PERGAMON

Engineering Applications of Artificial Intelligence 13 (2000) 391–396

Engineering Applications of
ARTIFICIAL INTELLIGENCE

www.elsevier.com/locate/engappai

Combining a neural network with a genetic algorithm for process parameter optimization

D.F. Cook*, C.T. Ragsdale, R.L. Major

Management Science and Information Technology Department (0235), Virginia Tech, 1007 Pamplin Hall, Blacksburg, VA 24061, USA

Abstract

A neural-network model has been developed to predict the value of a critical strength parameter (internal bond) in a particleboard manufacturing process, based on process operating parameters and conditions. A genetic algorithm was then applied to the trained neural network model to determine the process parameter values that would result in desired levels of the strength parameter for given operating conditions. The integrated NN–GA system was successful in determining the process parameter values needed under different conditions, and at various stages in the process, to provide the desired level of internal bond. The NN–GA tool allows a manufacturer to quickly determine the values of critical process parameters needed to achieve acceptable levels of board strength, based on current operating conditions and the stage of manufacturing.

Keywords: Neural-network; Genetic algorithm; Process optimization

1. Introduction

Manufacturers are sometimes hesitant to use statistically designed experiments to study their process because they fear the ramifications of purposefully taking the process out of or to the limits of control. In addition, they are often unable to hold certain process parameter values constant while varying the experimental variable (thus weakening the information gained from the designed experiment). This paper proposes the combination of a neural network (NN) and a genetic algorithm (GA) to develop a modeling and analysis tool to be used to investigate the relationships between various process and product parameters in a manufacturing process. Neural-network models are powerful tools when modeling data sets that are nonlinear and highly correlated. GAs are known as efficient search algorithms. The combination of a neural-network model for prediction with a genetic algorithm for process optimization offers potential opportunities for manufacturers to improve control and reduce the costs of their manufacturing process.

A neural-network model was developed to predict the value of critical strength parameters in a particleboard manufacturing process, on the basis of process operating parameters and conditions. A genetic algorithm then used the trained neural-network prediction model to determine the process parameter values that would result in the nearest to optimal value of the strength parameters that could be obtained under various operating conditions. This gives a manufacturer valuable information about the process parameter values that are required under various operating conditions and at various stages of the process in order to attain desired strength values.

2. Particleboard manufacturing process

Particleboard is a composite wood product, used in

* Corresponding author. Tel.: +1-540-231-4847; fax: +1-540-231-3752.

E-mail address: dcook@vt.edu (D.F. Cook).

0952-1976/00/$ - see front matter
PII: S0952-1976(00)00021-X

various furniture and building applications. The raw material input of planer shavings is steamed, refined, dried, and then combined with binding agents. Following the blending operation, the stock material is formed into individual mats that are pressed, cut, and sanded into final product form.

Various process parameters are measured during the manufacturing process (Table 1), and these measurements are the basis for process adjustments. The measured process parameters include the moisture content of the original particle material, dryer temperatures, in-process moisture contents, bonding treatments, and general press conditions represented by temperature and cycle time. Bonding treatment involves a calculation that represents the amount of resin (bonding agent) and wood, as well as the moisture content of the mixture. Increases in the amount of resin would be expected to cause the bonding treatment to increase.

The strength of the final board is a key quality characteristic of the product. Two measures of the board strength are the internal bond (IB) and the modulus of rupture (MOR). IB is an overall measure of the integrity of the board, that defines how well the internal core material is bonded together, and is determined using destructive testing methods on the final manufactured product. Measurements of IB were taken every 2 h at the mill under study. The recorded value of IB is an average of five samples taken from a randomly selected single board.

MOR is an index of the maximum bending strength of a board when loaded as a beam. MOR is dependent on particle geometry and board density and strength. MOR is also determined using destructive test methods on the final manufactured product. MOR measurements were taken every 2 h at the study mill. Each MOR value is an average of three samples, where two groups of MOR measurements are taken from a single, randomly selected board.

The results of both the IB and MOR tests are available only several hours after the actual manufacturing process, making it difficult for the operator to make process adjustments to improve IB and MOR. Consequently, a model that could predict resulting strength parameters based on current process operating conditions, and then give suggested adjustments to process parameters if specified strength values are not going to be met, would allow improved process control to an operator. This might result in significant reductions in the amount of board to be down-graded or scrapped.

Table 1
Particleboard process and process parameters for model development

Network inputs	Network outputs
Moisture contents	Internal bond (IB)
Dryer temperatures	Modulus of Rupture (MOR)
Bulk densities	
Conveyor speeds	
Blender infeed moisture contents	
Blender outfeed moisture contents	
Blender amps usage	
Bonding treatments	
Press time	
Press temperature	

3. Neural-network models

A neural network is a computational structure, consisting of a number of highly interconnected processing elements (or nodes), that produces a dynamic response to external input or stimuli (Burke, 1991). Neural networks were originally developed as approximations of the capabilities exhibited by biological neural systems. Much of the interest in neural networks arises from their ability to learn to recognize patterns in large data sets. This is accomplished by presenting the neural network with a series of examples of the conditions that the network is being trained to represent. The neural network then 'learns' the governing relationships in the data set by adjusting the weights between its nodes. In essence, a neural network can be viewed as a function that maps input vectors to output vectors.

Accurate prediction of the values of critical quality parameters of a product during the production process is a key factor in the success of a manufacturing operation. Neural networks have been used successfully to predict parameter values of manufacturing process output. Cook and Chiu (1997) collected particleboard process data throughout a manufacturing operation, along with the corresponding values of the strength parameters. They developed a radial basis function (RBF) neural-network model to predict the internal bond strength of particleboard, based on current process conditions. The process data included bulk density, temperatures, conveyor speed, blender and press conditions, and bonding treatment. The neural-network output was the predicted value of IB. The average prediction error of the RBF neural-network model was 12.5%, which represented a significant improvement over previously developed neural-network models, as well as a statistical regression model.

Neural-network technology was also applied to brownstock washer operations in a pulp and paper mill (Patrick, 1991). Forty-four variables were identified as possible parameters to include in the network training. The network was developed to maintain solids in the washing operation at a uniform level. Both the standard deviation and the coefficient of variation of solids uniformity showed an improvement of greater than 20% with the neural-network controller.

This improved control implies improved washing efficiency, resulting in quality and economic benefits. Chiu et al. (1995) developed a radial basis function (RBF) neural-network model of a critical process parameter in a pulping process. The RBF model provided a 30% increase in predictive accuracy over the mathematical model proposed by Masura (1993).

4. Design of neural network for particleboard manufacturing

The Neural Works Predict software package from NeuralWare was used in this study to develop the neural-network predictive model of the particleboard strength parameters. This product is an easy-to-use add-in for Microsoft Excel. Predict is based on a constructive approach to building networks, originally referred to as Cascade Correlation (Neural Works, 1997). Two learning rules are available in Predict, adaptive gradient rules and Kalman rules. The adaptive gradient rule is the more general learning rule, and was used in this application.

Three separate neural-network models were developed to model each of the three product strength parameters. The full network training data set consisted of 26 input parameters, 3 output parameters, and 127 data vectors. The test data set consisted of 55 data vectors that were not used in the training process. As expected, better predictive results were generated by designing and training a separate network to model IB, MOR1, and MOR2, as opposed to designing and training one network to predict all three strength parameters. Predict used a variable selection algorithm to determine which parameters should be included to result in the best predicting neural-network model. The full parameter data set (26 input parameters) was analyzed by Predict in each network model, and Predict selected the parameters to be included in the model (Table 2).

Accuracy is defined within Predict as the fraction of the instances at which the actual value is within a given percentage of the network output value. The default percentage, 20%, was used in this analysis. The networks were able to predict the IB value in the test data set with an accuracy of 92.7%, the MOR1 value with an accuracy of 81.81%, and the MOR2 value with an accuracy of 80%. The remaining analyses focused on IB, as this resulted in the best neural-network predictive model. Additional data collection is likely to be required to develop an improved model of MOR. Next, the IB neural-network model was coupled with a genetic algorithm for process analysis.

Table 2
Process parameters selected by Predict for inclusion in the strength network

Process parameter	IB network	MOR1 network	MOR2 network
% Face material	√	√	√
Core resin	√	√	√
Face resin	√		
Timer 1		√	√
Timer 3		√	√
Press temperature	√	√	√
Speed face line 1	√	√	√
Speed face line 2	√	√	√
Speed core line 1			
Speed core line 2	√		
Face bulk density	√	√	√
Core bulk density		√	√
Face infeed moisture content			
Core infeed moisture content	√	√	√
Face 1 psi	√		
Face 2 psi	√		
Core 1 psi			
Core 2 psi	√		
Face 1 temperature			
Face 2 temperature		√	√
Core 1 temperature	√	√	√
Core 2 temperature	√	√	√
Face 1 outfeed moisture content	√	√	√
Face 2 outfeed moisture content		√	√
Core 1 outfeed moisture content			
Core 2 outfeed moisture content	√	√	√

5. Genetic algorithms

Genetic algorithms (GAs) represent a powerful, general-purpose optimization paradigm in which the computational process mimics the theory of biological evolution (Davis, 1991; Holland, 1992; Storn and Price, 1997). Genetic algorithms have been used successfully for job-shop scheduling, production planning, line balancing, lumber cutting optimization, and process optimization (Conway and Venkataramanan, 1994; Falkenauer, and Delchambre, 1992; Cleveland and Smith, 1989; Cook and Wolfe, 1991; Fonseca and Fleming, 1993).

GAs start with a randomized population of parent chromosomes (numeric vectors) representing various possible solutions to a problem. The individual components (numeric values) within a chromosome are referred to as genes. New child chromosomes are created by crossover and/or mutation operations. Crossover occurs as a probabilistic exchange of genes between two or more chromosomes. Mutation involves the random replacement of genes in a chromosome. All chromosomes are then evaluated according to a fitness (or objective) function, with the fittest surviving into the next generation. The result is a gene pool that 'evolves' over time to produce better and better solutions to a problem.

GAs tend to efficiently explore various regions of the decision space with a high probability of finding improved solutions (Goldberg 1989). While there is no guarantee that the final solution obtained using a GA is the global optimal solution to a problem, Holland (1975) proved theoretically and empirically that these algorithms provide robust searches in complex spaces.

6. Design of a genetic algorithm model for internal bond

The GeneHunter (1997) software developed by Ward Systems, was used as the GA optimization engine in this study. This product is also an easy-to-use add-in for Microsoft Excel. The process parameters listed in Table 2 were used to represent the genes within the population of chromosomes. The neural-network model for IB was used as the fitness function within GeneHunter for evaluating individual chromosomes. The goal of the integrated NN–GA system is to determine the process parameter values needed to provide the desired level of IB at various stages in the process.

Fig. 1 illustrates an example of the NN–GA system in use in real time. The NN–GA system receives the current process parameter values of face and core infeed moisture content of the production material. The GA component of the system uses the predictive neural-network model as its fitness function, and uses the current process parameter values at the current stage of the process as input. The GA then calculates the values of face 1 and 2 and core 1 and 2 outfeed moisture content that must be attained to produce a board with an acceptable strength level. Those required parameter values for the outfeed moisture contents would be communicated to an operator, who would then adjust the values of face 1 and 2 and core

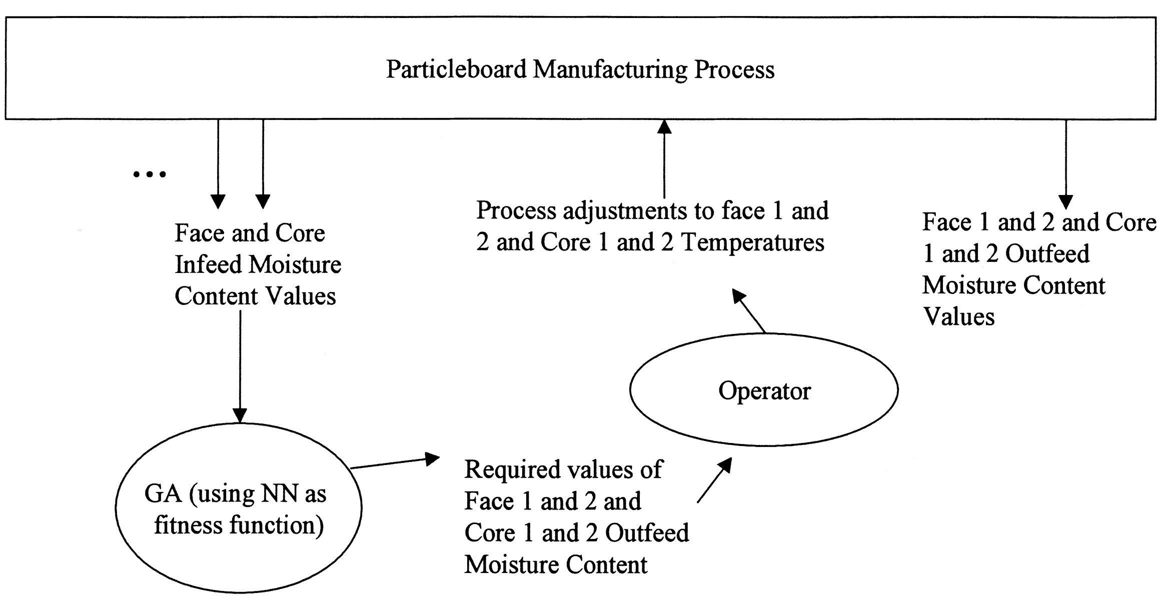

Fig. 1. Integrated NN–GA system.

Table 3
Process parameter values determined by the genetic algorithm to achieve desired levels of internal bond

% Face resin	Core resin	Face resin	Press temp	Belt speed 1	Belt speed 2	Belt speed 3	Face bulk density	Infeed moisture content	Blender pressure 1	Blender pressure 2	Blender pressure 3	Core temp 1	Core temp 2	Face moisture content	Core moisture content	IB
62.6	6.2	6.8	307.2	25	90	86.4	13.6	3.5	5.8	4	3.5	135	400.8	6.8	3.4	136.6
62.3	4.9	6.2	304.5	92.2	68	64.9	11.8	3.8	3	3.8	3.7	136.7	407.7	4.9	3.5	115
62.6	5.3	5.8	309.7	40.7	84.3	72.4	12	3.8	6	2.4	2.6	160.7	188	5.3	4.5	120
62.2	4	4	308.5	59.2	75.3	80.8	12.7	3.3	4.8	3.5	5.8	135.6	475.9	5.6	3.4	115
61.6	4	4	305.3	42.4	88.8	75.3	12.2	3.1	4.2	3.4	8.7	138.6	273.9	6.7	4.7	120
62.4	5	5.5	307.2	58	72.3	28.4	11.5	3.3	2.5	3.9	8.7	143.7	444.5	6.4	4.1	115
62.3	5	5.5	307.3	25.8	55.5	86.7	12	3.4	5.7	1.8	1.1	137.6	400.8	5	3.9	120
60.6	6	6.5	299.5	39.8	53.1	7.6	11.4	3.6	4.3	2.6	8.2	146	444.5	6.4	4.5	115
60.9	6	6.5	305.5	80.7	71.9	55.5	11.6	3.2	5.2	3.7	8.9	142.5	231.6	4.9	4.1	120
62.8	5	5.5	309.4	55	55	55	12.7	4.3	4.6	1.9	3	141.2	478.6	5.3	3.6	115
61.6	5	5.5	309.6	55	55	55	13.1	4	2	2.3	6.1	147.9	455.4	6	4.2	120
61.4	6	6.5	299.4	80	80	80	13.1	3.9	2.3	3	5.2	158.1	310.8	5.7	4.7	115
60.3	6	6.5	297.7	80	80	80	12.1	3.5	5.6	3.7	2.5	159.4	286.2	6.2	3.5	120

1 and 2 temperatures so that the required values of outfeed moisture content could be achieved.

Initially the NN–GA model was run with the assumption that the product was in the beginning stages of manufacture. Runs were made to determine process parameter settings that would result in the maximum value of IB, as well as several set values of IB. The maximum value of IB achieved with the NN–GA model was 136.6 (Table 3). The GA accomplished this value of IB primarily by maximizing the values of the face and core resin content. This coincides with general expectations of the physical process, as an increase in face and/or core bulk density would be expected to increase IB. However, in the case of particleboard manufacturing, a set value of IB may be the goal, as opposed to a maximum value. A maximum value of IB would be likely to be attained by increasing the resin content of the board material. Resin is the most costly of the ingredients used in particleboard manufacture, so manufacturers often attempt to attain a certain level of IB, say 115 or 120.

Additional experiments were conducted to determine if the NN–GA tool could be used as an aid for achieving desired levels of IB during the different stages of the manufacturing process (Table 3). Different process parameter values occurring early in the process were frozen, to simulate in-process operating conditions. First, core and face resin content were frozen at different levels, and the NN–GA tool was used to determine what values of remaining process parameters would be required to obtain a desired level of IB (115 and 120 were used as examples). The GA manipulated the remaining process parameters to achieve IB values of 115 and 120 (Table 3). The values of face and core resin content and all speeds were then frozen at different values to determine what values of the remaining process parameters would be required to obtain a desired level of IB (115 and 120 were again used as examples). In each case, the NN–GA tool identified process parameters that would result in the desired IB values.

7. Summary and conclusions

An integrated NN–GA tool for process modeling and analysis has been developed for a particleboard manufacturing facility. A neural-network model of the process was developed to predict final product characteristics. A GA model was then developed, using the neural-network model as the fitness function, to determine which process parameter values would result in the desired product characteristics. The process parameter values derived by the NN–GA tool were based on the functional mapping developed by the neural-network model. That functional mapping is representative of the training data set, and should be as accurate as the training data set.

The NN–GA tool could be used by plant personnel to study and evaluate the relationships between process parameters and final product characteristics, as well as to provide operators with information that will allow them to make required process adjustments in real time. Additional data collection would be likely to provide more information for process modeling. Data should be collected when the process is running both in-control and out-of-control, and additional NN–GA models should be developed on the basis of that data. An improved understanding of the relationships between process and product parameters would allow improved process control in most manufacturing operations.

References

Burke, L., 1991. Introduction to artificial neural systems for pattern recognition. Computers and Operations Research 18 (2), 211–220.

Chiu, C.-C., Cook, D.F., Pignatiello, J.J., 1995. Radial basis function neural network for Kraft pulping forecast. International Journal of Industrial Engineering 2 (3), 209–215.

Cleveland, G.A., Smith, S.F., 1989. Using genetic algorithms to schedule flow shop releases. In: Schaffer, J.D. (Ed.), Proceedings of 3rd International Conference on Genetic Algorithms. Morgan Kaufmann, Los Altos, pp. 160–169.

Conway, D.G., Venkataramanan, M.A., 1994. Genetic search and the dynamic facility layout problem. Computers and Operations Research 21, 955–960.

Cook, D.F., Chiu, C.C., 1997. Predicting the internal bond strength of particleboard utilizing a radial basis function neural network. Engineering Applications of AI 10 (2), 171–177.

Cook, D.F., Wolfe, M.L., 1991. Genetic algorithm approach to a lumber cutting optimization problem. Cybernetics and Systems 22, 357–365.

Davis, L., 1991. Handbook of Genetic Algorithms. Van Nostrand Reinhold, New York, NY.

Falkenauer, E., Delchambre, A., 1992. A genetic algorithm for bin packing and line balancing. In: Proceedings of the IEEE International Conference on Robotics and Automation.

Fonseca, C.M., Fleming, P.J., 1993. Genetic algorithms for multiobjective optimization: formulation, discussion, and generalization. In: Forrest, S. (Ed.), Proceedings of the 5th International Conference on Genetic Algorithms. Morgan Kaufmann, Los Altos, pp. 416–423.

GeneHunter, 1997. Ward Systems Group. Frederick, MD.

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley, Reading, MA.

Holland, J.H., 1975. Adaptation in Natural and Artificial Systems. University of Michigan Press, Ann Arbor, MI.

Holland, J.H., 1992. Genetic Algorithms. Scientific American 267 (1), 66–72.

Masura, V., 1993. A mathematical model for Kraft pulping expressed by a logarithmic straight-line equation. Tappi Journal 76, 105–109.

Neuralworks Predict, 1997. Technical Publications. NeuralWare, Pittsburg, PA.

Patrick, K.L., 1991. Neural network keeps BSW filtrate solids at maximum uniform levels. Pulp and Paper 65 (3), 55–58.

Storn, R., Price, K., 1997. Differential evolution — a simple and efficient heuristic for global optimization over continuous spaces. Journal of Global Optimization 11, 341–359.