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# PREDICTION OF PACKAGING LIFE-CYCLE DESIGN PERFORMANCE

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## ABSTRACT

We develop a back-propagation neural network (BPN) to predict the life-cycle design performance for transport packaging. The BPN is constructed and trained on the packaging design attributes to detect hidden relationships among historical or pre-existing life-cycle design data to predict a new concept design through supervised learning, by minimizing the squared difference between the actual and the predicted life-cycle design performance. To this end, the designer could use the predicted life-cycle design in a trade-off analysis and concept selection for a potential packaging design. A case example is used to illustrate the methodology.

## INTRODUCTION

Life-cycle design for transport packaging uses a decision-making methodology during the conceptual stage, by considering the packaging performance, environmental impairment and cost requirements [5]. Presently, life-cycle inventory and cost-analysis tools applied to packaging products offer guidelines for achieving better environmental design and management. However, these approaches can be expensive, time-consuming and labor intensive, and somewhat prohibitive from a modeling viewpoint because diverse and numerous ideas and quality information in the conceptual design phase may be difficult during multi-dimensional multi-attribute trade-offs.

In this paper, an artificial neural network (ANN) technique is employed to make better predictions for life-cycle design performance for *transport packaging* at the conceptual stage. A major advantage of ANN over other analytical tools is that ANN attempts to fit curves through data without utilizing a predetermined function with free parameters, resulting in quick data generation and transfer function with reasonable accuracy. The popular back-propagation (BP) learning algorithm is used to develop a robust system. This algorithm is based on learning capability of known information to predict life-cycle design performance for transport packaging. The BP neural network is constructed and trained on the packaging design attributes to detect hidden relationships among historical or pre-existing life-cycle design data to predict a new concept design through supervised learning, by minimizing the squared difference between the actual and the predicted life-cycle design.

A few attempts have been made in applying neural network for product designs. Hsiao and Huang [3] constructed a BP neural network to analyze the relationships between product forms and adjective image words at the design stage. Seo *et al.* [13] [14] developed an approximate method for providing the preliminary life cycle cost during conceptual design. However, to the best of our knowledge, while there are few studies that are conducted on cushioning-type packaging, none of the studies use ANN for life-cycle design of transport packaging. Zhang *et al.* [16] and Zhang and Fuh [17] proposed a BP neural network for estimating packaging costs. Lye *et al.* [11] proposed a design methodology for the design of protective packaging buffer configurations. In a series of papers, Liang *et al.* [6] [7] [8], and Liang and Zhou [9] modeled a BP neural network to identify nonlinear characteristics in cushioning type packaging. A combination approach between a fuzzy-adaptive BP and genetic algorithm is developed in their model to

increase the effectiveness and to enhance the adaptivity to be more practical for the real world applications of packaging dynamics.

## BACK-PROPAGATION NEURAL NETWORK (BPN)

BPN is a forward-supervised learning network with an input layer, an output layer, and some hidden layers. A neuron simply computes the sum of their weighted inputs, adds its bias to the sum, and passes the results through its transfer function (e.g. linear, Tan-sigmoid, or log-sigmoid). In a BPN, there are three stages involved: (1) the feed-forward of the input training pattern, (2) the calculation of the associated error, and (3) the adjustment of the weights. It starts with assigning random values to all the weights. An input is then presented to the network and the output from each neuron in each layer is propagated forward through the entire network to reach an actual output. The weights among the neurons on the output and hidden layers in the supervised learning network are adjusted by the deviation between the expected value of the input patterns and the actual outputs obtained from the network. However, the changes in weights involve a momentum factor ( $\mathbf{b}$ ) and a learning rate ( $\mathbf{a}$ ). Momentum helps the network avoid getting stuck in shallow minima that would prevent the network from finding a lower error solution. Learning rate is aimed to make the network learn quickly. The process of weight adjustment is performed layer by layer, and the training sets are used repeatedly during the training process. The individual weight ( $w_{ik}$ ) is updated by using the following formula:

$$W_{(t+1)} = W_{(t)} + \mathbf{a} \left( \frac{\partial E}{\partial W} \right) \Bigg|_{W_{(t)}} + \mathbf{b} (W_{(t)} - W_{(t-1)}) \quad (1)$$

The learning process may take a few thousands rounds (epochs), repeating the feed-forward and error back-propagation, before the predicted output gets very close to the target value. It is continued until the prediction error across all training samples in a weight matrix is minimized to a reasonable range or stabilized (convergence). In this way, the error is minimized and the network is said to have learnt.

One major problem in developing a BPN is the tendency to “over fit” the training data. Over fitting is dangerous because it can easily lead to predictions that are far beyond the range of the training data with many of the common types of neural nets. To avoid over fitting, a large number of training data should be provided. However, in some real-world conditions, since such data is only available at a great expense, a small number and spreading out (sparse) data may be observed. The sample observation may not be leveraged maximally, resulting in high variance and bias among the samples. In such cases, using re-sampling approach, which will allow the network model to be built on the entire observation samples, can solve this problem.

## NETWORK VARIABLE CONSIDERATIONS

### Life-cycle design performances (*Dependent variables*)

Here, there are three key elements used for measuring life-cycle design performance of transport packaging.

*Economic costs:* Economic costs can be defined in the form of monetary cost of production and disposal that make certain impacts in the price of packages and the price of solid waste management; hence the total cost for packaging is simply resulted by costs of acquisition of raw materials, forming or manufacturing the material into a finished package, and finally waste disposal.

*Environmental costs:* Environmental costs include land and ecosystem damages, environmental externalities, which are not reflected in the price of packaging. Usually, environmental costs are not monetized. Economists have developed several valuation methods in current environmental cost studies. The most used approach is the *control cost* method [1] [14]. This valuation method infers the value of environmental impacts by examining the pattern of public decisions recorded in regulations, laws, and court rulings. By determining the cost of the controls mandated by these decisions and their benefits in terms of environmental effects, the dollar value of those effects can be estimated.

*Packaging performance:* Although one of the simplest methods for evaluating packaging performance is a scoreboard approach [2] [10] [12] in which subjective rating of packaging performance is assigned, the outcome obtained from this approach can, however, be sensitive to which one the respondent may select. The subjective rating can be advantageous, as it also reflects the feelings about a package. Since packaging performance is defined by the functional requirements that significantly impact the package design, in the case of transport packaging, it should provide durability for a longer use life in favor of multiple uses. Thus, it is important that the weighting of packaging performance be evaluated based on the ability that a transport packaging survives a large number of trip life cycles without failure. Singh and Walker [15] have developed a systematic evaluation tool to be used in this manner. Packaging performance is defined in mathematical terms as

$$\left[ \frac{N}{C(WT_0) \times (1 + 0.5 \left[ \frac{WT - WT_0}{WT_0} \right])} \right] \times 100 \quad (2)$$

Packaging performance is directly proportional to the average number of individual test cycles before failure and inversely proportional to the price and weight of a transport packaging. The higher packaging performance value represents a better performance indicating that a transport packaging can survive the large number of trips before failure.

### **Package design attributes (*Independent variables*)**

Package design attributes (PDAs) are used as the independent variables in the network model. Though many significant design attributes for conceptual packaging have been identified, in this study however, the selected PDAs are defined below.

*Material type and content:* At the design phase, the material selection greatly impacts the product design. Not only does the use of materials indicate the total amount of container material used, it also indicates the ultimate operations for the material disposal. Transport packages and containers may come in a large variety of materials for different applications. These include plastic, corrugated cardboard and fiberboard, wood, and steel [4]. However, combinations of different materials can also be identified. Hence, the material selection attribute can be classified as: (1) mass percentage of woods (PDA<sub>1</sub>), (2) mass percentage of plastics (PDA<sub>2</sub>), (3) mass percentage of metals (PDA<sub>3</sub>), and (4) mass percentage of papers/cardboards (PDA<sub>4</sub>), that are made up for a transport packaging item.

*Handleability:* Transport packaging may range in size and shape from one-cubic foot totes to eighty-cubic foot bins, depending on whether the container is handled manually or mechanically. Hence, the handleability attribute can be categorized as: (1) dimension (i.e., volume) (PDA<sub>5</sub>), and (2) weight (PDA<sub>6</sub>) of a transport packaging. Small containers are usually designed with the ease of handling, opening and closing mechanisms in mind. Larger containers are often designed with variations in size (from pallet size to large bulk shipping

bins). Sometimes this type of containers may be integrated with a pallet-like bottom to allow for forklift access, and therefore being are used for bulk transfer.

*Modular efficiency:* The modular efficiency attribute relates to (1) cube efficiency (PDA<sub>7</sub>), and (2) nestability and collapsibility features (PDA<sub>8</sub>). Cube efficiency and ergonomics design play an important role for handling transport packaging either in motion or stationary position. Cube efficiency determined by the dimension and shape of transport packaging leads to the optimum utilization of available space (i.e., how well they are loaded into position inside transport vehicles and warehouses). Ergonomics design features of transport packaging include nestability and collapsibility. These features give space savings when an empty transport package is placed into one another for greater stacking heights in favor of handling facilitation, or the wall of the container may be designed to fold down to reduce the volume occupied from 15-35% of the size of the container when assembled.

*End-of-life (EOL) recovery:* At the end of packaging life cycle, a retired transport packaging should be designed to accommodate the disassemblability of its components so that they can either be reused in another package or for a cost-effective disposal and/or recycling. Transport packaging consisting of worn out or damaged components can be easily repaired without having to throw it away entirely. For example, many wooden transport packages are durable enough for repeated use. Such packages in good condition may simply be reused; wood from broken pallets may be used to rebuild or repair other pallets. If the packages are broken or damaged beyond repair, they can also be recycled by grinding them up for use as animal bedding, compost, soil amendment, or even core material for particle board. Hence, the EOL recovery attribute can be classified as: (1) percentage of mass for disassembled parts to be reused (PDA<sub>9</sub>), and (2) percentage of mass for disassembled parts to be recycled (PDA<sub>10</sub>).

## DISCUSSIONS ON CASE EXAMPLE

The implementation procedure as it pertains to life-cycle design of transport packaging at the conceptual design stage will be illustrated through a case example. Initial data is adapted from Singh and Walker [15] as the data used for life-cycle analysis of nestable *pallets*. The quantification of economic costs is investigated through the total cost for packaging material acquisition, manufacturing, and disposal. Environmental costs can be inferred from the value of environmental effects to monetary value by the control cost valuation method. Finally, packaging performance can be evaluated by using equation (2).

There are 39 existing samples that are chosen for training, validation and testing. In this case, 30 samples that are selected for the training, while the remaining 9 samples are selected for validation and testing. The validation aims for measuring the performance of the trained network model while the testing aims for monitoring the performance of the network model during training. The initial weights and biases are generated by random functions with values between -1 and 1. The Sigmoid transfer function is used in both hidden and output layers. The termination condition of the training process is set to 500 epochs. Additional parameters such as  $\mathbf{a}$ ,  $\mathbf{b}$ , the number of hidden layers, and the number of neurons in hidden layers are set to 0.2, 0.7, 2, and 6, respectively.

An error back-propagation learning method is adopted and the network parameters are determined based on the network convergence and the learning convergence. During the training stage, the inputs of the training set are used to start the learning process, then the weights between the neurons in the input layer and the hidden layer, and those between the hidden layer and the output layer are saved until the learning process is converged. In the recalling stage, the test cases, which have not been learned, are input to check whether or not the learning effect is good by calculating the percentage error between the actual and the estimated

outputs of each test sample. The percentage errors falling in the range between -30% and +50% (Seo *et al.* 2002) suggest that the network can be used as the estimation model. If the percentage errors of some validating samples are beyond the threshold, there must be important information in these validating samples that the network has not learnt. In this case, the network is re-trained and the validating process is repeated. After the learning process is converged to an acceptable level, the weights and bias among the input, hidden, and output layers are saved.

The BP-based neural network for the estimation of life-cycle design performance is implemented using the commercial software package NeuroSolutions 4.3 (NeuroDimensions Inc. 2004). To improve the generalization performance, cross validating the network during the training is also applied. When the convergence trend after the iteration of the learning process reaches 500 epochs, the capability of the trained neural network is tested by using the same sample set as the one for the validation. The training and the validation processes are repeated if it is observed that the network has not learnt. The results after 250 training times are shown in Table 1. From the results, we observe that all of the percentage errors are within the [-30%, +50%] range. This suggests that the trained network model is satisfactory.

**Table 1:** Comparison of actual and estimated outputs

Sample#	Economic costs (\$)			Environmental costs (\$)			Packaging performance			
	actual	estimated	%Error	actual	estimated	%Error	actual	estimated	%Error	
1	51.1364	43.0268	15.8585	17.0455	14.5080	14.8863	19.94	18.3867	7.7889	
2	28.1691	28.4514	-1.0021	9.3897	9.7238	-3.5581	3.1617	2.7902	11.7484	
3	36.4773	38.5142	-5.5841	12.1591	13.1407	-8.073	8.8749	9.8064	-10.4957	
4	28.4602	29.2272	-2.6954	9.4867	9.7073	-2.3256	2.2111	2.7423	-24.0242	
5	17.5227	19.5910	-11.8034	5.84091	6.3085	-8.0065	8.4581	9.6593	-14.2009	
6	37.5	39.8603	-6.2941	12.5	13.0894	-4.7151	17.453	15.5608	10.8434	
7	49.7727	43.4955	12.6116	16.5909	14.4564	12.8656	6.5429	6.5341	0.1345	
8	42.9545	41.3008	3.8499	14.3182	14.0705	1.7296	12.295	15.0809	-22.7971	
9	31.3636	30.8169	1.7435	10.4545	14.0705	-0.2312	3.4466	3.6295	-5.3067	
Mean absolute error			2.6780				1.1350			
Minimum absolute error			0.2822				0.0241			
Mean squared error (MSE)			13.6518				2.9331			

## CONCLUSIONS

The lack of flexibility of analytic estimation methods like life-cycle inventory and cost-analysis techniques for the design stage motivated the development of a neural network-based approach for estimating packaging life-cycle design performances concerning packaging performance, environmental impairment and cost requirements. In the present network model, ten meaningful packaging design attributes and three corresponding life-cycle design performances of transport packaging were described. These design elements were then used as the input and output variables in the network model for estimating life-cycle design performances for pallet-type packaging. In particular, the results obtained from the ANN with the back-propagation method possessed low percentage errors and showed the network's ability to estimate the desired outputs. Further, the results produced can be used for attempting to assess trends with respect to the ten packaging design attributes of potential pallet packaging. However, it is important to emphasize that this network model can be generalized only to pallet packaging products since diverse transport packaging products were not included here.

Despite the fact that the ANN technique provides comparative advantages with reasonable accuracy and quick generation and transfer related to information learning of historical data, the availability of actual data can be a crucial element in the development. Accurate historical data must be available. Other drawbacks include that training neural network requires experience. In addition, there is no guideline for determining network parameters such as the number of hidden layers, the number of neurons in the hidden layers, momentum, learning rate, and transfer function. To this end, a trial-and-error process must be applied, which can be time consuming.

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