in (8) and solving the equation, we get the generalized minimum variance controller:

$$X_t = \frac{1}{0.03113 + 32.12\lambda}[(-0.1613 - 27.78\lambda)X_{t-2} + 9.6\lambda X_{t-3} + 0.011X_{t-4} + 0.056X_{t-6} - 0.61Y_t - 0.86Y_{t-1} + 0.3Y_{t-2} - 0.344Y_{t-3} + 0.23Y_{t-4}] \quad (11)$$

Equation (11) shows the equation of controlled X_t (change in EMC). After simplifying (9), the equation of the Y_t (deviation from target) is:

$$Y_t = 0.66Y_{t-1} + 0.34Y_{t-4} - 0.23Y_{t-5} + 0.03X_{t-1} + 0.161X_{t-3} - 0.011X_{t-5} - 0.056X_{t-7} + \varepsilon_t - 1.27\varepsilon_{t-1} + 0.86\varepsilon_{t-2} - 0.3\varepsilon_{t-3} \quad (12)$$

A sample realization of the kiln-drying process for white hard maple after simulation is shown in Figs. 9 and 10. The value of λ used for the simulation was $\lambda \geq 0.5$, as below 0.5 the controllable factor diverges and gives infeasible results. The first figure shows the change in EMC (X_t) to be made after each observed value of deviation from target (Y_t) of −0.515% moisture removal rate per interval.

As evident from Fig. 10, the initial variation in Y_t is very high, but towards the end of the

```
                         Conditional Least Squares Estimation

                                Standard                Approx
Parameter      Estimate           Error    t Value    Pr > |t|     Lag    Variable    Shift

MA1,1           0.60960         0.12882       4.73      <.0001       1    y               0
MA1,2          -0.45557         0.12752      -3.57      0.0007       2    y               0
AR1,1           0.34390         0.13639       2.52      0.0046       4    y               0
NUM1            0.03113         0.04602       0.68      0.5015       0    x               1
NUM1,1         -0.16128         0.05873      -2.75      0.0081       2    x               1
DEN1,1          0.66029         0.14751       4.48      <.0001       1    x               1
                              Autoregressive Factors

                           Factor 1:  1 - 0.3439 B**(4)

                              Moving Average Factors

                    Factor 1:  1 - 0.6096 B**(1) + 0.45557 B**(2)

                                  Input Number 1

                                Input Variable    x
                                Shift             1

                                Numerator Factors

                          Factor 1:  0.03113 + 0.16128 B**(2)

                               Denominator Factors

                           Factor 1:  1 - 0.66029 B**(1)
```

FIG. 7. Conditional least square estimates and polynomials of the transfer function model.

graph the variation decreases. The reason for initial variation is that the first six values are the startup values for the simulation of the process. These startup values were directly taken from the initial data set on which the transfer function model was identified.

OPTIMAL-CONTROL OF DRYING PROCESS VS. CONTROL BASED ON SCHEDULE

This section gives the comparison between the feedback controlled drying process with the drying based on a conventional kiln schedule for hard maple (Simpson 1991). Since the SISO model was built for 30%>Moisture Content (MC)>15%, the simulations were also performed for the same MC level for both controlled and uncontrolled drying. The simulation runs were made for 100 sample realizations of schedule-control and the GMV controlled drying process at five different levels of lambda (λ). The mean squared deviation (MSD) from target was measured for each sample realization. After the computation of average MSD, two sample T-tests with unknown variances were done for testing the significance of the difference between the two controller policies. The mean squared deviation is the sum of variance of Y_t and square of the expected value of Y_t.

$$\mathrm{MSD} = \mathrm{Var}(Y_t) + E(Y_t)^2 \tag{13}$$

Table 1 gives the summary of results of the simulation runs. It clearly shows that average

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.61	3	0.1320	-0.076	0.157	-0.177	0.058	0.135	0.036
12	19.38	9	0.0221	0.142	-0.113	0.251	-0.104	0.166	-0.220
18	26.79	15	0.0305	0.148	0.017	0.216	0.096	0.067	0.078
24	33.98	21	0.0364	-0.040	0.145	-0.047	0.135	0.030	0.169

Autocorrelation Plot of Residuals

```
Lag   Covariance    Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

  0    0.125581       1.00000     |                    |********************|           0
  1   -0.0095549      -.07609     |                .  **|    .               |    0.128037
  2    0.019679       0.15671     |                .    |*** .               |    0.128776
  3   -0.022255       -.17722     |                . ***|    .               |    0.131865
  4    0.0073178      0.05827     |                .    |*   .               |    0.135713
  5    0.016917       0.13471     |                .    |*** .               |    0.136123
  6    0.0044821      0.03569     |               .     |*    .              |    0.138291
  7    0.017893       0.14248     |               .     |***  .              |    0.138442
  8   -0.014238       -.11338     |               .   **|     .              |    0.140825
  9    0.031545       0.15119     |               .     |***  .              |    0.142314
 10   -0.013116       -.10445     |               .   **|     .              |    0.149406
```

Crosscorrelation Check of Residuals with Input x

To Lag	Chi-Square	DF	Pr > ChiSq	Crosscorrelations					
5	1.13	3	0.7707	-0.037	-0.018	-0.048	-0.056	0.039	-0.101
11	2.05	9	0.9907	-0.008	-0.054	-0.052	-0.076	-0.049	-0.040
17	5.39	15	0.9883	-0.043	-0.068	-0.117	-0.095	-0.119	-0.112
23	11.31	21	0.9563	-0.105	-0.115	-0.131	-0.111	-0.147	-0.153

FIG. 8. Autocorrelation plot of residuals and cross-correlation of residuals with input X.

mean squared deviation of Y_t for the controlled drying is significantly lower for the simulation runs at different levels of lambda than for the corresponding results from the schedule-based controller. On average, MSD of controlled process was 16.95% lower than that of schedule-control.

The comparison of X's is shown in Table 2 for both the GMV controlled and schedule-based control process. As can be noted in the table, the average MSD for schedule-based control is the same with standard deviation 0. The reason can be accounted for by the fact that schedule-based control calls for changes in X, which are fixed and only dependent upon the moisture content steps. It means that only four adjustments in EMC were performed in every simulation.

If the difference is significant, as mentioned above, it clearly leads to the conclusion that in traditional kiln schedules, the drying is conservative in nature and there is considerable room for improvement in the overall drying process.

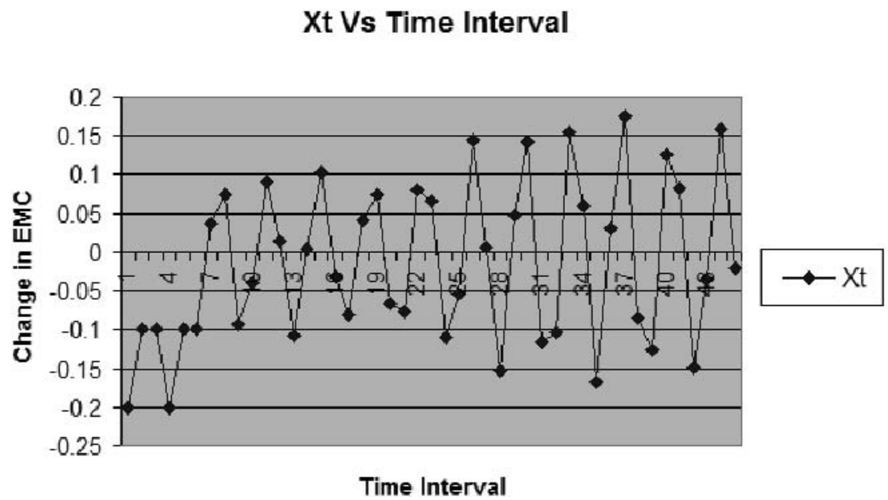

FIG. 9. X_t vs. time interval.

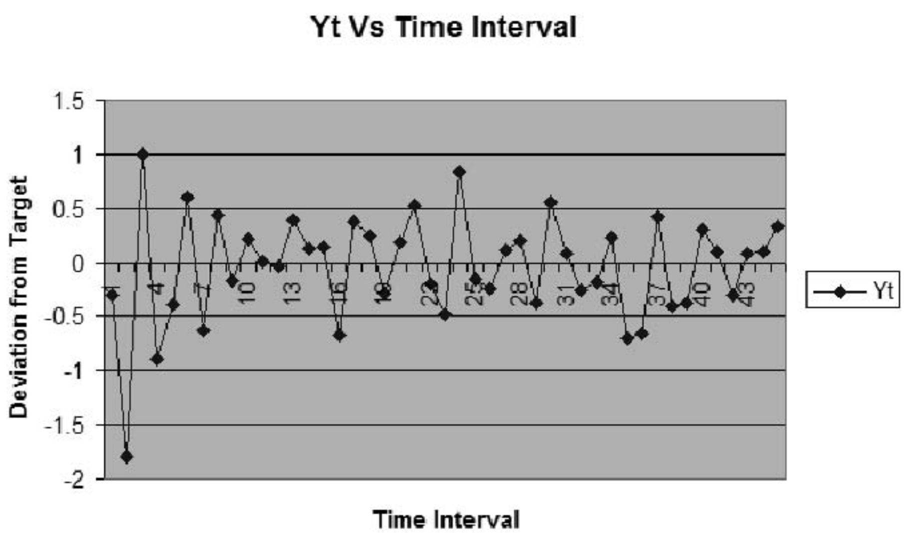

FIG. 10. Y_t vs. time interval.

Thus, the potential exists for traditional kiln-drying to give way to more scientific control strategies and optimized kiln control across pre-specified targets.

SUMMARY AND CONCLUSIONS

Time series techniques and feedback control strategies were adopted for the kiln-drying process for hard maple. SISO Box-Jenkins transfer function model for hard maple was found adequate in representing the drying process. The simulation of Generalized Minimum Variance (GMV) controller based on SISO model was compared against simulation of the traditional dry kiln schedule of hard maple. In most of the sample realizations of the drying process, GMV-controlled drying performed better than the schedule-controlled process. The variance of the deviation from the given target of 0.515% per

TABLE 1. *Comparison of* Y*'s at different levels of lambda.*

	GMV controller schedule		Schedule based		Two sample T-test	
Lambda	Avg MSD (Y_t)	Std error	Avg MSD (Y_t)	Std error	T-value	Pr > |t|
0.5	0.29245354	0.0137683	0.37198821	0.01516125	−20.88	<.0001
0.6	0.32672135	0.01599047	0.40086997	0.0162271	−21.61	<.0001
0.7	0.34305120	0.01615727	0.41065141	0.0163078	−16.58	<.0001
0.8	0.32711607	0.01543687	0.39039329	0.01589821	−18.72	<.0001
0.9	0.35556094	0.01301336	0.40668078	0.01353963	−13.51	<.0001

TABLE 2. *Comparison of* X*'s at different levels of lambda.*

	GMV controller schedule		Schedule based		Two sample T-test	
Lambda	Avg MSD (X_t)	Std error	Avg MSD (X_t)	Std error	T-value	Pr > |t|
0.5	10.577	8.8076	1.0714	0.0	10.79	<.0001
0.6	0.7915	0.6172	1.0714	0.0	−4.54	<.0001
0.7	0.0702	0.0627	1.0714	0.0	−159.62	<.0001
0.8	0.0143	0.011	1.0714	0.0	−959.71	<.0001
0.9	0.0034	0.0029	1.0714	0.0	−3697.8	<.0001

time interval for moisture removal rate (MRR) was lower than that for the traditional schedules. On an average, the mean squared deviation (MSD) of MRR for GMV controlled process was 16.95% lower than that of schedule-control process for hard maple wood species.

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APPENDIX A. TRANSFER FUNCTION IDENTIFICATION

For modeling and identification, the goal is to find the orders of denominator, numerator, and input-output lag (r, s, k) respectively of transfer function (TF) part and orders of autoregressive, differencing, and moving average terms (p, d, q) respectively of the noise part. The main assumption while modeling TF functions is that there is no feedback control present in the process. It means that the input factor X_t is not controlled based on the Y_t values.

The procedure for transfer function model identification outlined by Box et al. (1994) uses the sample cross-correlations between the prewhitened series to tentatively identify model form. Prewhitening is the procedure to make one of the time series to be a white noise sequence. If prewhitening is not done, then estimation of cross-correlation between the time series will not be good, because of the correlation present in individual time series.

The cross-correlation can be defined as the correlation between two series. The cross-correlation function at lag k can be represented mathematically as given below:

$$\rho_{xy}(k) = \frac{\gamma_{xy}(k)}{\sigma_x \sigma_y} \qquad k = 0, \pm 1, \pm 2, \ldots \tag{14}$$

$\gamma_{xy}(k)$ is the cross-covariance function at lag k and is given by:

$$\gamma_{xy}(k) = E[(X_t - \mu_x)(Y_{t+k} - \mu_y)] \quad k = 0, 1, 2, \ldots \tag{15}$$

The sample cross-correlation function is estimated from a sample realization of the stochastic process on the assumption that it represents the whole ensemble of realizations.

$$r_{xy}(k) = \frac{C_{xy}(k)}{S_x S_y} \tag{16}$$

where $C_{xy}(k)$ is the sample cross-covariance, S_x and S_y are sample variances of series X and Y respectively.

The sample cross-correlations between the prewhitened input and output reveal the relationship. The sample cross-correlations are equivalent to estimates of the impulse response weights. Thus, the pattern in the sample cross-correlation function is compared with impulse response weights that indicates a tentative transfer function model.

After fitting the tentative TF model, ARIMA noise model can be easily identified by looking at SACF and SPACF of the residuals.

APPENDIX B. TRANSFER FUNCTION DIAGNOSTIC CHECKING

The fitted model adequacy is checked by looking at the autocorrelation plot of residuals ($e_t = Y_t - \hat{Y}_t$) and cross-correlation of residuals with the input factor X.

- If the model is correct, autocorrelation will be absent in residuals and residuals will not be cross-correlated with X.
- If transfer function part of the model is correct but noise model is incorrect, then autocorrelation will be present, but there will be no cross-correlation between residuals and X.
- If transfer function part is incorrect, then residuals will be autocorrelated and also cross-correlated with X.