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Application of Neural Network for the Prediction of Loss in Mechanical Properties of Aramid Fabrics After Thermal Aging

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ABSTRACT

Aramid fabrics are used to produce most of the flame resistant protection clothes to fulfil the protection requirements. Even though aramid fibers have good thermal stability and flame resistance properties, fabrics used in protective clothing age and loss some of their essential functions under various environmental and operational conditions during their lifetime. These conditions cause serious limitations in the use of clothing. In this study, various woven fabrics produced from aramid (Nomex, Kevlar) fabrics were exposed to accelerated aging tests under varying temperature and time period in order to construct Neural Network models to predict weight loss and tensile strength loss percentages of the fabrics. The results of Artificial Neural Network models demonstrate that regression values are 0.98405 for weight loss percentages and 0.99935 for tensile strength loss percentages of the fabrics. Accordingly, the proposed Artificial Neural Network models were correctly constituted and the losses in determined fabric properties was successfully predicted.

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Aramid yarns, accelerated thermal aging, weight loss, tensile strength loss, artificial neural network

1. INTRODUCTION

Since textiles are used in many technical fields apart from the fashion industry today, predicting performance properties of these textiles in design phase has become even more important. Since textile structures are highly complex, features of fiber and yarn affect characteristic of the final fabric and fabric properties determine the performance of the end product [1, 2]. These behaviors of textiles have led researchers to use different computational modeling methods for forecasting. Artificial neural networks (ANN) are very effective tools in solving many prediction-related problems in textiles such as classification and analysis of defects, prediction of characteristics of textiles, process optimization, identification, marketing and planning [3,4]. Artificial neural networks attempt to mimic capabilities of human brain. In order to form the network, a large number of artificial neurons are connected to each other by weights of variables. The knowledge that is gained from the system is processed with some simple connecting functions and the network learns from the previously acquired experimental results [4, 5]. It learns from examples through iterations without any prior knowledge of relationship between variables under investigation. Unlike a computer, the network has the ability to process and learn patterns efficiently when properly trained [6]. Thus, artificial neural network modelling is a suitable tool to predict losses in performance properties of aramid fabrics.

The performance of materials used for protective clothing of workers at high risk of heat and flame exposure and firefighters, is critical for ensuring the safety of workers wearing them [7, 8]. They must also exhibit good mechanical performance to maintain the physical completeness of the clothing during service [9, 10]. However, during their lifetime, fabric structure of these garments degrades under the influence of many external factors like fire, extreme heat and hot water vapor. Furthermore, the loss in performance may not always be easily detected unless it has reached an extreme level. Therefore, it is of great importance to know and predict the mechanism underlying this aging process [11, 12].

Liu *et al.* [13] also indicated that predicting service life of firefighters' clothing before taking it out of service is

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necessary during the usage and maintenance of the uniform and they investigated the tensile strength of flame-retardant fabrics under fire exposure. They used regression analysis and ANN models to estimate the tensile strength of Kevlar/polybenzimidazole and polyimide/Kevlar fabrics. Lemmi *et al*. [14] investigated effects of aging temperature and time on the mechanical and surface structural properties of high tenacity polyester yarn. The investigation illustrated that aging time and temperature influenced the surface structure of fibers, tenacity and elongation properties of the yarn. In another study, thermal aging of high-performance fibers (Kevlar and PBI) was also investigated and tensile strength tests were carried out on aged and unaged samples. The tensile strength data was fitted using the Arrhenius model following two different approaches [15]. Some researchers [16, 17] used regression analysis to investigate the relationship between the tensile strength and reflection coefficient of flame-retardant fabrics and to estimate the tensile strength of these fabrics after heat exposure. The previous researches indicated that the multi linear regression (MLR) models could predict some properties of a fabric, however ANN model showed higher accuracy for prediction when compared with MLR model [13, 18, 19].

Factors like heat exposure time, temperature, and fabric type affect properties of fabrics after thermal aging process [20, 21, 22]. The temperature of the fabric during heat exposure procedure, such as glass transition, surface and degradation temperature can expound the thermal aging mechanisms in some degree. The loss in mechanical properties of the fabric may not be revealed visually and some measurements are essential to verify the losses after heat exposure [13]. Losses in weight and thickness of the fabrics occurred for aramid fabrics with the rise of heat exposure intensity and duration [23]. Thus, the best way to understand the damage occurred on the clothing is to predict the losses in the fabric mechanic properties without destruction by using modeling methods. For this purpose, woven fabrics with varying amounts of Kevlar and Nomex yarns were subjected to accelerated thermal aging processes for two different temperatures and four time periods. After the selected exposure durations, fabric tensile strength and weight values were measured and loss percentages of these fabric properties were calculated. Artificial neural network models were generated for the estimation of tensile strength and weight loss percentages.

The aim of this article is to predict the weight and strength loss percentages of aramid woven fabrics after accelerated thermal aging by using ANN models and to determine the best fit model to evaluate the service life of the fabrics. The models based on the developed neural network can describe and estimate the strength and weight loss of aramid fabrics under different conditions. The recommended models will be helpful for predicting service life of firefighter's clothing and ensuring the safety of workers wearing them.

2. MATERIAL AND METHOD

2.1 Material

Nm 50 Kevlar and Nomex yarns were procured from Erba Foreign Trade Ltd. Com. and woven fabrics were produced by using these yarns in various proportions. Plain woven fabric structure was selected for experiments since most ballistic and body protection fabrics made from Kevlar are manufactured as plain woven fabrics. Weft and warp densities for all fabric types were 20 weft/cm, 40 warp/cm, respectively. Five plain woven fabrics were manufactured for the experiments with varying Kevlar and Nomex contents: %100 Kevlar, %100 Nomex, %50 Kevlar/%50 Nomex, %33.3 Kevlar/%66.7 Nomex, %16.6 Kevlar/%83.4 Nomex.

2.2 Accelerated thermal aging test

Accelerated thermal aging tests were carried out with James Heal drying oven. 220°C and 300°C were selected for aging processes when the operating temperatures of Nomex and Kevlar were 200°C and 260°C, respectively. Since, it was reported that fire-fighters operate under 100–300°C standard conditions [15, 24]. The durations of cumulative exposures were 48, 240, 480, 720 hours for 220°C and 24, 48, 120, 240 hours for 300°C. The effects of accelerated aging process on weight and tensile strength loss were observed faster at high temperatures, thus the heat treatment durations for 220°C were chosen longer than the periods for 300°C [25].

2.3 Measurements of weight loss

Fabric samples were conditioned before weight measurements under standard atmospheric conditions and fabric weights were measured prior to thermal aging and after each selected exposure time. Percentage of variation in weight (%wl) after thermal aging was determined as:

$$\%wl = (\Delta w / w_0) \times 100 \qquad (1)$$

where $\Delta w = w_0 - w_{heat\ treated}$, w_0 and $w_{heat\ treated}$ is the weight of a fabric sample before and after heat treatment, respectively.

2.4 Measurements of tensile strength loss

Zwick/Roell Z010 universal testing machine was used to determine tensile strength of aramid fabrics before and after accelarated thermal aging periods. The tests were performed with 10 kN load cell and the cross-head speed of testing machine was 100 mm/minute according to the ISO 13934-1 standard [26].

2.5 ANN modelling

In this study, multilayer perceptron ANN modelling was performed to estimate weight loss percentages and tensile strength loss percentages of Kevlar/Nomex woven fabrics. ANN is a powerful modelling tool to determine and exhibit any type of connection between input and output variables. The ANN structure proposed for the estimation of fabric weight loss percentage and tensile strength loss percentage is shown in Figure 1. These networks consist of an input layer, hidden layer(s) and an output layer, respectively. The input variables were selected as Kevlar and Nomex yarn percentages in the fabrics, thermal aging temperature and aging duration. The output dependents were fabric weight loss percentage and tensile strength loss percentage.

The hidden layer is used for optimization of network and the number of hidden layers and neurons in each hidden layer are changed in order to find the best neural network architecture for the predictions with less error. According to the literature, the number of neurons were chosen as 5, 10, 15 and 20 in the hidden layer(s) [27 - 30]. Furthermore, various neuron numbers, close to the number of neurons in the best fit model, were also investigated for even better prediction results.

3. RESULTS AND DISCUSSION

3.1 Losses in fabric properties

The results of weight and tensile strength loss percentages of fabrics after thermal aging at 220°C and 300°C are given in Table 1 and Table 2, respectively. Weight loss percentages altered between 3.12% and 9.16% and average tensile strength loss percentages varied between 0.37% and 94.99%.

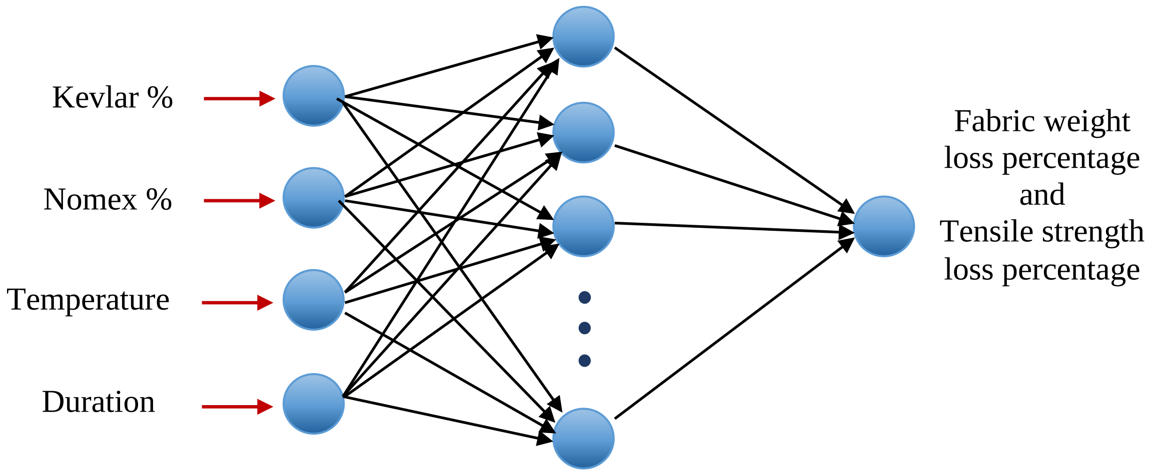

Figure 1. Structure of the proposed artificial neural network model

Tablo 1. Weight loss and tensile strength loss % of fabrics at 220°C

Experiment	Kevlar %	Nomex %	Duration (hours)	Weight Loss %	Tensile Strength Loss %
1	100	0	48	4.18	62.03
2	100	0	240	4.39	82.69
3	100	0	480	5.01	87.06
4	100	0	720	5.26	91.89
5	0	100	48	3.47	1.52
6	0	100	240	3.70	2.23
7	0	100	480	3.83	2.96
8	0	100	720	4.35	3.47
9	50	50	48	3.70	28.47
10	50	50	240	4.20	36.39
11	50	50	480	4.26	36.78
12	50	50	720	4.46	37.41
13	33.3	66.7	48	3.40	22.99
14	33.3	66.7	240	3.89	27.56
15	33.3	66.7	480	3.91	28.86
16	33.3	66.7	720	3.97	29.98
17	16.6	83.4	48	3.63	12.91
18	16.6	83.4	240	3.77	14.50
19	16.6	83.4	480	4.18	15.03
20	16.6	83.4	720	4.50	16.06

Tablo 2. Weight loss and tensile strength loss % of fabrics at 300ºC

Experiment	Kevlar %	Nomex %	Duration (hours)	Weight Loss %	Tensile Strength Loss %
21	100	0	48	4.00	53.63
22	100	0	240	4.11	64.32
23	100	0	480	7.01	91.06
24	100	0	720	9.16	94.99
25	0	100	48	3.12	1.37
26	0	100	240	3.17	1.64
27	0	100	480	4.57	1.79
28	0	100	720	4.98	4.10
29	50	50	48	4.01	34.02
30	50	50	240	4.83	34.19
31	50	50	480	5.15	36.58
32	50	50	720	6.59	39.15
33	33.3	66.7	48	4.71	26.73
34	33.3	66.7	240	4.86	27.19
35	33.3	66.7	480	5.27	29.16
36	33.3	66.7	720	6.59	30.24
37	16.6	83.4	48	4.06	11.99
38	16.6	83.4	240	4.49	12.90
39	16.6	83.4	480	5.11	13.88
40	16.6	83.4	720	5.89	18.21

Fabric produced with %100 Kevlar yarns reached the maximum thermal decomposition rate with a 94.99% tensile strength loss percentage and 9.19% weight loss percentage at 300ºC after 720 hours accelerated thermal aging process. The results showed that less tensile strength loss occurred when the Nomex yarn percentage was increased in the fabric composition. This was attributed to a disorder of the crystalline lattice in the perpendicular direction to the coplanar sheets that occurs simultaneously with an increase in the crystallite size in the direction parallel in the case of Kevlar [7]. Nomex shows a gradual decrease in crystallinity with increasing exposure time and this leaded to a reduction in tensile strength. Jain et.al. [31] investigated the weight loss after thermal aging and similarly it was observed that thermal aging was accompanied by the weight loss. This loss can be attributed to degradation and chemical reactions leading to flowing of gaseous components and small molecular weight compounds from the fabrics.

3.2 ANN model performance for weight loss percentages

In this study, the ANN models were implemented with Neural Network Toolbox of MATLAB R2021b software. The Levenberg-Marquardt [32] algorithm was used to train the proposed feed forward back propagation neural network model since previous studies showed that it is one of the most operative neural network training algorithms [33]. The training subset was first loaded to neural network in the Levenberg-Marquardt algorithm and the network parameters were updated and network was trained by utilizing the differences between the output and target values. After this process, another subset of parameters was used to verify the network. Required accuracy of training was achieved by repeating these processes for several times until the mean squared error (MSE) reaches to the minimum error value. The MSE was calculated as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i^{'} - y_i)^2 \qquad (2)$$

where y is an observed value and y’ is a predicted value [27, 34]. The Gradient Descent with Momentum (GDM) learning algorithm was applied for the learning algorithm in MATLAB software. A TANSIGMOID transfer function for the hidden layer nodes was used to produce faster output rates in this study.

Various combinations for the number of hidden layers and number of neurons were tested to find the best fit model with maximum correlation on a hit and trial basis. The condition at which the maximum regression value was obtained in terms of training, testing and validation was considered as the final model infrastructure. The ANN model with one hidden layer and 20 neurons was found as the best model to predict the weight loss values. Table 3 shows observed and predicted values of weight loss percentages for ANN models with different number of neurons in the hidden layer. The selected number of neurons are represented with S.

The observed and proposed results were found very similar in most of the experiments in Table 3. Moreover, various Multilayer Perceptron (MLP) ANNs were also investigated for better estimations. However, the regression values of these networks weren’t substantial as the ANN with one hidden layer/20 neurons. The results of the proposed networks for weight loss percentages in terms of MSE and regression (R) are exhibited in Table 4. R value measures the correlation between experiments and predictions.

Table 3. Observed and predicted weight loss percentage values for various ANN models

Experiment	Observed values for weight loss percentage	ANN (predicted) results				Difference (%) between observed and ANN results			
		S=5	S=10	S=15	S=20	S=5	S=10	S=15	S=20
1	4.18	4.68	3.12	4.34	4.24	11.96	25.36	3.76	1.37
2	4.39	4.43	3.12	4.54	4.45	0.98	28.92	3.32	1.39
3	5.01	4.45	4.96	5.01	5.30	11.12	1.02	0.03	5.82
4	5.26	5.35	5.26	5.17	5.27	1.66	0.02	1.71	0.25
5	3.47	3.66	3.62	3.43	3.39	5.39	4.20	1.11	2.23
6	3.7	3.60	3.65	3.52	3.72	2.77	1.34	4.86	0.51
7	3.83	3.64	3.84	3.76	3.87	4.91	0.39	1.75	1.13
8	4.35	4.03	4.46	4.32	4.35	7.26	2.57	0.66	0.05
9	3.7	3.92	3.64	3.71	3.64	5.86	1.62	0.29	1.56
10	4.2	3.87	4.23	4.17	4.18	7.92	0.74	0.75	0.56
11	4.26	4.02	4.56	4.38	4.25	5.65	6.96	2.88	0.35
12	4.46	4.78	4.42	4.19	4.47	7.24	0.90	6.05	0.23
13	3.4	3.75	3.51	3.53	3.49	10.19	3.10	3.94	2.61
14	3.89	3.68	3.79	3.88	3.91	5.36	2.44	0.23	0.52
15	3.91	3.78	4.00	4.09	4.05	3.26	2.24	4.62	3.63
16	3.97	4.40	3.93	4.27	4.51	10.75	1.04	7.47	13.59
17	3.63	3.68	3.59	3.47	3.39	1.45	1.12	4.53	6.62
18	3.77	3.62	3.75	3.60	3.75	4.10	0.60	4.40	0.47
19	4.18	3.67	4.18	3.69	3.93	12.22	0.02	11.65	5.89
20	4.5	4.11	4.35	4.32	4.44	8.63	3.37	4.11	1.34
21	4	5.21	4.04	4.85	4.03	30.34	1.06	21.28	0.70
22	4.11	5.38	4.56	5.20	4.52	30.82	10.99	26.49	9.97
23	7.01	5.93	7.11	6.51	7.03	15.40	1.44	7.20	0.33
24	9.16	6.88	9.01	8.22	9.03	24.94	1.63	10.27	1.39
25	3.12	3.95	3.61	3.63	3.44	26.73	15.58	16.49	10.31
26	3.17	4.02	3.73	3.69	3.56	26.96	17.66	16.47	12.41
27	4.57	4.32	4.53	3.99	4.09	5.54	0.92	12.63	10.43
28	4.98	5.16	8.32	5.08	5.04	3.61	67.09	1.99	1.21
29	4.01	4.84	4.32	4.43	4.11	20.74	7.75	10.38	2.48
30	4.83	4.97	4.50	4.67	4.33	2.87	6.83	3.38	10.35
31	5.15	5.43	5.16	5.61	5.14	5.50	0.18	8.88	0.13
32	6.59	6.39	6.66	7.15	6.55	2.96	1.13	8.44	0.56
33	4.71	4.60	4.80	4.52	4.59	2.24	1.96	4.11	2.62
34	4.86	4.72	4.94	4.68	4.84	2.84	1.67	3.76	0.36
35	5.27	5.16	5.43	5.27	5.56	2.06	3.08	0.02	5.55
36	6.59	6.14	6.54	6.37	6.39	6.86	0.77	3.30	3.02
37	4.06	4.24	4.30	4.07	4.05	4.45	5.83	0.22	0.35
38	4.49	4.34	4.41	4.14	4.30	3.35	1.69	7.82	4.27
39	5.11	4.73	4.84	4.49	5.13	7.49	5.21	12.18	0.30
40	5.89	5.70	6.03	5.61	5.97	3.24	2.41	4.82	1.31

Table 4. Results of some MLP-ANNs for weight loss percentages of fabrics after thermal aging

Number of hidden layers	Number of neurons in hidden layers	R values of weight loss %	MSE
1	5	0.86494	0.35425
1	10	0.87897	0.38205
1	15	0.94170	0.15010
1	20	**0.98405**	**0.04164**
2	5-5	0.96325	0.09655
2	10-5	0.92834	0.18360
2	10-10	0.97668	0.19425
3	5-5-5	0.96534	0.11076
3	10-10-10	0.96564	0.09286

As it is shown in Table 4, the R values are close to 1 for most of the proposed networks and vary between 0.86494 to 0.98405. The best R value, 0.98405, and minimum MSE, 0.04164, was obtained for ANN with 20 neurons in one hidden layer. The detailed results of training, validation and testing subsets of the ANN which gave the highest R value are shown in Figure 2. According to the results, the ANN model with 20 neurons in one hidden layer can be used as an effective model for prediction of weight loss percentage of aramid fabrics.

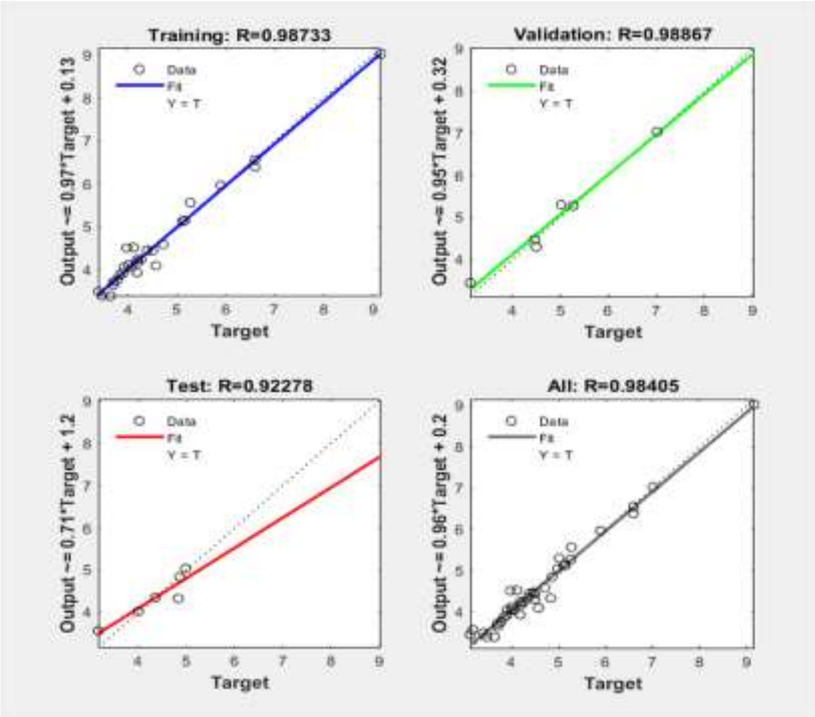

Figure 2. Results of the ANN for weight loss % (one hidden layer-20 neurons)

The performance of the ANN model is illustrated in Figure 3 for the estimated and observed values of weight loss percentages against the input variables.

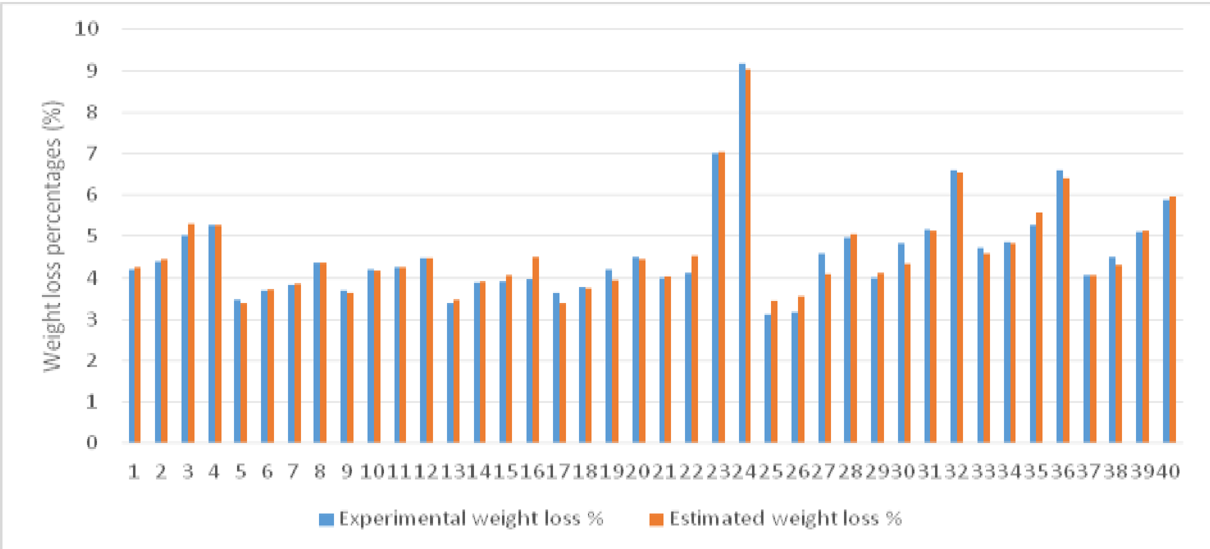

Figure 3. Comparative results for estimated and experimentally observed tensile strength loss percentages of aramid fabrics

3.3 ANN model performance for tensile strength loss percentages

Determining the amount of hidden layers and the number of neurons in each hidden layer is the challenge of using ANNs. Too many or too few number of neurons or layers will result in inaccurate output. Thus, different combinations for the number of hidden layers and neurons were tested for maximum correlation. The models with only one hidden layer didn't give good correlation between real experimental data and estimated values. Thus, the best fit models with two and three hidden layers were selected to be given on Table 5.

Table 5 shows the observed and predicted values of tensile strength loss percentages for ANN models with two and three hidden layers.

Table 5. Observed and predicted tensile strength loss percentage values for various ANN models

Experiment	Observed value for tensile strength loss %	ANN (predicted) results				Difference (%) between observed and ANN results			
		S=10,10	S=10,15	S=15,15	S=5,5,5	S=10,10	S=10,15	S=15,15	S=5,5,5
1	62.03	62.02	62.03	65.49	61.30	0.02	0.00	5.58	1.17
2	82.69	86.38	82.69	82.69	79.05	4.47	0.00	0.00	4.40
3	87.06	85.56	87.06	87.06	86.53	1.72	0.00	0.00	0.61
4	91.89	84.93	91.89	91.89	91.64	7.57	0.00	0.00	0.28
5	1.52	1.71	1.53	1.52	1.64	12.24	0.42	0.00	8.22
6	2.23	1.97	2.23	3.60	2.14	11.61	0.16	61.65	4.04
7	2.96	3.05	2.96	4.64	2.76	2.92	0.04	56.91	6.90
8	3.47	2.20	3.47	3.47	3.30	36.52	0.00	0.00	4.91
9	28.47	28.47	28.47	28.47	30.95	0.00	0.00	0.00	8.72
10	36.39	31.48	32.12	36.39	35.80	13.49	11.74	0.00	1.63
11	36.78	36.79	36.78	36.78	36.09	0.03	0.00	0.00	1.87
12	37.41	37.40	40.38	37.41	38.29	0.01	7.94	0.00	2.35
13	22.99	25.42	23.34	22.99	22.69	10.55	1.50	0.00	1.31
14	27.56	27.57	27.56	27.56	27.69	0.03	0.00	0.00	0.48
15	28.86	28.87	28.86	34.36	31.52	0.04	0.00	19.05	9.21
16	29.98	29.98	29.98	29.98	29.35	0.00	0.00	0.00	2.09
17	12.91	12.90	12.91	8.36	13.30	0.07	0.00	35.24	3.03
18	14.5	16.71	21.50	14.50	14.04	15.28	48.31	0.00	3.17
19	15.03	16.33	15.03	15.03	14.76	8.66	0.01	0.00	1.77
20	16.06	16.06	16.39	16.06	16.35	0.01	2.05	0.00	1.80
21	53.63	53.56	52.88	51.58	53.80	0.14	1.41	3.82	0.33
22	64.32	64.69	65.71	64.32	64.10	0.57	2.17	0.00	0.34
23	91.06	90.72	91.06	85.97	91.10	0.37	0.00	5.59	0.04
24	94.99	94.88	94.95	92.57	94.22	0.12	0.05	2.55	0.81
25	1.37	1.60	0.86	1.69	1.38	16.58	37.45	23.32	1.08
26	1.64	1.57	1.13	1.64	1.52	4.13	31.21	0.00	7.13
27	1.79	1.78	1.89	1.79	2.17	0.36	5.67	0.00	21.40
28	4.1	3.91	3.02	4.10	3.49	4.75	26.29	0.00	14.92
29	34.02	33.10	34.02	34.02	34.59	2.71	0.00	0.00	1.68
30	34.19	34.22	34.29	34.19	34.94	0.10	0.28	0.00	2.20
31	36.58	36.53	35.79	36.58	36.04	0.13	2.17	0.00	1.47
32	39.15	39.15	39.15	39.15	37.93	0.00	0.00	0.00	3.12
33	26.73	26.64	26.73	26.73	27.25	0.33	0.01	0.00	1.96
34	27.19	27.35	27.19	27.19	27.70	0.60	0.01	0.00	1.89
35	29.16	29.18	29.16	29.16	29.14	0.08	0.01	0.00	0.07
36	30.24	37.69	30.24	30.24	31.68	24.65	0.00	0.00	4.77
37	11.99	12.87	11.99	12.72	12.72	7.34	0.01	6.06	6.06
38	12.9	12.60	12.78	12.90	13.55	2.31	0.91	0.00	5.04
39	13.88	11.98	14.71	13.74	15.70	13.70	6.00	0.98	13.09
40	18.21	18.24	18.21	17.09	19.25	0.19	0.01	6.15	5.73

The MSE and regression (R) results of the proposed networks for tensile strength loss percentages are shown in Table 6.

Table 6. Results of some MLP-ANNs for tensile strength loss percentages of fabrics after thermal aging

Number of hidden layers	Number of neurons in hidden layers	R	MSE
2	10-10	0.99718	4.09710
2	10-15	0.99923	2.04817
2	10-20	0.97861	7.30801
2	15-15	0.99822	2.63852
3	5-5-5	**0.99935**	**1.04743**
3	10-10-10	0.99381	9.45802

The most suitable network model, which produced the minimum value of MSE and maximum regression value, was found as ANN with 3 hidden layers that included 15 neurons in hidden layers totally. The R value of this model was calculated as 0.99935 which indicated that the model had a very high potential for the prediction of tensile strength loss percentages of aramid woven fabrics close to the real experimental results. Thus, these results confirm that the neural network model reproduces tensile strength loss values for this system, within the experimental ranges adopted in the fitting model. The detailed training, validation and testing results of the proposed ANN with the highest R value are shown in Figure 4.

The results of the best fit ANN model were also observed by plotting the estimated and observed values of weight loss percentages against the varying parameters (Figure 5).

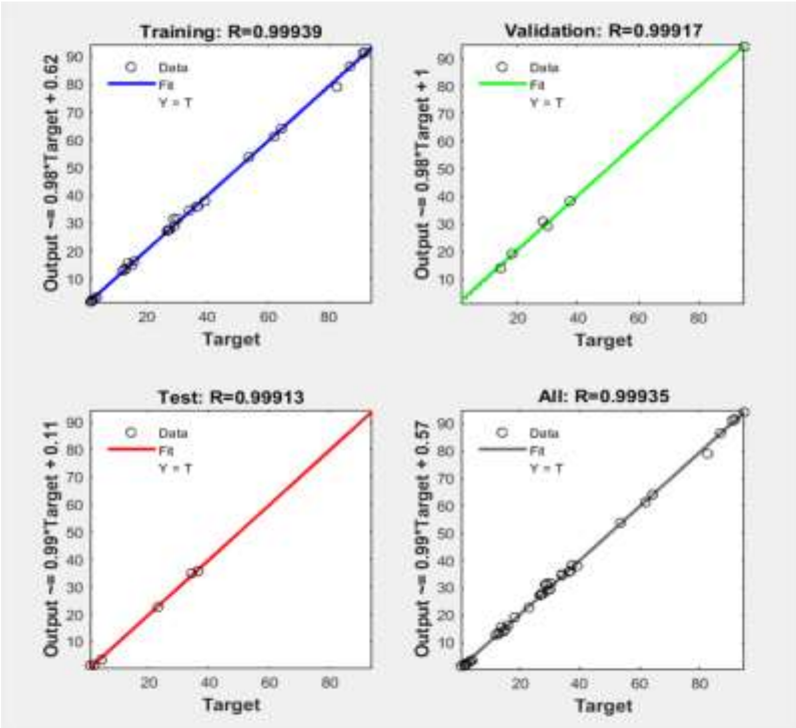

Figure 4. Results of the proposed MLP-ANN for tensile strength loss % (three hidden layers-5,5,5 neurons)

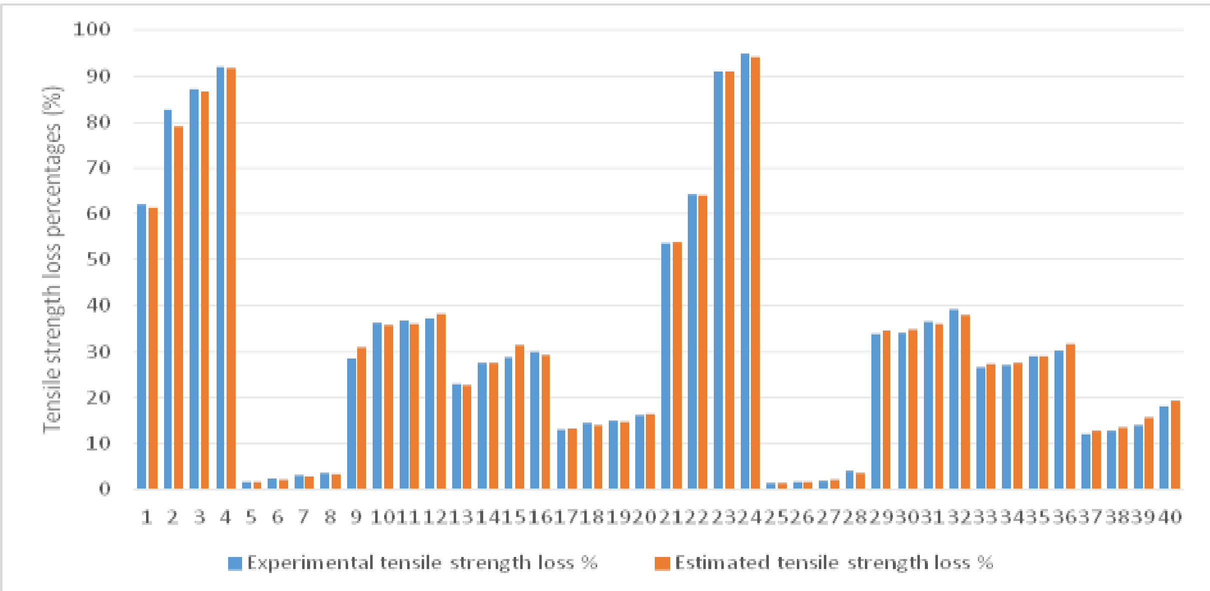

Figure 5. Comparison of results for estimated and experimentally observed tensile strength loss percentages of aramid fabrics

4. CONCLUSION

In this study, loss percentages of some physical properties of aramid woven fabrics after accelerated thermal aging processes were investigated and predicted by using artificial neural network. Repeated heat and flame exposures can cause continuous decreases in mechanical properties of materials and thermal protection given by flame-resistance protective clothing and increase injuries caused by body burn. Thus, it is important to determine the lifetime of the clothing for certain conditions before permanent damage occurs on the fabric structure. The losses in the properties of aramid fabrics after accelerated thermal aging process were successfully predicted by applying multi-layered neural networks and using a backpropagation algorithm in this study. On the basis of the proposed ANN models, it was possible to obtain quantitative information on changes in fabric properties for any temperature and exposure time. An analysis was also conducted to investigate the relationship between the estimated results of the proposed ANN models and the experimental data. As a result of using the ANN model, the values of the determination coefficient (R) for weight loss percentage and tensile strength loss percentage were found to be 0.98405 and 0.99923, respectively. The time required for the fibers to loss 50% of their original tensile strength is defined as the material thermal life. Thus, the ANN models generated in this study help to predict the lifetime of protective flame-retardant clothing according to the durations that the clothes expose to a certain degree of heat. Further studies could be investigated for other performance properties and thermal resistance of different fiber blended aramid fabrics after accelerated thermal aging.

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REFERENCES

1. Khaliq Z, Zulifqar A. 2020. Textile Mechanics: Fibers and Yarns. In J. Hu, B. Kumar and J. Lu (Eds), *Handbook of Fibrous Materials,* Wiley, 435-455.
2. Vassiliadis S, Rangoussi M, Cay A, Provatidis C. 2010. Artifi cial Neural Networks and Their Applications in the Engineering of Fabrics. In Dobnik Dubrovski P (Ed), *Woven Fabric Engineering*. IntechOpen, 111-134.
3. Bhattacharjee D, Kothari V.K. 2007. A Neural Network System for Prediction of Thermal Resistance of Textile Fabrics. *Textile Research Journal*, 77:4-12.
4. Chattopadhyay R, Guha A. 2004. Artificial Neural Networks: Applications to Textiles. *Textile Progress,* 35:1-46.
5. Arıkan Kargı VS. 2014. A Comparison of Artificial Neural Networks and Multiple Linear Regression Models as In Predictors of Fabric Weft Defects. *Tekstil ve Konfeksiyon*, 24 (3), 309-316.
6. Tarafdar A, Shahi NC, Singh A, Sroh R. 2018. Artificial Neural Network Modeling of Water Activity: A Low Energy Approach to Freeze Drying. *Food and Bioprocess Technology*, 11:164-171.
7. Dolez PI, Tomer NS, Malajati Y. 2019. A quantitative method to compare the effect of thermal aging on the mechanical performance of fire protective fabrics. *Journal of Applied Polymer Science*, 136(1):47045.
8. Deng M, Tian M, Wang Y, Wang M. 2020. Quantitatively evaluating the effects of flash fire exposure on the mechanical performance of thermal protective clothing. *International Journal of Clothing Science and Technology*, 32 (3), 412-429.
9. Hoque MS, Saha A, Chung HJ, Dolez PI. 2022. Hydrothermal aging of fire‐protective fabrics. *Journal of Applied Polymer Science*, 139 (30), e52666.
10. Wang M, Li J. 2016. Thermal protection retention of fire protective clothing after repeated flash fire exposure. *Journal of Industrial Textiles*, 46(3), 737-755.
11. Aidani R, Dolez PI, Vu-khanh T. 2011. Effect of Thermal Aging on the Mechanical and Barrier Properties of an e-PTFE/NomexVR Moisture Membrane Used in Firefighters' Protective Suits. *Journal of Applied Polymer Science*, 121:3101-3110.
12. Cho C, Nam SL, de la Mata AP, Harynuk JJ, Elias AL, Chung HJ, Dolez PI. 2022. Investigation of the accelerated thermal aging behavior of polyetherimide and lifetime prediction at elevated temperature. *Journal of Applied Polymer Science*, 139(15), 51955.
13. Liu X, Tian M, Wang Y, Su Y, Li J. 2021. Modeling to predict thermal aging for flame-retardant fabrics considering thermal stability under fire exposure. *Textile Research Journal*, 91:2656-2668.
14. Lemmi TS, Barburski M, Kabziński A, Frukacz K. 2021. Effect of Thermal Aging on the Mechanical Properties of High Tenacity Polyester Yarn. *Materials*, 14(7):1666-1676.
15. Arrieta C, David E, Dolez P, Toan V-KJ. 2010. Thermal Aging of a Blend of High-Performance Fibers, *Journal of Applied Polymer Science*, 115(5), 3031-3039.
16. Rezazadeh M, Torvi DA. 2011. Assessment of factors affecting the continuing performance of firefighters' protective clothing: a literature review. *Fire Technology*, 47(3):565-599.
17. Lu Y, Wang L, Gao Q. 2018. Predicting tensile strength of fabrics used in firefighters' protective clothing after multiple radiation exposures. *Journal of The Textile Institute*, 109:338-344.
18. Mandal S, Song G. 2014. An empirical analysis of thermal protective performance of fabrics used in protective clothing. *Annals of Occupational Hygiene*, 58(8):1065-1077.
19. Mandal S, Annaheim S, Greve J, Camenzind M, Rossi RM. 2019. Modeling for predicting the thermal protective and thermo-physiological comfort performance of fabrics used in firefighters' clothing. *Textile Research Journal*, 89(14), 2836-2849.
20. Iyer RV, Sudhakar A, Vijayan K. 2006. Decomposition behavior of Kevlar 49 fibres: Part II. At T values < Td. High Perform. *Polymers*, 18:495-517.
21. Tian M, Wang Q, Xiao Y, Su Y, Zhang X, Li J. 2020. Investigating the thermal-protective performance of fire-retardant fabrics considering garment aperture structures exposed to flames. *Materials*, 13(16), 3579.
22. Brown, J R, and Browne, N M. *Environmental effects on the mechanical properties of high-performance fibres. [PBI, Nomex, and Kevlar 49]*. United States: N. p., 1976. Web.
23. Talukdar P, Das A, Alagirusamy R. 2016. Heat and mass transfer through thermal protective clothing–A review. *International Journal of Thermal Sciences*, 106, 32-56.
24. Serban A. 2019. The Impact of Heat Stress in Firefighter Fatalities. Honeywell Safety and Productivity Solutions. https://sps.honeywell.com/us/en/support/blog/safety/the-impact-of-heat-stress-in-firefighter-fatalities, Accessed 06 Jan 2023
25. Ozgen B, Pamuk G. 2014. Effects of thermal aging on Kevlar and Nomex fabrics. *Industria Textila*, 65(5):254-262.

26. International Standards Office. (2013). ISO 13934-1–Textiles-tensile properties of fabrics-part 1: Determination of maximum force and elongation at maximum force using the strip method: Bibliographical references: Electronic documents.

27. Eyupoglu C, Eyupoglu S, Merdan N. 2019. Improvement of thermal insulation properties of polyester nonwoven and estimation of thermal conductivity coefficients using artificial neural network. *Journal of Testing and Evaluation*, 47(2):20180129.

28. Veit, D. (Ed.). 2012. Simulation in textile technology: Theory and applications. Woodhead Publishing.

29. Omerogullari Basyigit, Z., Eyupoglu, C., Eyupoglu, S., & Merdan, N. 2023. Investigation and Feed‐Forward Neural Network‐Based Estimation of Dyeing Properties of Air Plasma Treated Wool Fabric Dyed with Natural Dye Obtained from Hibiscus Sabdariffa. Coloration Technology.

30. Eyupoglu, C., Eyupoglu, S., & Merdan, N. 2022. Investigation of dyeing properties of mohair fiber dyed with natural dyes obtained from candelariella reflexa. *Journal of Natural Fibers*, 19(16), 12829-12848.

31. Jain, A., & Vijayan, K. 2002. Thermally induced structural changes in Nomex fibres. *Bulletin of Materials Science*, 25, 341-346.

32. More JJ. 1978. The Levenberg-Marquardt algorithm: Implementation and Theory. In Watson GA (Ed.) *Numerical Analysis*. Berlin, Heidelberg: Springer; 105–116.

33. Eyupoglu C, Eyupoglu S, Merdan N. 2021. A multilayer perceptron artificial neural network model for estimation of ultraviolet protection properties of polyester microfiber fabric. *Journal of The Textile Institute*, 112:1403-1416.

34. Wackerly D, Mendenhall W, Scheaffer RL. 2008. Mathematical Statistics with Applications. Thomson Brooks/Cole, Belmont.