

Prediction of Fabric Tensile Strength by Modelling the Woven Fabric

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1. Introduction

The variety of fabric structures is divided into four parts as wovens, knitts, braids and nonwovens. Comparing with other fabrics, woven fabrics display both good dimensional stability in the warp and weft directions and highest cover yarn packing density. One of the most important features for the characterization of woven fabric quality and fabric performance is tensile properties of fabric strength. Even though the end products of spinning and weaving are woven fabrics, they are raw materials for clothing and other industries such as composites and medical textiles. Every piece of woven fabric is an integration of warp and weft yarns through intersection. The extent of this intersection is largely dependent on the friction between fibres and yarns.

The study of woven fabric mechanics is came across in a work reported by Haas in the German aerodynamic literature in 1912 during development of airships. In English literature, the paper by Peirce (1937) who is the pioneer in the investigation of tensile deformation of woven fabrics presented a geometrical and a mathematical force model of the plain-weave structure which is highly theoretical, both of which have been used extensively and modified by subsequent workers in the field. Many researchers modified his geometrical model to analyze tensile behaviour. Considerable progress has been made over the last century in the development of the theory of geometrical structure and mechanical properties of fabrics.

The mathematical modelling of fabric stress- strain relationships is a very tough topic. During the last 60 years, many outstanding textile scientists have dedicated to their talents to this field. The development of mathematical models for woven fabrics is an extremely complicated and difficult task due to the large numbers of factors on which the behaviour of the fabric depends. Usually, a mathematical model requires a large number of assumptions, covering missing knowledge or inability to express some of the relevant factors.

Mathematical models based on the fundamental mechanics of woven fabrics often fail to yield satisfactory results, as it is hardly possible to incorporate all the complexities in the model. Moreover, the application range of mathematical models is also very specific. Therefore, it is necessary to introduce a different approach for the mathematical modelling of fabric constitutive equations. With fabric, fundamental distinctions may be made between three kinds of modelling, namely: predictive, descriptive and numerical models. The predictive models which form most of the existing research into fabric mechanics are based

on the consideration of at least the most important of the relevant factors, while the effect of the remaining ones is covered by suitable assumptions, defining the limits of validity and the accuracy of the resulting theories. Numerical models may ignore the exact mechanism taking place within the structure but emphasize the numerical relations of two variables such as stress– strain relations.

This method is based on statistical considerations; it needs fewer assumptions and provides, perhaps, an approach more relevant to real situations. There exist various methods for fitting a curve in many industrial or science fields. The descriptive models are largely empirical and reflect the need for simple mathematical relations, expressing the phenomenological behaviour of a fabric from the point of view of a particular property (Hu, 2004).

In addition to aforementioned models, in woven fabrics, parallel yarns are only in contact with each other over a fraction of their lengths, and crossover contact may act over relatively complex curved surfaces. Hence to produce an analytical model, a number of simplifications are required. Woven fabrics are well known to have non-linear mechanical properties. The tensile behaviour of woven fabrics is non-linear at low tensions, even if the yarn is linear in tension.

2. Importance of the study

Prediction of fabric mechanical properties such as strength, elongation, bending and shear is an intricate task, as it requires complete understanding of fabric structural mechanics and the interaction between warp and weft threads. Therefore, the solution of the fabric strength prediction problem could be performed by employing the empirical and computational models such as artificial neural network (ANN) or classical regression analysis (Majumdar et al, 2008).

In this study, the data obtained from Zeydan's paper (Zeydan, 2008) will be used for finding both the effect of some fibre, yarn and fabric parameters on the strength of jacquard woven mattress fabric and level configuration of parameters providing maximum fabric tensile strength. A new modelling methodology in the prediction of woven fabric strength will be introduced in this chapter and compared by using TDOE (Taguchi Design of Experiment), ANN, GA-ANN (Genetic Algorithm based Artificial Neural Network) Hybrid structure and multiple regression methodology. Initially, parameters affecting the fabric strength are chosen from experimental design perspective and then fabric strength is modelled based on the given parameters with TDOE, ANN, GA-ANN and multiple regression modelling approach. Besides, a hybrid model structure depending on GA-ANN is used to verify optimum woven fabrics manufacturing parameter configuration of TDOE. ANN and GA are two of the most important computational techniques of Artificial Intelligence. While ANN is a very powerful modelling method used in complex non-linear systems, GA can be suitable for parameter optimization. The performance criteria assessing appropriate model for the four approaches are root mean square error (RMSE) and MAE (Mean Absolute Error).

The following parameters collected from a Textile Factory producing jacquard woven bedding fabric have been identified as potentially important parameters affecting the strength of woven fabric as shown in the following Table 1.

While determining parameters of this study, parameters related to weaving process have been considered rather than yarn-based parameters. The firm that the research was carried

out purchases the yarn from its suppliers. But, it performs all weaving and treatment processes in its plant. Because of this reason, production process parameters of the firm were adjusted according to desired conditions during the sample production. Thus, parameters significantly affecting fabric strength such as yarn strength and twist could not be taken into consideration. Consequently, it was not possible to manufacture additional (extra) samples that are suitable for the aforementioned parameters. Fabric strength was tested at Titan fabric strength tester machine according to the ASTM D5035 testing method.

Levels		
Factors	1	2
A: Number of warp yarns at fabric width	7040	8658
B: Weft density (weft/cm)	8	16
C: Weft yarn count(denier)	300	600
D: Fibre Type of weft yarn	PF	CF
E: Warp density(warp/cm)	33	38
F: Warp yarn count (denier)	150	354
G: Fibre type of warp yarn	PF	CF

Table 1. Factors and Levels

Strip method (ASTM D5035) was adopted for the evaluation of breaking force of narrow fabrics in Titan fabric strength tester. Any fabric slippage from the tester jaws was recorded. Breaking force was recorded for evaluation. Five samples were tested at each group, which were 20 cm in length and 25mm in ravelled width. Gage length was set to 75mm and none the samples were failed at or close to the grip region. Only warp-wise testing was performed. Testing machine was set for a loading rate of 300 mm/min. All tests were performed under standard atmospheric conditions (per cent 65 \pm 2 relative humidity and 20 \pm 2 \pm 28C temperature) and the samples were conditioned hours under such conditions for 24 before testing (Zeydan, 2008). Jacquard woven fabrics are widely used in various sections of upholstery industry, where mattress cover is one of them. Although Jacquard fabrics are most often used for upholstery, they are becoming more and more popular in the apparel trades. Strength of jacquard woven mattress fabric depends on several factors. The objective of this study is to model the relationship between fibre, yarn and fabric parameters on the strength of fabric using artificial neural network (ANN), Taguchi design of experiment (TDOE), Multiple Regression and ANN-GA modelling methodologies. There have been some studies in the literature of Textile about the usage of Fabrics and woven Fabrics modelling with ANN. Keshavaraj et al. (1996) modelled air permeability of woven fabrics for airbags. Ogulata et al. (2006) used regression and ANN models to predict elongation and recovery test results of woven stretch fabric for warp and weft direction using different test points. Behera and Muttagi (2004) reported the possibility of woven fabric engineering. Majumdar et al. (2008) employed ANN to forecast the tensile strength of a woven fabric. Hadizadeh et al. (2009) predicted initial load-extension behaviour of plain weave and plain weave derivative fabrics. Tilocca et al. (2009) detected fabric defects using two kinds of optical patterns. Gong and Chen (1999) predicted the performance of fabrics in garment manufacturing. Behera and Karthikeyan (2006) made a design of canopy fabrics. However,

any research about comparing ANN, TDOE, multiple regression and ANN-GA in the literature hasn't been conducted on the strength prediction of woven fabric from fibre, yarn and fabric parameters using woven fabric modelling approaches with all together so far. Modelling the woven fabrics comes into existence in many forms.

In this study, traditional and computational modelling techniques are compared between each other. Compared the other classical modelling techniques, computational modelling methodology seems to have been more robust and appropriate. This study has many advantages to reduce the waste and scrap ratio before and during manufacturing. Therefore production planning will become more efficient in a textile plant. This study presents a new approach given in the following figure 1 about which woven fabric modelling is more efficient than the others.

2.1 Production cycle of weaving department at a textile factory

This study was made in a textile Factory in Turkey. The textile factory was founded in 2002. With over 1,000 employees, state of the art plants are made up of 120.000 m² open area of which 83.000 m² is closed area. It is a fully integrated facility consisting of weaving and knitting plants including narrow weaving, crochet knitting, fabric finishing, chenille yarn and Bulk continuous filament polypropylene yarn manufacturing sections. The company is the world's largest upholstery fabric manufacturer. The Factory ships (delivers) the great bulk of its output (approximately 80 %) to world markets. Its plants are regarded as the Europe's most modern Jacquard weaving facility comprising 150 full automatic Jacquard weaving looms and composes of several departments related to woven and knitted upholstery and bedding fabrics. Annually weaving production capacity are 30.000.000 meters. Average scrap of production is 5/1000. The reason of returning the production back is generally originated from vision-based.

Textile Factory composes of several departments related to woven and knitted upholstery and bedding fabrics. Production cycle of woven bedding fabrics starts with warping process. Warp and weft yarns are sourced from external companies and stored at yarn warehouse at the factory. Warp yarns needs to be wound into beams in order to weave fabrics in order. Conic warping machine is used to arrange warp yarns in order at the beam. After that, warp yarns are drawn-in and the weaving machine is ready for weaving. Weft yarns are fed into weaving process in the cone form. Design office in the company is responsible for preparing the jacquard design of fabric according to the customer preferences. The fabric design is transferred into jacquard system of weaving machine via floppy disk. Woven fabrics are wound into larger beams at the greige fabric control section of the factory. This initial quality control enables to evaluate the quality of weaving process and checking for the weaving faults. Depending on the demands of the customers, chemicals and finishing additives are applied to the greige fabric at the finishing department. Some of the widely preferred finishing processes are bulkiness finish, fire retardancy, soil and oil repellency, and water resistance. Stenter is the next step before packaging and final quality control. Dimensional stability and skewness of fabric are adjusted at the stenter. Chemicals and additives are also applied to fabrics at stenter. Fabrics are dried and further stability is generated at the drying section of the stenter called calendaring. Finished fabric quality control and packaging is performed based on the customer specifications and instructions. Finally fabrics are shipped to the customer. This production lay-out is schematized at Figure 2.

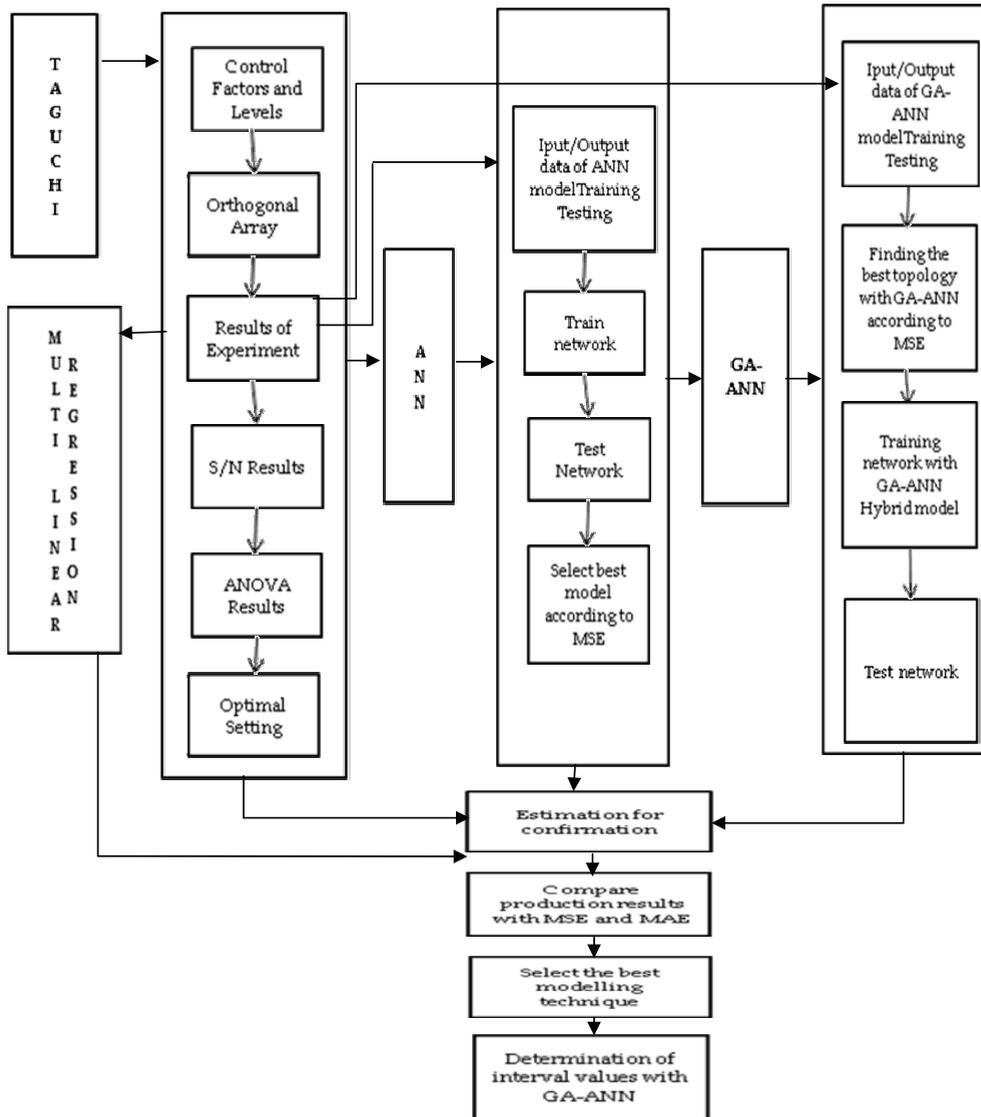


Fig. 1. Methodology of application

3. Modelling techniques

Here, Taguchi Design of Experiment Methodology will not be explained in detailed since this analyze was performed in Zeydan’s paper (2008). Orthogonal matrix is given in Table 2. According to the result of this analyze, the most efficient parameter affecting the woven fabric strength was warp density in terms of S (signal) to N (Noise) Ratio. Optimal parameter setting is $A_2B_2C_1D_2E_2F_2G_1$ which means A (8658), B (16), C (300/DN), D (PF),

E(38), F (30/2 DN), G (PF) the following stages will be considered according to the results obtained from TDOE.

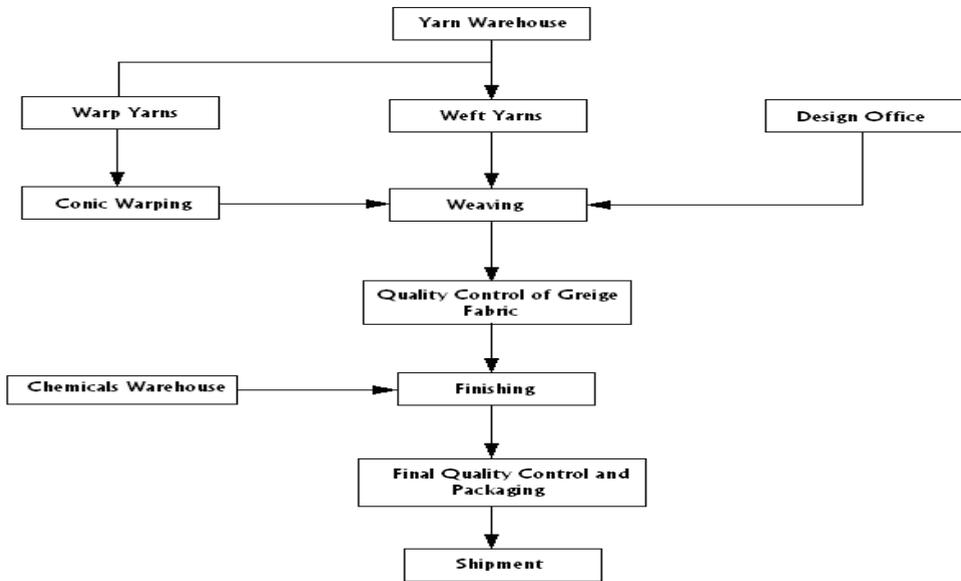


Fig. 2. Production work flow chart for jacquard woven bedding fabric

Parameters								
Order	A	B	C	D	E	F	G	Average Fabric Strength (N/m)
1	7040	8	300	PF	33	150	PF	1026 (21.6)
2	7040	8	300	CF	38	354	CF	1313 (32.7)
3	7040	16	600	PF	33	354	CF	1057 (26.9)
4	7040	16	600	CF	38	150	PF	1350 (32.7)
5	8658	8	600	PF	38	150	CF	1148 (34.2)
6	8658	8	600	CF	33	354	PF	1161 (38.0)
7	8658	16	300	PF	38	354	PF	1669 (36.3)
8	8658	16	300	CF	33	150	CF	1117 (34.9)

Table 2. Orthogonal matrix

L8 experimental design orthogonal matrix formed related with fabric strength is given in table 2. Total amount of data about fabric strength collected from the factory is 120.

3.1 Multiple Linear Regression

Multiple Linear Regression (MLR) is a well known statistical procedure trying to find a linear relationship between two or more explanatory variables and a dependent variable by observing data. It can be used for forecasting output values. Dependent variable (y) can be explained by the equation below:

$$y = a + \sum_{i=1}^n b_i x_i + \varepsilon \quad (1)$$

Before using ANN, multiple linear regression model is constructed. MLR is used as a verification and comparison model of ANN in the literature (Noori et al., 2010). It is claimed that ANN generally gives better results than MLR (Valverde Ramirez et al., 2005). Fabric strength is defined as dependent variable and explanatory variables are; number of warp yarns at fabric width, weft density, weft yarn count, fiber type of weft, warp density, warp yarn count and fiber type of warp yarn. Multiple Linear Regression equation defined as below by considering the mean fabric strength data:

$$y = 618 + 87.2A + 136B - 102C + 10.2D + 280E + 140F - 143G \quad (2)$$

3.2 Artificial Neural Network (ANN)

ANN is a nonlinear mapping system based on principles observed in nervous systems (Co, 2008). Complex nonlinear systems can be modelled efficiently by using ANN. In this study, multilayer perception is used for solving difficult predictive modelling problems. Multilayer perceptions networks consist of typically an input layer, single or more hidden layers, and one output layer. Hidden layers have one or more hidden neurons which performs nonlinear mapping between inputs and outputs (Lin and Choo, 2008). Activation functions are used to activate nodes. Here, sigmoid activation function is used, because generally MLP neural networks uses the logistic sigmoid function (Co, 2008) and using the sigmoid function in ANN topology provides a good nonlinear input-output mapping capability (Lo and Tsao, 2002). Choosing the proper learning algorithm is also very important while training the networks. For solving nonlinear optimization problems Levenberg-Marquardt algorithm is employed because of its efficient method (Sanjari et al., 2009). Besides, minimizing the MSE is the best known advantage of Levenberg-Marquardt (Purwanto et al., 2008). There is not a common sense about the number of the network layers, hidden nodes and generally a trial-and-error process approach is used for predetermining the optimal number of nodes in the hidden layer (Tu, 1996). Networks which contain different number of hidden layers and hidden neurons are being compared to find the best one (Wu et al., 2009). Mean square error (MSE) is generally used to judge the capability of networks while selecting the best one. Beside that, the simplest architecture is better than others (Didier, 2009). Therefore, the most important issue is to find the proper number of hidden neurons. Too much hidden neurons causes too much flexibility and this leads over fitting. But, too few hidden neurons prevent the learning capacity and decrease approximation performance of network (Haykin, 1994; and Xu and Chen, 2008). A single hidden layer can be chosen and it is sufficient for any continuous nonlinear mapping. But also, there have been many applications using two hidden layers (Behera and Karthikeyan, 2006). Recently, Artificial Neural Network became a popular modelling tool used in textile engineering area. It is commonly used in the applications of various types of fabrics. Defect detection and strength determination are some of the most known usage areas of ANN. In this study, ANN is also used to determine fabric strength. In Table 3, various options by comparing between 1 hidden layer and 2 hidden layers from one neuron to 10 neurons in terms of RMSE and MAE performance values, were tried to obtain the best ANN topology using trial and error method by considering literature claims. Results show that two hidden

layers and three neurons are better than the other conditions. RMSE is used to compare topologies. Minimum RMSE is found for 7 (input)-2 (first hidden layer) - 3 (Second Hidden Layer) -1 (output) topology.

Performance						
Neuron	1 Hidden Layer			2 Hidden Layer		
	MSE	MAE	R	MSE	MAE	R
1	55939.1	1783289	0.558749	43301.66	1676.322	0.552495
2	15146.21	8729215	0.88216	12243.38	7986.922	0.871783
3	5953217,0	460774	0.956546	4485.351	5224.486	0.947723
4	8482484,0	6068052	0.94131	6852.638	6452.752	0.949635
5	12120.4	6657714	0.88593	12905.09	7121.598	0.887804
6	10212.87	5989459	0.900652	13256.95	7198.211	0.884492
7	11772.05	6277868	0.887777	24378.05	1187.689	0.808354
8	13014.74	7426107	0.871812	28423.24	1272.778	0.732697
9	11243.09	6145195	0.894136	16736.9	9074.597	0.852666
10	19056.53	9939427	0.856076	11566.42	653.403	0.896996

Table 3. Performance Values of 1-2 Hidden Layers

3.3 Genetic algorithm based artificial neural network

Genetic algorithm is a combinatorial optimization technique which models natural biologic evaluation process. GA searches for finding global optimal but cannot guarantee to find best solution (Núñez-Letamendia, 2007). It has a special terminology. Population includes alternative solutions set, genes mean variables which build up a solution, and chromosome is the name of all individual in population, so it represents an alternative solution. Generation means iteration. Also, fitness function represents an objective function.

To create a population, genetic algorithm chooses randomly a chromosome from search space. Populations are evolved until the best fitness value can be found. These evolutions are done by selection, crossover and mutation operators in which chromosomes will be used in reproduction process is decided in selection process. In this step, best chromosomes are tried to be chosen depending on the fitness function that is regarded as objective function. By this way, a decision can be made whether a solution is bad or not (Shopova and Vaklieva-Bancheva, 2006).

After selection process, recombination operator is applied to alter solutions. It combines two selected parent chromosomes' features with a probability to form new children. When recombination process finishes, mutation starts. The mutation refers creating of a new chromosome from an individual by changing some genes of chromosome with a predefined probability. After selection, crossover and mutation operators are applied, the newly created offspring is inserted into the population. Parent chromosomes in which they were derived from are replaced and so a new generation is created. Until the optimization criterion is met, this cycle is performed. Stopping criteria can be a generation number.

GA is used to determine the best network architecture and training parameters of ANN in this study. Trial and error method takes long time and sometimes cannot determine best topology. But genetic algorithm has become a popular tool in neural networks, recently. It is generally used in three ways in the literature of ANN. The first one is to optimize hidden neurons, learning rate and momentum rate (Mohebbi et al., 2008 ; Torres, 2005). By this way,

time and effort required to find optimal architecture is minimized [Taheri, 2008; Kim et al., 2004; Saemi, 2007]. The second usage of GA in ANN is to train parameters of neural networks (Liu et al., 2004; Heckerling, 2004; Versace, 2000). And the final way is to set the weights in fixed architecture (Whitley, 1995). NeuroSolutions 5 is used to apply GA in ANN. It is an efficient software ANN optimization (Kim et al., 2004; Cheung et al., 2006).

In the first stage, GA is used to find best topology of ANN. Multilayer perception algorithm and 1 hidden layer is used. Sigmoid as an activation function and Levenberg Marquardt learning algorithm is chosen again, because of the mentioned advantages before. Under this circumstance, optimal processing element (PE) is determined by using GA which optimizes the architecture until the lowest error is found.

Results show that 1 hidden layer and four PEs are the best topology for our data. ANN-GA topology is 7-1-4-1. It was shown in Figure 3. After determining the optimal topology by using GA, next step is to perform genetic Training. Genetic training firstly creates an initial population of networks, randomly. All networks have different parameters. These are trained by considering minimum square error (MSE) that is defined as a threshold value. Threshold value is taken 0.01 for MSE. Properties of good networks are crossover and mutated to create better networks which include less MSE value than others. While selecting good chromosomes, Roulette wheel is used as selection operator. Selection depends on best fitness value.

The characteristics of the good networks are then combined and mutated to create a new population of networks. Again, the networks in this population are evaluated and the characteristics of the best networks are passed along to the next generations of networks. This process is stopped until the maximum generation is reached. Maximum generation number is 60 and maximum epoch is 1000 for this study. Population number is 50. Crossing over and mutation are done between 2 point with a probability of 0,9 and in uniform form with a probability of 0,01, respectively. Results show that GA-ANN gives better results than ANN.

Especially, testing MSE and correlation coefficientcy (R) of GA-ANN has a significant difference rather than ANN. Especially, testing MSE and r of GA-ANN has a significant difference rather than ANN. According to the table 3, since all performance measurement values for GA-ANN topology are better than ANN topology, we will use the GA-ANN topology for modelling studies.

Performance	ANN topology	GA-ANN topology
MSE	5953.217	1906.985069
MAE	46.0774	29.96099284
R	0.956546	0.981429488

Table 4. Comparison of ANN and GA-ANN topologies

GA-ANN procedures generally gives better results rather than ANN. 10 experimental parameter sets collected from the production process are tested to compare the modelling performance of all methods that are used. Table 4 shows the production (forecasting) values of methods obtained from modelling. Experimental results for fabric strength are the real values. According to the experimental values, all forecasting values obtained from modelling is compared with each other. At the end of this process, Optimal modelling technique for the smallest RMSE and MAE value is determined as GA-ANN.

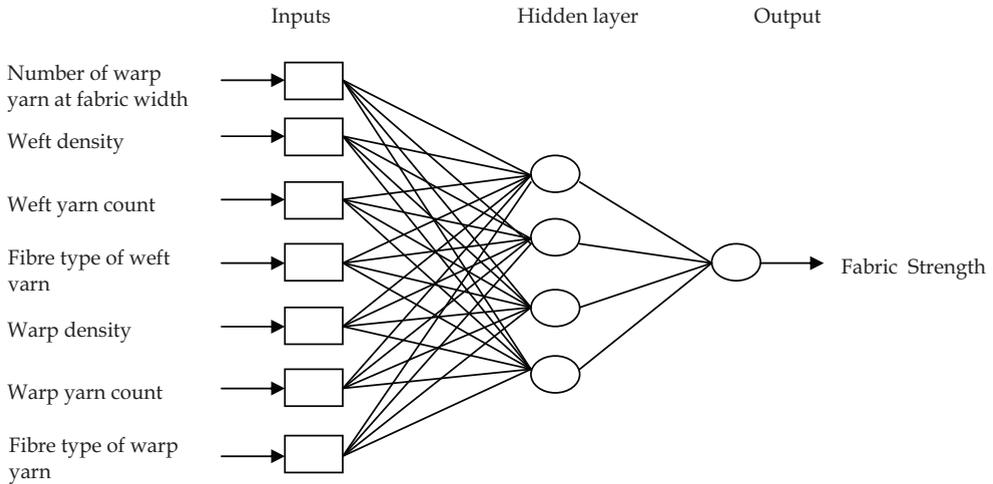


Fig. 3. ANN-GA Topology

Exp.	A	B	C	D	E	F	G	Experimental Results	Predicted Linear Regression	Predicted TDOE	Predicted ANN	Predicted GA-ANN
1	1	1	2	2	2	1	1	1250	1214.6	1213.75	1295879	1250
2	2	2	1	1	1	1	2	1098	1106.6	1106.75	1029.38	1098
3	1	1	2	1	1	2	2	1005	921.4	920.75	1035336	1005
4	2	2	1	2	2	2	2	1428	1536.8	1536.5	1518434	1428
5	1	1	2	2	2	1	2	1302	1071.6	1071	1252.7	1302
6	2	1	2	1	1	2	2	1052	1008.6	1008	1034977	1052
7	1	2	1	1	2	2	1	1637	1582.4	1581.75	1641925	1516912
8	2	1	1	1	2	1	2	1301	1250.6	1250.25	1294558	1224259
9	1	2	1	1	2	2	2	1544	1439.4	1439	1403969	1402.06
10	2	2	1	2	1	2	1	1498	1399.8	1399.5	1274407	1513988

Table 5. Comparison of experimental results with Linear Regression, TDOE, ANN and GA-ANN

RMSE and MAE values of linear regression, TDOE, ANN and GA-ANN are shown in Table 5. Also, Graphical representation of all modelling methods used is given by comparing with each other in figure 4 The best results are obtained with GA-ANN model.

	LINEAR REGRESSION	TDOE	ANN	GA-ANN
RMSE	100.6116	100.9521	93.97	63.80663
MAE	81.8	82.225	67.6584	35.47569

Table 6. RMSE and MAE values of modelling methods

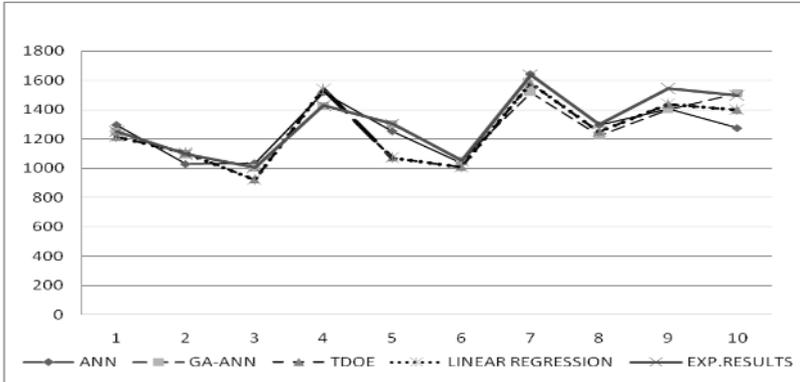


Fig. 4. Comparison of modelling methods

The final stage of the new modelling methodology is to make a verification of finding the optimum fabric strength with GA-ANN hybrid modelling technique as the best methodology. Warp density as the most important factor affecting the fabric strength is found with the Taguchi Design of Experiment Methodology and whether there have been in interval values of optimum parameter setting is tested by increasing from 33 to 38. The verification of TDOE results with GA-ANN hybrid modelling technique for interval values of warp density from 33 (warp/cm) to 38 (warp/cm) is shown in figure 5.

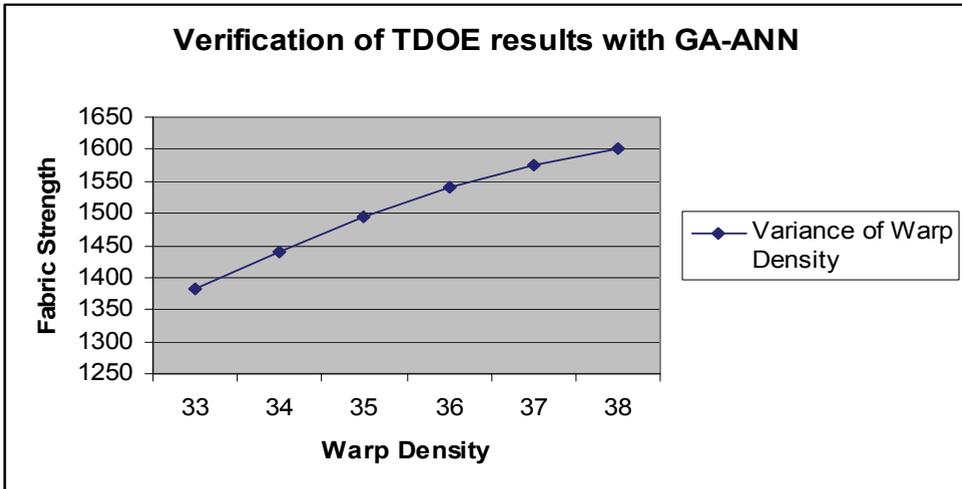


Fig. 5. Interval values of warp density

4. Conclusion

In this study, traditional and computational modelling techniques are compared between each other to predict woven fabric strength that is one of the main features for the characterization of woven fabric quality and fabric performance. Compared the other

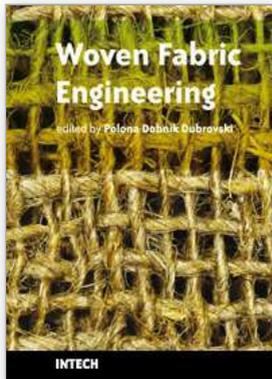
classical modelling techniques, computational modelling methodology seems to have been more robust and appropriate. This study made in a textile factory producing jacquard woven bedding fabric in Turkey has many benefits for textile manufacturers to reduce waste and scrap ratio before and during manufacturing. Firstly, production planning function in the plant will be able to predict the woven fabric strength easily to be known optimal parameter setting before manufacturing. Secondly, The significant parameter in the manufacturing was found as Warp Density. Thirdly, after finding the optimum parameter setting with TDOE, interval values of the sensitive parameters in the production was found with ANN approach. According to the data collected from manufacturing Process of factory in Zeydan's paper (2008), Taguchi Design of Experiment methodology was applied to find the most significant parameters. Seven significant parameters affecting the Woven Fabric tensile strength was considered. Warp density was found the most important factor affecting the Fabric strength by using S/N Ratio. The main purpose of this study is modelling the woven fabric strength by comparing different modelling techniques. However, any research about comparing ANN, TDOE, multiple regression and ANN-GA in the literature hasn't been conducted on the strength prediction of woven fabric from fibre, yarn and fabric parameters using woven fabric modelling approaches with all together so far. ANN, GA-ANN hybrid approach, Multiple-Linear regression, TDOE based on RMSE and MAE modelling performance criteria which is frequently used, are compared with each other. Finally, GA-ANN hybrid methodology was found as a suitable modelling technique. At the last stage of modelling methodology, verification of TDOE results with GA-ANN hybrid modelling technique for interval values of warp density was performed by increasing from 33 (warp/cm) to 38 (warp/cm). Parameter value giving optimum fabric strength for Warp Density was determined as 38 (warp/cm).

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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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