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Prediction using artificial neural networks of edgewise compression strength of corrugated fiberboards

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Abstract

Corrugated boxes are the most important type of distribution packaging made from natural resources. Optimization of the fiber used versus the strength requirement is necessary. This research compared a regression model, a backpropagation neural network (BPN) model and a radial basis function network (RBFN) model with traditional models, namely, the Whitsitt model and the Markström model, in predicting the edgewise compression strength (ECT) of corrugated fiberboard from related design factors. Three types of modeling patterns were studied: a model for single wall board, a model for double wall board and a model for both single and double wall boards. The results indicated that the predictive models for both the single and double wall boards were comparable to the other two in terms of prediction accuracy and were within an acceptable industrial error range. The 16-12-1 BPN model and the polynomial regression model were the two best choices for predicting the ECT of both single and double wall boards together in one model. The BPN model had a mean absolute percentage error (MAPE) of 4.23%, while the polynomial regression model had a MAPE of 5.14%. In addition, both models identified the most influential design factors affecting ECT: the basis weight of paper for the inner, middle and outer liners; the basis weight of the corrugated medium for the flute connected to the outer liner; the edge length of the corrugated board; and the height of the flute connected to the inner liner.

Introduction

Corrugated boxes are used extensively as transport packaging due to their light weight, environmental acceptance and structural design flexibility, by addressing transportation needs with an acceptable cost (Park and Kim, 2010). The strength of a corrugated box is the main concern during the design and development stage since it has a significant impact on stacking and space management decisions during transportation and storage, especially for ease of handling of fragile goods (Whitsitt and McKee, 1966; Talbi et al., 2009; Park and Kim, 2010).

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The composition and strength of corrugated fiberboards directly affect the strength of corrugated boxes and natural fibers derived from renewable resources that are either virgin or recycled can be mixed and converted into kraft liners for corrugated fiberboards and corrugated boxes production respectively (Archaviboonyobu et al., 2020). The ratio of fiber contents compared to other additives affects the strength of kraft liners and the final performance of corrugated boxes (Archaviboonyobu et al., 2020). Therefore, the optimization of the resources used versus the strength of the packaging materials need to be investigated. At present, accurate decision tools for packaging materials optimization are limited (Archaviboonyobu et al., 2020). However, all manufacturers, especially in the packaging and materials industries, have identified the urgent need for proof of their compliance with global guidelines under the circular economy concept (Archaviboonyobu et al., 2020).

Many tests are available to measure the strength of a corrugated fiberboard, including the edge crush test, the flat crush test and bursting strength. However, the edgewise compression strength (ECT) from an edge crust test has a direct relationship with the strength of a corrugated fiberboard and is commonly used as a major parameter to estimate the box compression strength (BCT) which represents the total strength of a corrugated box structure (McKee et al., 1963). Consequently, an accurate ECT estimation of corrugated boards from structural parameters, such as panel size, type of flute and composition, as well as grammage of paper combination, is advantageous for the design of corrugated boxes, ensuring that they have enough compression strength to protect the products within. This would allow designers to select the proper structure of a corrugated fiberboard in a shorter time and without performing costly strength analysis. Traditionally, mathematical models have been applied to predict the ECT of a corrugated fiberboard, using data from a ring crush test (RCT) or the board's components such as the basis weight of the inner liner, medium and outer liner. For example, Whitsitt (1990) described a mathematical model to predict the ECT of a corrugated fiberboard, for a single wall board and for a double wall board using Equations 1 and 2, respectively:

$$ECT = 0.8(L1 + tM + L2) + 2.1 \quad (1)$$

where ECT is the edge crush test value or edgewise compression strength, L1 is the ring crush value of the outer liner, t is the take-up factor of the medium, M is the ring crush value of the medium and L2 is the ring crush value of the inner liner.

$$ECT = 0.8(L1 + tM1 + L2 + tM2 + L3) + 2.1 \quad (2)$$

where ECT is the edge crush value, L1 is the ring crush value of the outer liner, M1 and M2 are the ring crush values of the flutes, L2 is the ring crush value of the middle layer liner and L3 is the ring crush value of the inner liner.

Whitsitt's model is very popular for determining the strength of corrugated fiberboards in practice since it is linear and straightforward to implement, although its limitation is that the constants 0.8 and 2.1 are applied for all structures of single wall and double wall board, respectively. Later, Markström (1999) generalized Whitsitt's model, as shown in Equation 3:

$$ECT = k(L1 + tM + L2) + c \quad (3)$$

where ECT is the edgewise compression strength, k and c are specific constants of the flute, L1 is the ring crush value of the outer liner, t is the take-up factor of the medium, M is the ring crush value of the medium and L2 is the ring crush value of the inner liner.

However, both models are only able to achieve low ECT prediction accuracy, since they are linear in nature and only take into account the take-up factor of the flute and the ring crush values, which may not represent the true relationship function. Less accurate models can pose a major problem in practice. Frank (2014) asserted that the current predictive models were acceptable; however, their performance was at least 10 times less accurate than material models for most other packaging. Furthermore, their scope was quite narrow, focusing on a single wall or double wall only. In fact, corrugated fiberboards have a complex composition. Typically, the content of corrugated liners is composed of virgin and recycled fibers as a skeleton matrix and starch-based or inorganic-based substances as fillers or additives. Various chemicals are also added to improve specific functionality of the formed paper. The compression strength of the corrugated fiberboards depends not only on the material composition but also on the design of flute structure, the converting process and storage environment (Pommier and Poustis, 1990; Srihirun, 2008; Nordstrand, 2004). Thus, ECT may be considered nonlinear since several factors contribute to the ultimate strength (Pommier and Poustis, 1990; Srihirun, 2008; Nordstrand, 2004; Archaviboonyobu et al., 2020).

Regression, the most popular empirical model, is capable of approximating the nonlinear relationship between several independent variables (input) and a dependent variable (output). The regression model's parameters (regression coefficients) are calculated from the observed pairs of data points (input-output) via least squares estimation. Regression models are very straightforward to implement; nevertheless, they require restrictive assumptions on the error terms, such as normal random errors, constant error variance and the absence of multicollinearity (Madu, 1990). Their performance also depends on the proper selection of functional forms (Kutner et al., 2008). In addition, high order regression tends to produce approximation functions that oscillate widely and thus lead to degraded prediction accuracy (Madu, 1990).

An alternative nonlinear empirical model is an artificial neural network (ANN) model that requires no *a priori* functional form or knowledge of the input-output relationship, does not adhere to any statistical assumptions and can accommodate several inputs and outputs. ANN models have been described in detail by Fausett (1994). In summary, an ANN model develops a map from the input variables to the output variables through an iterative learning process. It consists of a large number of processing elements (called artificial neurons) organized into a sequence of layers with connections between layers. Associated with each connection is a weight that represents the information being used to approximate the relationship in the data. These weights are iteratively adjusted by a learning process to optimal values that produce the best fit of the predicted outputs over the learning or training data. Input neurons receive the input data and pass them on to the next layer. Each neuron in the hidden or the output layer sums its input signals from the previous layer weighted by the connection weights and applies an activation function to determine its output signal. The ANN architecture (the arrangement of neurons into layers and the connection pattern within and between layers), a training or learning algorithm, and an activation function are used to characterize the ANN paradigm (Fausett, 1994). The current investigated and described in detail a backpropagation network and a radial basis function network.

A back propagation network (BPN) is a multi-layer neural network that utilizes a gradient-descent training algorithm with the aim of minimizing the total squared error of the output computed by the network (Rumelhart et al., 1986). The standard BPN training algorithm involves three stages: the feedforward of the input training set, calculation and backpropagation of error and adjustment of the weights. At the onset of training, all weights are randomly initialized. For a given set of inputs to the network, the output of each neuron in the output layer is computed using a nonlinear activation function and compared with the corresponding target output response. The errors associated with the output layer are propagated backward to the hidden layer and finally to the input layer to calculate the weight adjustments between the output and hidden layers as well as between the hidden and input layers. Finally, all weights in the network are updated. This learning or training process is repeated until the desired global error is achieved. Limitations of a BPN are the difficulty in selecting its architecture and training parameters such as the number of hidden layers and hidden neurons (Chaveesuk and Smith, 2003; Paliwal and Kumar, 2009).

A radial basis function network (RBFN) is a special case of a feedforward multi-layer network with one hidden layer (Moody and Darken, 1989; Poggio and Girosi, 1990; Haykin, 1999). Its architecture differs from a three-layer BPN as there is no weight associated with the connections between the input layer and the hidden or cluster layer. The input training set is passed directly to hidden neurons which compute their activation or output using the radial basis function called the kernel function. This function produces a localized, bounded and radially symmetric activation, that is, its maximum is at the center and drops off rapidly to zero away from the center. The connections between the hidden layer and output layer are weighted in the same fashion as in the BPN model. The activation of the output neuron can be computed by the sum of the weighted activation of individual hidden neurons or by the application of a nonlinear activation function. An RBFN trains faster than a BPN; however, some discriminatory information could be lost during the unsupervised training phase (Hassoun, 1995).

The current study pioneered examination of the use of regression, BPN and RBFN models for building a relationship between the design factors of corrugated fiberboards and the corresponding ECT; their accuracy was compared in predicting the ECT for various corrugated cardboard design configurations. Influential design factors were also identified from the most accurate model to gain some insight into their relationship.

Materials and Methods

Materials and properties

The corrugated fiberboards used were both single wall and double wall boards; the paper composition of the boards are listed in Table 1. All the corrugated fiberboards and liners were made by SCG (Bangkok, Thailand). B-flute, C-flute and E-flute corrugated fiberboards were used in the experiment.

Table 1 Paper composition of selected corrugated fiberboards

Trade name (paper application)	Basis weight (g/m^2)			
CA (for flute)	105	125		
KA (for liner)	125	150	185	230
KI (for liner)	125	150	185	
KS (for liner)	170			

Determination of edgewise compression strength values for various combinations of design factors

The design factors considered were: the number of paper layers in corrugated fiberboards, the paper type for liners and flutes and the edge length and height of the board panels. The edge lengths of test specimens were studied at 6 cm, 8 cm and 10 cm, while the heights of specimens were studied at 2 cm, 3 cm and 4 cm. These dimension combinations were in accordance with the ISO 3037:2013 international standard test method (ISO, 2013). The boards were cut using a Kongsberg XL20 cutting table (Esko; Ghent, Belgium). The ECT tests of the boards with different design combinations were performed using a universal testing machine (Micro 350; Testometric; Rochdale, UK), following ISO 3037:2013 (ISO, 2013). Each experiment was replicated 10 times.

Data preparation

The design factors in various combinations and their corresponding ECT values were arranged into input-output mapping, with 16 design factors as input variables and the corresponding ECT value (in newtons) as an output variable. For single wall board modeling, only 10 related design factors were used as input variables. Table 2, Fig. 1 and Fig. 2 describe all 16 input variables. An input-output data sample was collected from the combinations studied based on 10 replications.

Model building

Five modeling techniques were investigated consisting of two traditional models (Whitsitt and Markström models) and three alternative models (regression, BPN and RBFN models). Since the latter three could incorporate as many input variables as possible, they were used to construct: (1) a model to predict only single wall board; (2) a model to predict only double wall board; and (3) a model to predict both single wall and double wall boards. The entire data for building each of the three patterns were randomly divided into two distinct datasets with 80% for a training set and 20% for a validation set. The training set was used for model building, whereas the validation data set was used to assess model prediction accuracy and generalization capability.

Whitsitt models

The Whitsitt models were built separately for prediction of a single wall or a double wall board. The data on the design factors from the training data set were used to compute the corresponding RCT values and then fitted to Equations (1) and (2) for the prediction of single wall and double wall boards, respectively.

Table 2 Description of input variables and their values

Input variable	Description
B1	Paper type of liner 1
G1	Basis weight of paper for liner 1 (g/m^2)
B2	Paper type of flute 1
G2	Basis weight of paper for flute 1 (g/m^2)
B3	Paper type of liner 2
G3	Basis weight of paper for liner 2 (g/m^2)
B4	Paper type of flute 2
G4	Basis weight of paper for flute 2 (g/m^2)
B5	Paper type of liner 3
G5	Basis weight of paper for liner 3 (g/m^2)
L	Edge length of corrugated board (cm)
H	Height of corrugated board panel (cm)
F1M	Number of flutes/m for B2
F1H	Height of flute 1 (B2) (mm)
F2M	Number of flutes/m for B4
F2H	Height of flute 2 (B4) (mm)

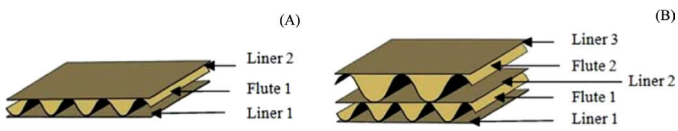


Fig. 1 Components of (A) single wall board; (B) double wall board

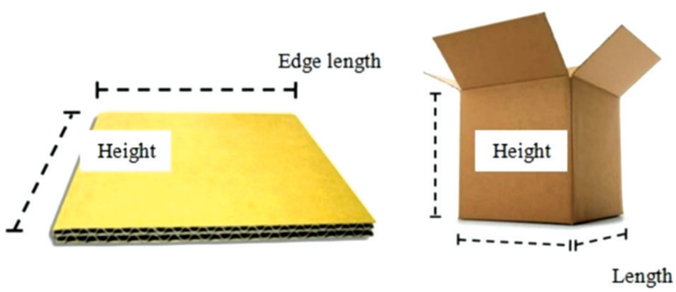


Fig. 2 Dimensions of fiberboard corresponding to those of corrugated box

Markström models

The Markström models were built separately for prediction of a single wall or a double wall board. The data on the design factors from the training data set were used to compute the corresponding RCT values; the parameters k and c were estimated to achieve the least prediction errors, using the Solver in the Microsoft Excel software package (Microsoft Corp.; Redmond, WA, USA) and were then included in Equation (3).

Regression models

The regression models were constructed from the training data using the SPSS Statistics 19 software (IBM Corp.; Armonk, NY, USA). Both multiple and polynomial regression were studied, using full model (enter), forward, backward and stepwise regressions. Each input factor was expressed as a deviation around its mean to avoid multicollinearity of input variables. Model parameters were selected based on the lowest ECT prediction error of the validation data in terms of mean absolute error (MAE), as computed using Equation 4.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \quad (4)$$

where y_i is the actual ECT value of data point i, y_i is the predicted ECT value of data point i and n is the number of data points over which the error was calculated.

The reliability of the model was evaluated using: 1) the Kolmogorov-Smirnov test for normal distribution of error; 2) Levene's test for constant variance of error; 3) standardized residuals for outliers; and 4) a variance inflation factor for multicollinearity (Kutner et al., 2008).

Backpropagation neural network and radial basis function network

The BPN and RBFN models were built using the NeuralWorks Explorer software (Pittsburgh, PA, USA), using design factors as input variables and the corresponding ECT value as an output variable from the training set. All variables were normalized to be in the range of the activation function, that was a hyperbolic tangent function in this research. One hidden layer has proven to be sufficient for modeling any continuous function (Basheer and Hajmeer, 2000) and was applied in this research. Several hidden neurons (1–15), learning rules (delta rule and extended delta-bar-delta rule) and sets of initial random weights were explored. To avoid overtraining, the model learning phase was stopped and evaluated with the validation set every 1,000 iterations up to a maximum of 500,000 iterations. The training was stopped when the MAE of the validation set continued to increase. The proper architecture and learning parameters were selected based on the lowest MAE of the validation data.

Model comparison

All models were compared for prediction accuracy for both training and validation data based on MAE and the coefficient of determination (R^2) from the plot of actual ECT and predicted ECT, and mean absolute percentage error (MAPE) as calculated using Equation 5:

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100}{n} \quad (5)$$

where y_i is the actual ECT value of data point i, $\hat{y}i$ is the predicted ECT value of data point i and n is the number of data points over which the error was calculated.

A superior model should possess good prediction accuracy for both training and validation data sets. In other words, its generalization capability (high accuracy for predicting data that are not used in the model building) should be retained (Chaveesuk and Seepung, 2007).

Identification of key design factors

Once the model had been built and validated, it was used to predict the ECT from various design configurations and to identify the design factors affecting the ECT prediction value. Chaveesuk and Seepung (2007) showed that both polynomial regression and a backpropagation neural network could identify the significant factors affecting the cost of corrugated boxes. In the case of polynomial regression models, an inference could be made from the magnitude of the standardized regression coefficients, with a large coefficient indicating an important effect of that design factor. For the BPN and RBFN models, varying each input variable by a certain percentage and computing how much the output changes is a means of observing key design factors, where the larger the percentage change, the greater the effect of that input variable (Chaveesuk and Seepung, 2007).

Results and Discussion

Predictive models for a single wall board

The model from each modeling technique that had the highest prediction accuracy and satisfied all the model assumptions was selected and shown in Table 3. It was clear that the BPN model with 10 hidden neurons, the delta rule and 10,000 learning iterations had the highest prediction accuracy, followed by the full multiple regression model. The traditional models (Whitsitt and Markström), as well as RBFN with 9 hidden neurons, were markedly inferior. Furthermore, a plot of the actual ECT values versus the predicted ECT values from the validation data of each model under study (Fig. 3) revealed that the 10-10-1 BPN model (R^2 = 94.5%) had the highest generalization capability and was selected for further study. All modeling techniques had poorer accuracy when predicting ECT over 300 N.

Predictive models for a double wall board

The model from each modeling technique that exhibited highest prediction accuracy and satisfied all model assumptions was selected and is displayed in Table 4. It was clear that the BPN, with two hidden neurons, the delta rule and 23,000 learning iterations, and the backward polynomial regression outperformed the traditional models of Whitsitt and Markström as well as the RBFN with seven hidden neurons. Both polynomial regression and BPN could represent the complicated and nonlinear relationship occurring in a double wall board compared with a single wall board. In fact, a BPN is by nature a universal approximator, as it can theoretically approximate any nonlinear relationship to any given degree of accuracy (Funahashi, 1989; Hornik et al., 1989).

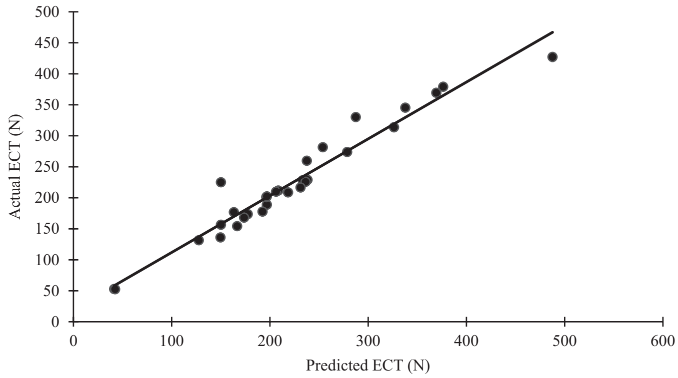


Fig. 3 Actual and predicted edgewise compression strength (ECT) values from validation data of 10-10-1 BPN (coefficient of determination = 94.5%) for a single wall board

Table 3 Model accuracy for predicting edgewise compression strength value of a single wall board

Modeling technique	MAE (N)		MAPE (%)		Description
	Training	Validation	Training	Validation	
Whitsitt	32.27	32.92	15.39	14.19	
Markström	31.49	27.72	14.97	16.59	k = 0.66, c = 3.33
Multiple regression	16.08	19.17	8.00	9.61	Satisfy all assumptions
10-10-1 BPN*	9.60	14.16	4.90	7.81	Delta rule, α of 0.1, Hyperbolic Tangent, 10,000 iterations
10-9-1 RBFN*	36.13	30.64	16.63	16.85	Delta rule, α of 0.1, Hyperbolic Tangent, 14,000 iterations

BPN = backpropagation neural network;
* number of input neurons/hidden neurons/output neurons;
MAE = mean absolute error; MAPE = mean absolute percentage error; α = learning rate

Table 4 Model accuracy for predicting edgewise compression strength value of a double wall board

Modeling technique	MAE (N)		MAPE (%)		Description
	Training	Validation	Training	Validation	
Whitsitt	161.15	187.08	30.87	31.68	
Markström	98.34	99.11	118.16	130.00	k = 0.57, c = 333
Polynomial regression	7.12	8.66	1.43	1.62	Satisfy all assumptions
16-2-1 BPN*	7.26	8.36	1.48	1.35	Delta rule, α of 0.1, Hyperbolic Tangent, 10,000 iterations
16-7-1 RBFN*	35.79	16.03	7.23	2.48	Delta rule, α of 0.1, Hyperbolic Tangent, 14,000 iterations

MAE = mean absolute error; MAPE = mean absolute percentage error; α = learning rate; BPN = backpropagation neural network;
* number of input neurons/hidden neurons/output neurons

However, in practice, this property is limited by finite learning samples, improper network training and a lack of some input variables. In fact, an RBFN is also a nonlinear model and has been proven as a universal approximator as well (Poggio and Girosi, 1989; Hartman et al., 1990; Park and Sandberg, 1991, 1993). However, based on its function in the hidden neurons, it performs a local fit to training data while the BPN model performs a global fit, leading to greater generalization capability of the BPN over the RBFN. For function approximation, the RBFN can achieve prediction accuracy comparable to the BPN, with 10 times or more data and more hidden units than the BPN. Plots of actual ECT values and predicted values from the validation data (Fig. 4) indicated that both the 16-2-1 BPN and stepwise polynomial regression models, with R^2 values greater than 99%, had high generalization capability and were selected for further study.

Predictive models for both single wall and double wall boards

The most accurate generalized predictive model for both single wall and double wall cardboard was the 16-12-1 BPN model with the delta rule and 10,000 learning iterations, followed closely by backward polynomial regression (Table 5). These results reinforced that the relationship between design factors and ECT values is not linear in nature. It was also apparent that the predictive model for both single wall and double wall cardboard was more complicated than the model for either single wall only or double wall only, as seen from the higher number (12) of hidden neurons. Fig. 5 reveals that both the stepwise polynomial regression and the 16-12-1 BPN models had R^2 values greater than 98%. Similar to the predictive models for single wall cardboard, the accuracy of the Whitsitt, Markström and 16-9-1 RBFN models deteriorated when the ECT values exceeded 400 N.

Determination of key design factors

An accurate model can be used for ECT estimation as well as for identification of the key design factors. Corrugated fiberboard manufacturers can focus on the key factors during design configuration selection to better control planning time and costs. The most accurate models for predicting the ECT of a single wall board only, a double wall board only, and both single and double wall boards, were used to identify the influential factors, as shown in Table 6.

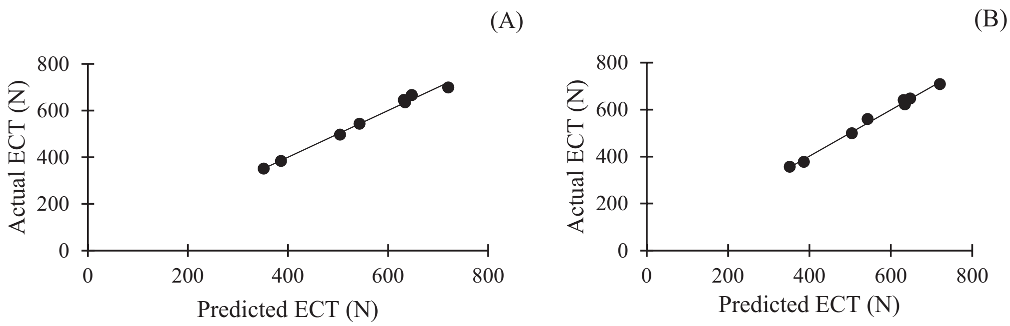
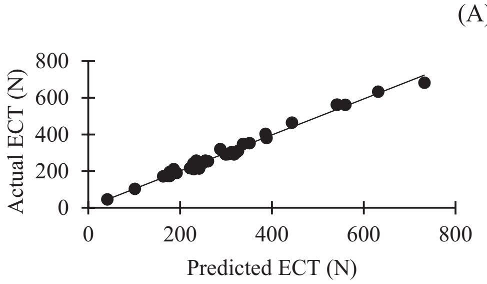


Fig. 4 Actual edgewise compression strength (ECT) and predicted ECT from validation data for a double wall board: (A)16-12-1 BPN (coefficient of determination, R^2 = 99.4%); (B) stepwise polynomial regression (R^2 = 99.1%)

Table 5 Model accuracy for predicting edgewise compression strength value of both single and double wall boards

Modeling technique	MAE (N)		MAPE (%)		Description
	Training	Validation	Training	Validation	
Whitsitt	68.25	36.64	19.29	13.17	
Markström	65.79	42.45	107.42	63.06	k = 0.57, c = 333
Polynomial regression	8.16	14.58	3.53	5.14	Satisfy all assumptions
16-12-1 BPN*	10.21	11.79	3.95	4.23	Delta rule, α of 0.1, Hyperbolic Tangent, 10,000 iterations
16-9-1 RBFN*	48.58	33.95	18.19	12.45	Delta rule, α of 0.1, Hyperbolic Tangent, 14,000 iterations

MAE = mean absolute error; MAPE = mean absolute percentage error; α = learning rate; BPN = backpropagation neural network;
* number of input neurons/hidden neurons/output neurons



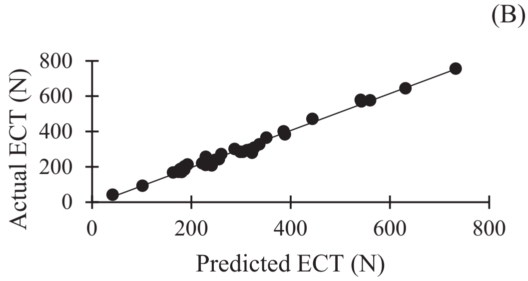


Fig. 5 Actual edgewise compression strength (ECT) and predicted ECT from validation data for both single and double wall boards: (A) 16-12-1 BPN model (coefficient of determination, R^2 = 98.8%); (B) stepwise polynomial regression (R^2 = 98.8%)

Table 6 Key design factors for predicting edgewise compression strength value

Modeling pattern	Model	Key design factors
Single wall	10-10-1 BPN*	Edge length of a corrugated board
		Basis weight of paper for flute 1
		Basis weight of paper for liner 2 or outer liner
Double wall	Stepwise polynomial regression	Basis weight of paper for flute 2
		Edge length of a corrugated board
		Basis weight of paper for liner 1 or inner liner
		Height of a corrugated board panel
		Basis weight of paper for liner 3 or outer liner
	16-2-1 BPN*	Edge length of a corrugated board
		Height of flute 1
		Paper type of liner 1 or inner liner
Both single and double wall	Stepwise polynomial regression	Basis weight of paper for liner 1 or inner liner
		Basis weight of paper for liner 2 or middle liner
		Height of flute 1
	16-9-1 BPN*	Basis weight of paper for liner 3 or outer liner
		Edge length of a corrugated board
		Basis weight of paper for flute 2

BPN = backpropagation neural network;
* number of input neurons/hidden neurons/output neurons

Analysis of Table 6 revealed that the common design factors strongly affecting the ECT value identified using the three modeling patterns were the edge length of the corrugated board and the basis weight of the paper for the related liner and flute. In other words, a small change in these design factors would lead to a large change in the ECT value. Notably, these changes would be in positive directions, that is: 1) the longer the edge length of a corrugated fiberboard, the greater the ECT value; and 2) the higher the basis weight of paper for the related liner and flute, the greater the ECT value.

Comparison of the edgewise compression strength prediction accuracy for three modeling patterns

A comparison of the ECT prediction accuracy for single wall, double wall and both single wall and double wall patterns (Table 7) indicated that the accuracy of the three modeling patterns differed little and they were all within the acceptable range for the industry (Biancolini and Brutti, 2003; Srihirun, 2008). Therefore, a model that could predict the ECT of both single and double wall boards (either the stepwise polynomial regression model or the 16-12-1 BPN model), may be further evaluated and selected by industry based on certain criteria such as the prediction accuracy and generalization capability, cost and time for development, cost and time for training and model update ability. However, Archaviboonyobu et al. (2020) have proven that the BPN model could accurately predict the corrugated fiberboard box compression strength with an R^2 value of 97%.

Table 7 Edgewise compression strength prediction accuracy of three modeling patterns

Modeling pattern	Model	MAE (N)		MAPE (%)	
		Training	Validation	Training	Validation
Single wall	10-10-1 BPN*	9.60	14.16	4.90	7.81
Double wall	Backward PR	7.12	8.66	1.43	1.62
	16-2-1 BPN*	7.26	8.36	1.48	1.35
Both single and double wall	Backward PR	8.16	14.58	3.53	5.14
	16-12-1 BPN*	10.21	11.79	3.95	4.23

MAE = mean absolute error; MAPE = mean absolute percentage error; PR = polynomial regression; BPN = backpropagation neural network;
* number of input neurons/hidden neurons/output neurons

The ECT prediction accuracy of the empirical predictive models for corrugated fiberboards, such as polynomial regression and BPN, were far better, compared with traditional models such as Whitsitt and Markström, regardless of the modeling pattern. The models for predicting the ECT of single wall and double wall cardboard at the same time had similar levels of prediction accuracy compared with the models for single wall or double wall cardboard only. Stepwise polynomial regression and 16-12-1 BPN were the two best predictive models for both single wall and double wall cardboard. The design factors that positively influenced the ECT value identified by both models were the basis weight of paper for the inner, middle and outer liners, the basis weight of the corrugated medium for the flute connected to the outer liner, the edge length of the corrugated board and the height of the flute connected to the inner liner. These four factors must be taken into careful consideration during the design and planning phases.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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