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An Approach to Spunlace Fabrics: A Prediction on the Tensile Strength Using Artificial Neural Network and the Improvement of the Production Quality Using Fuzzy-Logic Controller

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ABSTRACT

In this study, firstly, the tensile strength of the spunlace fabric has been estimated by Artificial Neural Networks (ANN) method. For this purpose, an artificial neural network model was developed by taking the tensile strength values of spunlace fabric samples as reference values. In the production of spunlace fabric with water jet, it is the water jet that provides the mechanical bonding of the fibers and hence affects directly the breaking and tearing strength values of the fabric. The water jet pressure is controlled by pressure sensors, and a blockage in the water jet causes the pressure sensors to measure incorrectly and, as a result, a quality failure. In this respect, secondly aim of this study is to conceive a method to controller the water jet pressure using a fuzzy-logic controller (FLC) instead of pressure sensor control. During the production, the DC electric motor revolutions used in the water jet were kept constant by the fuzzy logic controller according to these reference values. And hence, it was provided that the strength quality of the spunlace fabric were maintained.

1. Introduction

Spunlace fabric, which is a part of the growing technology in the field of on-woven textiles, is the preferred fabric in various areas of use such as cleaning cloths, make-up removal cloths, and cologne wipes. The fact that it is increasingly used in technical textiles and durable applications makes production quality more important. In the literature, there are many studies investigating the relationship between the mechanical, physical and permeability properties of fiber placement and fiber distribution characteristics. The production of spunlace fabrics with non-woven textiles is carried out by exposing the fibers to high pressure water and providing mechanical bonding to each other. The strength level of the bonds against tensiling and tearing shows the quality of the spunlace fabric, where the desired quality in production is achieved by adjusting the water jet pressure to the right level. As in every sector focused on quality production, necessary improvements are constantly made in the field of non-woven textiles in order to increase the amount of production and reduce production errors. Spunlace fabric is one of the areas in which quality production ought to be on the highest level. Consequently, increasing the quality of this type of fabric would be effective in advancing in foreign markets and in the development of the understanding of trade.

In the literature, there are various studies which focus on the usage areas and advantages of spunlace fabric with focus on the production of higher quality spunlace fabric in terms of mechanical properties. Uyanık and Baykal [1] emphasize the importance of spunlace fabric in terms of child health and argue that spunlace fabric should be used in diapers, which are among the most used products. Kalkancı [2] shows in his study that the clothes made of spunlace fabrics with antibacterial properties, which can be worn in various environments such as a hospital, play an important role in disinfection while the quality of these fabrics also affects their antibacterial properties. Lu and Xia [3] introduce the spunbond and spunlace combination technology in their research emphasizing the advantages of the spunbond-spunlace process. They suggest composite technology to be an effective method to develop new nonwovens; they mention that the advantages of spunbond and spunlace technique with strong bond can be used to produce high quality nonwoven products with excellent performance and high added value; finally, they show that this technology has very wide market perspectives due to its superior performances and wide applications. Considering that the demand for spunlace non-woven fabric has increased dynamically in recent years, Sąsiadek et al. [4] have planned an innovative technological line for the production of spunlace nonwoven fabric which would keep up with the newly developing and changing market conditions and competence, especially in African and South American countries. Jain et al. [5]report that the loss of spunlace fabric is very low and its rate of recycling is very high. Zhang et al . [6] mention the use of spunlace fabric in wet wipes and emphasize that smoothness and

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strength are important factors in wet wipes; while showing that the strength necessary to provide the desired quality in wet wipes should be in the range of 9.5N/50mm and 6.3N/50mm.

Jankowski [7] shows that spunlace fabric produced with non-woven textile has more than one layer, which increases its filtering property and quality ratio. Kalebek and Babaarslan [8] emphasize in their study that friction forces occurring in multi-layer spunlace fabrics vary according to the weights. They have observed that the friction force decreases as the weight of the fabric increases, and the friction force increases as the weight of the fabric decreases. Niedziela et al. [9] emphasize the importance of carding when producing spunlace fabric in non-woven textile. Many manufacturers have shown that they produce different carding machines, that these machines play an important role in delivering the products to water jets and in laying the fibers before they are bonded, and that the quality is affected as a result of these processes.

Civan et al. [10]have automatically determined the pore size distribution and fiber placement in non-woven fabrics using the image processing technique, and they have also examined the relationship with fabric weight. Later, Gültekin et al. [11] have obtained statistical data on surface properties from images taken from non-woven fabric samples with the algorithm which they developed using the image processing technique. They used these values as input values in the artificial neural networks model. They also used the values as output values for air permeability, tensile strength and elongation at break in machine direction and reverse machine direction. As a result, they could predict the air permeability, tensile strength and elongation at break values by using the texture characteristics obtained directly from the surface images of the fabric samples produced with spunlace technology. Concerning the correlation coefficient (R2) values between the experimental measurements and the results obtained by estimating with artificial neural networks, the scholars obtained 0.97 for air permeability, 0.90 for tensile strength, and 0.89 for elongation at tensile. Hajiani et al. [12] emphasize the importance of non-woven textile in their study and state that an important fabric type in this production method is spunlace fabric. They experimented with four different weights of spunlace fabric, namely 35, 40, 45, and 50 g/m2, and applied 3 different water jet pressures, namely of 50, 60 and 70 bar, to these four different fabrics. At the end of their experiment, they measured the ratio of thickness, mass and quality and observed that with the increase of water jet pressure, the thickness of the fabric also increases and there is an increase in the quality ratio too. In another study, Zhang et al. [13] have proved that the strength values of spunlace fabric decrease under low water jet pressures, while the strength values increase under high water jet pressures. Zhang and Jin [14] have observed that the strength values of spunlace fabric change under different pressures, and they have shown that fabrics with high g/m2 generally reach the desired quality values at high pressures. Chellamani et al. [15] have investigated the nonwoven production process of spunlace fabric and have shown that a high water jet pressure, which provides mechanical bonding of fibers, increases spunlace fabric strength. Jain et al. [16] have conducted a study on the structural analysis of spunlace fabric. According to this study, it can be observed that with the increase of water pressure, the pore diameter in the fabric decreases and has a lower thickness. There is a positive correlation between the air permeability of the fabric and the pore diameter, and, according to their experiment, the correlation value of this bond is found to be of 0.523. It can be also observed that there is a negative (r =-0.627) link between fabric weight and permeability. Gulhane et al. [17] have investigated the effects of water circulating parameters, such as jet diameter, jet spacing, manifold pressure and manifold number, on the structure and properties of spunlace fabric.

The estimation method with artificial neural networks, which is used in this study, reveals wide applicability in various fields and activities such as modeling the tensile test in virtual laboratory design [18], estimating the splitting tensile strength of glass fiber reinforced concrete [19], estimating the elastic modulus of recycled aggregate concrete [20], predicting the properties of waste crushed autoclaved aerated concrete aggregates [21], estimating the surface roughness of Al/SiC composite [22], and estimating the specific heat of hybrid nanofluids [23].

As it can be concluded from the studies mentioned above, there are many possibilities to examine the effects of various parameters, such as water jet speed, diameter and impact angle, on spunlace fabric structure and fabric properties. All of these studies prove that water jet pressure is directly related to spunlace fabric quality. It can be even claimed that the water jet pressure level is the primary parameter related to the spunlace fabric production quality. When the desired conditions are met in production, it is expected to continuously produce the fabric on this level. In this respect, making the production quality sustainable means properly maintaining the water jet pressure level. This should assert that the water jet pressure is controllable and stable on the desired level during production. In addition, the fact that the engine speed, when adjusted by the driver according to the information received from the pressure sensor, operates at the same speed during the production would create a situation directly related to the production quality and this idea is the focus of this study. In the literature, there is no study encompassing this focus.

The first stage of the present study consists of obtaining the transverse and longitudinal tensile strength values of spunlace fabric by estimating it as a result of training artificial neural networks. The second stage of the study consists of fuzzy-logic controller, which belongs to artificial intelligence technology, by taking this learned data as a reference, and transferring the electrical signal that would create the appropriate engine speed to the driver. This would make certain that the engine operates at the same speed until the end of production. This method prevents quality errors and waste caused by the system which determines the engine speed depending on the measurements made by the pressure sensor, thus improving the quality in production.

2. Material And Method

2.1. Spunlace Fabric

The non-woven fabric production technology consists of three stages: texture forming, texture fixing, and finishing [24, 25]. Texture creation methods are dry laying (mechanical, air, mechanical and air), wet laying, and continuous fiber laying (endless fiber laying, melt spraying, electrostatic laying). Texture fixation methods include mechanical methods (needling, water jet fixing, sewing), chemical methods (chemical impregnation, chemical spraying, chemical transferring, chemical powdering, chemical transfer with foam), and thermal methods (with hot rollers, hollow rollers, hot air, sound waves, radiation)) [25, 26]. The spunlace fabric examined in this study represents a product containing polyester and viscose fiber in different mixing ratios (Figure 1), depending on the desired raw material ratio. It has been produced by mechanical laying technique, which is one of the dry-laying techniques during the texture formation stage, and by the water jet fixation technique (Figure 2).

Fig. 1. Polyester and viscose raw material, [27, 28]

Fig. 2. Water jet and bond structure created [29]

A sample production line block diagram, in which the spunlace fabric production examined in the study is carried out, is given in Figure 3. Here, the pressure control interface is the interface where the pressure value suitable for the strength value of the spunlace fabric to be produced in the desired quality is entered. The direct current electric motor driver examined in the study produces electric current in the range of 0-10 Volts. It produces the appropriate electric current according to the reference signal which would come to the contact input X1-6 sending it to the direct current electric motor from the outputs of C1 and D1.

The rotation of the direct current motor occurs according to the current coming to the rotor by the driver, where the motor converts electrical energy into mechanical energy and provides the pressure of the water pump to which it is mechanically connected. Thus, according to the pressure produced by the water pump, the desired water jet pressure is provided with the appropriate flow rate from the water jet nozzles of fixed diameter. An increase in the speed of the electric motor means an increase in the pump pressure and thus an increase in the water jet pressure, and a decrease in the engine speed means a decrease in the pump pressure and consequently in water jet pressure. The electric motor examined in the study has a value in the range of 0-3000 rpm.

The industrial name of the high pressure water pump used in the system is “centrifugal pump”. The liquid discharge power of the pump used in the system is shown in Figure 4, [30]. As the power increases, the flooding power increases linearly. The factor affecting the pump's pumping power is the speed of the motor connected to the pump. As the engine speed increases, the pump's liquid discharge power increases linearly.

Owing to the pressurized liquid transfer of the pump, which is responsible for transmitting pressurized water to the water jets in the system, the desired pressure levels are formed in the water jet. The pressure (105Pa) values formed in the water jet in relation to the revolution (rpm) of the direct current electric motor connected to the pump are given graphically in Figure 5.

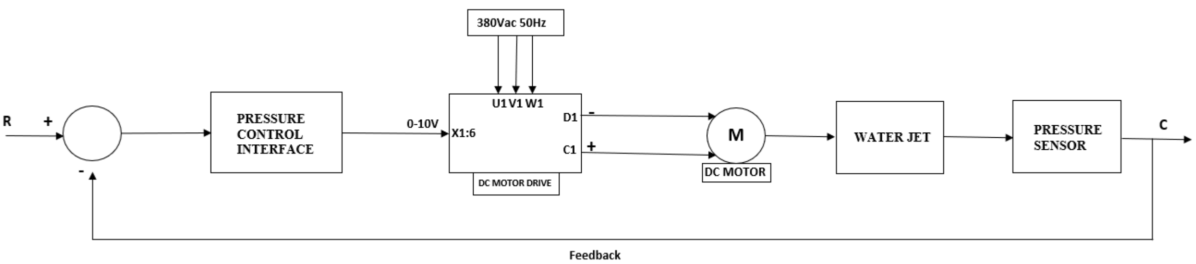


Fig. 3. Spunlace fabric production line block diagram

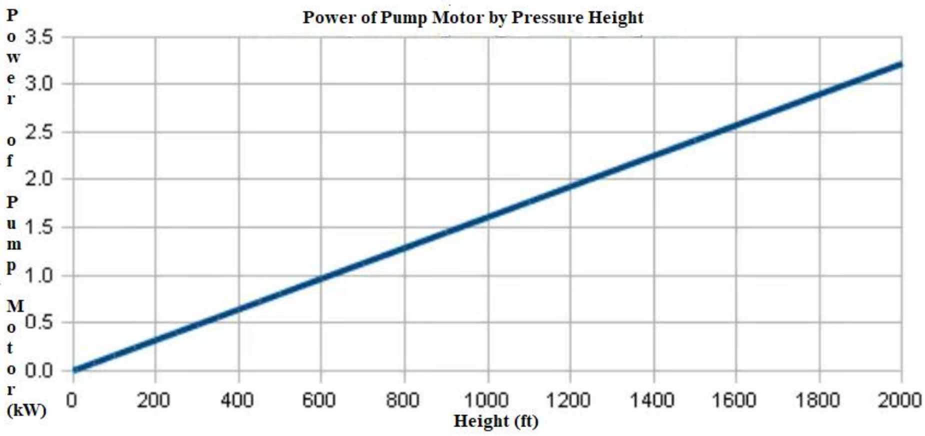


Fig. 4. Pump’s discharge power

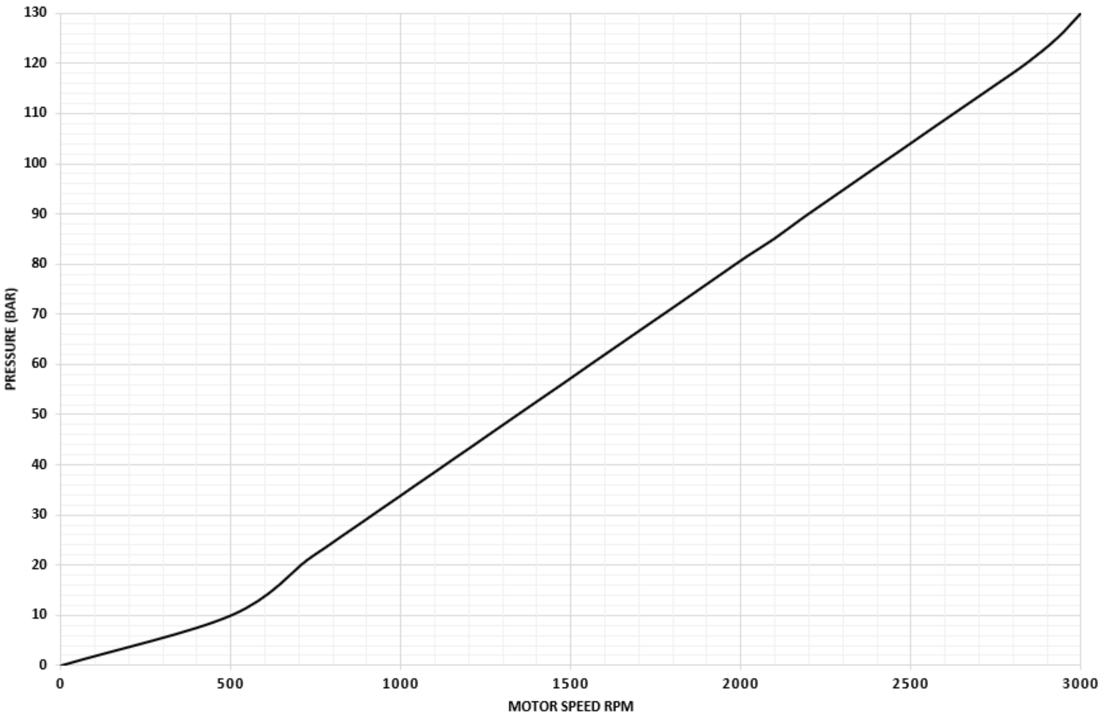


Fig. 5. Graph of pressure in the water jet depending on the revolution

The spunlace fabric production process is shown schematically in Figure 6 on a sample water jets layout. Accordingly, the raw material moves towards the first drum via the conveyor belt-1. The first water jet in the system wets the raw material and ensures that it sticks to the drum. The raw material adhering to the drum creates the first bonding process with the effect of the pressure created by the water jets 2 and 3. Water jets 2 and 3 are water jets that create the transverse tensile strength (N). The product moving towards the drum numbered 2 provides the longitudinal tensile strength (N) with the effect of the pressure created by the water jets 4 and 5. By adjusting the tension of the product formed by roller 2 and roller 1, products with the desired values are created from the conveyor belt numbered 2. The water jets which ensure the quality here are the water jets 2-3 and 4-5.

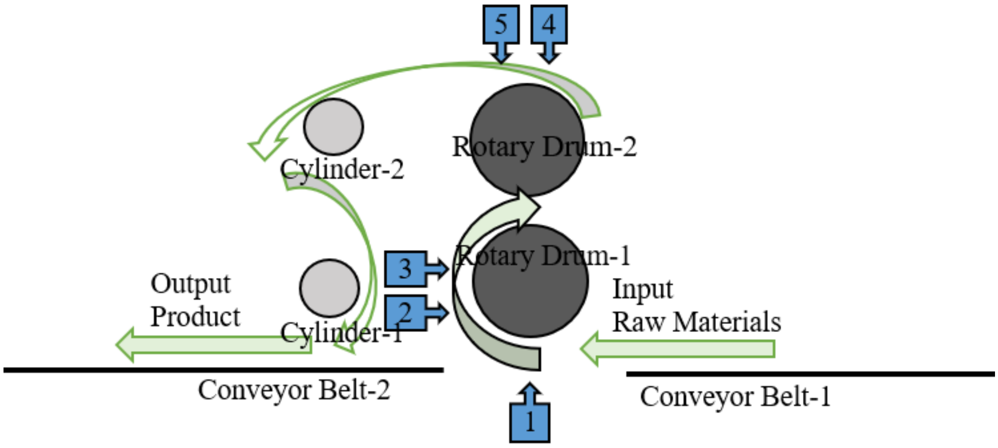


Fig. 6. Water jets layout

There is a pressure sensor in the system which measures the pressure formed in the water jet. This pressure sensor continuously measures the water jet pressure during the production and transfers the information to the pressure control interface in case of a change in the water jet pressure providing the control of the engine speed. However, for various reasons and from time to time, the speed control performed depending on the pressure in the water jet may cause the pressure sensor to measure incorrectly. This may determine the engine speed to change, although it must remain constant during the same production period due to the information transmitted to the system driver. As a result, quality drops and even spunlace fabric waste may occur.

2.2. Artificial Neural Networks (ANN)

Artificial neural networks collect linear and non-linear data with certain examples and provide analysis of these data. When a new example is encounted, it prompts the solution about the examples by using the information learned before. Artificial neural networks constitute a computer program designed for using artificial intelligence technology to exchange data inspired by a human brain [31, 32]. Artificial neural networks simulate the functioning of the biological nervous system, which is made up of small units called neurons. An input layer, one or more hidden (intermediate) layers, and an output layer are used to organize neurons (Fig. 7) [33-36].

Artificial neural networks are grouped as feed-forward and feedback neural networks according to their sequence; as supervised, unsupervised and reinforcement learning according to learning algorithms, and as static learning and dynamic learning according to learning time. The artificial neural network model created in this study is in a feed-forward neural network structure. This structure, which the layers are arranged regularly from the input to the output; which a layer is only linked to the next layers, and the input values are first loaded into the input layer, then it is processed through the intermediate layers respectively, and it reaches the output layer and exits to the external environment. A neuron consists of five main parts: input values, weights, summation function, activation function, and output. Figure 7 shows a simple neuron model with a feed-forward neural network structure. Also, it has a supervised learning structure in which output values are produced for the input values given to artificial neural network. Also, in terms of learning time, it has a static learning structure in which artificial neural networks is trained before use.

Input values are input parameters to neurons. The effect of these values to be produced on the output can be adjusted by multiplying the input values coming to the neuron with the weights of the connections they come from before they are transmitted to the nucleus. While the values of the weights can be positive, negative or zero, the input values with a zero weight value have no effect on the output. The addition function adds the input values to a neuron by multiplying it with weights, and thus calculates the net input of that cell. The activation function, also known as the transfer function, processes the net input to the cell and determines the output that the cell will produce in response to this input. In order for the artificial neural networks to determine correctly the outputs corresponding to the given input values, the weight values must be correctly determined

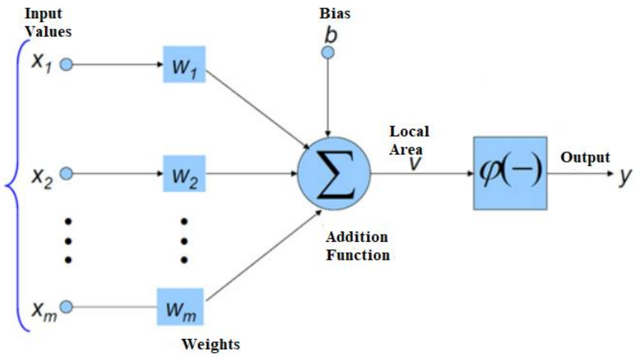


Fig. 7. A simple neuron model

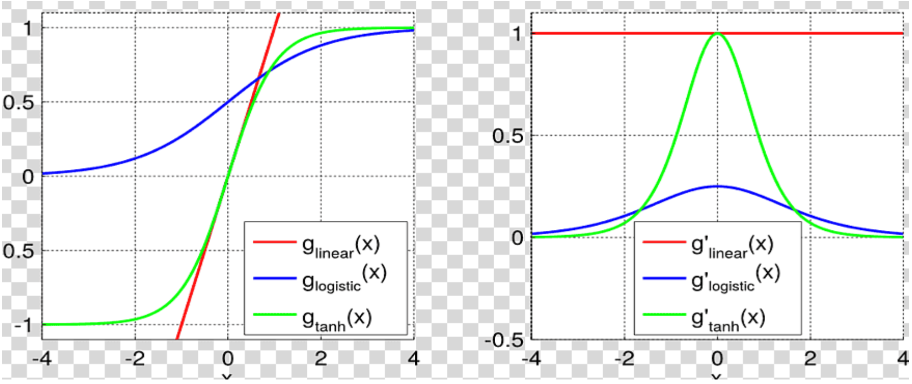


Fig. 8. Activation functions and derivative

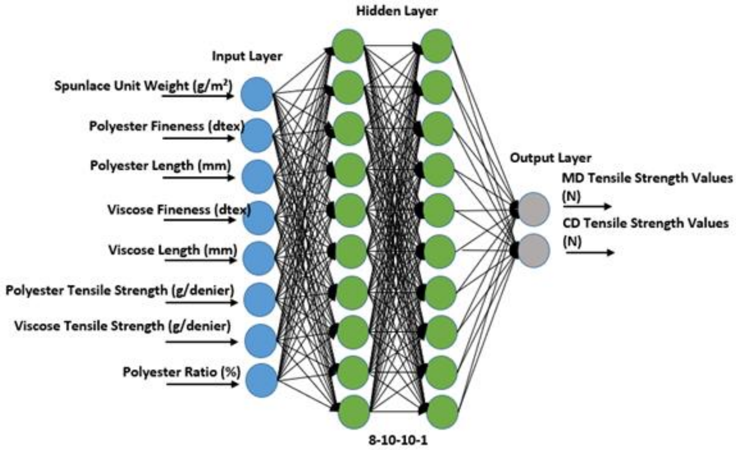


Fig. 9. Artificial neural network cell schematic structure

and an appropriate activation function must be selected. Activation functions are often chosen as nonlinear functions. The fact that the activation function is not a linear function makes the artificial neural networks non-linear. The fact that the derivative of the function can be easily calculated is another factor to be considered in the selection of the activation function. As in this study, the activation function used in the "multilayer perceptron" model, which is more preferred today, is mostly the "sigmoid function" and the most general sigmoid function is the "logistical function". Other sigmoid functions are “hyperbolic tangent” and “arc tan” functions, Figure 8.

The activation function determines the output value and, if necessary, the output transferred to the external environment can be used again inside the artificial neural network. Although each cell has more than one input value, its output is always unique and this output can be connected to any number of cells [37].

In this study, the output parameter is the spunlace fabric tensile strength. The fineness, length, tensile strength and mixing ratio of polyester and viscose, which are raw materials, have been determined as input parameters which determine directly the fabric tensile strength results. Logistic function, which is the sigmoid activation function, has been preferred as the activation function. The (out)j output of the j th neuron is calculated using the logistic function Eq. 1, [38-40].

$$\mathbf{(out)_j = f(net)_j = \frac{1}{1 + e^{-\alpha(net)_j}}} \qquad (1)$$

Here α is a constant representing the slope of the semi-linear region. The sigmoid function represented by Eq. (1) outputs in (0,1). If desired, the outputs of this function can be adjusted to the range (1,1). In this study, the outputs of the sigmoid function are taken as (0,1). Because of its derivatives, the variable (net)j can be easily determined according to the parameters in [38-40].

The network topology of the artificial neural network model created in this study was arranged as 4 layers, 1 input, 2 hidden and 1 output layer, and the number of neurons in the network structure was determined as 8-10-10-1, Figure 9.

Training the artificial neural network is the process of determining the most appropriate values of the weights, and the process of constantly renewing the weights until the desired result is achieved is called “learning”. In this study, TRAINLM function is used for training and LEARNGDM function is used for learning. The performance of the artificial neural network has been measured with the mean square error (MSE) function. The MSE function is an indicator which measures the performance of artificial neural network and machine learning methods. The MSE function is calculated as given in Eq.(2).

$$\mathbf{MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2} \qquad (2)$$

Here, yi shows the actual value obtained experimentally for each sample and the estimated value obtained for each sample with the established artificial neural networks model.

The number of epochs used in the training of artificial neural networks has been determined as 1000, the target error value has been determined as 0.00001, and the learning rate has been accepted as 0.015. Here, the number of neurons determined as 10 in the hidden layers has been determined purely intuitively. Momentum back-propagation algorithm has been applied in the process of changing the weights in order to reduce the error until the lowest MSE value is obtained. The artificial neural networks has been trained for 5 times, and the estimation results have been achieved with the targeted precision.

The artificial neural network model used in this study has been designed in the MATLAB environment. The initial values of the weight and bias coefficients created separately for each layer have been determined randomly and these values can be changed with subsequent iterations.

2.3. Fuzzy Logic Controller

Fuzzy logic controller, which is used in the control of systems with nonlinear structure whose mathematical model cannot be fully established, is gaining momentum in various researches. In this study, the fuzzy logic controller has been used to control direct current electric motors. It consists of three basic units: fuzzification, rule-based inference mechanism, and clarification. The fuzzifier acts as an interface which converts the control input information received from the system as error (e) and error variation (de) into symbolic values, which are linguistic qualifiers. This is achieved by selecting appropriate membership functions. Membership functions commonly used in applications are triangular, trapezoidal, bell curve, gaussian and sigmoidal membership functions [41]. The rule-based inference mechanism unit is a two-process unit of the rule base and the decision mechanism. The rule base is the part where the control rules, which characterize the expert's knowledge and skill control strategy, are expressed linguistically. These rules are then fired to the fuzzificated outputs along with the membership functions to calculate the fuzzy output for each rule. Fuzzy inference rules have a linguistic essence and are written as if-then statements. These fuzzy inference rules are created manually based on the properties of the input variables. The fuzzy inference engine, which represents the decision mechanism, executes fuzzy logic on the rules and establishes a connection between the input and output space using the fuzzy rule base. In this unit, information is usually modeled through rules such as Mamdani's min (minimum rule), Larsen's product operation (product rule), Zadeh's arithmetic product (arithmetic rule), and Boolean rule [42]. The final process is clarification and it involves transforming the fuzzy outputs obtained from the inference engine into precise outputs by methods such as maximum membership, centroid, weighted average and average of maximums membership.

In this study, in the fuzzy-logic controller, which consists of two inputs and one output, as the error and the change of the error; triangular and trapezoidal membership functions as input membership functions, a triangle membership function has been chosen as the output membership functions. For membership functions created for error, change in error and output, some 49 items created using seven different verbal variables regard NB (Negative Large), NO (Negative Medium), NK (Negative Small), S (Zero), PK (Positive Small), PO (Positive Medium), and PB (Positive Large) rule table with rule, which is given in Table 1. In this study, Mamdani's min inference rule has been used as an inference mechanism. The weighted average method has been used in the clarification process.

In the system examined in the study, the engine operates in the range of 0-3000 rpm and provides a pressure of 13 MPa (130 bar) at maximum speed (3000 rpm). The water jet pressure error and the change values in the water jet pressure error have been used as inputs for the designed fuzzy-logic controller, whereas the limit values of the input membership functions in the fuzzy-logic controller, which would correspond to the engine speed, have been taken as the pressure in the range of 0-13 Mpa (0-130 bar), as shown in Figure 10. As it can be seen in Figure 11, the output of the fuzzy-logic controller is limited between 0-10 V in accordance with the driver to which it transmits the signal, where the value of 0 represents the minimum engine speed and the value of 10 represents the maximum engine speed (3000 rpm).

Table 1. Rules table [43]

e/de	NB	NO	NK	S	PK	PO	PB
NB	NB	NB	NB	NO	NO	NK	S
NO	NB	NB	NB	NO	NK	S	PK
NK	NB	NO	NO	NK	S	PK	PO
S	NB	NK	NK	S	PK	PO	PB
PK	NO	NK	S	PK	PO	PB	PB
PO	NK	S	PK	PO	PB	PB	PB
PB	S	PK	PO	PO	PB	PB	PB

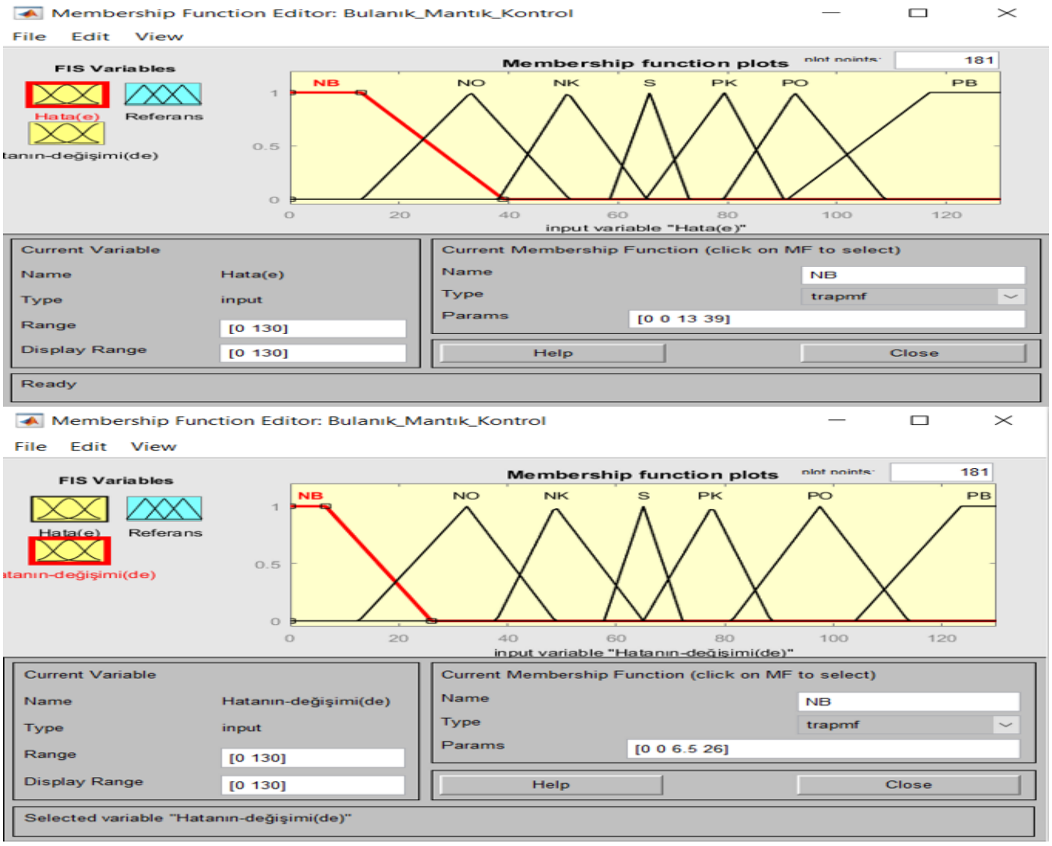


Fig. 10. Input membership functions

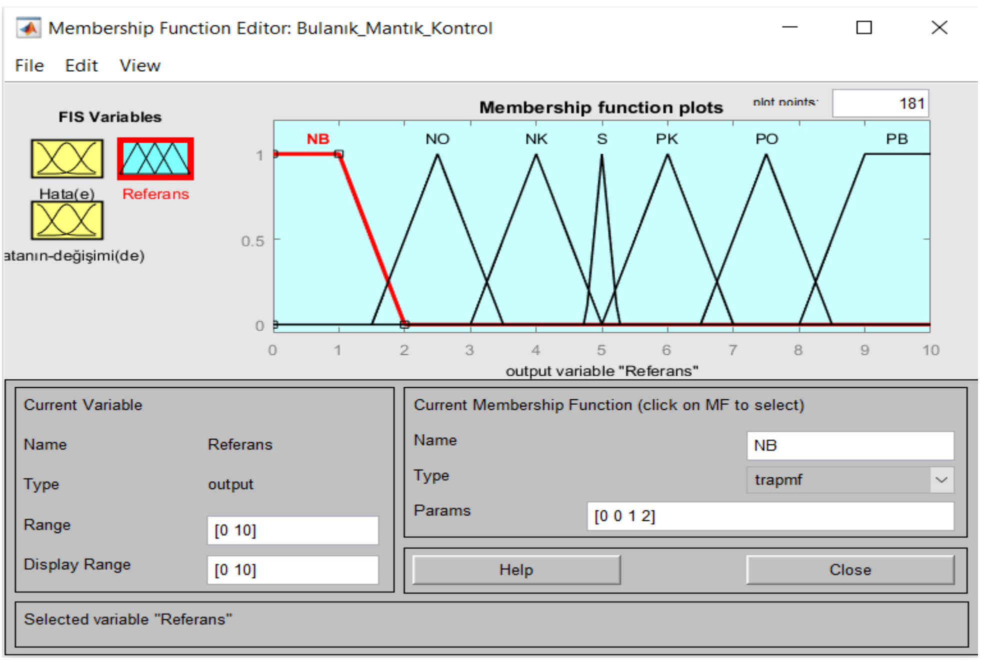


Fig. 11. Output membership function

In this study, it has been planned to control the engine speed with the fuzzy-logic controller, not the pressure sensor, and the block diagram of the examined spunlace fabric production line, created by fuzzy-logic controller, is given in Figure 12. The fuzzy-logic controller determines the appropriate reference signal which should provide the appropriate engine speed to establish the desired water jet pressure and to control the engine speed by transmitting it as an electrical signal through a microprocessor to a driver generating a 0-10 Volt reference signal, by this ensuring that the engine speed works continuously at the desired speed.

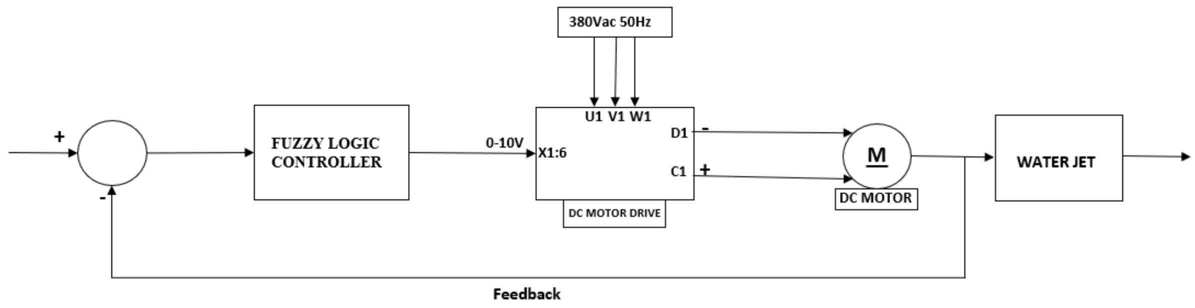


Fig. 12. Block diagram of spunlace fabric production line created with fuzzy-logic controller

3. Results and Discussion

The production of non-woven fabrics is carried out by the direct use of fibers without being brought into yarn form. Because of this, these type of fabrics do not have directions defined; as weft/warp as in woven fabrics; or as loop row/loop bar direction as in knitted fabrics. Concepts such as Machine Direction (MD) and Cross Direction (CD) have been developed to correspond to these. MD indicates the direction to which the fabric moves during production and corresponds to the warp direction in the woven fabric. CD represents the direction perpendicular to the machine direction and corresponds to the weft direction in the woven fabric.

In addition to these aspects, the concepts of isotropic and anisotropic structure, which express the structural properties of such fabrics, are also used. The mechanical properties of a nonwoven fabric with an isotropic structure, such as tensile strength in the MD and CD directions, are the same. Non-woven fabrics in which the fibers forming the texture are randomly oriented show an isotropic structure. The properties of an anisotropic nonwoven fabric in the MD and CD directions are different from each other. Non-woven fabrics, in which the fibers forming the texture are oriented in a certain direction, show the anisotropic structure [26]. The spunlace fabric examined in this study has an anisotropic structure and the test and measurement data of polyester (PES) fiber and viscose (CV) fiber, which are the raw materials of the fabric, are given in Table 2.

The spunlace fabric examined in the study has a 90/10% PES/CV mix ratio. The defined technical properties of 12 spunlace fabrics with a width of 5 cm and a density in the range of 35-90 g/m2 have been obtained by taking measurements from 4 samples at each density value and averaging the results.

Table 2. Spunlace fabric raw materials experiment and measurement data

Material	Fineness (dtex)	Length (mm)	Tensile Strength (g/denye)
Polyester (PES)	1,62	38	2,98
Viscose (CV)	1,71	52	6,1

In the artificial neural network model, the tensile strength values measured in the MD and CD directions of the spunlace fabric have been used as reference values. Tensile strength of 12 samples which in the range of 35-90 g/m2 unit weights obtained by test method. However, the unit weight of the spunlace fabric used in the facility where the study has been carried out varies between 35-300 g/m2. For this reason, the tensile strength values of spunlace fabrics in the 95-300 g/m2 unit weight range have been determined by regression analysis with the acceptance of production under the same conditions. The relations used in the regression analysis as follow.

$$\mathbf{a} = \left[\frac{\sum \mathbf{y} \sum \mathbf{x}^2 - \sum \mathbf{x} \sum \mathbf{xy}}{\mathbf{n} \sum \mathbf{x}^2 - (\sum \mathbf{x})^2}\right] \tag{3}$$

$$\mathbf{b} = \left[\frac{\mathbf{n} \sum \mathbf{xy} - \sum \mathbf{x} \sum \mathbf{y}}{\mathbf{n} \sum \mathbf{x}^2 - (\sum \mathbf{x})^2}\right] \tag{4}$$

$$\mathbf{y} = \mathbf{bx} + \mathbf{a} \tag{5}$$

Here, the variable x represents the independent variable (gr/m2), the variable y is the dependent variable (strength data), and n is the number of variables. The function values obtained when the regression analysis is made with reference to the experimental data; "y=0.476x+97.741" and r=0.989985068548424 high positively correlated for MD direction tensile strength; the CD direction was determined as "y=0.287x+11.018" and r=0.990338784131687 with high positive correlation for tensile strength. By using these functions, strength values between 95gr/m2 and 300gr/m2 have been obtained by making logical estimations based on the relationship between actual data (35gr/m2 - 90gr/m2).

MATLAB Neural Network toolbox has been used within the scope of the study. The input parameters have determined as fineness, length, tensile strength, and mixing ratio of polyester and viscose, which are the raw materials of spunlace fabric, whereas the output parameters have been determined as spunlace fabric tensile strength. Out of a total of 54 data, 38 (70%) were used for training, 8 (15%) for validation, and 8 (15%) for testing. The generated mesh models were trained for 5 times and the results of four separate regression analyzes between the input and output data for the tensile strength estimations are given in Figure 13. The obtained regression value is R=0.97, meaning that it is quite high.

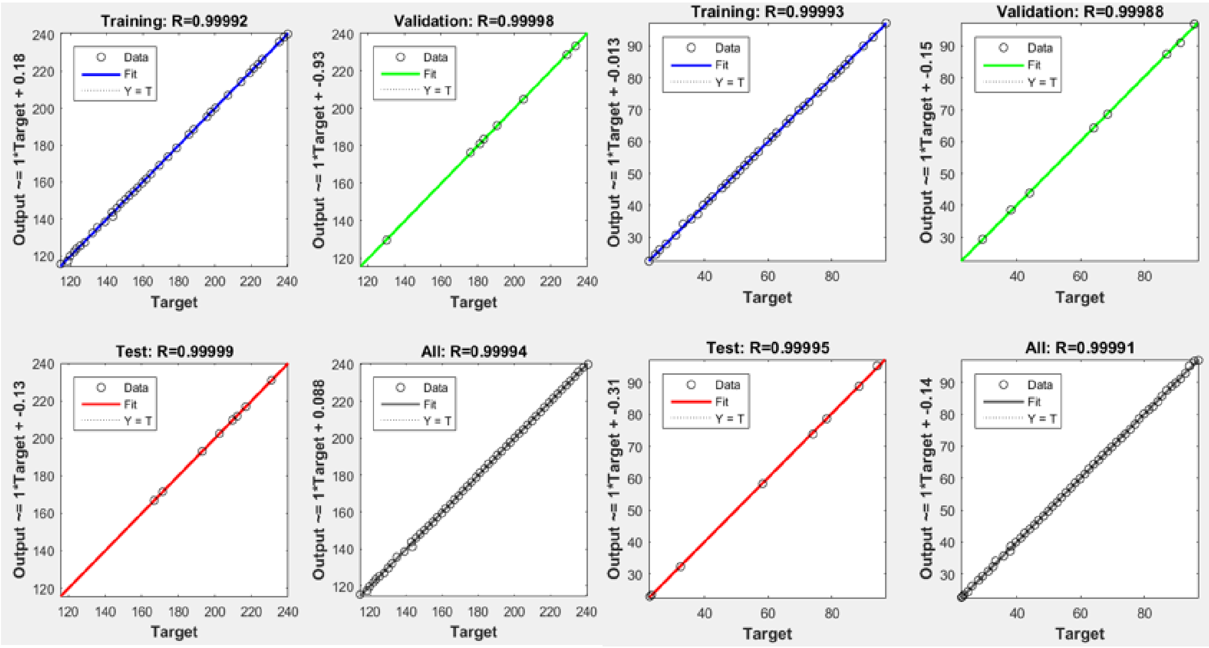


Fig. 13. Artificial neural network model regression MD-CD

In Figure 13, it can be seen that the regression coefficient is very close to 1 among the data used by the artificial neural network, which is formed from the groups separated for validation and testing. In order to determine the success level of the created artificial neural network model, the experimentally measured results for the MD direction and CD direction of the spunlace fabric tensile strength and estimated by artificial neural network and the error percentages calculated using the equation given in Eq.2 are given in Table 3.

Table 3. Artificial neural network estimation results of spunlace fabric tensile strength

Spunlace unit weight (g/m^2)	Average MD tensile strength			Average CD tensile strength		
	Experimental results (N/5cm)	ANN results (N/5cm)	Error (%)	Experimental results (N/5cm)	ANNresults (N/5cm)	Error (%)
35	114,3	115,5613	-1,26126	22,5	22,551	-0,05097
40	118,4	117,4339	0,966139	22,9	22,8678	0,032151
45	119,9	119,7693	0,130711	23,4	23,4339	-0,03393
50	121,8	121,9366	-0,13657	24,6	24,4559	0,144094
55	123,3	123,7681	-0,46809	26,0	26,1444	-0,14443
60	125,4	125,4235	-0,02353	28,1	27,9513	0,14873
65	127,7	127,1875	0,51253	29,3	29,3025	-0,00253
70	130,1	129,3917	0,708341	31,1	30,7188	0,381188
75	132,2	132,2398	-0,0398	32,5	32,3886	0,111386
80	134,7	135,4917	-0,7917	33,2	34,0928	-0,89285
85	138,9	138,6065	0,293523	35,8	35,706	0,094002
90	143,2	141,3194	1,88063	37,9	37,211	0,688985
95	142,961	143,7119	-0,75091	38,283	38,632	-0,34898
100	145,341	145,9441	-0,60308	39,718	40	-0,28201
105	147,721	148,1261	-0,40513	41,153	41,3418	-0,18878
110	150,101	150,3145	-0,21352	42,588	42,6771	-0,08911
115	152,481	152,5335	-0,0525	44,023	44,0196	0,003425
120	154,861	154,791	0,069955	45,458	45,3777	0,080305
125	157,241	157,0874	0,153649	46,893	46,7562	0,136803
130	159,621	159,419	0,201953	48,328	48,157	0,171018
135	162,001	161,7811	0,21985	49,763	49,5799	0,18312
140	164,381	164,168	0,212981	51,198	51,0232	0,174794
145	166,761	166,5739	0,187148	52,633	52,4842	0,148824
150	169,141	168,993	0,14804	54,068	53,9592	0,108783
155	171,521	171,42	0,101042	55,503	55,4442	0,058795
160	173,901	173,8499	0,051101	56,938	56,9347	0,003343

165	176,281	176,2784	0,002613	58,373	58,4259	-0,05287
170	178,661	178,7017	-0,04067	59,808	59,9131	-0,10508
175	181,041	181,1167	-0,07573	61,243	61,3915	-0,14853
180	183,421	183,5213	-0,10032	62,678	62,8566	-0,17861
185	185,801	185,9141	-0,11306	64,113	64,304	-0,19095
190	188,181	188,2944	-0,11343	65,548	65,7296	-0,18158
195	190,561	190,6628	-0,1018	66,983	67,1302	-0,1472
200	192,941	193,0204	-0,07941	68,418	68,5038	-0,08577
205	195,321	195,3693	-0,04833	69,853	69,8509	0,002066
210	197,701	197,7124	-0,0114	71,288	71,1782	0,109753
215	200,081	200,0531	0,02793	72,723	72,5053	0,217741
220	202,461	202,3952	0,065771	74,158	73,876	0,282028
225	204,841	204,7429	0,098063	75,593	75,3601	0,232851
230	207,221	207,1001	0,120946	77,028	76,9892	0,038833
235	209,601	209,4698	0,131233	78,463	78,633	-0,17004
240	211,981	211,854	0,127017	79,898	80,0935	-0,1955
245	214,361	214,2526	0,108395	81,333	81,3603	-0,0273
250	216,741	216,6627	0,078264	82,768	82,5999	0,16811
255	219,121	219,078	0,043019	84,203	84,0322	0,17083
260	221,501	221,4882	0,012834	85,638	85,7589	-0,12094
265	223,881	223,8803	0,000714	87,073	87,4956	-0,42262
270	226,261	226,2422	0,01881	88,508	88,8562	-0,34825
275	228,641	228,5718	0,069168	89,943	89,9105	0,032542
280	231,021	230,8955	0,125526	91,378	91,059	0,318961
285	233,401	233,2898	0,111221	92,813	92,8093	0,003668
290	235,781	235,846	-0,065	94,248	95,2184	-0,9704
295	238,161	238,3672	-0,2062	95,683	96,8196	-1,13656
300	240,541	240,0079	0,533119	97,118	97,104	0,013985

As it can be seen in Table 3, the lowest and highest error rates in the MD direction are of 18.18% and 0.25%, respectively, and the lowest and highest error rates in the CD direction are of 18.18% and 0.25%, respectively. The relationship between the experimental measurement in the MD direction and the CD direction and the prediction results with artificial neural network are given in Figure 14 and Figure 15, respectively. It can be seen that there is consistency between the experimental results and artificial neural network and estimation results for both directions.

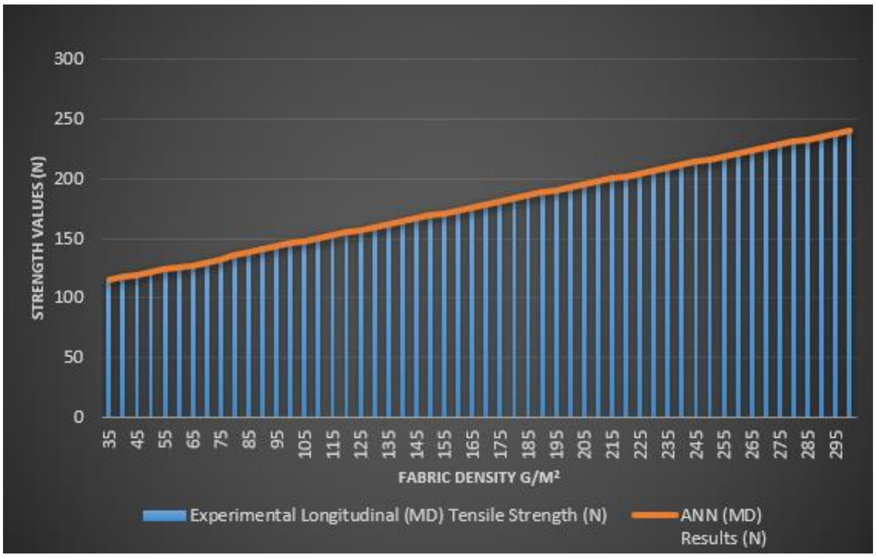


Fig. 14. Comparison of experimental and artificial neural network prediction results for MD direction tensile strength

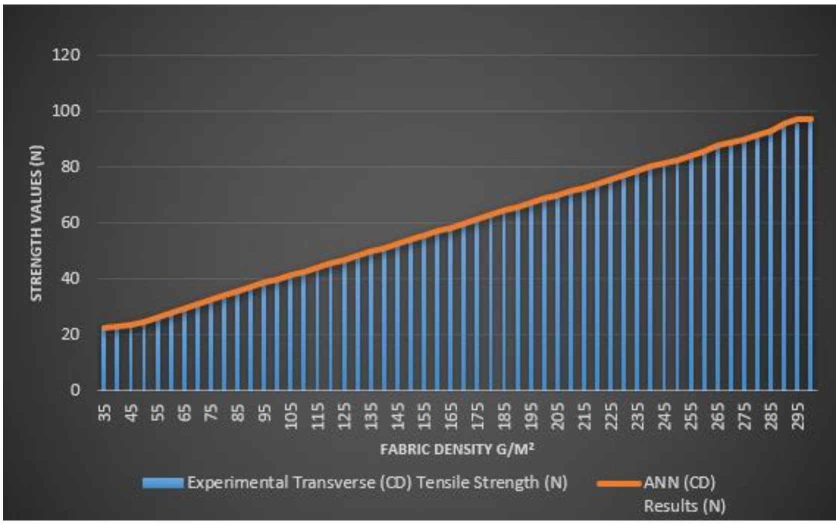


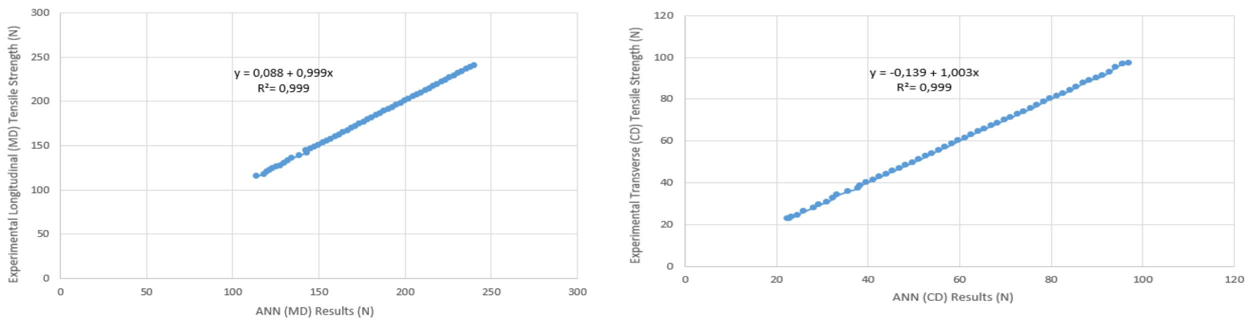
Fig. 15. Comparison of experimental and artificial neural network prediction results for MD direction tensile strength

The linear regression between the experimental and predicted tensile strength values by artificial neural networks have been obtained as R2=0.999 in the MD direction (Figure 16a) and R2=0.999 in the CD direction (Figure 16b). Here, the R2 value approaching 1 indicates that the actual values and the estimated values are consistent, and that the tensile strength performance of water-jet bonded fabrics can be predicted with high accuracy by artificial neural networks.

In the second phase of the study, the data estimated by artificial neural network has been used as reference strength values. It has been planned that the electrical signal, which creates the appropriate engine speed, should be transferred to the driver with a fuzzy-logic controller and the engine speed should be realized with a fuzzy-logic controller, not through the pressure sensor.

In order to obtain the MD and CD tensile strengths, the revolutions per minute of the direct current electric motor must be controlled. The pressure level created by the water jet should increase and decrease according to the revolution of the engine, and, due to these pressure levels, the required MD and CD tensile strength values will be formed. In order to reach the desired strength values, the direct current electric motor in the system must rotate at a constant speed according to the reference value. In the system, which has been in the production phase for a long time, the engine speed and pressure values change spontaneously for various reasons during the period of operation of the engine. These changing pressure values are an obstacle to quality production. The main reason for the change in pressure values is represented by the residues in the water. These residues cause the pressure sensor in the water jet to give wrong information and the system to change the speed of the electric motor, and for this reasons the targeted pressure cannot be achieved. Since the targeted pressure changes, quality production cannot be made at the desired level. In order to ensure the continuity of quality production, the engine speed should be constantly controlled and taken care of in order to keep the engine speed constant throughout the production. To do this, it is necessary to cancel the pressure sensor and control the DC electric motor according to the reference values. In this study, this control is provided by the fuzzy-logic controller. Reference values are needed when using fuzzy-logic controller. The reference values are the revolutions of the engine which create the pressure values. In the current system, this engine speed is controlled by a voltage of 0-10 volts.

Following these process steps, the motor driver reference values, pressure values, and motor revolutions, which form the CD and MD tensile strength values, are given in Table 4 and Table 5, respectively. When Table 4 and Table 5 are examined, it can be seen that the applied pressures are different in order to obtain the CD and MD tensile strength values at the determined fabric density. The reason why these pressures are different is that, firstly, CD tensile strengths and, secondly, MD tensile



(a) (b)

Fig. 16. Q-Q plot of experimental and artificial neural network estimated tensile strength values

Table 4. For CD tensile strength values; motor driver reference values, pressure and motor revolutions

Spunlace unit weight (g/m^2)	ANN results (N/5cm)	Average Pressure (10^5Pa)	DC Motor Driver Reference (V)	Average Engine RPM
35	22,555	21,0	2,41	723
40	22,793	23,5	2,59	777
45	23,44	26,0	2,77	830
50	24,596	28,5	2,95	884
55	26,135	31,0	3,12	937
60	27,829	33,5	3,3	991
65	29,501	36,0	3,48	1044
70	31,065	38,5	3,66	1098
75	32,494	41,0	3,84	1151
80	33,76	43,5	4,02	1205
85	35,808	46,0	4,19	1258
90	37,908	49,0	4,41	1322

Table 5. For MD tensile strength values; motor driver reference values, pressure and motor revolutions

Spunlace unit weight (g/m^2)	**ANN results (N/5cm)**	**Average Pressure (10^5Pa)**	**DC Motor Driver Reference (V)**	**Average Engine RPM**
35	114,301	50,0	4,48	1344
40	118,375	51,5	4,59	1376
45	119,935	53,5	4,73	1418
50	121,593	55,5	4,87	1461
55	123,454	57,0	4,98	1493
60	125,483	59,0	5,12	1536
65	127,643	61,0	5,26	1579
70	129,895	62,5	5,37	1611
75	132,211	64,5	5,51	1654
80	134,666	66,0	5,62	1686
85	138,908	68,0	5,76	1728
90	143,209	70,0	5,9	1771

strengths are formed while the product is being produced. Since the fibers of the raw material, which is in the form of fibers, are not connected to each other while CD tensile strengths are formed, a certain level of pressure is applied to bind these fibers together without tensile them. Due to this applied pressure, the fibers are connected to each other and a durable product begins to form. In order to increase the MD tensile strength values of these fibers, which are then connected to each other, more pressure is applied than the pressure level used in CD tensile strengths and the product reaches the desired strength values.

In fuzzy-logic controlled production, the pressure sensors in the water jets are disabled and the reference signals corresponding to the appropriate engine speeds, given in Tables 4 and 5, are created in the fuzzy-logic controller. Thus, the pressure sensor has been prevented from deceiving the system due to the residues formed in the water, the engine revolutions have been kept constant according to the reference values until the end of the production, and the product has been produced at the desired pressure values. By deactivating the pressure sensors, it is not implied that the flow rate (cycle) depending on the system pressure is not controlled and the system pressure is not measured. Experimental study has been carried out for 3 different products with fabric densities of 35-40 and 55 g/m2. In fuzzy-logic controlled production, the pressure sensors of the second and third water jets were canceled for the CD tensile strength and the pressure sensors of the fourth and fifth water jets were left active. For MD tensile strength, the pressure sensors of the water jets numbered 4 and 5 were canceled and the pressure sensors of the water jets numbered 2 and 3 were left active. The CD and MD tensile strength values obtained with fuzzy-logic controlled production and pressure sensor-controlled production are given in Table 6 in comparison with the artificial neural network estimation results.

The pressure sensors of the water jets 2 and 3 used for CD tensile strengths were canceled and these jets were checked by fuzzy-logic controller. While the pressure sensors of the water jets 4 and 5 used for MD tensile strengths were active, the strength values of the produced product were below the quality standard. The desired pressure values could not be achieved until the end of production, because the pressure sensor in the water jets numbered 4 and 5 misled the system due to the residues formed in the water over time. When the pressures of water jets 2 and 3 were controlled by fuzzy-logic controller, the desired pressure values remained constant until the end of production. In the product created in this way, it has been observed that the MD tensile strength values are noticeably low and the CD tensile strength values are slightly decreased. Based on this, while CD tensile strength values have been formed, MD tensile strength values are found to have a small effect.

The pressure sensors of water jets 2 and 3 used for CD tensile strengths were kept active. The required pressures of water jets 4 and 5 used for MD tensile strengths were checked with fuzzy-logic controller. Even if the pressure sensors of the water jets numbered 4 and 5, which constitute the MD tensile strength values, are canceled and the required pressures are kept constant with a fuzzy-logic controller, it can be seen that the desired values cannot be obtained. The reason for this is that the

Table 6. Average tensile strength values obtained with fuzzy-logic controller and pressure sensor-controlled production

Spunlace unit weight (g/m^2)	ANN results		Pressure sensor and FLC production		FLC production	
	MD tensile strength (N/5cm)	CD tensile strength (N/5cm)	MD tensile strength (N/5cm)	CD tensile strength (N/5cm)	MD tensile strength (N/5cm)	CD tensile strength (N/5cm)
35	115,5613	22,551	95,000	19,600	116,400	22,800
40	117,4339	22,8678	101,400 (55g/m²)	24,900 (55g/m²)	118,000	23,000
55	123,7681	26,1444	107,900	21,000	124,100	26,500

CD tensile strength values are formed firstly while the product is produced. The fact that these values are low also greatly affects the MD tensile strength values.

In Table 6, it can be seen that the desired quality values are obtained in fuzzy-logic controlled production, and the strength values are low when the pressure sensors are active, which means that the created produced does not comply with the desired quality standards.

4. Conclusion

In this study, the strength values of the products manufactured in series have been taken as reference values. It has been shown that the CD and MD tensile strength values of the mass-produced products can be easily predicted in a short time with artificial neural networks.

Based on some previous studies, it has been emphasized that the strength values, which are the most important factors in quality production, are formed by an appropriate water jet pressure. However, the levels of water pressure, which occur at the desired reference values, do not remain constant until the end of production due to reasons such as residues in the water, or changes in pressure sensors may cause the system to mislead the process and by this to produce faulty or low quality products. In order to prevent this, the residues formed in the water must be constantly cleaned by water jets during the production process. The cleaning phase requires the machine to stop or slow down, and each stop and slowdown means time wasted, less production and higher costs. According to the proposed method in this study, the pressure sensors in the system are canceled and pressure control is provided by fuzzy-logic controller. As a result, it can be seen that with the proposed fuzzy-logic controller controlled method, production stops are reduced and faulty and low quality production, which occurs continuously throughout the production, can be prevented. In this way, it is ensured that the products are produced without failures and at the desired quality. Ensuring the continuity of production under the desired conditions is considered as a positive development in mass production.

Declaration

Author Contribution: Conceive – S.Ö., B.U.; Design – S.Ö., B.U.; Supervision – S.Ö., B.U.; Experimental Performance, Data Collection and/or Processing S.Ö., B.U.; Analysis and/or Interpretation S.Ö.,B.U.; Literature Review- S.Ö.; Writer- S.Ö.; Critical Reviews – S.Ö., B.U.;

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