PREDICTING THE PROPERTIES OF CORRUGATED BASE PAPERS USING MULTIPLE LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The difficulty in predicting the properties and behavior of paper products produced by heterogeneous raw materials with high percentages of recovered fibres poses restrictions on their efficient and effective use as corrugated packaging materials. This paper presents predictive models of mechanical properties of corrugated base papers (liner and fluting-medium) using multiple linear regression and artificial neural networks. The most significant results were obtained for the prediction of zero-span tensile strength in liners from the origin (wood type, pulp method) and percentage by weight of fibres with linear regression, and the prediction of compressive strength according to short-span test in machine direction for fluting-medium from a neural network with one hidden layer with 6 neurons, with coefficients of determination 99.06% and 99.28% respectively.

Keywords: recovered fibres, linerboard, corrugating medium, fibre characteristics, paper properties, multiple linear regression, artificial neural networks.

INTRODUCTION

Corrugated paperboard is currently the most popular raw material for transporting goods, such as fresh fruit and vegetables, household appliances and industrial equipment, as about 60% of goods transport packaging is made of corrugated it. Due to favourable legislation (Commission 1994, Commission 2004, Commission 2005) and environmental restrictions placed on the use of forest-based materials, corrugated base papers (liner and fluting-medium) contain 80 to 100% recovered fibres (Adamopoulos and Oliver 2006, FEFCO 2012). The pulp produced from recycled paper originates from a mixture of different paper types and varies in content form source to source or even from the same source in time (Virtanen and Nilsson 2013). Due to the mechanical action of repulping and repeated rewetting and drying cycles, recovered fibres tend to be broken or damaged and have different physical properties (e.g. hornification effect) to virgin fibres (Ellis and Sedlachek 1993, Brancato 2008).

Numerous studies have been conducted on the potential of papermaking from recovered fibres, most of which have shown that the strength properties of fibres and paper are reduced upon recycling (Badar 1992, Howard and Bichard 1992, Nazhad and Paszner 1994, Avijit 1995, Batchelor 1999, Nazhad 2005). The effects of drying are presumed to be the main factors in reducing the strength properties of recovered fibres. Drying influences fibre strength, fibre swelling and bonding potential, which are the important factors to the strength of paper made from recovered fibres (Ellis and Sedlachek 1993). These differences in fibre properties contribute to weaker interfibre bonding and thus lower the quality (strength) of recovered paper or paperboard products (Ince 2004, Adamopoulos et al. 2007). Therefore, the use of additional process technology is necessary (mechanical refining, coatings, sizing, bonding adhesives, etc.) to compensate for the inherent disadvantages of recovered fibres. The process additions, however, increase manufacturing costs.

The difficulty in predicting the properties of paper products produced from heterogeneous sources puts several limitations, which therefore lead to severe economic losses (Abubakr et al. 1995). The main limitation related to the possibility of the prediction of paper properties based on fibre characteristics is the lack of universal mathematical descriptions of this relationship. Due to the non-linear relationship between fibre characteristics and paper physical and mechanical properties, the development of non-linear models, such as artificial neural networks (ANNs) (Bishop 1995, El-Sebakhy 2006) has been proposed as promising solution, as they provide fast and elastic response, tolerance to damage and an ability to learn (Ciesielski and Olejnik 2014). Kim et al. in (Kim, Shen et al. 1993) applied ANNs for the prediction of grammage and moisture content based on machine characteristics, such as the Kappa number in a digester and the brightness in a bleaching plant. Gianeswhar et al. 2001 developed a model based on neural networks for the prediction of paper properties, such as tensile strength, opacity and grammage, from pulp chemical characteristics, such as pH and CSF value. Additional research works has been done on the prediction of paper properties from fibre characteristics, such as origin of the pulp and fibre length, based on neural networks (Scharcanski and Dodson 1996, Olejnik and Ciesielski 2004, Nieminen et al. 2011, Ciesielski and Olejnik 2014), however none of them focused on paper from recovered fibres. Another study using simple regression analysis showed that grammage could serve as a good estimator of the strength properties of the most common categories of corrugated base papers in Europe (Adamopoulos et al. 2014).

Corrugated packaging companies are in need of methods and tools to predict the strength properties of heterogeneous (e.g. corrugated base papers) and to utilize the data in an optimal manner. This study deals with this common technical problem of the corrugated board industry. Specifically, the main objective of the study was to support the competitiveness of the corrugated board companies by creating models for the prediction of corrugated base paper properties from data on fibres (qualitative, quantitative, morphological) used in their production. To this end, in this paper two different methods were used, multiple linear regression and artificial neural networks, for the development of appropriate models that could effectively predict paper properties from heterogeneous sources using fibre characteristics, such as the origin of fibres, and paper physical properties, such as grammage and thickness.

MATERIALS AND METHODS

Paper materials and testing

Thirty two (32) papers used by the corrugated packaging industry were used to analyse their fibre composition and morphological characteristics. The papers represent different qualities of liner (8 brown kraftliner, 8 brown testliner) and fluting-medium (8 semi-chemical fluting, 8 recycled fluting) available in Greece for the production of corrugated board. The papers were provided by different paper suppliers from the global market coming from 11 European countries, Turkey, and USA.

Qualitative and quantitative determination of the fibre components of the papers as regards the method of processing (chemical, mechanical, rag, semi-chemical and chemi-mechanical pulp) was carried out according to the Herzberg staining test method (ISO 9184-3: 1990). After their staining with the Herzberg stain, fibres were viewed and systematically counted under an Eclipse 50i light microscope equipped with a digital Sight DS-5M-L1 camera (both Nikon). The fibres were classed into softwood, hardwood and non-wood fibre categories based on their morphology (Ilvessalo-Pfäffli 1995). Weight percentages of different fibre categories were calculated by using predetermined weight factors recommended by ISO 9184-1: 1990. The information regarding the origin, classification and fibre content of the selected corrugated base papers are presented in Table 1.

Table 1. *Information on the selected corrugated base papers and weight percentages of fibre components*[1]

	Liners		**Fluting-medium**	
	Kraftliners (KL)	Testliners (TL)	Semi-chemical fluting (SCF)	Recycled fluting (RF)
Origin	France, Norway, Portugal, Switzerland, UK, USA	Greece, Portugal, Romania, Spain, Turkey	Bulgaria, Croatia, Finland, Romania, Sweden, Switzerland, Spain	Greece, Portugal, Spain, Turkey
Classification[2]	Brown	Brown testliner:	Semi chemical	Recycled fluting –

		kraftliner: predominantly made from primary kraft pulp	predominantly recycled fibre based, substance equal or over 120 g/m2	fluting: predominantly made from semi chemical primary fibres pulp	medium: predominantly recycled fibre based, substance equal or over 100 g/m2
Origin of fibres[3] (wt%)	Softwood	56.31/14.63	33.19/9.89	29.63/12.76	26.19/7.05
	Hardwood	38.89/13.93	61.69/7.12	66.99/12.18	65.23/7.09
	Non-wood	4.8/2.02	5.12/4.44	3.38/2.83	8.58/1.81
Whole fibres (wt%)		87/2.84	82/6.15	91/5.93	84/7.02
Fibres originating from chemical pulp (wt%)		59/6.25	33/20.33	25/11.2	52/3.57
Number of whole fibres originating from softwood		167/101.38	56/19.23	52/46.67	45/22.43
Total number of fragments originating from softwood fibres		55/23.63	71/27.9	37/23.15	58/22.94
Total number of fibres originating from the chemical pulp of softwood		171/85.43	55/15.8	36/27.33	72/13.55
Total number of fibres originating from hardwood		349/134.04	438/51.7	510/63.37	437/43.31
Total number of fibres originating from non-wood		33/12.98	31/20.85	27/25.73	61/14.17

[1]mean value/standard deviation
[2]according to (CEPI 2012)
[3]based on their morphology

All the papers were tested for the following physical and mechanical properties: grammage (ISO 534: 2005), thickness (ISO 534: 2005), compressive strength according to short-span test SCT (ISO 9895: 2008), tensile strength (ISO 1924-3: 2005), and tearing strength (ISO 1974 :2012).Tensile strength was also determined for liners according to the zero span testing (TAPPI T-231: 1996). Before testing, the samples were conditioned at 23ºC and 50% RH according to ISO 187: 1990.The information regarding the physical and mechanical properties of the selected corrugated base papers are presented in Table 2.

Table 2. *Physical and mechanical properties of the selected corrugated base papers[1]*

		Liners		Fluting-medium	
		Kraftliners (KL)	Testliners (TL)	Semi-chemical fluting (SCF)	Recycled fluting (RF)
Grammage (g/m[2])		149.93/26.23	130.90/26.71	137.26/18.33	111.82/13.5
Thickness (μm)		0.24/0.05	0.21/0.05	0.21/0.04	0.2/0.04
SCT[2] (kN/m)	MD	6.16/1.60	4.51/0.83	6.33/1.98	4.00/0.77
	CD	3.44/0.84	2.44/0.61	3.53/0.97	2.18/0.40
Tensile Strength[2] (kN/m)	MD	8.72/0.05	7.17/0.73	8.38/0.69	6.99/0.75
	CD	6.23/1.38	2.65/0.80	4.47/0.95	2.46/0.28
Tearing Strength[2] (mN)	MD	151.32/46.62	64.64/15.43	61.51/10.19	68.05/18.60
	CD	171.14/67.20	82.77/7.61	89.75/16.15	85.43/9.84
Zero-span Strength[2] (kN/m)	MD	17.57/1.98	12.15/1.75	20.73/2.34	13.98/1.08
	CD	19.48/3.26	7.18/1.98	13.54/1.53	9.13/0.70

[1]mean value/standard deviation
[2]machine direction (MD) and cross direction (CD)

Modelling methods

Multiple linear regression (MLR) and feed forward artificial neural networks (ANN) were used to predict the mechanical properties of corrugated base papers produced from heterogeneous fibre sources.

Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. Considering x_1, x_2,…, x_n to be a set of n independent variables (estimators) associated with a value of the dependent variable y, the linear regression model for the j^{th} sample unit has the following form:

$$y_j = \beta_0 + \beta_1 x_{j1} + \beta_2 x_{j2} + \cdots + \beta_n x_{jn} + \varepsilon \qquad (1)$$

Where, ε is a random error and $\beta_i (i = 0, 1, 2, \dots, n)$ are the unknown regression parameters.The MLR parameters are estimated using the least squares model where the best-fitting line for the observed data is calculated by minimizing the sum of the squares of the vertical deviations from each data point to the line (if a point lies on the fitted line exactly, then its vertical deviation is 0).

Although MLR models are simply based on linear and additive associations of the explanatory variables, they have been extensively used with satisfactory results. In this work, from a multitude of variables, only the statistically significant linear regression equations (ANOVA, p-value ≤ 5%) where reported.

However, due to the non-linear relationship between fibre characteristics and paper physical and mechanical properties, the development of non-linear models, such as artificial neural networks, emerges as a promising solution. These models perform a non-linear transformation of input data to approximate output data, learning from experimental data examples and exhibiting some ability for generalization beyond training data. The most common artificial neural network is the multilayer feedforward artificial neural network where the nodes are grouped into three types of layers, i.e. input, hidden and output layers. Input data are provided to the nodes in the input layer which are then being transferred to the subsequent layers. Cybenko (1989) has shown that a one hidden layer ANN is enough to approximate any function, if presenting enough hidden nodes. The topology of the network, along with the neuron processing function, determines the accuracy and degree of representation of the model developed to correctly represent the system behaviour.

The output value of each node is obtained through an activation function, which can be a sigmoid, a hyperbolic tangent or an exponential. Each node in the hidden and output layers has a bias value which is known as the activation threshold. ANNs are obtained by dividing data into three categories: training, validation and testing. Training data is used to determine the network topology and the associated weights by solving a non-linear optimization problem with the objective function being dictated by the mean squared error (MSE). The validation data is used to compute the ANN performance and the testing data is used to assess the performance of the network.

A disadvantage of ANNs in comparison with MLR is the difficulty in explaining the relation between independent and dependent variables because of use of ambiguously defined weights, which is a black box. In contrast, MLR analysis can provide quantitative confidence to estimated coefficients (Lou and Nakai 2001).

In this work, ANNs were trained using Statistica™ Neural Networks, Version 12 (Inc. 2015). The network configuration for each paper grade, liner and fluting-medium, was approached empirically by testing various possibilities and selecting the one that provided the minimum training and validation error and maximum correlation coefficient. The weights were randomly set at the start of the network training phase according to the chosen algorithm.70% of the total sample data from each paper grade where used to train the network, 15% for validation and 15% for testing.

RESULTS AND DISCUSSION

The most significant MLR models regarding the prediction of mechanical properties from fibre characteristics and physical properties for both corrugated base paper categories (liner and fluting-medium) are presented in Table 3. Correlation between mechanical properties and grammage (weight per unit area expressed as g/m^2), which by definition is the most fundamental physical property of papers in general, gave some good results regarding the prediction of zero-span tensile strength in the cross direction in liners, and marginally good results were obtained for the prediction of zero-span tensile strength in the machine direction in liners, with coefficients of determination 77.95% and 74.59% respectively. In fluting-medium, the influence of grammage in tearing strength had a weak positive relationship, with coefficient of determination equal to 66.53%.

The most significant results were obtained for the prediction of zero-span tensile strength in liners from the origin (wood type, pulp) and the percentage by weight of fibres, with coefficient of determination 99.06%. Equally significant were the models developed for the prediction of tensile and tearing strength in the cross direction in liners from the origin and characteristics of fibres, with coefficient of determination 95.14% and 94.86% respectively. In fluting-medium, the most significant results were obtained for the prediction of compressive strength according to short-span test in the machine direction from the origin (wood type, pulp) and the percentage by weight of fibres, with coefficient of determination 94.13%.

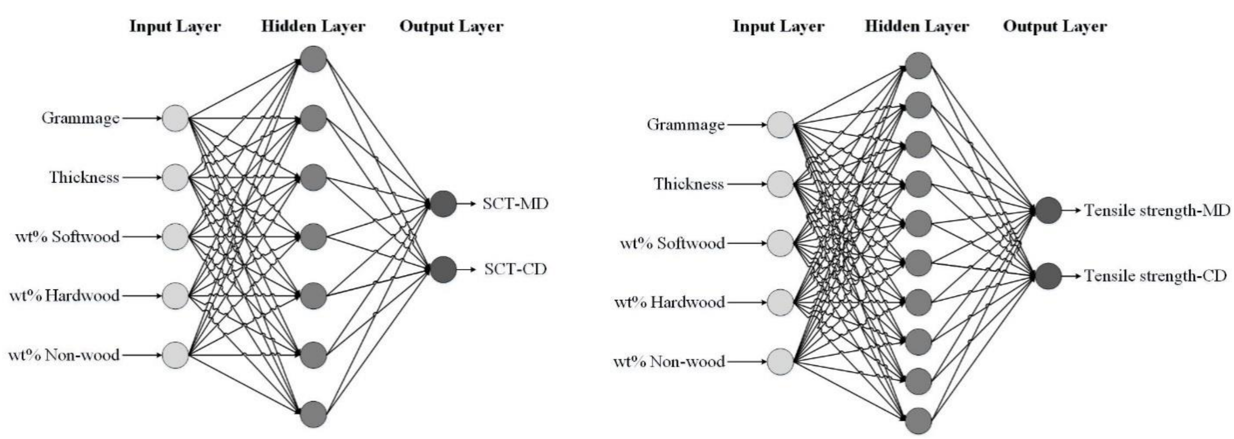
Table 3. *Linear model for the prediction of corrugated board mechanical properties[1] from fibre characteristics and corrugated board physical properties*

	y	Estimators	regression	Correlation coefficient R^2
Liners	Zero span − MD	x_1 = Grammage x_2 = Thickness	$y = 2.26 + 0.1345x_1 - 28.3x_2$	74.59%
	Zero span − CD	x_1 = Grammage x_2 = Thickness	$y = -11.29 + 0.3576x_1 - 118.7x_2$	77.95%
	Zero span − CD	x_1 = wt% of chemical fibres x_2 = wt% of whole fibres x_3 = wt% of Softwood	$y = -27406 + 0.1392x_1 + 0.681x_2$	99.06%

		$x_4 = \text{wt\% of Hardwood}$ $x_5 = \text{wt\% of Non}-\text{wood}$	$+273.8x_3 + 273.5x_4$	
	Tensile strength − CD	$x_1 = \text{Softwood whole fiber}$ $x_2 = \text{Fragmented count}$ $x_3 = \text{Total SW chemical}$ $x_4 = \text{Hardwood fibre}$ $x_5 = \text{Non}-\text{wood fibres}$	$y = 1.95 - 2.482x_1$ $-2542x_2 + 2.53x_3$ $+0.00891x_4$ $-0.1623x_5$	95.14%
	Tearing strength − CD	$x_1 = \text{Softwood whole fiber}$ $x_2 = \text{Fragmented count}$ $x_3 = \text{Total SW chemical}$ $x_4 = \text{Hardwood fibre}$ $x_5 = \text{Non}-\text{wood fibres}$	$y = 63.7 + 70.6x_1$ $+69.4x_2 - 69.4x_3$ $+0.313x_4 - 6.98x_5$	94.86%
Fluting-medium	Tearing strength − CD	$x_1 = \text{Grammage}$	$y = 24.4 + 0.494x_1$	66.53%
	SCT − MD	$x_1 = \text{wt\% of chemical fibres}$ $x_2 = \text{wt\% of whole fibres}$ $x_3 = \text{wt\% of Softwood}$ $x_4 = \text{wt\% of Hardwood}$ $x_5 = \text{wt\% of Non}-\text{wood}$	$y = -28003$ $+0.217x_1$ $-0.0354x_2 + 280x_3$ $+280x_4 + 280x_5$	94.13%

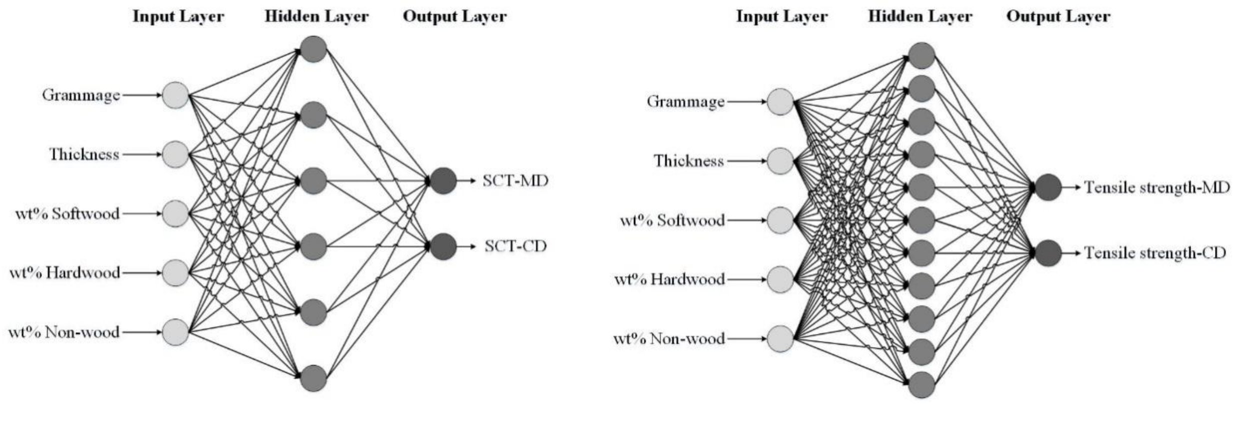
[1]machine direction (MD) and cross direction (CD)

The neural networks selected for the prediction of compressive strength according to short-span test and tensile strength from the percentage by weight of the origin of fibres and physical properties (grammage and thickness) for liner and fluting-medium are presented in Figures 1 and 2, respectively. The most significant results were obtained for the prediction of compressive strength according to short-span test in the machine and cross directions for fluting-medium from a neural network with 6 neurons in the hidden layer and coefficient of determination 99.28% and 98.86%, respectively. The information for each neural network developed is provided in Table 4.



(a) (b)

Figure 1.*Structure of the neural network for the prediction of (a) compressive strength (SCT) and (b) tensile strength in liners. MD = machine direction, CD = cross direction*



(a) (b)

Figure 2. *Structure of the neural network for the prediction of (a) compressive strength (SCT) and (b) tensile strength in flutings-medium. MD = machine direction, CD = cross direction*

Table 4. *Summary of the training and verification results of the proposed neural network*

Paper grade	Input layer	Output layer	Number of neurons in hidden layer	Training error	Training performance	Activation function: Hidden layer	Activation function: Output layer	Correlation coefficient R^2
Liners	Grammage Thickness wt% of Softwood wt% of Hardwood wt% of Non − wood	SCT − MD	7	0.084544	0.978894	Logistic Sigmoid	Exponential	94.74%
		SCT − CD						96.92%
		Tensile strength − MD	10	0.081165	0.985123	Logistic Sigmoid	Identity	96.83%
		Tensile strength − CD						97.27%
Fluting-medium	Grammage Thickness wt% of Softwood wt% of Hardwood wt% of Non − wood	SCT − MD	6	0.014838	0.995334	Hyperbolic Tangent	Identity	99.28%
		SCT − CD						98.86%
		Tensile strength − MD	11	0.109555	0.954121	Exponential	Identity	87.15%
		Tensile strength − CD						95%

Both approaches, MLR and ANN, have provided significant models for the prediction of tensile strength in the cross direction in liners, with coefficients of determination equal to 95% and 97.27%, and compressive strength in the machine direction in fluting-medium, with coefficient of determination 94.13% and 99.28%, respectively. While both approaches provided models with high coefficient of determination for each dependent variable, we can say that ANN models outperform MLR models due to the difficulty in the linear correlation between input and output variables.

It is evident that the models based on the physical properties of papers are closer to the industrial practice, where the selection of papers for a specific corrugated packaging use is based on availability, cost and empirical quantification of performance. The more advanced models using fibre origin and morphology data require access to advanced techniques such as fibre analysis and fibre morphology analysers, and thus their usefulness might be limited.

CONCLUSIONS

The main objective of the work presented was to develop models for the prediction of mechanical properties of corrugated base papers, based on fibre characteristics and paper physical properties using multiple linear regression and artificial neural networks. Various fibre characteristics and paper physical properties were used as independent variables, such as the origin of fibres and grammage. These variables were used for the prediction of mechanical properties, such as tensile, tearing and compressive strength. While both approaches provided significant models that could be used in the practical testing, the results show that the use of ANN led to more accurate results than linear models, due to the account of non-linearities. As future work, we plan on developing a software tool implementing the provided models in order to estimate paper properties for extrapolations in corrugated board performance.

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