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Research article

Compression strength prediction of regular-slotted-container corrugated fiberboard boxes based on 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 regular-slotted-container (RSC) corrugated boxes could be used as an effective packaging design tool for industry.

Objectives: To apply material and design parameters for RSC corrugated box strength prediction using artificial backpropagation neural network modelling (BPN).

Materials and Methods: In total, 7 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 were randomly grouped during the model development based on a training set-to-test set-to-validation set ratio of 80:10:10, respectively.

Results: The backpropagation neural network BPN17-13-1 model (17 inputs, 13 hidden layers and 1 output) produced the highest prediction performance with a coefficient of determination (R^2) value of 0.982 compared to calculations based on the simplified McKee's formula that produced an R^2 value of 0.737. Of the material parameters, flute 2 as well as grammage of the liner 2 and medium 2 had a greater influence on the predicted BCT than flute 1 and the grammage of the middle layer and outer liner. Fiber composition had less influence than the grammage factor. In the packaging design, the contributions to BCT of the height, length and width of the boxes were 9.94%, 5.62% and 1.64% respectively. Furthermore, the printing area contributed more toward BCT than the printing position.

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

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Introduction

Corrugated fiberboard containers have been recognized as the most economical and efficient form of 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 toward any specific distribution lane by modifying the fiberboard structure and flute size; selecting the optimum composition and grammage of the linerboard and corrugating medium; or maximizing the box strength through structural design; or a mixture of these factors (Foster, 1997; Steadman, 2002; Dekker, 2005; Frank, 2014). Additionally, the associated conversion and distribution processes influence the compressive strength and the overall performance of the corrugated fiberboard boxes during their logistical journey (Steadman 2002; Dekker, 2005; Frank, 2014). Converting processes relate to those used during the production of the containers such as printing/decorating and die cutting, while 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 safety factors during the design stage to prevent potential damage to the boxes and the products.

Laboratory-based physical testing to determine the compression strength of corrugated fiberboard containers is important for internal quality control as well as assuring compliance with various distribution standards. In addition, laboratory-based testing is critical in addressing the research objectives of optimizing the fiberboard component and minimizing the strength reduction potential. In this regard, 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 have been reported for the compressive strength values and this can further impede strength properties prediction (Steadman, 2002). Various studies have confirmed that RCT and ECT, as well as other design parameters, such as board caliper, box perimeter, shape and size of hand holes and ventilation holes, are substantially associated with the 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 provides useful BCT values for corrugated fiberboard containers, the major trade-offs include resources such as time and cost. Compression strength prediction of the corrugated fiberboard containers based on either linear or nonlinear mathematical models have been proposed to aid in more effective decision making related to the engineering design concept (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. Notably, most of the existing compression strength prediction models for corrugated fiberboard containers are based on regular slotted container (RSC; FEFCO 201) style boxes. Primarily, this is due to the global adoption of this style of box, resulting from the effective and efficient use of corrugated fiberboard, as well as its generally acceptable performance when distributing packaged products through the commonly used logistical strategies. In addition, the RSC structural pattern is simple compared to the complex geometry of die-cut boxes.

Among 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 is presented in Eq. 1, based on an empirical relationship between board caliper or board thickness, geometric mean flexural stiffness and edgewise compression of the board (McKee et al., 1963; Steadman, 2002):

$$C = 5.8745 \times Pm \times \sqrt{Zt} \tag{1}$$

where C is the box compression strength (measured in kilogram-force, kgf) and Pm is the edge crush test (ECT) result (measured in kgf per centimeter), Z is the box perimeter (2 × length + 2 × width; measured in centimeters) and t is the thickness of the corrugated board (measured in centimeters).

This simplified version of McKee's formula is particularly popular amongst engineers working at the design stage for estimating corrugated fiberboard box strength in field use (Dekker, 2005).

Numerical finite element method (FEM) or 3D digital image stereo-correlation techniques have been widely researched to overcome the problem of the earlier compression strength prediction models being unable to provide a detailed analysis of critical stress points of the structure and the related failure characteristics (Beldie et al., 2001; 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; 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 behavior 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 limit the prediction capability of this approach for effective industry practice (Adamopoulos et al., 2016).

More recently, researchers have started exploring another promising modelling technique, the artificial neural network (ANN) approach, for strength property prediction of corrugated fiberboard panels and containers, using tested data such as ECT or board stiffness with the dimensions 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 was conducted to identify the possibility of developing ANNs using a wider range of related parameters to predict the ultimate compression strength of the corrugated fiberboard such as fiber composition or grammage of the liner or medium, flute type and printing appearance. Applying related multiple parameters simultaneously for compression strength prediction should be more accurate than using a few laboratory tested input values. This concept is encouraging, as such prediction models could effectively support the packaging engineering goals of an optimal packaging cost to strength offset.

The working principle of ANNs can be found in many available published articles, where the different networks of ANNs have been applied for pattern recognition, prediction and modelling (Fausett, 1994; Haykin, 1999; Dreiseitll and Machado, 2002; Kumar and Paliwal, 2009). In theory, ANNs are composed of a sequence of layers—the input, hidden (artificial neurons or processing elements, PE) and output layers—that are connected by coefficients (weights). ANNs work by connecting neurons in a network and attempting to minimize the prediction error of the output through adjustable weighted inputs and non-linear transfer function. The accuracy of the prediction models depends 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). The backpropagation network (BPN) and radial basis function network (RBFN) categories are two types of ANN applications that have been applied successfully, with a BPN needing a longer training time, but the results can be better globalized, whereas RBFN is generally powerful for text classification with a shorter training time (Haykin, 1999; Dreiseitll and Machado, 2002).

The current 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 the factors considered are readily measured by packaging engineers without requiring additional laboratory testing. The goal was to develop an accurate BCT prediction model through ANN modelling and using datasets of parameters derived from commercially produced, single-wall and double-wall corrugated fiberboard boxes in Thailand. The BPN approach (a feedforward multi-layer neural network) was selected to design the prediction model because of its globalization capability.

Materials and Methods

Materials

The commercially produced samples of corrugated fiberboard boxes were procured from corrugated manufacturers in Thailand. The tested single-wall and double-wall RSC style boxes (Fig.1C) had no 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 27ºC and 65% relative humidity (RH; Sigma-II NS II-Q; Japan) according to ISO 2233 (2000) before compression testing (ISO, 2000; Tappi, 2006). For this research, 27°C and 65% RH was used to represent the hot, humid storage conditions in Thailand and other tropical countries.

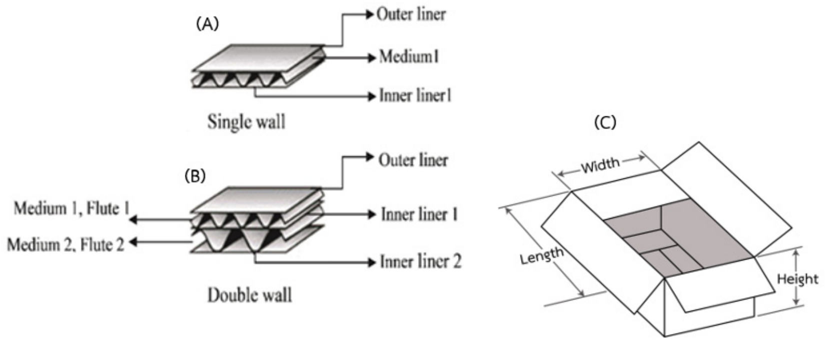

Fig. 1 Corrugated fiberboard structure and dimensions of regular-slotted-container (RSC) corrugated box: (A) single wall; (B) double wall; (C) dimensions

Table 1 Input parameters for compression strength prediction of corrugated boxes

Material and design parameter	Input parameter (code)	Coding (units)
Box dimension	Length (X1)	(mm)
	Width (X2)	(mm)
	Height (X3)	(mm)
Board composition	Outer liner composition (X4)	Fully recycled = 1; partly recycled= 2
	Outer liner grammage (X5)	(g/m^2)
	Medium 1 composition (X6)	Fully recycled= 1; partly recycled= 2
	Medium 1 grammage (X7)	(g/m^2)
	Type of Flute 1 (X8)	B = 1, C = 2, E = 3
	Inner liner 1 composition (X9)	Fully recycled = 1; partly recycled = 2
	Inner liner 1 grammage (X10)	(g/m^2)
	Medium 2 composition (X11)	Fully recycled = 1; partly recycled = 2
	Medium 2 grammage (X12)	(g/m^2)
	Type of Flute 2 (X13)	B = 1, C = 2
	Inner liner 2 composition (X14)	Fully recycled liner = 1; partly recycled liner=2
	Inner liner 2 grammage (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

Box compression test data preparation

The BCT (measured in newtons) was used as the output parameter for this study and the related testing was conducted using a compression tester (Emerson Apparatus 7200; USA) in accordance with TAPPI (2006). In total, 630 data series including the BCT tested output parameters were selected for the ANN model development.

Box compression test calculation and artificial neural network model development

The BCT calculation was performed for the corrugated fiberboard box samples in the validation set using McKee's simplified formula (Equation 1), with the results being used as benchmarks with the laboratory test results. In addition, the BCT prediction using the validation dataset derived from the most accurate ANN model was compared with the test results. The prediction accuracy of McKee's simplified formula and the ANN model was compared.

BPN models were developed using the 630 data series. During the model development, all data series were broken down into three sets, with 80%,10% and 10% for the training, the test and validation sets, respectively. The training sets were used to train and adjust the prediction weights in the neural network. The test sets were used to minimize overfitting and the validation set was used to validate the accuracy and to test the generalization capability of the model. The BPN network structure used is shown in Fig. 2.

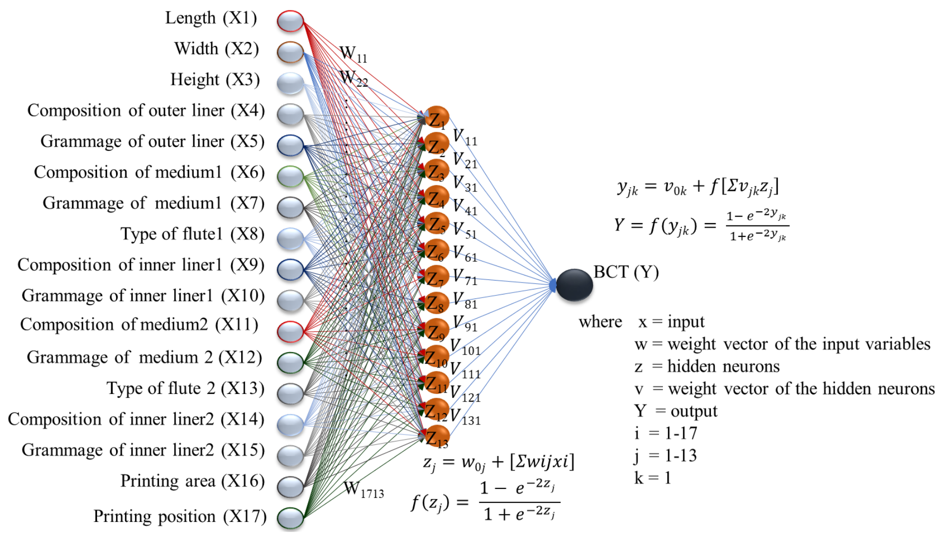

Fig. 2 BPN 17-13-1 network structure, where BCT = box container test

During the model development, the number of potential hidden neurons was tested in the range 1–20, the 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) covered the entire data in the training set. The BPN artificial neural network models were developed utilizing the NeuralWorks Explorer software (USA). The input parameters used are provided in Table 1. The only output parameter of interest was the BCT value. For BPN, the hyperbolic tangent function (Eq. 2) was chosen as the activation function:

$$f(x) = [1 - exp(^{-2x})]/[1+ exp(^{-2x})] \quad (2)$$

where 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), as shown in Eq. 3–6.

$$\mathrm{MAE} = \Sigma_{i=1}^{n} |\mathrm{o} - \mathrm{t}|/\mathrm{n} \quad (3)$$

$$\mathrm{RMSE} = \sqrt{(1/n) \times \Sigma_{i=1}^{n}(\mathrm{o} - \mathrm{t})^2} \quad (4)$$

$$\mathrm{MAPE} = [\Sigma_{i=1}^{n} | [\mathrm{o} - \mathrm{t}]/\mathrm{o}|]/\mathrm{n}] \times 100 \quad (5)$$

$$R^2 = 1 - [\Sigma_{i=1}^{n}(o - t)^2 / \Sigma_{i=1}^{n}(o - \bar{o})^2] \quad (6)$$

where o is the actual output, t is the predicted output and n is the total number of training and test patterns.

Analysis of influence level caused by input parameters toward box container test prediction

After the final BPN artificial neural network model had been selected, the influence levels of the input parameters on the output parameter were investigated using the Explain function in the NeuralWorks Explorer software.

Results and Discussion

Artificial neural network model development and prediction performance

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

Table 2 Prediction performance of artificial neural network models in training and validation sets

Model	Training set				Validation 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

MAE = mean absolute error; RMSE = root mean-squared error; MAPE = mean absolute percentage error; R^2 = coefficient of determination.

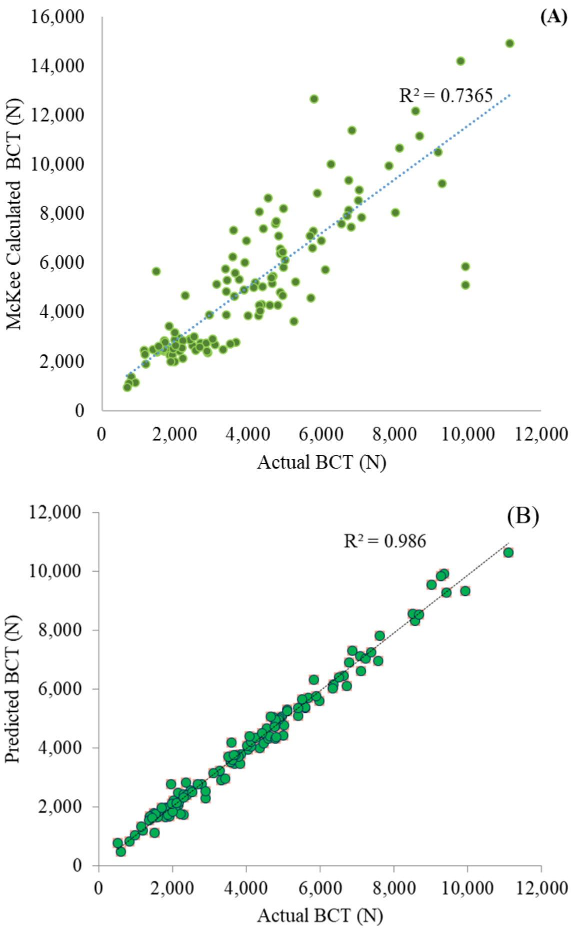

Fig. 3 Prediction performance based on box compression test (BCT): (A) McKee formula; (B) BPN 17-13-1 model

In general, BPN is a universal approximator that can theoretically approximate nonlinear relationships (Haykin, 1999). Therefore, based on the current result, ANN models using BPN could better predict the BCT due to the complex interaction of multiple parameters. The simplified McKee's formula (Eq. 1) uses 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 greatly, since it excludes many related design parameters from the prediction such as box height, board composition and printing characteristics. McKee's model has some additional limitations because it was developed based on square, single-wall corrugated fiberboard boxes produced in the USA in the early 1960s that might not have included higher preforming fiberboard combinations (Mckee et al., 1963; Steadman, 2002). Hence, the BCT prediction based on the BPN17-13-1 model was more accurate and more generally applicable since it included both single-wall and double-wall fiberboard boxes. Furthermore, the model took into account various material and design parameters synchronously.

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

Based on the current results for double-wall corrugated fiberboard boxes, type of flute 2 had the greatest influence on 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, respectively, were the major contributors. In most cases, grammage had a greater role than fiber composition, especially the grammage of medium 2, grammage of inner liner 2, and the grammage of inner liner 1 that are glued together in the board structure (Fig.1). However, the outcome might have been different if the RH value were to affect the measurements, which was not considered in the current study.

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, with the smaller flute (which provides higher resistance to potential flute damage during printing) placed on the outside. The current results validated this commonly used industry practice.

The current results were consistent with Adamopoulos et al. (2016), who reported that the height of a corrugated fiberboard box contributed more to the BCT than its length and width. 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 indicated that the type of flute 2 accounted for 13.78% of the BCT prediction (Fig. 4). Based on the validation dataset, there 64 data series of the single-wall and 63 data series of double-wall types. During the model development, the type of flute 2 parameter was set to 0 for a single-wall box and to 1 or 2 for a double wall box having a B or C flute as flute 2, respectively. All commercially produced double-wall corrugated fiberboard boxes in Thailand use the B or C flute type; hence, the type of flute 2 parameter was always coded as 2. The BPN model developed in the current study can be trained to have much higher BCT values for double-wall cases. As a result, a higher calculation weight was used for this parameter, resulting in the type of flute 2 parameter having the highest percentage influence in BCT, specifically at least a 13.78% increase in the BCT prediction. Further data analysis of the corrugated fiberboard box samples with the same values as the other design parameters showed that the BCT increased 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 increased the BCT by 17.2%. however, these results were based on commercially produced samples in Thailand;

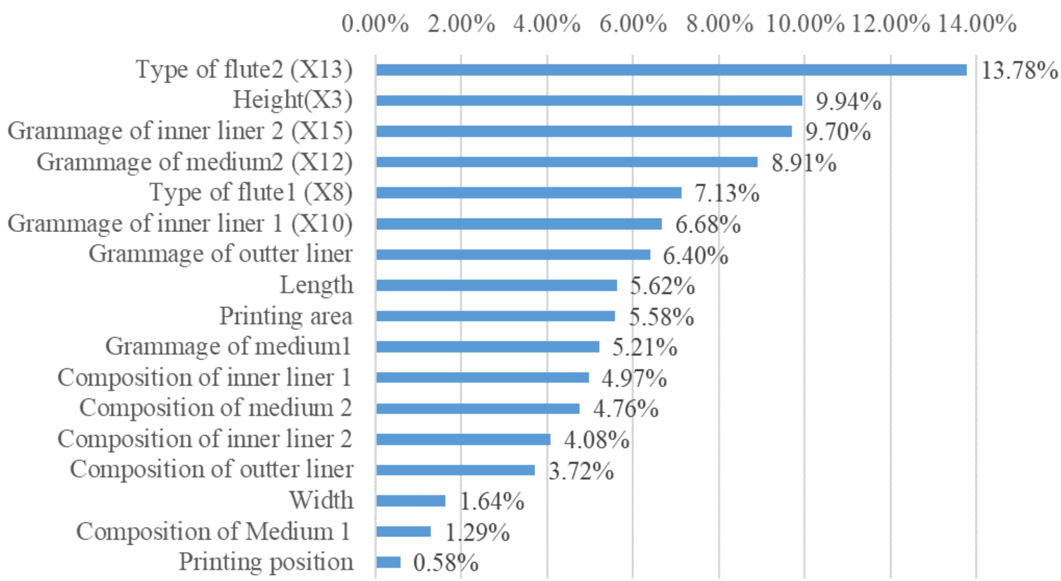

Fig. 4 Influence of material and design parameters on compressive strength of corrugated fiberboard boxes

thus, variation in results could be expected for samples obtained from other sources. The influence of different flute sizes or flute types were in agreement with other 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 dimensions

Based on the current results for the BPN ANN model, the box dimensions greatly affected the BCT values. Box height contributed the most towards the change in BCT, followed by box length and box width, respectively. Numerous studies reported that the box perimeter as well as the length-to-width ratio affected its load carrying capability (Killicutt and Landt, 1952; Mckee et al., 1963; Kawanishi, 1989; Adamopoulos et al., 2016; Archaviboonyobul et al., 2020), while Zhou et al. (2012) reported a negative contribution to the compression strength from increasing box height or lowering the length-to-height ratio. Based on the current BPN model, 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 might have some boundaries, with the results perhaps being influenced by the flexural stiffness of the board panel and interaction effects with other dimension parameters (length and width). Taller boxes could improve the load resistance but may introduce buckling at extreme heights. Based on the data series in the current study, the perimeter-to-height ratio or length-to-height ratio and BCT had low levels of linear correlation (Fig. 5)

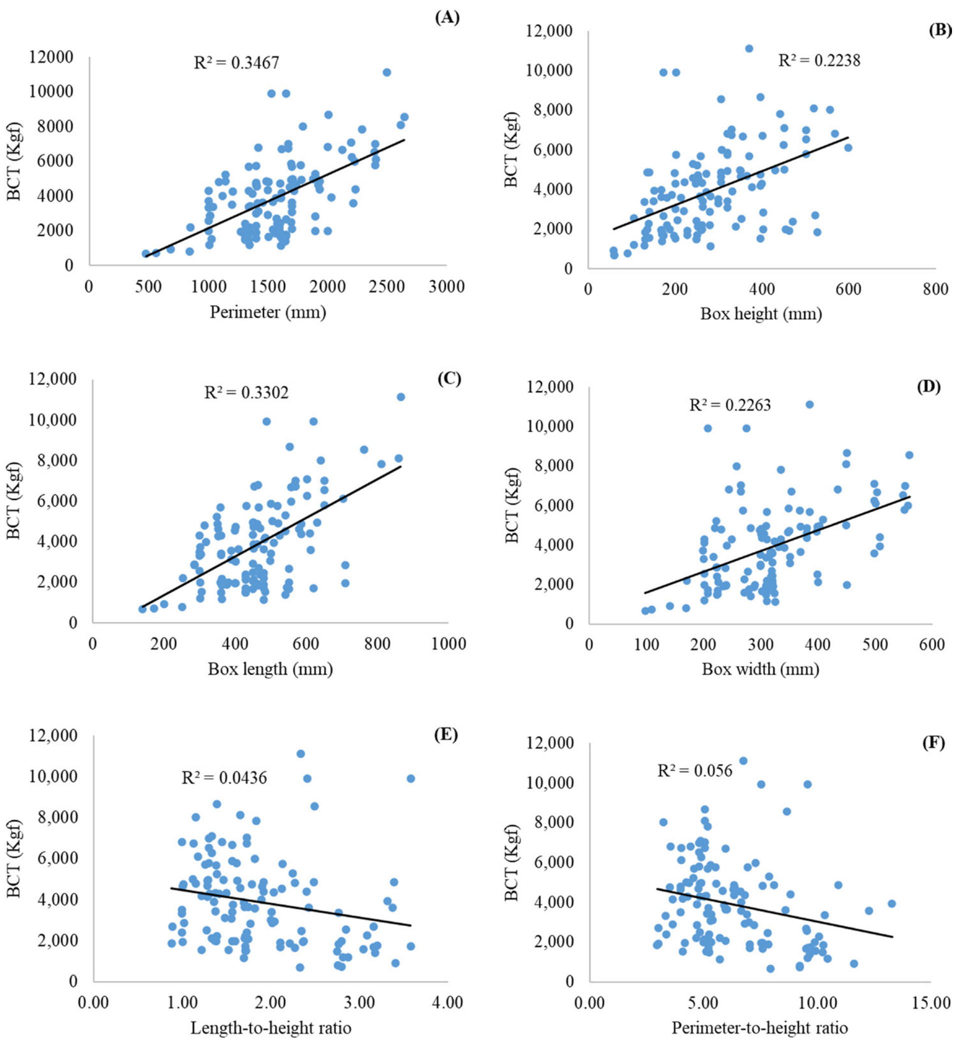

Fig. 5 Linear relationship of box dimension parameters in box compression test (BCT): (A) BCT versus perimeter; (B) BCT versus box height; (C) BCT versus box length; (D) BCT versus box width; (E) BCT versus length-to-height ratio; (F) BCT versus perimeter-to height ratio, where R^2 = coefficient of determination

because these parameters exhibit nonlinear behavior. The high predicted BCT accuracy was the result of the ANN model including complex nonlinear relationships among the parameters. However, understanding the linear relationship among the dimension parameters and the BCT can be useful especially for packaging engineers in adjusting the box dimensions to accommodate distribution requirements while maximizing the BCT value. Based on the linear relationship of the dimension parameters of the boxes with the BCT, the current results indicated that the box perimeter, box height, box length and box width, had higher R^2 values than for the perimeter-to-height ratio and length-to-height ratio. Samples in the validation dataset had average perimeter and box height values of 1,590 mm and 276 mm, respectively, with an average length-to-width-to-height ratio of 1.7:1.2:1. In addition, the length-to-height and perimeter-to-height ratios in this dataset were in the ranges 0.9–3.6 and 3.0–13.3, respectively, and this ratio seemed to have a slightly negative correlation with the BCT, indicating that the lower the ratio, the marginally greater the BCT.

Effects of grammage and fiber composition

In the BPN17-13-1 model, the grammage of the liner and medium of the corrugated fiberboard had a larger impact on the BCT of the boxes compared to their composition (fully or partially recycled pulp). The values for grammage of inner liner 2 and grammage of medium 2 contributed 9.70% and 8.91%, respectively, to the box compression strength, which was higher than the contribution by the values for grammage of inner liner 1 (6.68%) and grammage of outer liner (6.40%) (Fig. 4). For example, with the other parameters being the same, if grammage of inner liner 2 were increased from 125 g/m^2 to 175 g/m^2, the predicted BCT would increase at an average of 5.70%, perhaps because corrugating medium 2 was the main top-load bearing structure and the inner liner 2 (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 imbalance in strength between the outer liner and the inner side of the corrugated board. These results were in accordance with the laboratory-based test results reported elsewhere that mentioned the importance of the grammage of the liner or corrugating medium on board strength (Schaepe and Popil, 2006; Popil and Hojjatie, 2010; Popil, 2012; Syed and Bhoomkar, 2013). Furthermore, some researchers have reported that the influence of liner or medium grammage on ECT was non-linear (Popil, 2012; Syed and Bhoomkar, 2013; Adamopoulos et al., 2016)

Two types of liners and mediums were investigated: 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%. Notably, the composition of the outer liner was slightly less important than 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 need to be controlled or monitored, as well as the other strength properties.

Effects of printing area and printing position

All the fabricated corrugated board boxes were printed using the flexography printing method. The printing area of the corrugated fiberboard box samples was classified into three groups: no printing; 0%–10%; and 10%–20% printing. None of the samples had a printing area greater than 20% of their outside surface area. Additionally, the printing positions were separated into three 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 than the printing position. In addition, the printing position was the least influencing parameter in the BCT compared to the other material and design parameters. Based on the analysis, changing the printing area from 0% to 20%, decreased the predicted BCT by 3.06%. Furthermore, changing the printing position from printing on all sides to all sides plus top and bottom, the predicted BCT decreased by only 0.08%, implying that additional printing on the top and bottom of the corrugated fiberboard boxes did not greatly affect the BCT results, since the maximum compression stress was normally on the side panels.

Generally, high quality graphics involve large amounts of print coverage and multiple colors. The effect of printing on the reduction of BCT of the corrugated fiberboard boxes could be reduced by using pre-printed liners (Cui et al., 2020). However, this approach raises concerns associated with additional conversion steps and higher costs. With pre-printed corrugated containers, the linerboards are printed before being combined with the single facer at the corrugator. This eliminates the prospect of crushing the corrugated fiberboard due to the pressure applied during the printing process.

Conclusion

This study successfully achieved its goal of developing a BPN ANN model to accurately predict the BCT for corrugated fiberboard boxes. In addition, the model developed was 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 had the highest predicted accuracy with values for R^2 and MAPE of 0.982 and the 7.99%, respectively, compared to the simplified McKee's formula (R^2 and MAPE of 0.737 and 37.16%, respectively). Although various materials and design parameters were considered, future research could improve the prediction performance by incorporating other factors into the BCT prediction models such as humidity, storage time, stacking patterns or distribution environment.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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