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Artificial Neural Networks and Their Applications in the Engineering of Fabrics

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1. Introduction

Historically the main use of the textile fabrics has been limited mainly to clothing and domestic applications. The technical uses were of minor importance. However in the last decades the use of the textile structures has started to spread over other sectors like construction, medicine, vehicles, aeronautics, etc. The increased interest in technical applications have improved the fabric design and engineeringprocedures, given that the final products must be characterized by certain mechanical, electrical etc. properties. The performance of the fabrics should be predictable right from the design phase. The design of a fabric is focusing on the materials selection as well as on the definition of its structural parameters, so that the requirements of the end use be fulfilled.

These changes in the application field of the textile structures caused a move from the esthetic design to the total technical design, where the fabric appearance and the particular properties affecting its final performance are taken in account. However, the textile structures are highly complex. A textile fabric consists of yarns; yarns in turn consist of fibres. Thus the mechanical performance of the fabrics is characterized by the structural geometrical complexity and non-linearity, as well as from the non-linearities of the materials themselves. This double non-linear bahaviour of the textile fabrics increases the difficulty in the fabric design and engineering processes. The complex structure and the difficulties introduced by the raw materials do not allow the use of precise analytical models for the technical design of the fabrics.

Fabric engineering activities are increasingly based on computational models that aim at the prediction of the properties and the performance of the fabrics under consideration. Various computational tools have been used in order to represent the fabrics in a computational environment and to predict their final properties. Among others, Finite Element Method (FEM) analysis has supported mainly the prediction of the behaviour of the complex textile structures under mechanical loads. In the case of classification problems Artificial Neural Networks (ANNs) have proved a very efficient tool for the fast and precise solution. ANNs have found an increasing application in the textile field in the classification as well as in the

prediction of properties and optimization problems (Chattopadhyay & Guha 2004). In parallel or complementarily to the ANNs, fuzzy logic and genetic algorithms techniques have been used in the textile field (Guruprasad & Behera, 2010). The applications of the ANNs in the textile classification and prediction problems cover the fields of fibres, yarns and fabrics as well as color, wet processing and clothing.

2. ANN applications in the textile engineering field

It is mainly since 1990 that the applications of ANNs in the textile engineering field have become more and more popular. Gradually it was proven that they can address successfully complex engineering problems. Many researchers have turned to ANNs when they were in front of a multiparameter and non-linear problem, without an obvious or straightforward analytical solution. In the following paragraphs, a thematic overview of the uses of the ANNs in the various textile fields will be presented.

2.1 Fibres
The implementation of the ANNs presupposes an initial phase of features extraction, which will be used later to feed the ANN. It includes the processing of the given data or measurements, typically in the form of a signal, an image etc. One of the most typical problems of the animal fibres classification has been faced using Artificial Neural Networks (She et al., 2002). In the case of cotton, ANNs have been used for the grading of the color of the raw fibres (Cheng et al., 1999; Xu et al., 2000; Kang et al., 2002). An attempt for the classification of the cotton lint has been also based on the use of ANNs (Mwasiagi et al., 2009). A method for the selection of cotton bales based on certain criteria was established (Majumdar et al., 2004). In the case of synthetic fibres, the ANNs have supported the identification of the production control parameters (Allan et al., 2001) and the prediction of the properties of the melt spun fibers (Kuo, 2004). ANNs have been used in conjunction with NIR spectroscopy for the identification of the textile fibres (Jasper & Kovacs 1994). A system for the optimization of the yarn production based on the blend characteristics and the process parameters has been developed based also on the use of ANNs (Sette & van Langenhove, 2002).

2.2 Yarns
The spinning of the staple fibres for the production of the yarns is a multistage procedure including many parameters, which influence the characteristics of the end product, the spun yarn. The examination of the image of the web produced by a carding machine and the detection of faults has been made possible in an automatic sense using ANN's (Kuo et al., 1999; Shiau et al., 2000). The autolevelling and thus the linear density control in the draw frame has been achieved using ANNs (Huang & Chang, 2001; Farooq & Cherif, 2008). In the main spinning phase, the optimization of the top roller diameter as well as the study of the ring ballon has been examined via the use of ANNs (Ghane et al., 2008; Tran et al., 2010).
The overall process performance in the case of the worsted spinning was estimated (Beltran et al., 2004), while the selection of the suitable parameters was the target of other researchers (Wu et al., 1994; Yin & Yu, 2007). The spinning process and its role on the prediction of the cotton-polyester yarn properties were examined using ANNs (Lu et al., 2007; Jackowska-Strumiłło et al., 2008). The effect of the fibres properties on the yarn characteristics is a topic

of great interest for many researchers, with different points of view or dealing with specific fibres or spinning method cases (Dayik, 2009; Jayadeva et al., 2003; Majunmdar et al., 2006). A method based on a combination of Genetic Algorithms and Neural Networks has been used for the prediction and optimization of the yarns properties (Subramanian et al., 2007). In a similar sense, a combination of an adaptive neuro-fuzzy system has been developed for the prediction of fiber to yarn relation (Admuthe & Apte, 2010).

The prediction of the tensile properties of yarns is of main interests of the international research community. Many publications appeared dealing with the prediction of the tensile properties of the yarns under general (Ramesh et al., 1995; Guha et al., 2001; Majumdar & Majumdar, 2004; Nurwaha & Wang, 2008; Üreyen & Gürkan, 2008; Mwasiagi et al., 2008; Nurwaha & Wang, 2010) or under specific conditions, such as is the case of core spun yarns (Gharehaghaji et al., 2007), air-jet spun yarns (Zeng et al., 2004) or for the estimation of the torque of worsted yarns (Tran & Phillips, 2007). The ANN prediction method is compared with the Support Vector Machine (SVM) approach and conditions under which each method is better suited are investigated (Ghosh & Chatterjee, 2010). The warp breakage rate during the weaving is a complex function of the yarn properties and thus an application field of an ANN model (Yao, 2005). The prediction of the yarn evenness and hairiness is of great practical interest. ANNs have been used for the prediction of hairiness of worsted wool yarns (Khan et al., 2009) and of cotton yarns (Babay et al., 2005; Majumdar, 2010). In a similar way, ANNs have been used for the prediction of the evenness of ring spun worsted yarns (Wang & Zeng, 2008) and cotton yarns (Majumdar et al., 2008; Üreyen & Gürkan, 2008; Majumdar, 2010) or the evenness of blended rotor yarns (Demiryurek & Koc, 2009).

As it is known, when two yarn ends must be joined, instead of knotting they are subjected in the splicing process. Splicing positions are of special interest because they could affect heavily the mechanical performance of the yarn in total. Evaluation and comparison of the properties of the spliced yarns have been made based also on ANNs (Cheng & Lam, 2003). Later studies have used ANNs to predict the properties of the spliced yarns (Lewandowski & Drobina, 2008). Latest studies have contributed to the prediction of the spliced yarns tensile properties as well as to the prediction of the retained yarn diameter, thus covering the mechanical and the visible results of the presence of the splicing points in the yarn (Gürkan-Ünal et al., 2010). ANNs have also been used for the appearance analysis of false twist textured yarn packages (Chiu et al., 2001), for the prediction of yarn shrinkage (Lin, 2007) or for the modelling of the relaxation behaviour of yarns (Vangheluwe et al., 1996).

2.3 Fabrics

Textile fabrics are often the final product of the textile process. Their properties must directly meet the user requirements; obviously, the prediction of their properties and their final behaviour is very important. The fabrics are complex structures, if their micromechanical structure is considered. The structural complexity in conjunction with the materials complexity do not usually permit the development of Computer Aided Engineering tools for the support of the design phase, as it usually the case in other engineering fields such as mechanical, structural, naval, electrical, etc. Therefore, a lot of effort has been given towards the development of computational tools for the prediction of the behaviour of the fabrics (Basu et al., 2002).

The inspection of the fabrics for the detection of faults is a very important operation, traditionally carried out by skilled operators. Many attempts have been made in order to

perform the inspection automatically. Consequently the task of automated defects detection is popular and many research teams have focused their interest on it, while many of them have used ANNs to support the fault detection task, (Tsai et al., 1995; Sette & Bullard, 1996; Tilocca et al., 2002, Kumar, 2003; Islam et al., 2006; Shady et al., 2006; Behera & Mani, 2007; Mursalin at al., 2008). Another similar approach is the combined use of fuzzy systems (Choi et al., 2001; Huang & Chen, 2003) or wavelet packet bases (Hu & Tsai, 2000; Jianli & Baoqi, 2007). Defects can be detected also by a dynamic gray cloth inspecting machine system (Kuo et al., 2008). The detection and recognition of the patterns on a fabric is of the same class of problems and thus a candidate for the use of ANNs (Jeon et al., 2003; Chiou et al., 2009; Liu et al., 2009). Using the same principles, stitch inspection can be achieved (Yuen et al., 2009).

Drapability is far the most complex mechanical property of the fabrics and it is essential for many applications of the textile fabrics. The prediction of the drape has been made using ANNs (Fan et al., 2006). In parallel the engineering of the drapability of the fabrics became possible though a predictive tool (Stylios & Powel, 2003). Fabric hand is a property that combines the mechanical properties of a fabric with the sensory perception of the fabric by the humans when they touch it. It is difficult to give an objective description of the fabric handle, because a subjective evaluation takes place in practice. However, there have been developed some complex systematic approaches for the definition of the fabric hand, which include the full set of the low stress mechanical properties of the fabrics. Obviously the prediction of the fabric hand is equivalent to the prediction of the low stress mechanical properties of the fabrics. The prediction of the fabric hand is a complex, highly non-linear problem and therefore an early target for the application of ANNs (Youssefi & Faez, 1999; Hui et al., 2004; Shyr et al., 2004; Matsudaira, 2006). The data from the FAST system were used to approach the hand of the fabrics (Sang-Song & Tsung-Huang, 2007), while fuzzy logic has been combined with ANN for the evaluation of the fabric hand (Park et al., 2000; Park et al., 2001). ANNs in combination with fuzzy logic have been used in the case of the prediction of the sensory properties of the fabrics, as well (Jequirim et al., 2009). Cosely related applications are the objective evaluation of the textile fabric appearance (Cherkassky & Weinberg, 2010) and the emotion based textile indexing using ANNs (Kim et al., 2007)

The prediction of the simpler mechanical properties of the textile fabrics is an essential technical requirement. ANNs have been used for the prediction of the tensile strength (Majumdar et al., 2008) and for the initial stress-strain curve of the fabrics (Hadizadeh et al., 2009). The same problem has been solved using an adaptive neuro-fuzzy system (Hadizadeh et al., 2010). The shear stiffness of the worsted fabrics (Chen et al., 2009) and their compression properties have been successfully modelled (Murthyguru, 2005; Gurumurthy, 2007). In general, the prediction of the properties of a fabric enables the support of the design phase, (Behera & Muttagi, 2004).

The prediction of bursting using ANNs for knitted fabrics (Ertugrul & Ucar, 2000) as well as for woven fabrics (Vassiliadis et al., 2010) has been achieved with satisfactory results. The permeability of the woven fabrics has been modelled using ANNs as well (Tokarska, 2004; Çay et al., 2007). Further on, the impact permeability has been studied (Tokarska & Gniotek, 2009) and the quality of the neural models has been assessed (Tokarska, 2006). The pilling propensity of the fabrics has been predicted (Beltran et al., 2005) and the pilling of the fabrics has been evaluated (Chen & Huang, 2004; Zhang et al., 2010), while the presence of fuzz fibres has been modelled (Ucar & Ertugrul, 2007). The evaluation of the wrinkle of the fabrics has been realized on an objective basis with a system based on ANNs (Su & Xu, 1999; Kim, 1999; Mori & Komiyama, 2002). Prediction of the spirality of the relaxed knitted fabrics

(Murrells et al., 2009) as well as knit global quality (Slah et al., 2006) and subjective assessment of the knit fabrics (Ju & Ryu, 2006) have been implemented.

Prediction of the thermal resistance and the thermal conductivity of the textile fabrics has been realized with the help of ANNs (Bhattacharjee & Kothari, 2007; Fayala et al., 2008). Moisture and heat transfer in knitted fabrics has been also studied similarly (Yasdi et al., 2009). Engineering of fabrics used in safety and protection applications is supported by ANNs (Keshavaraj et al., 1995; Ramaiah et al., 2010). Prediction of the fabrics end use is also possible via the same method (Chen et al., 2001). Optimization of the application of a repellent coating has also been approached by the ANN model (Allan et al., 2002).

2.4 Color

The color measurement, comparison, evaluation and prediction are major actions in the dying and finishing field of the textile process. Although color measurement is possible in the laboratory with the help of specialized equipment like the spectrophotometers, few capabilities exist for the prediction of the color changes or the final color appearance, because the problem is multivariable. A model for the prediction of color change after the spinning process has been developed (Thevenet et al., 2003). The prediction of the color and the color solidity of a jigger dyed cellulose based fabric has been achieved by using cascade ANNs. In the field of printing, the color recipee specification has been made possible using radial basis function neural networks (Rautenberg & Todesco, 1999). The pigment combinations for the textile printing can be determined (Golob et al., 2008), the color of the printed fabric images can be identified and the color separation can take place by using different ANN types (Xu & Lin, 2002; Kuo et al., 2007). The prediction of CIELAB values is possible for color changes after chemical processes (Balci & Ogulata, 2009), for nylon 6,6 and for stripped cotton fabrics (Balci et al., 2008). The optimization of the processing conditions and the prediction of the dyeing quality of nylon and lycra fabrics and the classification of dyeing defects have been carried out with the help of ANNs and fuzzy neural networks respectively (Kuo & Fang, 2006; Huang & Yu, 2001).

2.5 Making up and clothing

Clothing articles are the end product of the main stream of the textile production flow. Although precision of the prediction of properties is not that critical as in technical applications, estimation of the final properties is essential for the clothing design, the selection of raw materials and their required properties. One of the most important factors affecting the garment quality is related to the seam, the result of the sewing process. Indeed, prediction of the seam strength is very important, especially for parachutes (Oanl et al., 2009). The thread consumption is predicted via an ANN model (Jaouadi et al., 2006), while the seam puckering is evaluated and the sewing thread is optimized through ANN models, respectively (Mak & Li, 2007; Lin, 2004). The prediction of the sewing performance is also possible using ANNs (Hui & Ng, 2005; Hui et al., 2007; Hui & Ng, 2009).

The human psychological perceptions of the clothing sensory comfort and the analysis of the tactile perception of the textile materials can be carried out using ANN approaches (Wong et al., 2003; Karthikeyan & Sztandera, 2010). Prediction of the performance of the fabrics in garment manufacturing and fit garment design have been realized based on ANN systems (Hu et al., 2009; Gong & Chen, 1999). Cases of special interest, like the selection of the optimal interlinings, or of broad interest, like the simulation of a textile supply chain, have been successfully modelled by ANNs (Jeong et al., 2000; Nuttle et al., 2000).

2.6 Nonwovens

The nonwoven is a specific category of fabrics, made directly of fibres and not of yarns. The nonwoven fabrics find many technical applications and their role is essential. The nonwoven fabrics undergo a process of inspection in order to ensure quality of the delivered material. A visual inspection system has been based on wavelet texture analysis and robust bayesian ANNs (Liu et al., 2010), or similarly wavelet transforms and ANNs (Huang & Lin, 2008), while a neuro-fractal approach has been used for the recognition and classification of nonwoven web images (Payvand et al., 2010). Many quality issues are addressed via ANN methods, like the structure-properties relations of the nonwoven fabrics (Chen et al., 2007), the construction of a quality prediction system (Kuo et al., 2007), the modeling of the compression properties of needle-punched nonwoven fabrics (Debnath & Madhusoothanan, 2008), the simulation of the drawing of spunbonding nowoven process (Chen et al., 2008) and also the objective evaluation of the pilling on nonwoven fabrics (Zhang et al., 2010).

3. Artificial Neural Networks

3.1 Functionalities of interest for textile engineering

Artificial Neural Networks (ANNs) are algorithmic structures derived from a simplified concept of the human brain structure. They belong to the Soft Computing family of methods, along with fuzzy logic / fuzzy control algorithms and genetic algorithms, (Zadeh, 1994). They all share an iterative, non-linear search for optimal or suboptimal solutions to a given problem, without the presupposition of a model of any type for the underlying system or process, (Keeler, 1992). Various different ANN types have already been successfully employed in a wide variety of application fields, (Haykin, 1998). Major ANN functionalities are

i.   Function approximation: this functionality is exploited in system input-output modeling and prediction, and

ii. Classification: this functionality is exploited in pattern recognition / classification problems, (Lippman, 1987).

•   In their capacity as function approximators, ANNs have long been studied as to the required properties of the target function as well as to the structure of the ANN, in order to guarrantee convergence of the – typically iterative – approximation algorithm. The first brain-inspired ANN structure was proposed by McCulloch and Pitts in 1943, along with a proof that it could approximate any deterministic function, (Hertz et. al., 1991). In light of the Cybenko theorem, (Cybenko, 1989), ANNs are recognized today as 'universal approximators', i.e. they can approximate arbitrarilly closely any function on a compact subset of R^n, under certain general assumptions on the function. The property was proved for a specific ANN structure (the standard multilayer feed-forward network with a single hidden layer that contains a finite number of hidden neurons, with a sigmoid activation function and a linear output layer). Similar results exist for arbitrary activation functions, (Hornik, 1989) and other ANN strucutres, as well, (e.g., Lin, 1994). A common prerequisite for the ANN to operate as approximator is the linearity of its output node(s).

    Under their function approximator form, ANNs have served as a powerful modeling tool, able to capture and represent almost any type of input-output relation, either linear or nonlinear. The shortcoming of such an ANN-based modeling solution is that the model is implicit. Indeed, rather than formulating an explicit input-output analytic

expression, either linear or nonlinear, an ANN processes examples of inputs and outputs, to capture and store knowledge on the system. It can subsequently simulate the system, or predict output values; yet, it cannot offer a closed-form description of the system.

In a textiles context, the function approximation capacity of ANNs is of great practical interest because a variety of quantities that characterize yarns and/or fabrics depend on (i.e., are functions of) the yarn or fabric consistency, structure and weaving characteristics. Air permeability of a woven fabric, for example, depends on such parameters as warp and weft yarn density and mass per unit area. These dependencies do not always lend themselves to accurate description by an analytic mathematical function; yet, the ability to estimate or predict the value of such a quantity of interest given the yarn or fabirc parameters – before actually constructing the yarn or fabricating the fabric – is highly desirable in the textiles design and production phases. Research has turned to ANNs for estimation and prediction tasks in various textile applications, (Stylios & Parsons-Moore, 1993), (Stylios & Sotomi, 1996), (Ertugul & Ucar, 2000), (Majumdar, 2004), (Lin, 2007), (Bhattacharjee & Kothari, 2007), (Gurumurthy, 2007), (Guruprasad & Behera, 2010).

- In their capacity as classifiers, on the other hand, ANNs have found extensive and successful application in virtually all pattern recognition tasks, including 1-D and 2-D signal (image) processing applications, clustering, etc. In such problems, unknown input data are classified as belonging to one of a finite number of known classes or categories. ANN structures with an output layer of nodes (neurons) of the 'competitive' type are suitable for classification tasks. Individual binary outputs of the output layer nodes are vectorized in order to enumerate the class where incoming data belong, in typical classification problems. Single and multiple-layer perceptrons, self-organizing maps and other types of ANN structures serve as classifiers. Among them, of practical interest are networks that compute probabilities that a given input belongs to one of the considered classes, rather than deterministic outputs. They can thus subsititue multi-expert decision algorithms, such as majority-voting, etc. Probabilities can subsequently be handled in a variety of ways to obtain final answers in the output.

The classification capacity of ANNs in a textiles context finds extended use in classification of yarn or fabric types or other visual properties, such as color, defects, weaving / knitting pattern, percentage consistency in various materials and the like, (Guruprasad & Behera, 2010). These tasks are affordable in time and equipment investment thanks to the recent technological advances (a) in image capturing equipment of high quality and very low cost and (b) in hardware processors of increased processing power that allow for real or quasi-real time applications.

3.2 Architecture and training algorithms

The structure or 'architecture' of an ANN contains a number of nodes, called neurons, organized in a number of layers and interconnected to form a network. Neurons are rather simple algorithmic structures that can perform parallel computation for data processing and knowledge representation, (Brasquet & LeCloirec, 2000). Weighted averaging, followed by linear or non-linear (thresholding) operations, with the possibility of feedback between layers, constitute the main processing operations in an ANN. The acquired knowledge is stored as the weight values of the nodes. The real power of this model, therefore, lies in the

mesh of simple but highly interconnected nodes rather than the power or sofistication of each node. Although inspired from the way neurons are interconnected in the human brain and nervous system to transfer messages by chemo-electrical procedures, no further analogy between ANNs and the human brain operation is claimed as to the functionalities achieved.
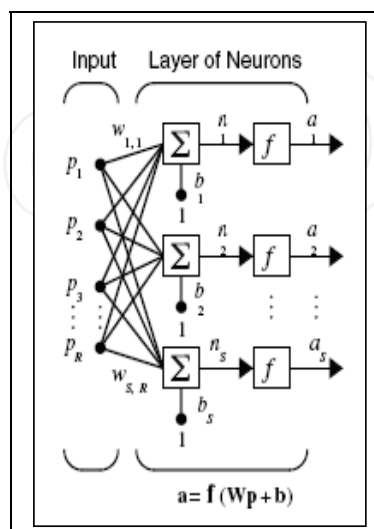

Fig. 1. A sample ANN architecture (one single layer of S nodes or neurons).

The architecture of a single layer of nodes for a sample ANN is shown in Figure 1, (Matlab, 2005). There exist S nodes in this layer. In the i-th node, a linear combination of a vector of R inputs $[p_1, ...p_R]$ is computed. In it, inputs are weighted by weights $[w_{i1}, ..., w_{iR}]$ and a bias term b_i is added. The scalar value produced undergoes a transformation by a generally nonlinear activation function $f(\cdot)$ to yield the corresponding i-th output, for all $i = 1, 2, ...,S$. Sigmoid, log-sigmoid, hard-limiter or even linear types of functions are employed, resulting in accordingly varying properties of the network.

In general, the ANN architecture is characterized by:

• A large number of simple, neuron-like processing elements;
• A large number of weighted connections between elements. The weights of these connections store the 'knowledge' of the network. The adaptive adjustment of the weight values, while moving down an error surface to a minimum point, constitutes the 'learning process' of the network;
• Highly parallel and distributed control; and
• An emphasis on learning internal system representations automatically, (Rich & Knight, 1991).

Apart from the topology and node characteristics (type of activation function, etc.), an ANN model is specified by the training rules or training algorithm employed to adapt its weights. These rules define an initial set of values for the weights and indicate how weights should be iteratively adapted to improve the performance of the network by minimizing the error between actual and ideal outputs, when the network is presented with a set of known inputs. A variety of different network models have already been proposed and used in practical applications, such as the Perceptron, the Multilayer Perceptron, the Hopfield network, the Carpenter-Grossberg classifier, the Back-propagation network, the Self-organizing Map, the Radial Basis Function Network, the Probabilistic Network, etc., (Ramesh et al., 1995), (Lippman, 1987).

In terms of operation, an ANN undergoes a training phase, where a rich set of examples matched in pairs of input - output values and called the 'training set' is presented to the network input. The weights in the nodes of the network are iteratively optimized by a gradient-type algorithm, so as to produce correct outputs for all inputs in the training set. As iterations proceed, the algorithm leads to sets of weights that minimize the error between ideal and actual ANN outputs – usually, in the least squares sense. Once trained, the network enters the so-called test phase, where it is 'questioned' to produce outputs for unknown inputs presented to it. Decisions are made (i.e., outputs are produced) on the basis of the experience gained by the network over the training set. During the test phase, the network is expected to 'generalize' successfully, i.e., to exploit the experience stored in its elements during the training phase in order to make correct decisions on incoming data that are similar but not identical to the training set data. Satisfactory generalization implies

- a correct choice of the network type in relation to the problem at hand and
- a successful training phase, in the sense that:
  - the training set was rich and informative enough to represent adequately the space of the input vectors, and
  - the training algorithm was allowed an adequate number of iteration to converge.

Major reasons for non-convergence of the training algorithm are

i. the choice of an inappropriate ANN structure (e.g., one with too many / not enough nodes or too many / not enough layers of nodes), and

ii. the unavailability of a rich training set, which means that more data or measurements are necessary to solve the problem at hand.

The second problem is more crucial in practice, as it is not always straightforward how more data are to be obtained or measured in real field applications. The first problem, on the other hand, can be efficiently addressed by simulations during the design phase of the whole application.

In order to illustrate the above, an example is provided in the following section, where an ANN is employed to predict or estimate a fabric property in terms of a set of structural weaving parameters of the yarns used and of the fabric itself.

4. A sample application of ANNs in fabric air permeability prediction

4.1 Problem description

Vacuum drying is a method for removing the water content from wet fabrics by suction. In a typical industrial fabric production process, vacuum drying is a pre-drying stage, positioned before the main drying unit, which operates by heating the wet fabric (stenter). The behavior of woven fabrics during vacuum drying is primarily influenced by their air permeability. Air permeability can be calculated from the porosity of the fabric. This approach, however, is not used in practice, because of known difficulties in determining basic porosity calculation parameters, such as the shape factor. Alternatively, air permeability can be measured in the laboratory after the production of the fabric. Of practical interest, however, is the possibility to predict air permeability during the design phase, based on technical, micro-structural characteristics of the fabric. This would allow for the prediction of the behavior of a fabric during vacuum drying and would thus support a realistic and optimized planning of the production process.

Air permeability depends both on the material(s) of the yarn and on the structural parameters of the fabric, through a generally complex, nonlinear relation, (Backer, 1951). In

order to 'capture' this relation and use it later as a predictor, the nonlinear approach of ANNs is adopted, (Cay et. al., 2007). Given the construction process of woven fabrics, three structural parameters are intuitively more attractive for this task, namely,

- warp yarn density,
- weft yarn density and
- mass per unit area.

They are advantageous in that their values either are predefined in the weaving process (warp and weft densities) or can be easily and accurately measured (mass per unit area), while at the same time they influence directly the properties of the woven fabric.

4.2 Network type selection

As discussed in section 3, the choice of the appropriate type of ANN depends on the peculiarities of the problem investigated. Several types of ANNs are promising candidates for the problem under consideration. In fact, any neural network that can take on the form of a universal function approximator will do. These are networks whose output layer nodes operate linearly and can therefore produce practically any real value in the output – as opposed to the limited output values possible when nonlinear / thresholding nodes are employed in the output layer.

The major network families in this class are

1. Multilayer Perceptrons,
2. Radial Basis Function Networks; more specifically, Generalized Regression Neural Networks, (Chen et al., 1991), and
3. Elman Networks, (Elman, 1990).

Among these three alternatives, Generalized Regression Neural Networks (GRNNs), are selected because

- they are known to approximate arbitrarily closely any desired function with finite discontinuities, and
- although they require an increased number of nodes in their architecture, they can be designed in far less time than necessary for the design and training of, e.g., a multiplayer perceptron.

GRNNs work by measuring how far a given sample pattern lies from patterns in the training set, in the N-dimensional space defined by the cardinality of the input set. When a new pattern is presented to the network, it is compared in the N-dimensional space to all patterns in the training set to determine how far in distance it lies from each one of them. The output that is predicted by the network is proportional to all outputs produced by the training set. The proportion value depends upon the distance between the incoming pattern and the given patterns in the training set. Euclidean or city-block distance metrics are used.
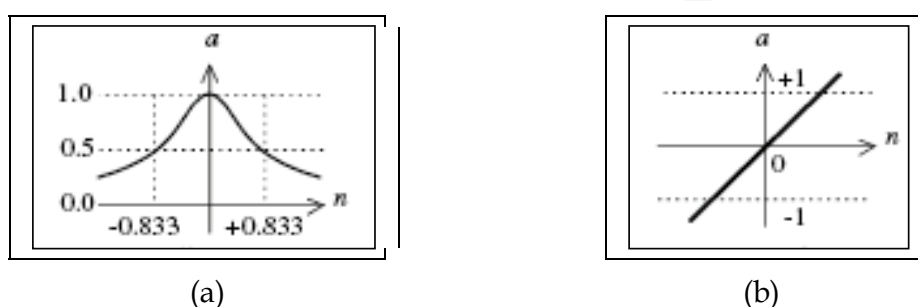

Fig. 2. A radial basis (a) and a linear (b) neuron transfer function.

In terms of structure, a GRNN contains two layers of neurons, each consisting of N neurons, where N is the cardinality of the training set (number of the input - output pairs available for training). The first, hidden layer consists of radial basis function (RBF) neurons while the second, output layer consists of linear neurons of special structure. Thanks to the later, the network can produce any real value in its output. Figure 2a shows a RBF neuron sample transfer function. An RBF neuron 'fires' or produces an output of 1 when its input lies on or fairly close to its central coordinates. Thanks to its symmetry and finite radial support controlled by a spread parameter, it responds only to local inputs, i.e. those befalling within a neighbourhood of controlled radius. Figure 2b shows a linear neuron sample transfer function. The linear layer of a GRNN is special in that its weights are set equal to the output values contained in the training set. When a value equal or close to 1 is produced by the first layer and propagated to the second layer, it produces by means of an inner product operation a significantly non-zero value at a certain output and practically zero values at the rest of the outputs.

During the design phase of the GRNN, the centres of the RBF neurons in the first layer are set equal to the input vectors in the training set. During the test phase, when an unknown input close (similar) to one of the training set inputs appears, the corresponding RBF neuron (or neighbouring set of neurons) fires a value equal or close to 1. The second layer performs an inner product between the vector of the first layer outputs and the vector of training set outputs. Training set outputs matched with values close to 1 in this inner product contribute significantly to the output, while the contribution of the rest is negligible. This is how the GRNN generalizes from the training set to unknown inputs.

The major shortcoming of a GRNN is that both its layers consist of a number of nodes equal to the number N of vectors in the training set. Given the fact that the training set should be rich enough to be representative of the input space, this number may grow large for a given application. As a counter-balance, however, it has been proved that the GRNN can be designed to produce zero error for any given training set in a very short time.

4.3 Experimental setup

A set of different samples of woven fabrics are produced and tested experimentally. All fabric types used are made of 100% cotton yarns and they are of plain weave structure. The warp and weft yarn linear densities are Ne 40 and Ne 50, respectively. The warp and weft yarn densities of the samples vary in incremental steps. Six (6) different weft densities and five (5) different warp densities are combined to produce a set of 6 x 5 = 30 different fabric types in total.

The air permeability of these fabrics is measured under constant pressure drop. Actually, rather than being directly measured, the air permeability is estimated by the measurement of air velocity. Air permeability in ($cm^3/s/cm^2$) is measured via the standard BS5636 method, using the Shirley FX 3300-5 air permeability tester. For each one of the thirty (30) fabric types constructed, the air permeability measurement is repeated across five (5) different samples of the same fabric, thus producing a total of 30 x 5 = 150 measurements. The five measurements of the same fabric are averaged to produce an average air permeability value, in order to reduce non-systematic measurement errors. The structural fabric parameters, the respective air permeability values (averages across five samples) and the standard deviation of the measurements are given in the Table I.

As it can be seen in Table 1, air permeability values decrease when warp and weft yarn densities increase – an expected behaviour because the dimensions of the pores through

which air flows are getting smaller when moving from looser towards tighter fabric types, where resistance to the airflow is higher.

Warp and weft yarn densities and mass per unit area form the input vector to the ANN. Therefore, each input – output pair in the training set contains a vector of these three inputs and a single output (air permeability). As mentioned earlier, air permeability measurements are averaged across sets of five samples for each fabric type. Therefore the data set consists of thirty (30) independent combinations of values of the three independent input variables along with the respective averaged air permeability value per case.

Sample No.	Warp yarn density (ends/cm)	Weft yarn density (picks/cm)	Mass per unit area (gr/m2)	Average Air permeability (cm3/s/cm2)	STDEV of Air permeability	Sample No.	Warp yarn density (ends/cm)	Weft yarn density (picks/cm)	Mass per unit area (gr/m2)	Average Air permeability (cm3/s/cm2)	STDEV of Air permeability
1	54	20	101.0	45.74	1.80	**16**	60	35	141.4	4.56	0.41
2	54	25	110.3	27.02	2.44	**17**	60	40	151.2	2.12	0.07
3	54	30	119.5	15.68	0.68	**18**	60	45	153.7	1.70	0.05
4	54	35	127.3	8.76	0.39	**19**	63	20	109.0	27.68	0.55
5	54	40	136.7	4.37	0.15	**20**	63	25	119.1	15.24	0.64
6	54	45	144.1	2.90	0.40	**21**	63	30	129.1	7.23	0.13
7	57	20	101.2	47.94	1.83	**22**	63	35	148.5	3.22	0.42
8	57	25	111.1	27.52	0.78	**23**	63	40	150.3	1.89	0.08
9	57	30	120.5	14.84	0.97	**24**	63	42	154.4	1.61	0.05
10	57	35	130.7	8.99	0.48	**25**	66	20	111.2	27.28	1.68
11	57	40	142.0	3.98	0.24	**26**	66	25	123.0	14.42	1.39
12	57	45	146.3	2.68	0.12	**27**	66	30	134.0	6.90	0.21
13	60	20	107.9	33.98	1.16	**28**	66	35	144.4	3.19	0.17
14	60	25	118.7	17.01	0.79	**29**	66	40	155.0	1.65	0.06
15	60	30	129.5	9.75	0.41	**30**	66	42	160.2	1.38	0.05

Table 1. Structural parameters and corresponding air permeability measurements for 30 fabric types.

Twenty-four (24) out of the thirty (30) cases are used for training while the remaining six (6) cases are retained for testing. This leads to a GRNN architecture of 24 neurons in each of the two layers. Furthermore, in order to reduce the dependency of the results on a specific partition of the data into training and testing sets, a five-ways cross validation test is carried out, i.e., the data are partitioned in five (5) different ways and finally results are averaged across all five (5) partitions. Figure 4 show results of one out of the five (5) different experiments of the five-ways cross-validation. The upper plot shows results where the

training set per se is used as the test set, while the lower plot shows results where the test set is disjoint to the training set. Within each plot, stars (*) and circles (o) indicate measured and estimated air permeability values, respectively, while dots (·) indicate the ANN performance error (difference between measured and estimated air permeability values).
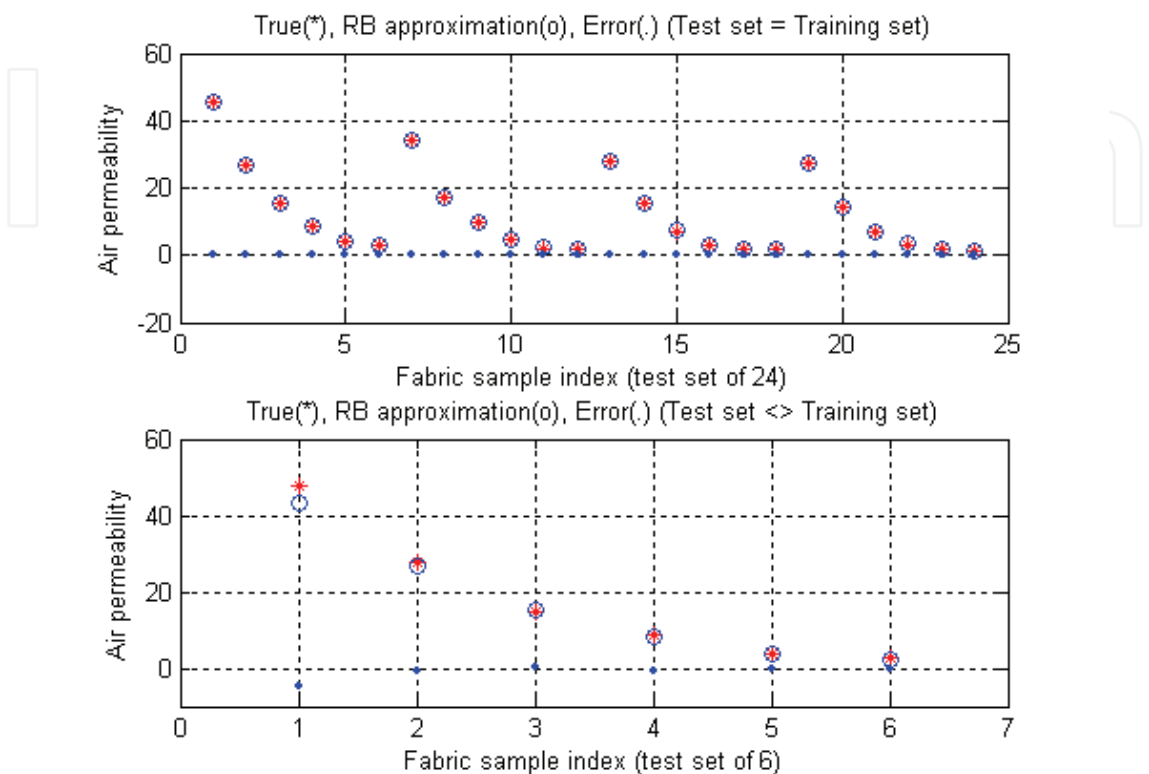

Fig. 4. Air permeability estimated (approximated) by the GRNN (partition no. 2).

As it can be seen in Figure 4, the network employed approximates air permeability values with a very low output error – a result observed regardless of the specific data partition into training and test sets. Error (sum-of-squares) values, given in Table 2, are indeed very low.

Data Partition No.	Error (sum-of-squares)
1	16.62
2	22.64
3	17.10
4	17.52
5	94.49
Average error (sum-of-squares)	33.27

Table 2. Sum-of-squares error across five partitions and average.

Although the relation under investigation is clearly non-linear, due to the complex dynamics involved in the underlying physical phenomena, a multiple linear regression is performed on the data of Table 1, in order to obtain

a. a crude linear approximation of the relation sought and

b. a clue as to the relative importance of the three intuitively chosen structural parameters within this relation.

```
The regression equation is
C4 = 105 - 0,679 C1 - 0,392 C2 - 0,355 C3

Predictor      Coef   SE Coef       T       P
Constant     105,04     16,36    6,42   0,000
C1          -0,6793    0,7280   -0,93   0,359
C2          -0,3920    0,5694   -0,69   0,497
C3          -0,3551    0,3655   -0,97   0,340

S = 5,59416   R-Sq = 84,0%   R-Sq(adj) = 82,2%

Analysis of Variance

Source          DF      SS       MS       F       P
Regression       3   4285,9   1428,6   45,65   0,000
Residual Error  26    813,7     31,3
Total           29   5099,6

Source  DF  Seq SS
C1       1  3825,8
C2       1   430,6
C3       1    29,5

Unusual Observations

Obs    C1      C4      Fit   SE Fit   Residual   St Resid
  1  20,0   45,74   34,42     2,54      11,32      2,27R
  7  20,0   47,94   33,17     2,05      14,77      2,84R

R  denotes  an  observation  with  a  large  standardized
residual.
```

Table 3. Multiple linear regression analysis on the data of Table 1.

The results are given in Table 3. Data in columns C1, C2, C3 contain weft densities, warp densities and mass per unit area data, respectively, while column C4 contains average air permeability values.

In Table 3, the P-value in the Analysis of Variance section is less than 10^{-3}, showing that the regression per se is indeed significant, i.e. there does exist an influential relation between the dependent variable (air permeability) and the three independent variables selected here. The R^2 value is 84% (adjusted R^2 is 82,2%), showing that 84% of the variability in the air permeability data is 'explained' by the linear combination of the specific three independent variables. This percentage is high enough to indicate that a linear relation could certainly be used as a crude approximation of the true relation and, at the same time, low enough to justify the investigation of nonlinear alternatives τo explain the remaining variability in the data.

It is interesting to notice that the (appropriately scaled) average error produced by the ANN approach in Table 2 (33.68 * 30 / 6 = 168.4) compares favourably to the respective error produced by the multiple linear regression approach (813.7). The later is a very encouraging result, as it justifies the extra effort required by the nonlinear approach. Indeed, in terms of the multiple linear regression, it can be claimed that the ANN structure leaves unexplained only the (168.4 / 5099.6 =) 3,3% of the total variability in the air permeability data, thus offering a five times better result than the respective 16% of the linear regression approach.

An error pattern apparent in the lower plot of Figure 4 associates looser fabric types (towards the left side of the horizontal axis) with error values higher than the respective error values for dense fabrics (towards the right side of the horizontal axis). For loose fabrics the pores or openings between the yarns are bigger so the yarn mobility is higher, thus the pore dimensions become bigger because of the deformation during the airflow. On the contrary, dense fabrics have very small pores and high resistance to airflow and can preserve their compactness during airflow.

Finally, Figure 5 shows the strong correlation between the measured and the predicted by the ANN air permeability values.
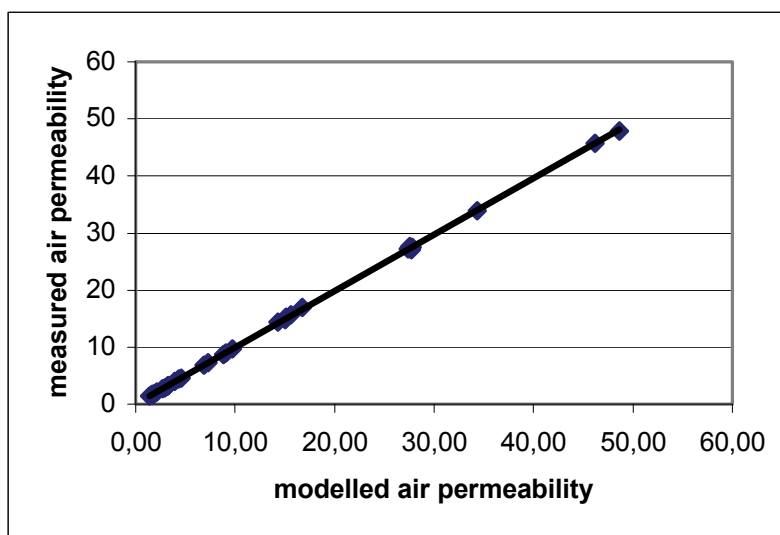
Fig. 5. Correlation between measured and ANN-predicted air permeability values.

5. Conclusions – future trends

An extended overview of the application of artificial neural networks methods for the solution of textile problems is provided in an attempt to cover this evolving field up to the current research and technology advances. It is clear to the reader that related publications on the field are produced in increasing numbers from the research community. Starting from the decade of the nineties a continuously increasing number of ANN applications has provided solutions to complex and multivariable textile problems. It seems that the textile community has been familiarized with this powerful tool and it trusts it more and more. The continuous increase of the computational power of the personal computers reduces the drawback of the computational cost that the use of ANNs requires. Therefore, it is expected that ANNs will augment their percentage of participation in solving complex textile problems and they will support the design and the computer aided engineering concepts in the textile field.

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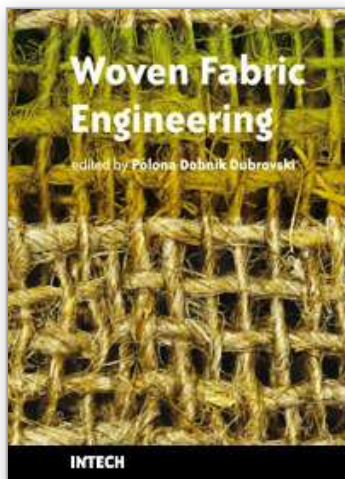
Woven Fabric Engineering

Edited by Polona Dobnik Dubrovski

The main goal in preparing this book was to publish contemporary concepts, new discoveries and innovative ideas in the field of woven fabric engineering, predominantly for the technical applications, as well as in the field of production engineering and to stress some problems connected with the use of woven fabrics in composites. The advantage of the book Woven Fabric Engineering is its open access fully searchable by anyone anywhere, and in this way it provides the forum for dissemination and exchange of the latest scientific information on theoretical as well as applied areas of knowledge in the field of woven fabric engineering. It is strongly recommended for all those who are connected with woven fabrics, for industrial engineers, researchers and graduate students.

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