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Research Article

Compression Strength Prediction of RSC Corrugated Fiberboard Boxes by Artificial Neural Network using Multiple Materials and Design Parameters

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Abstract

Importance of the work: An accurate compression strength prediction model of RSC corrugated boxes could be used as an effective packaging design tool for industry.

Objectives: This research applied the material and design parameters for RSC corrugated box strength prediction using artificial backpropagation neural network modelling (BPN).

Materials and Methods: Total of 17 material and design factors from 630 commercially corrugated box samples in Thailand were recorded as input parameters along with their box compression test (BCT) values as output parameter. Data was randomly grouped as 80:10:10 during the model development for training set, testing set and validating set, respectively.

Results: The backpropagation neural network BPN17-13-1 model (inputs: hidden layers: output) provided the highest prediction performance with R^2 of 0.982 compared to calculations from simplified McKee's formula that having R^2 of 0.737. With regards to the material parameters, flute 2 as well as grammage of the liner 2 and medium 2 had a higher influence toward the predicted BCT ($p \leq 0.05$) compared to flute 1 and the grammage of the middle layer and outer liner. Fiber composition showed a lesser influence level than the grammage factor. For the packaging design, the contribution to BCT of height, length, and width of the boxes were 9.94%, 5.62% and 1.64 % respectively. Further, printing area contributed more toward BCT than printing position.

Main finding: The developed compression strength prediction model was more accurate than the simplified McKee's formula applied in the industry. Important material parameters were type of flute and grammage. Moreover, important packaging design parameters were box height, box length and printing area.

Introduction

Corrugated fiberboard containers have been established as the most economical and efficient distribution packaging for a multitude of products since their introduction in the early 1900s (Foster, 1997). These containers can be constructed to provide optimal compression strength towards any specific distribution lane by modifying the fiberboard structure and flute size; selecting optimum composition and grammage of the linerboard and corrugating medium; and/or maximizing the box strength through structural design (Dekker, 2005; Foster, 1997; Frank, 2014; Steadman, 2002). Additionally, the associated converting and distribution

processes also influence the compressive strength and the overall performance of the corrugated fiberboard boxes through their logistical journey (Dekker, 2005; Frank, 2014; Steadman 2002). Converting processes relate to those used during the production of the containers such as printing/decorating and die cutting and the distribution processes include ambient and physical factors such as humidity, temperature, stacking pattern and storage time. The relationship or influence levels of these multiple factors on the compressive strength of corrugated fiberboard containers is complex, making it challenging to predict and model. Understanding the influence of these factors toward the compression strength prediction of corrugated fiberboard boxes is essential since packaging engineers need to consider factor of safety during the design stage to prevent potential damage to the boxes and the products.

Lab based physical testing towards the determination of compression strength of corrugated fiberboard containers is important for internal quality control as well as towards assuring compliance with various distribution standards. Lab based testing is also critical towards addressing research objectives of optimizing the fiberboard component and to minimize the strength reduction potential. Relatedly, machine direction (MD) or cross direction (CD) compression strength of the corrugated fiberboard liners, cross direction edgewise compression strength of the corrugated fiberboard panels and the top-to-bottom compressive strength of the corrugated fiberboard containers are commonly elevated by ring crush test (RCT), edge crush test (ECT) and box compression test (BCT), respectively. Variation of up to 30% among different test standards may be observed for the compressive strength values and this can further impede the strength properties prediction (Steadman, 2002). Various studies have confirmed that RCT, ECT as well as other design parameters such as board caliper, box perimeter, shape and size of hand holes and ventilation holes are significantly associated with bending stiffness of the fiberboard panels and, ultimately, influence the strength properties including the BCT values of the containers (Killicutt and Landt, 1952; Mckee et al., 1963; Urbanik, 1997; Jinkarn et al., 2006; Urbanik and Frank, 2006; Singh et al., 2008; Sohrabpour and Hellström, 2010; Zhou et al., 2012; Opara and Pathare, 2014; Adamopoulos et al., 2016; Fadijia et al., 2016; Fadijia and Opara, 2017; Fadijia et al., 2018; Archaviboonyobul et al., 2020;).

Although physical testing using standard procedures provide useful BCT values for corrugated fiberboard containers, the major trade-offs include resources such as time and cost. Towards more effective decision making related to the engineering design concept, compression strength prediction of the corrugated fiberboard containers based on either linear or nonlinear mathematical models have been proposed (Jinkarn et al., 2006; Adamopoulos et

al., 2016; Archaviboonyobul et al., 2020, Chaveesuk et al., 2021, Gu et al., 2023). Parameters that are commonly included for the existing compression strength prediction formulas include RCT, ECT, flexural stiffness, box dimension, board caliper and flute types. It may also be noted here that most of the existing compression strength prediction models for corrugated fiberboard containers are based on Regular Slotted Container (RSC, FEFCO 201) style boxes. This is primarily due to the global adoption of this style of boxes resulting from the effective and efficient use of corrugated fiberboard as well as the generally acceptable performance when distributing packaged products through the commonly used logistical strategies. The RSC structural pattern is also simple compared to complex geometry of die-cut boxes.

Amongst the several existing compression strength prediction models, McKee's formula is one of the most commonly cited engineering models due to its acceptable approximation and simplicity (McKee et al., 1963). A simplified version of McKee's formula based on an empirical relationship between board caliper or board thickness, geometric mean flexural stiffness and edgewise compression of the board is presented in Equation 1 (McKee et al., 1963; Steadman, 2002). This simplified version of McKee's formula is particularly popular amongst engineers working at the design stage towards estimating corrugated fiberboard box strength in field use.

$$C = 5.8745 P_m \sqrt{Zt} \quad (1)$$

Where C is the box compression strength (kgf) and P_m is the Edge Crush Test (ECT)(kgf/cm) and Z is the box perimeter ($2 \times \text{length} + 2 \times \text{width}$) (cm) and t is the thickness of the corrugated board (cm).

Since the earlier compression strength prediction models were incapable of providing a detailed analysis of critical stress points of the structure and the related failure characteristics, numerical finite element method (FEM) or 3D digital image stereo-correlation techniques have been widely researched (Biancolini and Brutti, 2003; Urbanik and Saliklis, 2003; Nordstrand, 2004; Han and Park, 2007; Gospodinov et al., 2011; Viguié et al., 2011; Djilali et al., 2012; Beldie, Bronlund et al., 2014; Zhang et al., 2014; Åslund et al., 2015; Fadijia et al., 2018; Bai et al., 2019; Wang et al., 2019; Gu et al., 2020;). The FEM nonlinear model, which addresses the transfer of material behaviour from elastic to plastic, is very useful for structural analysis of the corrugated fiberboard and related containers. However, the complexity and non-uniform

material properties of corrugated fiberboard limits the prediction capability of this approach for effective industry practice (Adamopoulos et al., 2016).

Researchers have recently started exploring another promising modelling technique, the artificial neural network (ANN) approach, toward strength property prediction of the corrugated fiberboard panels and containers using tested data such as ECT or board stiffness with dimension of the board and boxes as the inputs (Adamopoulos et al., 2016; Archaviboonyobul, et al., 2020; Chaveesuk et al., 2021; Gu et al., 2023). However, none of the existing research has been conducted to identify the possibility of developing ANNs using a wider range of related parameters of the corrugated fiberboard such as fiber composition or grammage of the liner or medium, flute type, and printing appearance to predict the ultimate compression strength. Applying related multiple parameters simultaneously for compression strength prediction promises a higher accuracy than using a few laboratory tested input values. This concept is encouraging, and such prediction models can effectively support packaging engineers' goals of an optimal packaging cost to strength offset.

The working principle of ANNs can be found in many available literatures where the different networks of ANNs have been applied for pattern recognition, prediction and modelling (Fausett, 1994; Haykin, 1999; Dreiseitl and Machado, 2002; Kumar and Paliwal, 2009). Accuracy of the prediction models depend on the complexity of factors associated with the predicted values as well as the ANN structures (Chaveesuk et al., 2021; Gu et al., 2023). ANNs are an interconnected group of nodes inspired by a simplification of neurons in a human brain. ANNs increase their capability by recognizing the data and relationship patterns and are activated to learn through training, not from programming (Haykin, 1999). Theoretically, ANNs are composed of a sequence of layers: the input, hidden (artificial neurons or processing elements, PE), and output layers that are connected with coefficients (weights). ANNs work by connecting neurons in a network and attempting to minimize prediction error of the output through adjustable weighted inputs and non-linear transfer function. Backpropagation network (BPN) and radial basis function network (RBFN) are the two successful categories of ANNs applications. For comparison, BPN needs longer training time, but the results can better globalize whereas RBFN is generally powerful for text classification with shorter training time (Haykin, 1999; Dreiseitl and Machado, 2002).

This research aimed to explore the influence of multiple factors related to the corrugated fiberboard material and the design of corrugated fiberboard boxes on the top-to-bottom compression strength. The input values of all selected factors can be quickly noted by the packaging engineers without additional lab-based test. The final goal was to develop an

accurate BCT prediction model through ANN modelling and using data sets of parameters derived from commercially produced single-wall and double-wall corrugated fiberboard boxes in Thailand. The input data sets included corrugated fiberboard composition, liner and medium grammage, flute type, box dimension, printing area, and printing position. The influence levels of each factor on the predicted BCT were analysed. Backpropagation network (BPN), which is a feedforward multi-layer neural network was selected to design the prediction model because of its globalization capability.

Materials and methods

Materials

Commercially produced samples of corrugated fiberboard boxes included in this study were procured by corrugated manufacturers in Thailand. The single-wall and double-wall RSC style boxes included in this study (Fig.1C) were without any handholds or ventilation and were produced within Thailand for various commercial products. The boxes were randomly sampled and collected from different production batches involving various specifications related to the material and design parameters of the boxes. Input parameters that were taken into consideration for the BCT prediction models through this research are presented in Table 1 and Fig. 1. All samples were conditioned at 27 °C and 65% RH (Sigma-II NS II-Q, Japan) according to ISO 2233 (Packaging - Complete, Filled Transport Packages and Unit Loads - Conditioning for Testing) before the compression testing (ISO, 2000; Tappi, 2006). For this research, 27°C and 65% RH was used to represent hot and humid storage condition in Thailand and other tropical countries.

Box compression test data preparation

BCT (N) was an output parameter for this study and the related testing was conducted using a compression tester (Emerson Apparatus 7200, USA) in accordance with TAPPI T804 (Tappi, 2006). A total of 630 data series along with the BCT tested output parameters were selected for the ANN model development.

BCT calculation and ANN model development

For this study, BCT calculation was performed for corrugated fiberboard box samples under the validating set using McKee's simplified formula (Equation 1) and the calculation results were used as benchmarks with the laboratory test results. Moreover, the BCT prediction using data under the validating set derived from the most accurate ANN model was also compared with the test results. Prediction accuracy of McKee's simplified formula and ANN model were compared.

Backpropagation neural network (BPN) models were developed according to 630 data series. During the model development, all data series were broken down to 3 sets; 80%:10%:10% for the training set, the testing set and the validating set of the model, respectively. Training sets were used to train and adjust the predicting weights in the neural network. Testing sets were used to minimize over fitting and a validating set was used to validate the accuracy and to test the generalization capability of the model. The BPN network structure used towards this study is shown in Fig. 2.

During the model development, the number of potential hidden neurons were tested from 1-20. Learning rate was 0.01-1.00 with the momentum factor between 0.1-1.0 and the learning cycle, 1-2,000,000. Each cycle (1 epoch) covers the entire data available of the training set. The BPN artificial neural network models were developed utilizing the NeuralWorks Explorer software (Pittsburgh, PA, USA). The input parameters used are indicated in Table 1. The only output parameter of interest was the BCT value. For BPN, the hyperbolic tangent function (Equation 2) was chosen as an activation function.

$$f(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)} \quad (2)$$

Whereas x is the weighted sum of the input variable.

Prediction performance measurement

The prediction performance for the developed BPN models were expressed in terms of mean absolute error (MAE), root mean-squared error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R^2) (Equations 3-6).

$$MAE = \frac{\sum_{i=1}^n |o - t_i|}{n} \quad (3)$$

$$RMSE = \sqrt{\left(\frac{1}{n}\right) \times \sum_{i=1}^n (o - t)^2} \quad (4)$$

$$MAPE = \frac{\sum_{i=1}^n \left| \frac{o-t}{o} \right|}{n} \times 100 \quad (5)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^n (o-t)^2}{\sum_{i=1}^n (o-\bar{o})^2} \right) \quad (6)$$

Where o is the actual output and t is predicted output and n is the total number of training and testing patterns

Analysis of Influence level caused by input parameters toward BCT prediction

After the final BPN artificial neural network model was selected, the influencing level of the input parameters toward the output parameter were investigated through the Explain function of NeuralWorks Explorer software (Pittsburgh, PA, USA).

Results and Discussion

ANN neural network model development and prediction performance

The best neural network model for BCT prediction was BPN17-13-1, having the MAE of 243.63 N, RMSE of 308.86 N, MAPE of 7.99% and R^2 of 0.982 (Table 2). The prediction performance was tested using data under the validation set consisting of 127 BCT test results of corrugated fiberboard boxes. The BPN17-13-1 model is composed of 17 input parameters, 13 hidden layers and one output parameter of the BCT value. This novel model demonstrated better prediction performance than McKee's formula which provides the MAE of 1,322.03 N, RMSE of 1,826.76 N, MAPE of 37.16% and R^2 of 0.737 (Fig. 3). MAPE of the developed BPN17-13-1 model was in the same range with similar ANN prediction models that applied lab tested inputs such as ECT or stiffness (Chaveesuk et al., 2021; Gu et al., 2023).

In general, BPN is a universal approximator that can theoretically approximate nonlinear relationships (Haykin, 1999). Therefore, according to this result, ANN models via BPN could better predict the BCT due to the complex interaction of multiple parameters. The

simplified McKee's formula deploys ECT, board caliper, and box perimeter to predict the box compression strength and does not incorporate bending stiffness directly into the calculation. As a result of this trade-off for prediction simplicity, a higher predictive error might be observed. Despite applying the original McKee's formula, the prediction performance might not improve significantly since it excludes many related design parameters into the prediction such as box height, board composition and printing characteristics. McKee's model has some additional limitations because it was developed based on the square single-wall corrugated fiberboard boxes produced in the United States in the early 1960s which might not have included higher preforming fiberboard combinations (McKee et al., 1963; Steadman, 2002). Hence, the BCT prediction through the BPN17-13-1 model under this study was more accurate and more representative since it included both single-wall and double-wall fiberboard boxes. The model also took various material and design parameters into consideration synchronously.

Influence level of material and design parameters on compressive strength of corrugated fiberboard boxes

According to the results of this research, for double-wall corrugated fiberboard boxes, type of flute 2 exhibited the greatest influence level toward the BCT prediction followed by box height, grammage of inner liner 2, grammage of medium 2, type of flute 1, grammage of inner liner 1 and grammage of outer liner respectively (Fig. 4). However, for the single-wall boxes, box height, type of flute 1, grammage of inner liner 1 and grammage of outer liner were consecutively the major contributors. In most cases, grammage played better role than fiber composition especially the grammage of medium 2 and grammage of inner liner 2 as well as grammage of inner liner 1 that are glued together in the board structure (Fig.1). However, the outcome might be different if humidity were affected which was not in the analytical scope of this research.

As reflected in Fig. 1B, the optimal sequence of flutes in a double-wall structure requires the larger flute (flute 2), which provides a higher compressive resistance, to be placed on the inside and the smaller flute, which provides higher resistance to the potential flute damage during printing, to be placed on the outside. The observations from this research validate this commonly used industry practice.

Aligned with a previous study, this research also validates that the height of a corrugated fiberboard box contributes more to the BCT as compared to its length and width

(Adamopoulos et al., 2016). The influence levels of these important material and design parameters on the eventual compression strength of corrugated fiberboard boxes can be used by packaging engineers to optimize the cost associated with altering the design parameters and the resulting compression strength.

Effects of flute type

The developed BPN model indicates that type of flute 2 accounted for 13.78% for the BCT prediction (Fig. 4). According to the data series in the validation set, 64 data series were single-wall and another 63 data series were double-wall. During the model development, type of flute 2 parameter was equal 0 for a single-wall box and equal 1 or 2 for a double wall box having B or C flute as flute 2 respectively. All commercially produced double-wall corrugated fiberboard boxes in Thailand were B/C flute and hence the type of flute 2 were all coded as “2”. The BPN model developed in this study can be trained to have much higher BCT values for double-wall cases. As a result, a higher calculation weightage was adjusted for this parameter which resulted in the type of flute 2 parameter having the highest percentage on the influence level for BCT. For this study, the type of flute 2 parameter in the model represents the cases of double-wall corrugated fiberboard boxes and it can be concluded it influenced at least 13.78% increase of BCT prediction. Further data analysis of the corrugated fiberboard box samples with the same values as the other design parameters shows that the BCT increases by 35.7% when switching from a single-wall B flute to a double-wall BC flute box. However, a switch from a single-wall B flute to a larger single-wall C flute only increases the BCT by 17.2%. This conclusion is based on the commercially produced samples from Thailand and variation in results can be expected for samples obtained from other sources. The influences of flute size or flute type were found to be in agreement with previous studies (Schaepe and Popil, 2006; Urbanik and Frank, 2006; Sohrabpour and Hellström, 2010; Popil, 2012; Syed and Bhoomkar, 2013; Adamopoulos et al., 2016; Archaviboonyobul et al., 2020).

Effects of box dimension

Per the BPN artificial neural network model used in this study, the box dimensions significantly affected the BCT values. Box height contributed the most towards the change of BCT followed by the length and the width respectively. Numerous studies agree that the box perimeter as well as the length-to-width ratio effect its load carrying capability (Killicutt and Landt, 1952; Mckee et al., 1963; Kawanishi, 1989; Adamopoulos et al., 2016; Archaviboonyobul et al., 2020). A past research also indicates a negative contribution of

increasing box height or a lower length-to-height ratio on the compression strength (Zhou et al., 2012). The BPN model developed in this study showed that when the box height of the square footprint (300 cm × 300 cm) boxes increased from 200 cm to 300 cm, the BCT increased by 13.6%. However, when the height of the same samples increased further from 300 cm to 400 cm, the BCT increased only by 6.6%. The strength augmentation from the increasing box height in this study might have some boundary and the results could also be influenced by the flexural stiffness of the board panel with the interaction effects of other dimension parameters (length and width). Taller boxes could improve the load resistance but may introduce buckling at extreme height. According to the data series of this study, perimeter-to-height ratio or length-to-height ratio and BCT had low level of linear correlation (Fig. 5). This is because linear relationships are not strongly representative of these parameters because of their nonlinear behavior. The high predicted BCT accuracy arises from the ANN's ability to model complex nonlinear relationships among the parameters. However, understanding of linear relationship among dimension parameters and the BCT can be useful especially for packaging engineers to adjust the box dimension accommodating distribution requirement while maximizing the BCT value. Looking at the linear relationship of the dimension parameters of the boxes with the BCT, the results indicated that the box perimeter, box height, box length and box width, had higher coefficient of determination than perimeter-to-height ratio and length-to-height ratio. Samples under the validation set of this research have the average perimeter and box height of 1,590 mm and 276 mm respectively, with the average length-width-height ratio of 1.7:1.2:1. In addition, the length-to-height ratio and perimeter-to-height ratio of this data set ranged from 0.9-3.6 and 3.0-3.3 and this ratio seemed to convey a slightly negative correlation with the BCT indicating that the lower the ratio, the marginally greater the BCT.

Effects of grammage and fiber composition

For this study, BPN17-13-1 indicated that the grammage of the liner and medium of the corrugated fiberboard had a larger impact on the BCT of the boxes compared to their compositions (fully or partially recycled pulp). Grammage of inner liner 2 and grammage of medium 2 contributed 9.70% and 8.91% respectively toward the box compression strength which was higher than the influence level of grammage of inner liner 1 (6.68%) and grammage of outer liner (6.40%) (Table 1). For example, with the other parameters being the same, if grammage of inner liner 2 was increased from 125 g/m² to 175 g/m², the predicted BCT increased at an average of 5.70%. This phenomenon might be because corrugating medium 2 was the main top-load bearing structure, and the inner liner 2, which was glued to flute 2

performed the critical function of supporting the flute strength and integrity. However, bending failure could potentially take place if there was an unbalance in strength between the outer liner and the inner side of the corrugated board. The results were in accordance with laboratory test based results of several previous researches that mentioned the importance of grammage of the liner or corrugating medium on the board strength (Schaepe and Popil, 2006; Popil and Hojjatie, 2010; Popil, 2012; Syed and Bhoomkar, 2013). Some of the previous researches also found that the influence of liner or medium grammage on ECT was non-linear (Popil, 2012; Syed and Bhoomkar, 2013; Adamopoulos et al., 2016)

With regard to the liner composition, two types of liners and mediums were investigated including fully recycled pulp and partially recycled pulp. The influence percentage of the composition of all inner liners and as well as corrugating medium 2 was similar at approximately 4%. Interestingly, composition of the outer liner was slightly less significant compared to the inner liners. The influence percentage of the composition of corrugating medium 1 was marginal at around 1.29%. As a result, changing to fully recycled pulp for these two layers might be possible, however, the quality of the recycled pulp as well as the other strength properties need to be controlled or monitored.

Effects of printing area and printing position

All boxes included in this study were printed after fabricating the corrugated board using the flexography printing method. The printing area of the corrugated fiberboard box samples was classified into 3 groups: no printing; 0%-10%; and 10%-20 % printing, respectively. None of the samples had a printing area greater than 20%. Additionally, the printing positions were also separated into 3 groups: none; all sides and top; and all sides plus top and bottom. The analysis indicated that the printing area had a larger influence on the BCT compared to the printing position. Printing position was also the least influencing parameter toward BCT compared to other material and design parameters. According to the analysis performed, when changing the printing area from 0% to 20%, that predicted BCT decreased by 3.06% and when changing the printing position from printing on all sides to all sides plus top and bottom, the predicted BCT decreased by 0.08% only. This finding implied that additional printing on the top and bottom of the corrugated fiberboard boxes was not significantly affected the BCT since the maximum compression stress was normally found at the side panels.

Generally, high quality graphics always involve large amount of print coverage and multiple colors. The effect of printing on the reduction of BCT of the corrugated fiberboard boxes can be reduced through pre-printed liners (Cui et al., 2020). However, this approach

raises the concern of additional converting steps and higher cost. For pre-printed corrugated containers, the linerboards are printed before being combined with the single facer at the corrugator. This eliminates the prospect of crushing of the corrugated fiberboard due to the pressure applied during the printing process.

Conclusion

This study successfully achieved its goal of developing a BPN artificial neural network model to accurately predict the BCT of corrugated fiberboard boxes. The model developed is also capable of identifying the influence levels of multiple material and design input parameters related to the corrugated fiberboard boxes. The BPN 17-13-1 model demonstrated the highest predicted accuracy with the R^2 of 0.982 and the MAPE of 7.99% as compared to the simplified McKee's formula which had the R^2 of 0.737 and the MAPE of 37.16%. Although various materials and design parameters were considered, future research may mutually incorporate other factors into the BCT prediction models such as humidity, storage time, stacking patterns or distribution environment for better prediction performance.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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Table 1 Input parameters for compression strength prediction of corrugated boxes

Material and Design Parameters	Input Parameters	Code/ Units
Box dimension	Length (X1)	mm
	Width (X2)	mm
	Height (X3)	mm
Board composition	Composition of Outer Liner (X4)	fully recycled = 1; partly recycled= 2
	Grammage of Outer Liner (X5)	g/m
	Composition of Medium1 (X6)	fully recycled= 1; partly recycled= 2
	Grammage of Medium1 (X7)	g/m ²
	Type of Flute1 (X8)	B = 1, C = 2, E = 3
	Composition of Inner Liner1 (X9)	fully recycled = 1; partly recycled = 2
	Grammage of Inner Liner1 (X10)	g/m ²
	Composition of Medium2 (X11)	fully recycled = 1; partly recycled = 2
	Grammage of Medium2 (X12)	g/m ²
	Type of Flute2 (X13)	B = 1, C = 2
	Composition of Inner Liner2(X14)	fully recycled liner = 1; partly recycled liner=2
	Grammage of Inner Liner2 (X15)	g/m ²
Printing appearance	Printing Area (X16)	none =0, 1=1-10%, 2=10-20%
	Printing Position (X17)	none = 0; all sides panels = 1; all sides panels +top =2; all sides panels + top+ bottom =3

Table 2 Prediction performance of ANN models in the training set and the validating set

Model	Training set				Validating set			
	MAE	RMSE	MAPE	R ²	MAE	RMSE	MAPE	R ²
BPN 17-2-1	386.91	486.95	12.41%	0.955	481.79	604.27	14.46%	0.937
BPN 17-3-1	378.40	485.83	11.63%	0.956	468.24	586.15	14.11%	0.939
BPN 17-4-1	339.65	437.78	10.51%	0.964	414.26	553.32	13.30%	0.948
BPN 17-5-1	289.87	363.71	9.47%	0.975	377.42	476.52	11.63%	0.956
BPN 17-6-1	302.54	392.59	10.17%	0.970	396.37	516.13	12.66%	0.953
BPN 17-7-1	268.19	355.79	9.05%	0.976	332.44	427.66	10.25%	0.965
BPN 17-8-1	284.37	367.32	9.67%	0.974	370.57	499.33	10.87%	0.961
BPN 17-9-1	275.74	355.87	8.98%	0.976	326.65	417.78	10.58%	0.965
BPN 17-10-1	225.43	296.99	7.04%	0.983	318.56	405.39	10.38%	0.967
BPN 17-11-1	215.84	290.01	7.02%	0.984	341.60	442.84	10.40%	0.966
BPN 17-12-1	246.72	318.68	8.03%	0.981	350.66	461.96	10.49%	0.965
BPN 17-13-1	209.86	274.08	6.83%	0.986	243.63	308.86	7.99%	0.982
BPN 17-14-1	240.50	332.18	8.05%	0.979	356.55	504.89	12.33%	0.958
BPN 17-15-1	223.21	299.94	7.33%	0.983	302.54	392.59	10.17%	0.970
BPN 17-16-1	256.91	341.30	8.26%	0.978	398.90	535.66	12.84%	0.951
BPN 17-17-1	287.43	393.91	9.76%	0.973	389.14	536.52	12.80%	0.951
BPN 17-18-1	369.24	452.95	10.84%	0.961	438.32	567.79	13.44%	0.942
BPN 17-19-1	399.26	536.87	12.77%	0.952	479.45	599.54	14.57%	0.937
BPN 17-20-1	405.54	549.74	13.27%	0.949	486.84	617.55	14.79%	0.930

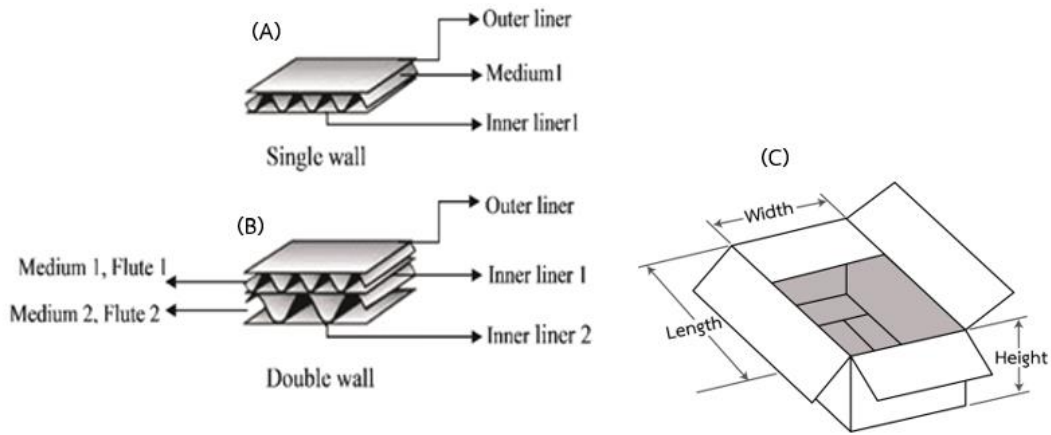


Fig. 1 Identification of corrugated fiberboard structure and dimension of RSC corrugated box;
(A) Single wall; (B) Double wall; (C) RSC corrugated box dimension

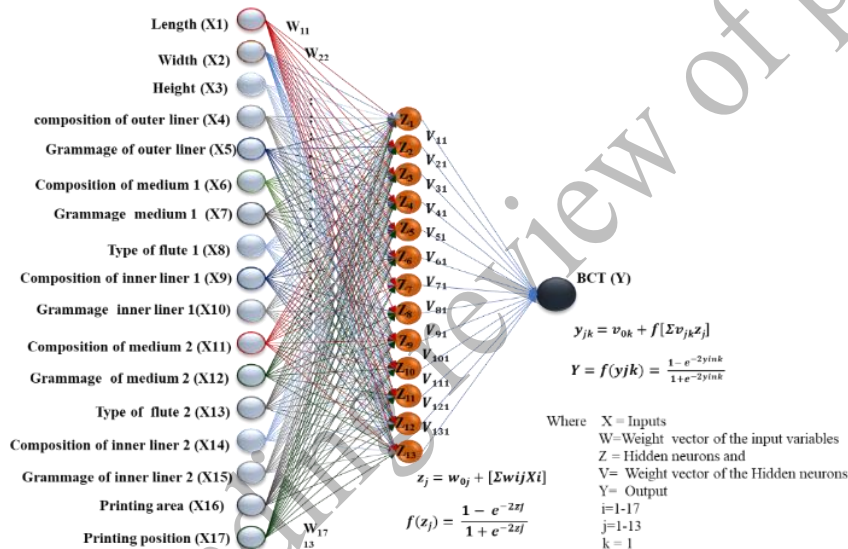


Fig. 2 BPN 17-13-1 network structure

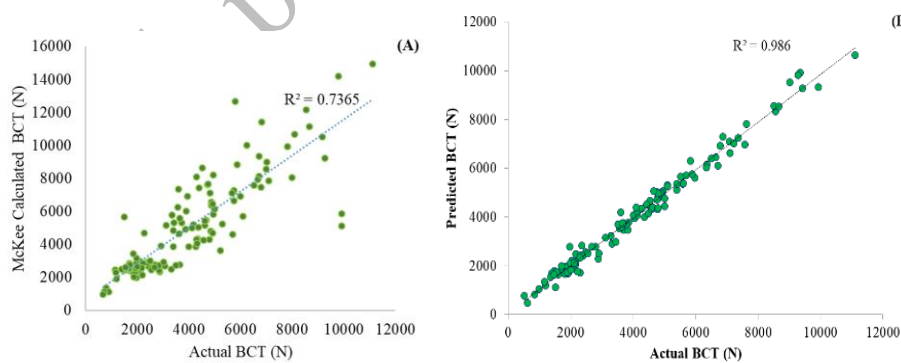


Fig. 3 Prediction performance; (A) McKee formula; (B) BPN 17-13-1 model

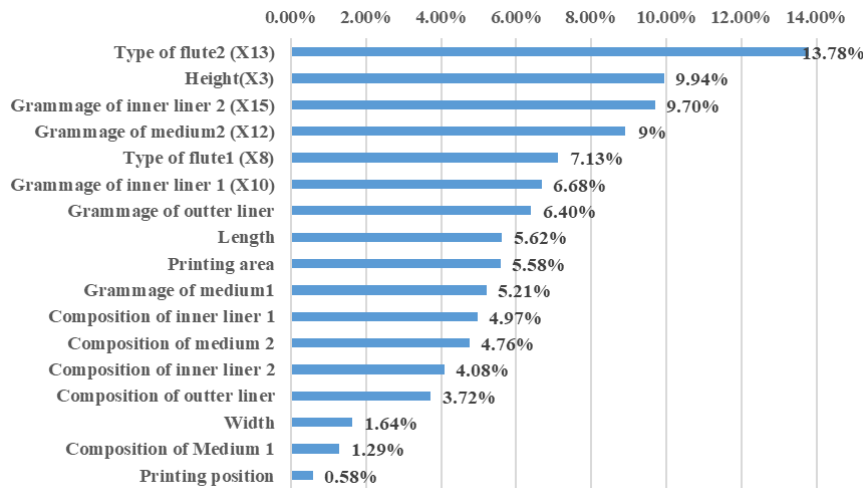


Fig. 4 Influence level of material and design parameters on compressive strength of corrugated fiberboard boxes.

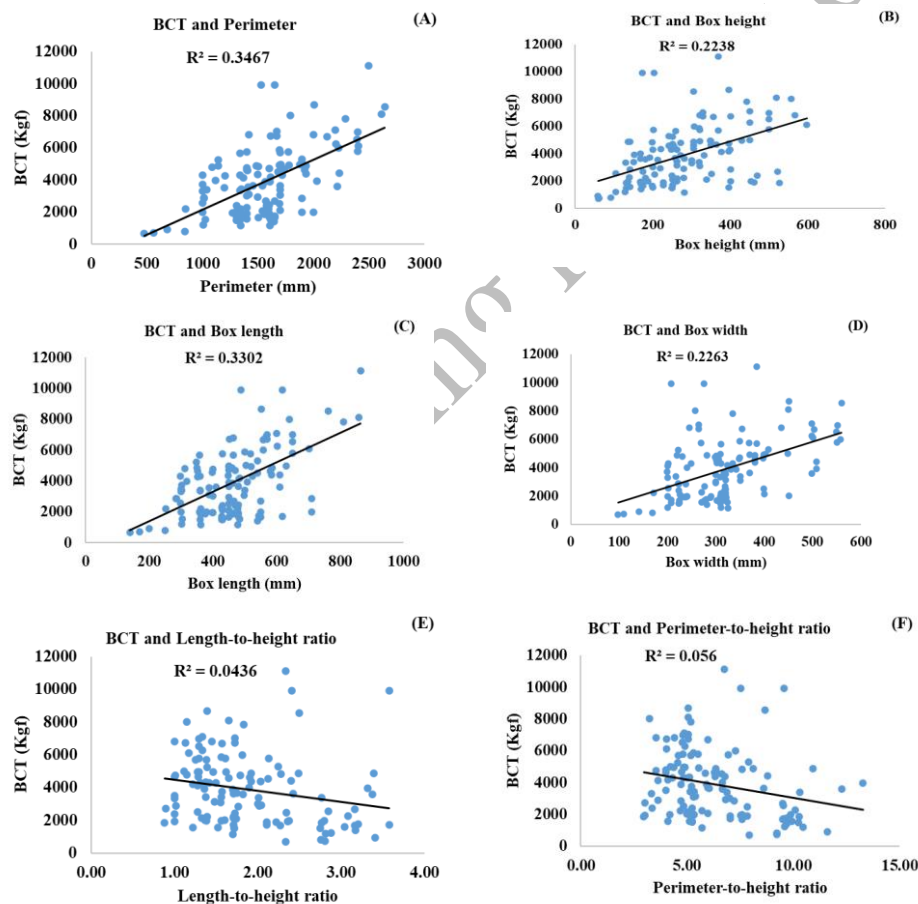


Fig. 5 Linear relationship of box dimension parameters on BCT: (A) BCT and Perimeter; (B) BCT and Box height; (C) BCT and Box length; (D) BCT and Box width; (E) BCT and Length-to-height ratio; (F) BCT and Perimeter-to height ratio