Predictive modeling the internal bond of medium density fiberboard using a modified principal component analysis

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Abstract

In this paper, real-time process data are aligned in time-order with destructive test data to reduce cost by better predictive modeling. A modified principal component analysis (PCA) is used to develop an empirical model to predict the internal bond of MDF based on a selected subset of process variables. These process variables are selected by picking variables with the highest absolute correlations with internal bond. Our modified PCA is used on these selected standardized process variables to obtain transformed composite variables or modes. The 10 modes are reduced to three using correlation criteria and the three best modes are used to generate an empirical model to predict internal bond. Results for the most produced thickness category of MDF are presented primarily, while some comments are made on two other thickness categories. The root mean square error relative to the mean of each category varied from 9.3 percent to 11.2 percent, which are quite helpful improvements in this manufacturing setting. More attention to the collection of the current process variables via information quality efforts might be useful for additional future improvements. Even though the plant had 179 quantitative process variables, our PCA and correlation analyses suggests some other variable(s) need exploring and collecting to further reduce these error rates.

It is critical to minimize cost due to panels being downgraded because of low strength and the waste due to excessive raw material use to compensate for undetected process changes; therefore, predictive modeling is important. This paper outlines a creative, modified use of principal components analysis (PCA) to predict the internal bond (IB) strength of medium density fiberboard (MDF) and identifies key sources of process variation that lead to IB variation (compare for ordinary PCA in Stone and Cutler 1996). Utilizing this approach may lead to improved IB strength, lower density targets, less waste, lower costs, and improved business competitiveness. This is in agreement with the general strategy of Deming (1986 and 1993). See comments in Young and Guess (1994) on improving reliability via processes, etc. Though we focus in this paper on MDF improvements, the same approach can be applied to many other wood products and manufacturers.

The wood composites manufacturing process for MDF has a large number of interdependent process variables that have complex functional forms, which influence final mechanical board properties. Raw material passes through many processing stages that may influence mechanical board properties. Key process variables may include wood chip dimensions, fiber dimension, fiber-resin formation, mat-forming consistency, line speed, press closing characteristics, etc. At the time of production, the IB strength of the board is unknown; samples are analyzed later using destructive testing. The time between destructive tests can reach 2 hours, during which production continues; hence, a significant volume of unacceptable MDF production may go undetected. Significant cost savings from accurately predicting IB before destructive testing may be realized by a reduction in waste, reduced customer

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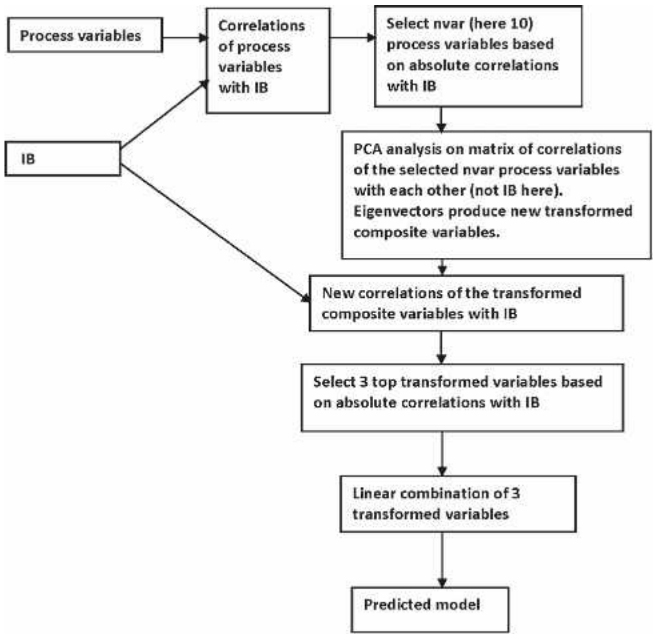

Figure 1. — Flowchart of Modified Principle Component Analysis approach.

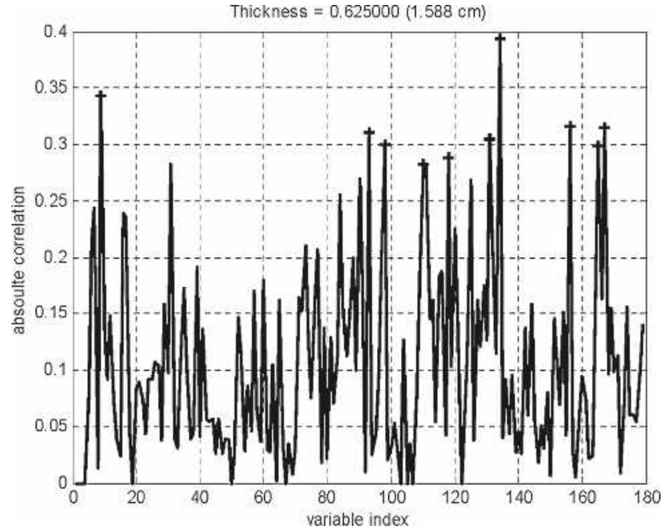

Figure 2. — Absolute values of the correlations of process variables with IB for thickness of 0.625 inches (15.88 mm) where the top 10 are marked as crosses.

claims, faster press cycles, lower wood usage, lower resin usage, and lower energy usage.

Most wood composite manufacturers have real-time data warehousing platforms that collect and store large quantities of process data (Greubel 1999, Bernardy and Scherff 1998, 1999; Young and Winistorfer 1999, Young et al. 2004). However, engineered wood manufacturers are only moderately successful at understanding key real-time relationships between process parameters and final mechanical board properties. Most wood composite manufacturers have not linked mechanical board properties data measured during destructive testing with real-time process data. The purpose of this study is to develop methods for industry to minimize these knowledge gaps.

Methods

The objective of this research is to develop a methodology to predict the IB, using a select set of process variables. The data set for the analysis has 184 entries with 179 different online sensor process variables that are numerically aligned with the IB of MDF. Three data sets for three thickness categories are selected, each yielding a sample of 100 observations for analysis. The thickness categories are 0.500 inches (12.70 mm), 0.625 inches (15.88 mm), and 0.6875 inches (17.46 mm). We focus primarily on the second thickness since it is the most often produced product.

Real-time relational database

A real-time, automated relational database is created that aligns real-time process sensor data with the destructive test data of the laboratory. Real-time process data are collected using Wonderware IndustrialSQL™ 8.0 (www.wonderware.com) and are combined with the laboratory test results by product type at the instant when a panel is extracted from the production line for testing. The process data are collected using a median value from the last 100 sensor values (e.g., for most of the 184 different sensor variables, this represents a 2- to 3-minute time interval). Lag times, corresponding to the time required for the material to travel through the process from the point where a given parameter has an influence to the point where the panel is extracted for destructive testing, are taken into account when collecting process data with IndustrialSQL. A unique number (idnum) is generated when the panel is extracted from the process, and this number is later used to match process data with corresponding test results.

When the test results are matched with the process data, the combined data are recorded in two tables that appear in a combined SQL database, yielding a relational database of real-time sensor data and destructive test data. The real-time relational database is automatically updated as new test samples are taken using Microsoft Transact SQL code with Microsoft SQL "Jobs" and "Stored Procedures" (Young and Guess 2002).

Correlation analysis technique

We first outline (via an algorithm) our approach, then provide more technical details.

Outline:

1. We first select the top 10 process variables out of the 179 numerical process variables based on those with the highest (absolute value) correlation of each variable with IB. For example, the correlation of process variable "Core Refiner Total Steam Flow" with IB is in the top 10 for each of three products, ranging from 0.5 inches (12.70 mm) to 0.6875 inches (17.46 mm), **Figure 1** and **Table 1**. Note the number 10 is arbitrary. It is readily possible to expand to larger (or less) than 10 variables, also.
2. We next construct a 10 × 10 (or other size as needed) matrix of the correlations of these 10 process variables with each other. Note carefully the correlation of the process variable is not with IB at this step, but the correlation with each of the other independent variables. For example, we calculate the correlation of process variable "Core Refiner Total Steam Flow" with process variable "Core Resin Pressure" as one element in the correlation matrix for product 0.625 inches (15.88 mm).

Table 1. — Ten largest (by absolute value) correlations of process variables with IB by thickness product type (common variables across thickness categories are highlighted in bold).

Process variable original index	Process variable name	Correlation with IB
	Product: 0.500 inches (12.70 mm)	
91	Core humidifier temperature	−0.494162
161	Core refiner total steam flow	0.430287
171	Face humidifier temperature	0.423236
149	Swing main motor power	0.397664
96	Face humidifier temperature 2	0.376511
38	Swing separator outlet pressure	−0.374294
26	Face resin to wood set point	0.372677
174	Relative humidity	−0.367590
64	Core dryer outlet temperature	−0.365446
22	Face plate position of refiner	0.357881
	Product: 0.625 inches (15.88 mm)	
Process variable original index	Process variable name	Correlation with IB
139	Face plug feeder screw speed	−0.393538
14	Chips percent of raw material	0.342740
161	Core refiner total steam flow	0.316009
172	Face humidity	0.314649
98	Humidifier supply pressure	−0.311030
136	Core resin pressure	−0.304242
103	Shave off mat thickness	0.299450
170	Pressure of steam flow	0.298284
123	Press pre position	−0.288227
115	Press final position hold time	−0.282230
	Product: 0.6875 inches (17.46 mm)	
Process variable original index	Process variable name	Correlation with IB
182	Position time at press	0.340046
173	Outside head temperature	−0.335775
46	Swing plate position of refiner	−0.323889
58	Core dust speed	−0.317065
146	Resin water tank temperature	0.315587
161	Core refiner total steam flow	0.308229
156	Core dust ratio	−0.300089
57	Core digester pressure	−0.291343
22	Face plate position of refiner	0.284425
139	Face plug feeder screw speed	−0.266567

3. We find the eigenvector and eigenvalues of this "correlation" matrix of the top 10 process variables with each other (see **Fig. 2** for these eigenvalues).
4. With these eigenvectors we transform the original 10 selected standardized process variables into new transformed variables or "composite" variables. These new transformed composite variables are linear transformations of the original standardized variables by the appropriate eigenvectors. These transformed variables have the advantage that they are orthogonal or independent of each other. The original (or standardized) process variables do not have this helpful property. See Equation [**8**] where $cvec(k, j)$ represent the kth transformed variable for the jth observation, where j runs from 1 to 100, from our sample size of 100.
5. We next check and calculate new correlations of these transformed composite variables with IB. The single highest (absolute valued) correlated transformed variable with IB of these composite variables is selected to predict IB. We select the top three transformed variables based on their correlation with IB. See **Figure 2** (where the larger dots are for the eigenvalues of associate transformed variables with the higher correlations with IB) and **Table 2** (where the indices are relabeled in **Table 2** in order of their correlation, e.g., original label 10 becomes 1). These top three transformed variables are later combined via a weighted linear combination to better predict IB. The coefficients that make this linear combination are the transformed variables correlations with IB. Note: three is used for illustration, but any other number could have been used. You can use the law of diminishing returns, e.g., adding another transformed variable to the linear combination does not improve the total correlation with IB much.

Note in the above outline that three separate types of correlations are calculated to help increase predictability. This approach is a modification and improvement of a typical principal component analysis (**Fig. 1**).

Details

To build a method of predicting the IB from measured data, a way of selecting a subset of 10 process sensors from the total set of 179 process sensors is developed. Correlation analysis is used to determine the process variables that best predict the standardized IB (Rencher 1995). The correlation analysis is based on normalized signal fluctuations (Haddad and Parsens 1991, Stone and Cutler 1996). The first step in the analysis is selecting the number of values to use in the correlation calculation. The correlation process uses a sample size of 100 for a given thickness. A normalization technique is used to generate a standardized variable for use in the correlation analysis (Ramsay and Silverman 1997). Let the set of measured process variables be defined by $s(i,j)$ where the $i = 1, \ldots, 179$ index defines the measured process variable, and the $j = 1, \ldots, 100$ index defines the sample number. For example, for product 0.625 inches (15.88 mm) index $i = 136$ is "Core Resin Pressure," while $j = 3$ would be the third observation of that process variable. The average value for a signal or process variable is calculated by

$$savg(i) = \frac{1}{100}\sum_{j=1}^{100} s(i,j). \qquad [\mathbf{1}]$$

Table 2. — *Correlations of transformed composite variables with IB by thickness product type.*

Transformed Variable Relabeled Index	Eigenvalue	Correlation of Transformed Variable with IB
Product: 0.500 inches (12.70 mm)		
1	4.494327	0.585555
2	0.8271829	0.156461
3	0.1275780	0.127578
Linear combination of three variables above		0.617777
Product: 0.625 inches (15.88 mm)		
Transformed Variable Relabeled Index	Eigenvalue	Correlation of Transformed Variable with IB
1	3.694971	0.47772
2	0.9308886	–0.353916
3	0.6097161	0.145076
Linear combination of three variables above		0.611981
Product: 0.6875 inches (17.46 mm)		
Transformed Variable Relabeled Index	Eigenvalue	Correlation of Transformed Variable with IB
1	4.263849	0.451150
2	0.4241965	0.220625
3	0.9933302	−0.218155
Linear combination of three variables above		0.547543

The signal fluctuation or standardized process variable, $snfl(i,j)$, is obtained by using the following equations:

$$sfl(i,j) = s(i,j) - savg(i), \qquad [2]$$

$$mssfl(i) = \sum_{j=1}^{100} sfl(i,j) \times sfl(i,j), \qquad [3]$$

$$msfl(i) = \frac{1}{\sqrt{mssfl(i)}}, \qquad [4]$$

$$snfl(i,j) = msfl(i) \times sfl(i,j). \qquad [5]$$

Note Eq. [**5**] can be interpreted by $snfl(i, j) \times (\sqrt{n-1})$ is simply the *i*th process variable's *j*th observation normalized by subtracting the sample mean and dividing by sample SD. The standardized control variable (IB), $ync(j)$, is determined using the same procedure that produced Eq. [**5**]. The equations and standardizations we use allow for computational savings and further usefulness in the following calculations.

The correlation coefficients, $cc(i)$, are determined for i = 1, . . . , 179 by

$$cc(i) = \sum_{j=1}^{100} ync(j) \times snfl(i,j). \qquad [6]$$

For example, for process variable $i = 136$ then $cc(i)$ is mathematically equivalent to the sample correlation of the "Core Resin Pressure" with IB. The absolute values of all correlation coefficients are sorted to obtain the top 10 process variables with the largest (absolute) correlation values with IB. See **Figure 2** where these are marked with crosses. These top 10 standardized process variables are relabeled as $snkfl(l,j)$ (where l = 1, . . . , 10 for their respective sample number of j = 1, . . . , 100) and are used to generate a new correlation matrix whose elements are correlations of the process variables with each other defined by

$$cm(l,m) = \sum_{j=1}^{100} snkfl(l,j) \times snkfl(m,j) \qquad [7]$$

For example, from **Table 1**, when thickness 0.625 inches (15.88 mm) we have cm(1, 6) is equivalent to the correlation between the process variables of "Face Plug Feeder Screw Speed" ($l = 1$ with original index of $i = 139$) and "Core Resin Pressure" ($l = 6$ with original index of $i = 136$). This 10 × 10 correlation matrix is used to obtain eigenvalues and eigenvectors that are used in principal component decomposition (Palacios et al. 1998). The eigenvalues, $eva(k)$, give an indication of the signal strength of the transformed composite variables or modes generated by using the corresponding eigenvector to combine the original 10 standardized process variables (Uenohara and Kanade 1997). Each eigenvector produces a new transformed composite variable. These transformed variables are sorted, and the three transformed variables having the strongest correlation with IB are used to select the eigenvalue index that will generate three transformed variables. The eigenvectors, $evec(k',l)$, where the original k' index is for the eigenvalues having the strongest correlation with IB and the l index is for the process variables, are used to generate transformed composite variables by

$$cvec(k',j) = \sum_{l=1}^{10} evec(k',l) \times xnkfl(l,j). \qquad [8]$$

In **Figure 2**, for example $k' = 10$ will be relabeled as a new $k = 1$, while $k' = 7$ will be relabeled as a new $k = 2$ in **Table 2.** The new three transformed variables determined by $cvec(k,j)$ for relabeled $k = 1$ to 3 are standardized by scaling the transformed variables to obtain a mean square value of one and are defined by now $cvecn(k,j)$. The standardized transformed variables are used to obtain correlation for the transformed variables with IB by

$$corc(k) = \sum_{j=1}^{100} cvecn(k,j) \times ync(j). \qquad [9]$$

These transformed variables can be recombined using the correlation coefficients, $corc(k)$, as scaling factors to obtain a predicted value, $yp(j)$, for the control variable of the IB;

$$yp(j) = \sum_{k=1}^{3} corc(k) \times cvecn(k,j). \qquad [10]$$

This predicted value is standardized using the same technique to obtain $ypn(j)$. The combined correlation with IB is then calculated by

$$corcom = \sum_{j=1}^{100} ypn(j) \times ync(j). \qquad [11]$$

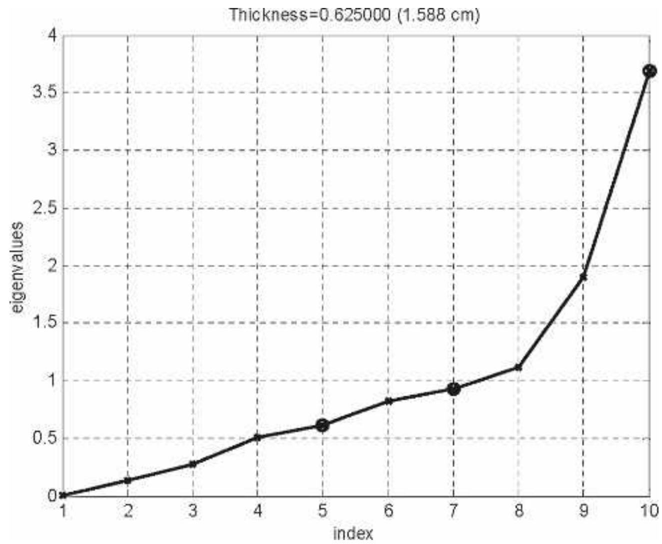

Figure 3. — Ten eigenvalues for process variables shown in Table 1 for thickness of 0.625 inches (15.88 mm), larger dots are for the associate transformed composite variables with the higher absolute correlations with IB with their associated indices are later relabeled as 1 (highest), 2, and 3 respectively.

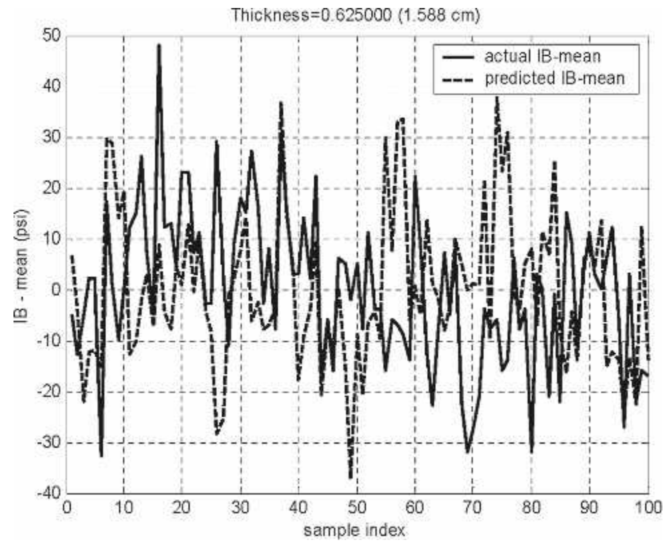

Figure 4. — Observed internal bond with mean IB subtracted and predicted IB with mean subtracted from first dominant transformed composite variable for thickness of 0.625 inches (15.88 mm).

Results and discussion

Correlation analysis of the data

Each data set was recorded between May and November of 2005. Information for the top 10 process variables for each thickness is presented briefly in **Table 1** for comparison. The eigenvectors corresponding to the three key eigenvalues (see Clapp et al. 2007 for more details) are used to generate three dominant transformed composite variable process variables. These three key eigenvalues are chosen by their corresponding transformed variables having the largest correlation with IB. **Table 2** shows the correlation coefficients for the three dominant transformed variables and for the linear combination of all three.

Thickness of 0.500 inches (12.70 mm). — The root mean square error (RMSE) between the observed IB and the predicted value using a combination of the three dominant transformed variables is 12.8 pounds per square inch (p.s.i.) (or 0.0883 MPa) with a maximum deviation of 28.6 p.s.i. (1.97 MPa) and a minimum deviation of -36.2 p.s.i. (−0.250 MPa). The average IB for 100 samples is 137.6 p.s.i. (0.949 MPa) with a maximum value of 179 p.s.i. (1.234 MPa) and a minimum value of 100 p.s.i (0.689 MPa).

An analysis of each data record revealed that residuals are greater when there is a time gap between production runs for a thickness category (see Clapp et al. 2007). For example, the first two records of 0.500 inches (12.70 mm) correspond to one production run for a customer order. Twenty-seven days passed before the next production run of 0.500 inches (12.70 mm), indicated by records three through seven in the data. Fifty-eight days passed before the next production run of records 8 through 12. The effect of larger residuals for time gaps in production runs was less pronounced for the combined transformed variables predictions. The larger residual at the beginning of a production run may indicate that some other factor is affecting the process, which is not measured by the 184 sensor variables, e.g., raw material change, change in operating set points not measured by the 184 sensors, refiner plate wear not measured by the 184 sensors, human dimension, etc. A more detailed summary of all results is presented in the technical report by Clapp et al. (2007).

Thickness of 0.625 inches (15.88 mm). — The 10 process variables with the largest (absolute) correlation coefficients are shown as crosses at the top peaks in **Figure 2**. The values of the correlation coefficients for the 0.625 inch (15.88 mm) samples are slightly smaller than the values for the 0.500 inch (12.70 mm) samples (**Table 1**). Six of the 10 sensors with the largest correlation coefficients are different from the sensors for a thickness of 0.500 inches (12.70 mm). Recall three dominant eigenvectors are used to generate three transformed composite variable. The eigenvectors corresponding to the three largest correlation (of their respective transformed composite variables) are marked with larger dots in **Figure 3** for their corresponding eigenvalues (i.e., indices are relabeled in **Table 2** so 10 becomes 1 due to it having the largest correlation with IB, while 5 becomes 2 due to it yielding the second largest correlation, then 7 becomes 3 index in **Table 2**, respectively). The correlation coefficient for the three combined transformed variables for the 0.625 inch (15.88 mm) thickness samples (0.612) is slightly smaller than the correlation coefficient for the 0.500 inch (12.70 mm) thickness samples (0.618), **Table 2.**

The sorted set of eigenvalues for the samples with a thickness of 0.625 inches (15.88 mm) is shown in **Table 2.** The relation between IB and the first dominant transformed variable for these samples is shown in **Figure 4.** The composite signal is determined by combining three transformed variables. The results of the combined transformed variables are shown in **Figure 5.** The RMSE between the IB and the predicted value that uses a combination of the three dominant transformed variables is 13.8 p.s.i. (0.0951 MPa) with a maximum deviation of 39.5 p.s.i. (0.272 MPa) and a minimum deviation of −36.3 p.s.i. (−0.250 MPa). The average IB for 100 samples is 136.9 p.s.i. (0.944 MPa) with a maximum value of 185 p.s.i. (1.276 MPa) and a minimum value of 104 p.s.i.

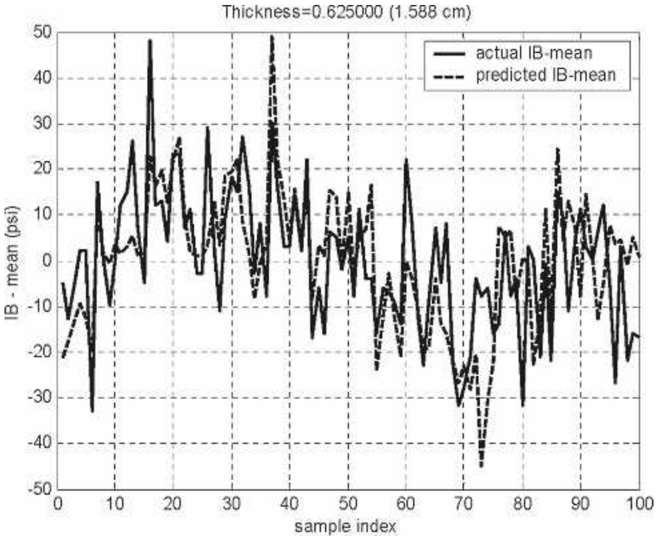

Figure 5. — Observed internal bond with mean subtracted and predicted IB with mean subtracted from linear combination of all three dominant transformed composite variables for thickness of 0.625 inches (15.88 mm).

(0.717 MPa). The relationship between the predicted IB minus its mean and the observed IB minus its mean for the combined transformed variables for the sample with a thickness of 0.625 inches (15.88 mm) is shown in **Figure 5.**

Thickness of 0.6875 inches (17.46 mm). — The RMSE between the IB and the predicted IB values using a combination of the three dominant transformed variables is 15.2 p.s.i. (0.105 MPa), with a maximum deviation of 29.4 p.s.i. (0.203 MPa) and a minimum deviation of −39.6 p.s.i. (−0.273 MPa). The average IB for 100 samples is 135.8 p.s.i. (0.936 MPa) with a maximum value of 193 p.s.i. (1.331 MPa) and a minimum value of 94 p.s.i. (0.648 MPa).

Conclusions

Examining the correlation results of the three thickness values show that one sensor, "Core Refiner Total Steam Flow," is found in the three different sets of the 10 largest correlation coefficients. "Core Refiner Total Steam Flow" seems to decrease in order of importance as thickness increases. The sensor "Face Plate Position of Refiner" is found in the sets of 10 correlation coefficients for the 0.500 inch (12.70 mm) and 0.6875 inch (17.46 mm) data sets. The sensor "Face Plug Feeder Screw Speed" is found in the 0.625 inch (15.88 mm) and 0.6875 inches (17.46 mm) data sets. The variation in the other parameters may indicate that the parameter set does not contain the necessary information to more precisely predict the IB.

It is also noted that the accuracy of the predicted value of the IB decreases as the MDF thickness increases. This phenomenon may indicate that manufacturing process design and process capability is dependent on MDF thickness. For example, it may be that the capability of the MDF mat formers change by thickness. Another example may be that pressing technology and capability is dependent on thickness, i.e., thinner MDF is produced at faster press cycle times and faster line speeds than thicker MDF. These changes in the sets of eigenvalues and the set of 10 variables for prediction among thickness categories may represent other sources of unknown variables affecting IB, e.g., human factors or shift variations that need further exploring. One might conjecture that additional variations may occur with increasing product thickness. Evidence of this may be the declining size of correlation coefficients for increasing thicknesses categories.

One of the important outcomes of this research is the identification of sources of variation acting on IB that are common across all product thickness categories. This may greatly benefit manufacturers by identifying sources of variation for additional root-cause analysis and facilitate continuous improvement. This may also help the practitioner identify important process variables for the implementation of statistical process control and designed experiments.

The time-lagging of process sensor data corresponding to the time required for the furnish to travel through the process from the point where a given parameter had an influence to the point where the panel is extracted for destructive testing was implemented for the press cycle and line speed related to the nominally produced product, i.e., 0.625 inches (15.88 mm) MDF. This static time-lagging may be another factor contributing to the RMSE predictions. The eigenvalues in **Figure 2** suggest that the time-lag of sensors can be improved, i.e., the most influential eigenvalues (large dots) should theoretically be in order as indices 8, 9, and 10. This was not the case where the most influential eigenvalues for prediction vary in size and order across the top 10 eigenvalues. Dynamic time-lagging by product type, which accounts for changes in press cycle time and line speed, is beyond the scope and funding support of this project. The authors hope to improve the time-lagging of sensor data and improve the predictability of IB if more funding is available. We believe that the automated real-time relational database developed as part of this study is unique in itself to the wood composites industry and is an important foundation for predictive modeling research.

The authors also hope to further investigate the phenomenon of larger residuals between actual and predicted IB for products with increased thickness levels at the start of a production run. It is apparent that factors are acting on IB variability that are not measured by the 179 process online sensors that were available for this analysis. As noted, these factors may be raw material changes, undetected changes in operator settings, refiner plate wear not measured by sensors, human dimensions, etc. One of the challenges of this type of industrial-based research is the dependence on data provided by a manufacturer, i.e., not all possible data are measured by sensors and stored in the data warehouse.

Real-time predictive modeling of the final mechanical properties of wood composites can benefit the forest products industry by preventing the manufacture of defective products, reducing woodwaste, and facilitating lower operating density and resin targets. The modeling method presented in this paper quantifies known and unknown sources of process variation for the practitioner. Quantifying sources of variation is an important first-step in reducing variation for any continuous improvement process.

In conclusion, the root mean square error relative to the mean of each category varied from 9.3 percent to 11.2 percent, which are quite helpful improvements in this manufacturing setting. More attention to the collection of the current process variables via information quality efforts might be useful for additional future improvements. Even though the plant had 179 quantitative process variables, our PCA and correlation analyses suggests some other variable(s) need exploring and collecting to further reduce these error rates.

Literature cited

Bernardy, G. and B. Scherff. 1998. Saving costs with process control, engineering and statistical process optimization. *In*: Proc. 2nd European Panel Products Symp. (EPPS), Llandudno, Wales.

__________ and __________. 1999. Process modeling provides on-line quality control and process optimization in particle and fiberboard production. ATR Industrie-Elektronik GmbH and Co. KG—Textilstrasse, Viersen, Germany.

Clapp, N.E., Jr., T.M. Young, and F.M. Guess. 2007. Predictive modeling the internal bond of medium density fiberboard using principal component analysis. Tech. Rept., The Univ. of Tennessee, Forest Products Center (contact: Tmyoung1@utk.edu).

Deming, W.E. 1986. Out of the Crisis. Massachusetts Inst. of Tech., Center for Advanced Engineering Study, Cambridge, Massachusetts. 507 pp.

__________. 1993. The New Economics. Massachusetts Inst. of Tech., Center for Advanced Engineering Study, Cambridge, Massachusetts. 240 pp.

Greubel, D. 1999. Practical experiences with a process simulation model in particleboard and MDF production. *In*: Proc. 2nd European Wood-Based Panel Symp., Hanover, Germany.

Haddad, R.A. and T.W. Parsens. 1991. Digital Signal Processing Theory, Applications, and Hardware. Computer Sci. Press (ISBN 0-7167-8206-5). Newman, A. J. 1996. Model Reduction via the Karhunen-Loeve Expansion. Part II: Some elementary examples. T.R. 96-33, Inst. Systems Res., April 2, 1996.

Palacios, A.G., H. Gemunu, M. Gorman, and K.A. Robbins. 1998. Karhunen-Loeve analysis of spatiotemporal flame patterns. Phys. Rev. E 57(5):5958-5971.

Ramsay, J.O. and B.W. Silverman. 1997. Functional Data Analysis. Springer-Verlag (ISBN 0-387-94956-9).

Rencher, A.C. 1995. Methods of Multivariate Analysis. John Wiley and Sons, Inc. (ISBN 0-471-57152-0).

Stone, E. and A. Cutler. 1996. Introduction to archetypal analysis of spatio-temporal dynamics. Physica D. 96:110-131.

Uenohara, M. and T. Kanade. 1997. Use of Fourier and Karhunen-Loeve decomposition for fast pattern matching with a large set of templates. IEEE Trans. Pattern Anal. Mach. Intell. 19(8):891-897.

Young, T. and F.M. Guess. 1994. Reliability processes and structures. Microelectron. Reliab. 34:1107-1119.

Young, T.M. and F.M. Guess. 2002. Developing and mining higher quality information in automated relational databases for forest products manufacture. Inter. J. of Reliability and Application 3(4):155-164.

__________ and P.M. Winistorfer. 1999. Statistical process control and the forest products industry. Forest Prod. J. 49(3):10-17.

__________, N. André, and C.W. Huber. 2004. Predictive modeling of the internal bond of MDF using genetic algorithms with distributed data fusion. *In*: Proc. 8th European Panel Products Symp., Llandudno, United Kingdom. pp. 45-59.