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

The difficulty in predicting the properties and behaviour of paper products produced using heterogeneous raw materials with high percentages of recovered fibres poses restrictions on their efficient and effective use as corrugated packaging materials. This work presents predictive models for the mechanical properties of corrugated base papers (liner and fluting-medium) from fibre and physical property data using multiple linear regression and artificial neural networks. The most significant results were obtained for the prediction of the tensile strength of liners in the cross direction from the origin (wood type, pulp method) of the fibres using linear regression, and the prediction of the compressive strength of fluting-medium in the longitudinal (machine) direction, according to the short-span test, using a neural network with one hidden layer with 6 neurons, with coefficients of determination at 95.14% and 99.28%, respectively.

Introduction

Corrugated board is currently the most popular material for transporting goods, such as fresh fruit and vegetables, household appliances and industrial equipment, as about 60% packaging for the transport of goods is made of it. Due to favourable legislation [European Commission 1994, 2004, 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

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recycled paper originates from a mixture of different paper types and varies in content from source to source or even from the same source over 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. the hornification effect) to virgin fibres [Ellis and Sedlachek 1993; Brancato 2008].

Numerous studies have been conducted on the potential of papermaking using recovered fibres, most of which have shown that the strength properties of fibres and paper are reduced upon recycling [Howard and Bichard 1992; Nazhad and Paszner 1994; Avijit 1995; Batchelor 1999; Nazhad 2005]. The effects of drying are presumed to be the main reason for the reduction in the strength properties of the 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; 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. However, these additional processes increase manufacturing costs.

The difficulty in predicting the properties of paper products produced using heterogeneous sources imposes several limitations, which can therefore lead to substantial economic loss [Abubakr et al. 1995]. The main limitation related to the possibility of predicting 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 the physical and mechanical properties of paper, the development of non-linear models, such as artificial neural networks [ANNs] [Bishop 1995; El-Sebakhy 2006] has been proposed as a promising solution, as they provide a fast and elastic response, are tolerant of damage and have the ability to learn [Ciesielski and Olejnik 2014]. Kim et al. [1993] applied ANNs to predict the grammage and moisture content of paper based on machine characteristics, such as the Kappa number in a digester and the brightness in a bleaching plant. Gianeswhar et al. [2000] developed a model based on neural networks for the prediction of paper properties, such as tensile strength, opacity and grammage, from pulp characteristics, such as the pH and CSF values. Additional research based on ANNs has been undertaken on predicting paper properties from fibre characteristics, such as the origin of the pulp and the fibre length [Scharcanski and Dodson 1997; Olejnik and Ciesielski 2004; Nieminen et al. 2011; Ciesielski and Olejnik 2014]. 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 materials (e.g. corrugated base papers) and to utilize them in an optimal manner. This study deals with this common

technical problem for the corrugated board industry. The main objective of the study was to specifically create models to predict corrugated base paper properties from data on the fibres [qualitative, quantitative, morphological] used in their production. To this end, two different methods were used, multiple linear regression and ANNs, for the development of appropriate models that could effectively predict the mechanical properties of paper using data on their fibres (composition and morphology) and physical properties (grammage and thickness).

Materials and methods

Paper materials and testing

The fibre composition and morphological characteristics of thirty two (32) papers used by the corrugated packaging industry were analysed. The papers represented different qualities of liner (8 brown kraftliner and 8 brown testliner) and fluting-medium (8 semi-chemical fluting and 8 recycled fluting) available in Greece for the production of corrugated board. The papers were provided by different paper suppliers from 11 European countries, Turkey and the USA (tab. 1).

Table 1. Information on the origin and classification of the papers

	Liner		Fluting-medium	
	Kraftliner [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
Classi-fication[1]	Mainly from primary kraft pulp [brown kraftliner]	Mainly from pulp of recycled fibres, substance equal to or over 120 g/m^2 [Brown testliner]	Mainly from pulp of semi-chemical primary fibres	Mainly from pulp of recycled fibres, substance equal to or over 100 g/m^2

[1]According to CEPI Containerboard [2012].

A 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 staining with the Herzberg stain, the 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]. The weight percentages of the different fibre categories were calculated by using predetermined weight factors recommended by ISO 9184-1:1990.

The papers were tested for the following physical and mechanical properties: grammage [ISO 536:2012], thickness [ISO 534:2005], compressive strength according to the short-span test SCT [ISO 9895:2008], tensile strength [ISO 1924-3:2005] and tearing strength [ISO 1974:2012]. Before testing, the samples were conditioned at 23°C and 50% RH, according to ISO 187:1990.

Modelling methods

Multiple linear regression [MLR] and feed forward artificial neural networks (ANNs) were used to predict the mechanical properties of the papers.

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 jth sample unit has the following form:

$$y_j = \beta_0 + \beta_1 x_{j1} + \beta_2 x_{j2} + \ldots + \beta_n x_{jn} + \varepsilon \tag{1}$$

Where ε is a random error and β_i ($i = 0, 1, 2, …, n$) 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 $\leq$ 5%) were reported.

However, due to the non-linear relationship between fibre characteristics and the physical and mechanical properties of paper, the development of non-linear models, such as ANNs, 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 to generalise beyond the training data. The most common ANN is the multilayer feedforward one where the nodes are grouped into three types of layers, i.e. input, hidden and output layers. The nodes are provided with input data in the input layer, which are then transferred to the subsequent layers. Cybenko [1989] has shown that an ANN with one hidden layer 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 behaviour of the system. 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 relationship between independent and dependent variables because of the use of ambiguously defined weights. In contrast, MLR analysis can provide quantitative confidence to estimated coefficients [Lou and Nakai 2001]. In this work, the 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 the 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 was used to train the network, while 15% was for validation and 15% for testing.

Results and discussion

The results of the fibre composition and physico-mechanical properties of the selected corrugated base papers are presented in table 2. The findings are in alignment with previous studies showing the great variation in the fibre characteristics and properties of papers used in corrugated board manufacturing as a result of recycling [Adamopoulos et al. 2007; Adamopoulos et al. 2009; Adamopoulos et al. 2013].

The most significant MLR models for predicting the mechanical properties from the fibre characteristics and physical properties for both corrugated base paper categories [liner and fluting-medium] are presented in table 3. Significant MLR models were obtained for predicting the tensile and tearing strength of liners in the cross direction from the origin and characteristics of the fibres, with the coefficient of determination at 95.14% and 94.86%, respectively. For the fluting-medium, equally significant results were obtained for predicting, according to the short-span test, the compressive strength in the machine direction from the origin (type and pulp) and the percentage by weight of the fibres, with the coefficient of determination at 94.13%. Grammage (weight per unit area expressed as g/m^2) had a weak positive relationship with the tearing strength of the fluting-medium in the cross-direction, with the coefficient of determination equal to 66.53%.

Table 2. Fibre composition and properties of the papers (mean value/standard deviation)

		Liners		Fluting-medium	
		kraftliners (KL)	testliners (TL)	semi-chemical fluting (SCF)	recycled fluting (RF)
Origin of fibres[1] [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	4.80/2.02	5.12/4.44	3.38/2.83	8.58/1.81
Whole fibres [wt%]		87/2.8	82/6.2	91/5.9	84/7.0
Chemical pulp fibres [wt%]		59/6.25	33/20.33	25/11.2	52/3.6
Number of whole softwood fibres		167/101.4	56/19.2	52/46.7	45/22.4
Number of fragments from softwood fibres		55/23.7	71/27.9	37/23.2	58/22.9
Number of softwood chemical pulp fibres		171/85.4	55/15.8	36/27.3	72/13.6
Number of hardwood fibres		349/134.0	438/51.7	510/63.4	437/43.3
Number of non-wood fibres		33/13.0	31/20.9	27/25.7	61/14.2
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 [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 [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 [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

[1]Based on their morphology.
Note: machine direction [MD], cross direction [CD].

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

Table 3. Linear model for prediction of mechanical properties of corrugated board from fibre characteristics and physical properties of corrugated board

	y	Estimators	Regression	R^2
Liners	Tensile strength CD	x_1 = Whole softwood fibres x_2 = Fragment count x_3 = Total softwood chemical x_4 = Hardwood fibres x_5 = Non-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 = Whole softwood fibres x_2 = Fragment count x_3 = Total softwood chemical x_4 = Hardwood fibres x_5 = Non-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 = Grammage	$y = 24.4 + 0.494x_1$	66.53%
	SCT MD	x_1 = wt% chemical fibres x_2 = wt% whole fibres x_3 = wt% softwood x_4 = wt% hardwood x_5 = wt% non-wood	$y = -28003 + 0.217x_1 +$ $- 0.0354x_2 + 280x_3 + 280x_4 +$ $+ 280x_5$	94.13%

Note: machine direction [MD], cross direction [CD].

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

This study can be seen as a follow up of previous work [Adamopoulos et al. 2014], which showed that the variety of packaging paper grades produced from heterogeneous recycled pulp in Europe can be characterized by their physical property data (e.g. grammage), irrespective of the paper category or subcategory to which they belong. This enables a better classification of the different grades, thus allowing the selection of the appropriate raw material for each end-use (packaging application). In the present study, potential paper strength predictions

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

| Paper grade | Input layer | Output layer | Number of neurons in hidden layer | Training error | Training performance | Activation function | | Correlation coefficient R^2 |
						hidden layer	output layer	
Liner	grammage thickness wt% softwood wt% hardwood wt% 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	sigmoid logistic	identity	96.83%
		tensile strength-CD						97.27%
Fluting-medium	grammage thickness wt% softwood wt% hardwood wt% 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						95.00%

were also sought from the fibre property data. It should be noted that the intention was not to identify the extent to which the strength of a specific paper grade within a defined liner or fluting-medium category is influenced by its fibre or physical data. This approach would, of course, require a different experimental design, taking into account a number of pulping and papermaking parameters. Therefore, a universal sampling and testing approach was selected involving a number of papers to cover different grades of corrugated liners and fluting-medium available on the Greek market for the production of corrugated

board, and searching for dependencies in each of the liners and fluting-medium categories.

It is evident that the models based on the physical properties of the grammage and thickness of the papers are closer to industrial practice, where the 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 morphological data require access to advanced techniques, such as fibre analysis and fibre morphology analysers, and thus their practical usefulness might be limited.
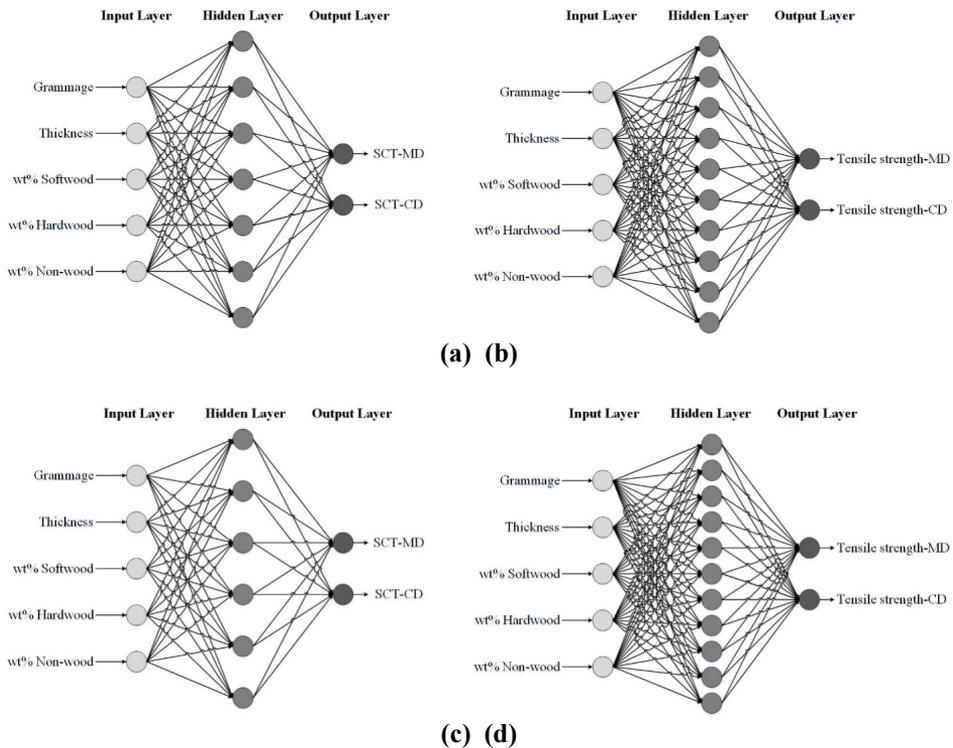

(a) (b)

(c) (d)

Fig. 1. Structure of the neural network for the prediction of compressive strength SCT (a, c) and tensile strength (b, d) of liners (a, b) and fluting-medium (c, d). MD= machine direction, CD = cross direction

Conclusions

The main objective of the work presented was to develop models for the prediction of the mechanical properties of corrugated base papers from data gathered on their fibre characteristics and physical properties by using multiple linear regression and artificial neural networks (ANNs). While both approaches provided significant models which could be used in practical testing, the results

show that the use of ANNs led to more accurate results than the use of linear models, due to non-linearities. In future research, the focus will be on developing a software tool implementing the provided models in order to estimate paper properties and fit them to known equations for extrapolations in corrugated board and packaging performance.

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ISO 9895:2008 Paper and board. Compressive strength. Short-span test

ISO 1974:2012 Paper. Determination of tearing resistance. Elmendorf method

ISO 9184-1:1990 Paper, board and pulps. Fibre furnish analysis – Part 1: General method

ISO 9184-3:1990 Paper, board and pulps. Fibre furnish analysis – Part 3: Herzberg staining test

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