

THE USE OF ARTIFICIAL NEURAL NETWORKS TO ESTIMATE THERMAL RESISTANCE OF KNITTED FABRICS

ÖRME FUTTER KUMAŞLARIN İSİL DAYANIMININ TAHMİNİ İÇİN YAPAY SİNİR AĞLARININ KULLANIMI

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ABSTRACT

This study aims to develop a model for the prediction of thermal resistance of fleece fabric by using regression analysis and artificial neural network technique. Primarily fleece fabrics protect human body from heat loss during cold weather. Its second purpose is to absorb sweat from human skin. Fleece fabric is commonly used to make sweatshirts, trousers, and jackets for cold weather. Higher thermal resistance of fleece is one of the main demands of users. Many factors can influence the thermal resistance efficiency of fleece. We have used porosity, thickness of fabric, thermal conductivity of fabric, overall moisture management capacity, thermal absorptivity, percentage of cotton, and polyester and planner weight as independent variables for the prediction of thermal resistance of fleece fabric. We have found that there was a significant difference between regression and artificial neural network analysis in the selection of most significant factor. Nevertheless, both models are significant. Moreover, we have also found that there is a significant correlation between two most significant variables selected during regression analysis and artificial neural network. Keeping all these in view, we can say that both models are capable of finding the thermal resistance of fabric despite the fact that artificial neural network techniques give better explanations.

Keywords: Regression Analysis, Artificial Neural Network, Fleece Fabrics, Thermal Resistance.

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INTRODUCTION

Clothing is used for thermal, sensorial, psychological, and activity comfort. Thermal comfort depends upon the balance of heat produced by the human body with the environment. More precisely, we can say that thermal comfort depends upon the heat and moisture transfer properties of clothing. Thermal resistance is one factor, which plays a crucial role in providing thermo physiological comfort. Thermal resistance is a ratio of thermal conductivity and thickness of any substance. In case of textile, it is associated with effective thermal conductivity of fabric instead of thermal conductivity of individual fibers and its thickness. Nevertheless, thermal absorptivity ($\text{W}^{-1}\text{m}^{-2}\text{K}^{-1}$) is another parameter which depicts the warm-cool feeling of the fabric[1].

Thermal conductivity of fabric depends upon the type of used fibers and porosity of fabric. A fabric is composed of

three substances; polymers (fibers), air trapped inside the fabric area and amount of moisture present inside the fabric. There is a significant relationship between thermo physiological comfort and thermal conductivity of a fabric. Nevertheless, there are many factors, which resist a linear relationship.

One of the objectives of clothing is to provide thermo physiological comfort to users. Thermo physiological comfort is an outcome of required heat and moisture flow between human body and the environment. It becomes significant in case when the temperature of the environment is either too high or too low. In case of severe cold, people wear jackets, sweat shirts, and trousers etc. which are made up of thick fabrics to have a higher thermal resistance.

Heat transfer takes place through conduction, convection and radiation. Heat transfer through radiation and

convection is quite low. Garimella[2] explains that radiation does not play a significant role below 500°C. In case of human skin, maximum temperature under normal conditions is 34°C. Moreover, there is no big flow of air, which is necessary for heat transfer through convection. It suggests that all or maximum heat transfer will be through conduction.

Thermal Resistance Measuring Methods

Thermal resistance indicates the property of any substance to stop the heat flow across the boundaries. It is measured with the help of thickness and thermal conductivity of that material.

$$R = \frac{h}{\lambda}$$

Where, R indicates the thermal resistance ($\text{m}^2 \text{KW}^{-1}$), h shows thickness (m), and λ is effective thermal conductivity ($\text{Wm}^{-1}\text{K}^{-1}$) of a substance. There are many instruments, which are commonly used to measure thermal resistance of fabrics. Bhattacharjee and Kothari[3] explained following methods to measure thermal resistance (thermal insulation):

1. Cooling method
2. Disc method
3. Measurement of propagation of waves (heat pulses)
4. Constant temperature method
5. Hot cylinder type
6. Hot semi-cylinder type (guarded)
7. Hot plate type (Guarded)
8. Sweating plate for heat and moisture in fabrics

It is well understood from the above discussion that there are many ways to measure thermal resistance of any material. For this study, we have used Alambeta for the measurement of thermal resistance and fleece thickness. Alambeta was selected that it take very short time to get the accurate measurement of Thermal properties of fabric and in our case we have used thick fleece fabric which was well observed by Alambeta, for this reason Alambeta has been used

Thermal Resistance Prediction Models

There is a continuous effort by researchers to develop a valid and proved equation to describe relationship between fabric parameters and thermal resistance. Such efforts are much useful for clothing designers, manufacturers and engineers. There are many factors, which can influence the thermal resistance of fabrics. Morris [4] has categorized such factors into main three categories:

1. Factors contributing thermal resistance which keeps human body from losing its heat
2. Factors contributing to cold feeling during initial contact between human body and fabric
3. Chillproofness, which means the reduction in effects of sudden changes in environmental humidity and temperature.

Qian and Fan [5] have worked to develop a regression model for the prediction of thermal insulation and vapor resistance. This model has a substantial agreement with actual values. There is a big debate in clothing literature about the correlation between thickness and thermal resistance. Few people believe that there is a linear relationship between thickness and thermal resistance [3]. Apparently it looks logical but we cannot ignore many other factors which can play a role. Moreover, this model mainly deals with impact of walking on thermal resistance and moisture transfer.

Instead of linear regression model, people prefer using artificial neural network (ANN) for non-linear relationship [6-8]. Fayala et al. [7] used knitted fabric for their research. Their outcome variable was thermal conductivity of knit fabric. They used thermal conductivity of yarn, planner weight, and air permeability as input variables. Luo et al. [8] used fuzzy neural network (FNN) technique for the prediction of thermal resistance of technical textile. Bhattacharjee et al. [3] observed the variation due to forced and natural convection. Garimella[2] developed a model for the prediction of heat flow. This model is totally based on the contact points. In case of fleece, there are many dependent variables. There is a big difference in thermal conductivity of polyester and cotton. As quoted by Ullmann's Fibers **[Hata! Köprü başvurusu geçerli değil.]**, thermal conductivity of cotton is between $0.3\text{-}0.5 \text{ Wm}^{-1}\text{K}^{-1}$ and thermal conductivity of polyester is between $0.2\text{-}0.3 \text{ Wm}^{-1}\text{K}^{-1}$. It shows that any change in polyester/cotton ratio in fabric will change the effective thermal conductivity and consequently, it will affect the thermal resistance of fleece fabric. All above discussion shows that there is an increasing trend in the application of ANN for non-linear relationship.

Artificial Neural Network Architecture

Artificial Neural Network (ANN), also called as Neural Network, is a mathematical model based on interconnected group of artificial neurons. Connectionist approach to computation is used for modeling complex relationship. It is much useful for non-linear relationship. ANA is much inspired by the natural neurons. Natural neuron or nerve cells are excitable cell, which receive signals and transmit them after processing.

ANA was first described in 1943 when Warren McCulloch, a neurophysiologist, and Walter Pitts, a young mathematician, published their effort to explain the neurons' network working pattern¹. In the last 60 years, there is a great development in the application of ANN in various fields. It is presumed that there will be a significant development in ANN in coming years.

Sarle[10] has explained the application of ANN in depth. In the following lines, we will give a brief of Sarle's findings. Sarle says that ANN is also called multilayer perceptron. These are basically non-linear regression and discriminant models. In ANN, variables are called inputs, predicted values are known as outputs and dependent variables are called as target or training variables. Estimation is identified as training, adaptation and observations are acknowledged

¹<http://www.psych.utoronto.ca/users/reingold/courses/ai/cache/neural4.html>

as pattern or training pairs while regression and discriminant analysis is recognized as supervised learning [10].

A Simple Artificial Neuron

Orr [11] has explained ANN in depth. Orr says that basic computational element (model neuron) is known as node or unit. Node receives input from other sources and each input is given a certain weight (w). It is modified so that it may work as model synaptic learning. It is further described as function f of the weighted sum of its inputs and written as:

$$y_i = f\left(\sum_j w_{ij} y_j\right)$$

In Figure 1, the weighted sum, which is also called net input to unit i , is often written as net_i . It is also observe that w_{ij} describes the weight from unit j to unit i (not the other way around) and function f is the unit's activation function. Moreover, f is the identity function and unit's output is its net input, which is called linear unit.

EXPERIMENTAL PART

Sample Manufacturing

Clothing is to protect human body from cold weather and keep internal temperature within required limits along with absorption of sweat [12-16]. Details of Samples in following table:

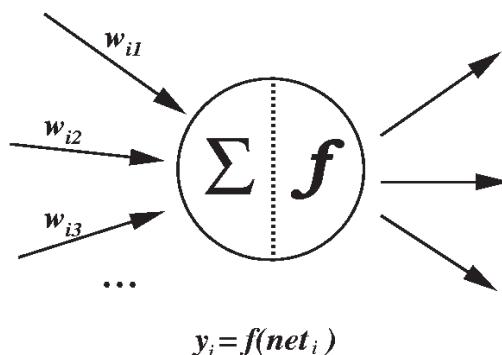


Figure 1. Weightage of Input and net function

Table 1. Fleece Data detail

S.No	Color	Planner weight Kg	Polyester %	Cotton %
1	Black	0.31	31	70
2	Navy	0.31	38	62
3	Orange	0.36	35	65
4	F.E.Blue	0.3	52	48
5	Black	0.31	23	77
6	Black	0.33	20	80
7	Gold	0.29	20	80
8	Orange	0.36	16	84
9	Black	0.37	18	82
10	Gold	0.28	20	80
11	Lt Green	0.29	20	80
12	Red	0.31	15	85
13	Black	0.35	35	65
14	Royal	0.3	18	82
15	Black	0.3	35	65
16	Turquois	0.3	35	65
17	Royal	0.28	20	80
18	Lt Blue	0.3	50	50
19	CRM Peach	0.22	60	40
20	G Htr	0.28	60	40
21	Lt Green	0.26	58	42
22	Porcaline	0.24	57	43
23	Black	0.35	0	100
24	Indigo	0.29	50	50
25	Crimson	0.3	80	20
26	Black	0.34	0	100
27	Ind/Stone y/d	0.22	60	40
28	Black	0.37	25	75
29	Dk Navy	0.32	90	10
30	Khaki	0.34	65	35

We developed 30 different samples of fleece fabric. Different combinations of polyester and cotton were used and various brushing levels were achieved. Moreover, there was a big variation in the count of yarn uses. There are three types of fleece; three-thread fleece, two-thread fleece and low-shrinkage fleece. Finally, we got fleece fabric, which has variation in thickness, planner weight, porosity and ratio of polyester and cotton. Moreover, all samples were dyed in same bath to have similar effect of washing and dyeing. However, no finishing chemicals were applied to avoid any effect of chemicals.

Testing Material

All samples were kept in lab, where temperature was between 20-22 °C and relative humidity [RH] was between 25-28 % to standardize all samples. Alambeta, which is a known product of Sensorsa Czech Republic, was used for the measurement of thermal resistance and sample thickness [1, 17-21]. Sample was placed between two plates and pressure of upper plates was kept 200Pa. When hot plate touches the surface of fabric, heat passes from hot plate to other plate, and heat flow is measured with the help of heating sensors. Upper plate is heated to 32°C using the heater. This temperature is the average human skin temperature. However, the sample is kept at room temperature, which is 22-24°C in our case. Alambeta notes the sudden changes in temperature of fabric and also measures the thickness of fabric. Every sample was tested three times for a better average.

Moisture Management Tester (MMT) developed by SDL ATLAS according to AATCC 195. MMT measure movements of water and finally gives overall moisture management capability (OMMC). We have used OMMC as one factor.

Factors contributing to thermal resistance

Alambeta was used to measure thermal parameters of the fleece fabric planner weight was measured by cutting a specific area of the fabric. Porosity was calculated by using sample thickness, planner weight and density of fibers. Overall Moisture Management Capability (OMMC) was measured by using Moisture Management Tester. Selection of these parameters is based on different studies. Many people have taken these parameters for the prediction of thermal resistance [7, 8, 22]. All such values are given in Table 2.

Conditioning of Samples

All samples were tested under controlled environmental conditions. Lab temperature was maintained between 20 - 22 degree centigrade and relative humidity (RH) was around 25-28. Changed

Statistical analysis

We used SPSS version 20 for analysis. Using stepwise selection carried out linear and neutral network was developed to know the significance of different factors. F test criterion was used to know the significance of model. An equation based on regression analysis was developed

which shows the impact of different factors on thermal resistance, which is our dependent variable. As per stat rules, models were examined on the basis of residual plots presented, Rsquare value and small mean square error along with p-values. Moreover models were tested by using predicting values and actual values along with contribution of different factors with the help of graphs.

Table 2. Contributing factor explanation

1	Cotton percentage in sample [cotton]		%
2	Polyester percentage in sample [PET]	(PET) Polyester	%
3	Thickness [h]		mm
4	Porosity [p]		[1]
5	OMMC	(OMMC) Overal moisture management capability	%
6	Thermal resistance [R]		[m ² KW ⁻¹]
7	Thermal conductivity [K]		[Wm ⁻¹ K ⁻¹]
8	Thermal absorptivity [b]		[Ws ^{1/2} K ⁻¹ m ⁻¹]
9	Planner Weight [gsm]		[Kgm ⁻³]

Artificial Neural Network Development

In this study, thermal resistance has been selected as dependent variable, which we have tried to predict with the help of linear regression and ANN. Eight factors have been selected as inputs.

There were total 30 samples, system excluded 8 values because of the fact that there planner weight is almost the same and they are not making a major impact on the results. However there ratio percentage are different but major impact is done by their weight, 21 values were used as training and one for testing. We used eight variables as input and one variable as our target variable. There is one hidden layer with 12 units. We tried by putting two layers but better results were found with one layer. Hyperbolic tangent was applied in activation function. For output layers, standard method was applied for rescaling of dependent variable along with identity. Sum of square of errors for testing and training is an indicator of reliability of the model. We did partition by having 7 values in training and 3 in testing and no value was hold. Batch training criteria was selected.

RESULTS AND DISCUSSION

Regression and artificial neural network, which is an advance and refined form of „, was applied and developed two models based on it.

Regression analysis

We used eight variables as inputs and adopted stepwise process. Model summary (Table 3) shows that in second model Adjusted R Square value is 0.853, which shows that 83.5% changes in dependent variable are due to thickness and thermal conductivity of fabric. Moreover, Durbin-Watson value is 2.051, which is more than 2. It is an indicator of no autocorrelation. "ANOVA (Table 3) tells about the significance of model". Results show that the model has high statistical significance and it can be used for the prediction of thermal resistance of fabric.

We have developed the following equation from the regression analysis.

$$R = 0.025 + 1.004h - 0.231K$$

This equation shows that increase in thickness by one unit will increase 1.004 units of thermal resistance and thermal conductivity has a negative correlation with thermal resistance.

Artificial neural network

In previous lines, we have explained artificial neural network. In the following lines, we will discuss the results of artificial neural network.

Normal P-P Plot of Regression Standardized Residual

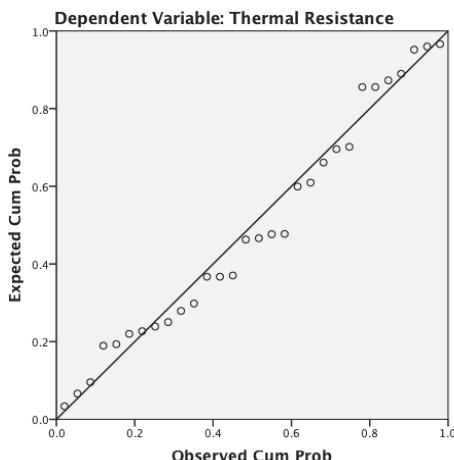


Figure 2. P-P Plot of Regression Analysis

Table 3. Model Summary Regression Analyses

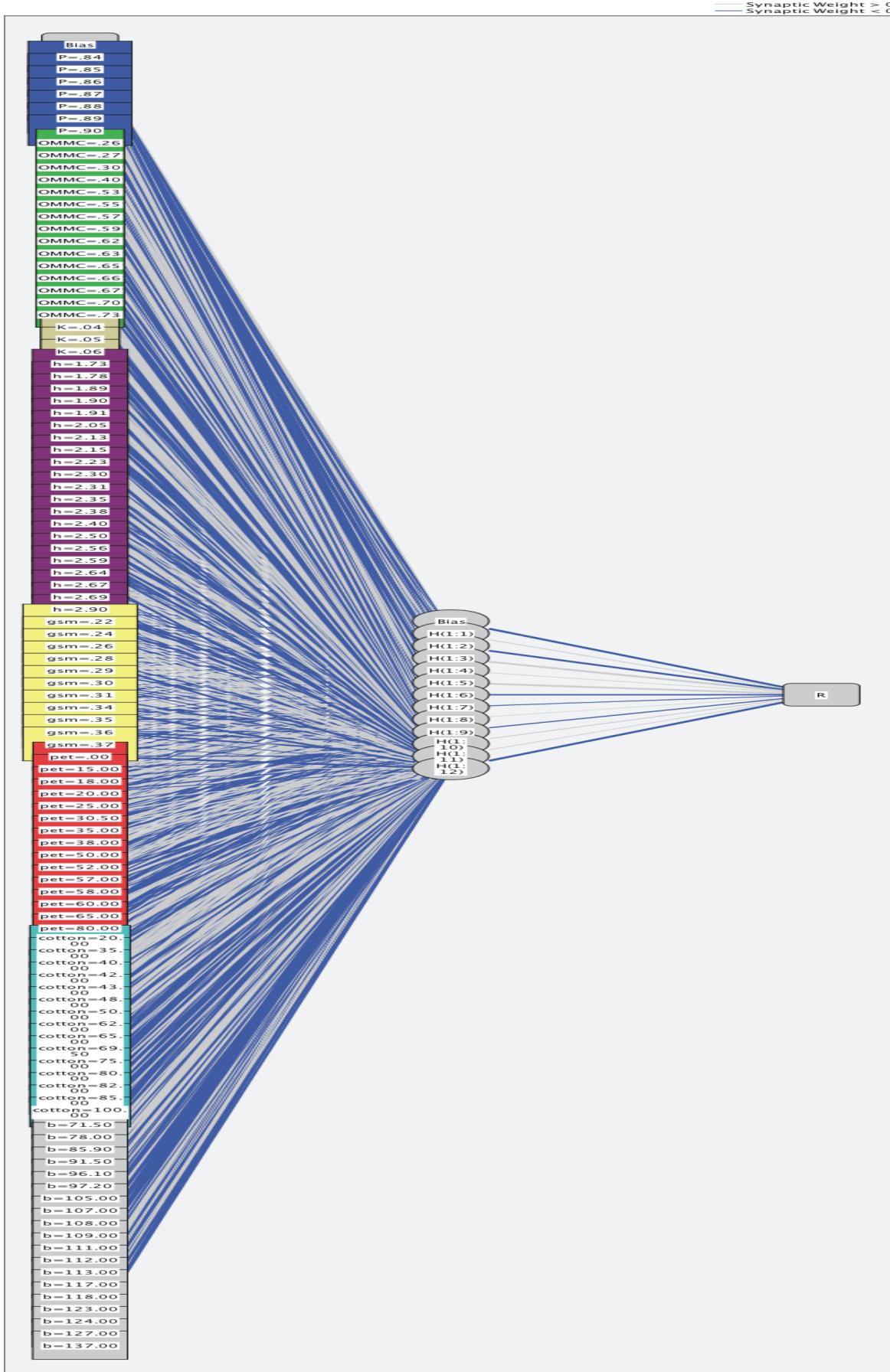
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.905 ^a	.820	.813	.002157	
2	.929 ^b	.864	.853	.001911	2.051

a. Predictors: (Constant), Sample Thickness
b. Predictors: (Constant), Sample Thickness, Thermal Conductivity
c. Dependent Variable: Thermal Resistance

Table 4. ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.001	1	.001	127.378	.000 ^b
	Residual	.000	28	.000		
	Total	.001	29			
2	Regression	.001	2	.000	85.423	.000 ^c
	Residual	.000	27	.000		
	Total	.001	29			

a. Dependent Variable: Thermal Resistance
b. Predictors: (Constant), Sample Thickness
c. Predictors: (Constant), Sample Thickness, Thermal Conductivity



Hidden layer activation function: Hyperbolic tangent
Output layer activation function: Identity

Figure 3. ANN Activation Function

Model summary

Model summary shows that sum of square of error is 0.393 whereas relative error is 0.039 and for training, stopping rule has been used which is a consecutive step with no error reduction. Training time was 0:00:00.02. Sum of the square error for testing was quite negligible. It is 4.895E-006.

Figure 5 shows the relationship with actual and predicted values. In this case, R square value is 0.974, which is too high and shows the coefficient of determination.

The planner weight has the highest importance for the prediction of thermal resistance and porosity is next to it for its importance. Nevertheless, thermal conductivity has the lowest importance

Table 5. ANN Model Summary

	Sum of Squares Error	.393
	Relative Error	.039
Training	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00.02
Testing	Sum of Squares Error	4.895E-006
	Relative Error	^b .
Dependent Variable: Thermal Resistance		
a. Error computations are based on the testing sample.		
b. Cannot be computed. The dependent variable may be constant in the testing sample.		

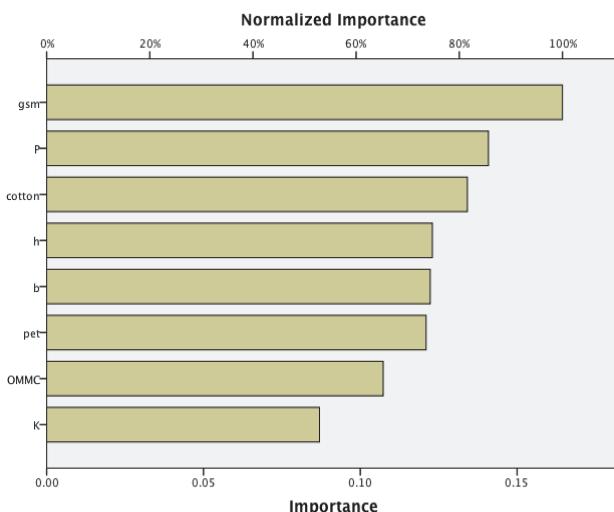


Figure 3. Importance of Different Variables

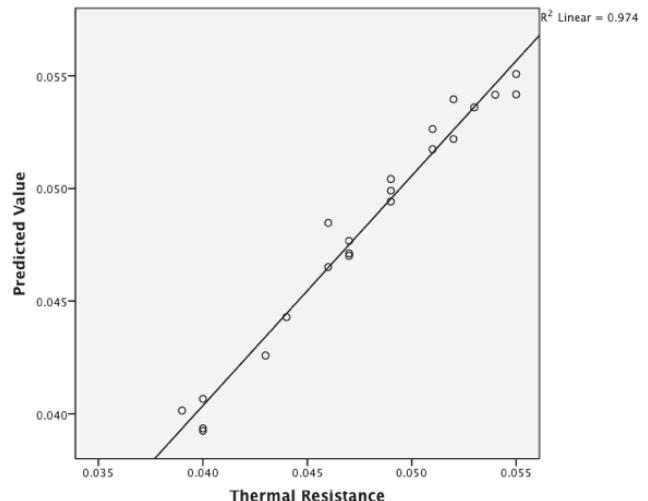


Figure 4. Predicted and Measured Values of Thermal Resistance

Comparison of artificial neural network and regression models

As discussed earlier, we have used eight input variables and one output variable. Regression and artificial neural network technique was applied. We found that in regression model, thickness has positive relation with 1.004 coefficients whereas thermal conductivity has a negative relationship with 0.231 coefficients. It shows that during stepwise regression analysis, system has removed other six variables and has only considered these two variables as significant. Moreover, R square value (0.853) shows that 85.3% variation in dependent variable is due to thermal conductivity and fabric thickness.

In artificial neural network, we observe different values. Artificial neural network tells that the most important factor is planner weight and after that porosity and cotton percentage has third place whereas thermal conductivity has lowest contribution.

We do not have any third way to measure the impact of eight selected factors on thermal resistance. Keeping above constraint in view, we can say that there is a difference in both models. We tested correlation between planner weight taken as major contributor in case of artificial neural network and thickness, which is major contributor in case of linear regression analysis. We found that there is a significant correlation between these two factors and correlation coefficient is 0.6, which is considerably high.

We can derive that both models have their own significance and they can be used to determine the thermal resistance of fleece fabric.

Evaluation of Results

Table 6. Thermal and other related parameters of testers

S.No	KGsm2	PET %	Cotton %	Porosity [1]	OMMC [1]	Thermal Conductivity	Thermal Absorptivity	Thickness [mm]	Thermal Resistance
1	0.3	30.5	69.5	0.84	0.57	0.05	137	1.78	0.039
2	0.31	38	62	0.85	0.4	0.05	123	1.91	0.04
3	0.36	35	65	0.87	0.26	0.05	123	2.69	0.053
4	0.3	52	48	0.89	0.65	0.05	111	2.56	0.052
5	0.31	23	77	0.87	0.62	0.05	113	2.35	0.051
6	0.33	20	80	0.86	0.65	0.05	125	2.16	0.044
7	0.29	20	80	0.87	0.7	0.05	105	2.35	0.052
8	0.36	16	84	0.87	0.57	0.05	123	2.4	0.047
9	0.37	18	82	0.87	0.59	0.05	117	2.59	0.051
10	0.28	20	80	0.87	0.59	0.05	109	2.13	0.047
11	0.29	20	80	0.88	0.53	0.05	107	2.3	0.051
12	0.31	15	85	0.84	0.55	0.05	109	1.9	0.04
13	0.35	35	65	0.89	0.55	0.05	114	2.86	0.058
14	0.3	18	82	0.88	0.53	0.05	80	2.29	0.046
15	0.3	35	65	0.88	0.49	0.05	83.6	2.3	0.05
16	0.3	35	65	0.9	0.53	0.05	97.2	2.67	0.055
17	0.28	20	80	0.89	0.27	0.05	112	2.31	0.049
18	0.3	50	50	0.88	0.63	0.05	113	2.38	0.049
19	0.22	60	40	0.88	0.66	0.04	97.2	1.89	0.044
20	0.28	60	40	0.89	0.58	0.05	103	2.52	0.055
21	0.26	58	42	0.88	0.73	0.05	71.5	2.13	0.047
22	0.24	57	43	0.86	0.62	0.04	96.1	1.73	0.04
23	0.35	0	100	0.88	0.62	0.05	127	2.4	0.046
24	0.29	50	50	0.86	0.66	0.05	118	2.05	0.043
25	0.3	80	20	0.87	0.67	0.05	78	2.23	0.046
26	0.34	0	100	0.9	0.62	0.05	91.5	2.9	0.055
27	0.22	60	40	0.88	0.3	0.04	85.9	2.15	0.049
28	0.37	25	75	0.88	0.3	0.06	124	2.5	0.047
29	0.32	90	10	0.87	0.3	0.05	111	2.23	0.046
30	0.34	65	35	0.88	0.3	0.05	108	2.64	0.054

Table 7. Independent Variable Importance

	Importance	Normalized Importance
Porosity	.141	85.7%
OMMC	.107	65.2%
Thermal Conductivity	.087	52.9%
Sample Thickness	.123	74.8%
Planner Weight Kg per Meter Square	.164	100.0%
Polyester %	.121	73.6%
Cotton Percentage	.134	81.6%
ThermalAbsorptivity	.122	74.4%

Table 8. Correlation between Thermal Conductivity and Sample Thickness

		Sample Thickness	Planner Weight Kg per Meter Square	
Sample Thickness		Pearson Correlation	1	.601**
		Sig. (2-tailed)		.000
		N	30	30
Planner Weight Kg per Meter Square		Pearson Correlation	.601**	1
		Sig. (2-tailed)	.000	
		N	30	30

**. Correlation is significant at the 0.01 level (2-tailed).

CONCLUSION

Thermal resistance is a significant and vital factor for users and a major factor of clothing comfort particularly in cold weather. Knitted fleece fabric is commonly used to make clothing for cold weather. We developed 30 fleece samples to find the role of different factors in insulation provided by the fleece fabric. For this purpose, eight independent variables were selected and using regression analysis and applying artificial neural network carried out tests. We found that there is a difference in the results of both techniques. It was found that in regression analysis, thickness and thermal conductivity are major contributors. It is evident from the R

square value, which is 0.835. Nevertheless, artificial neural network gives that planner weight is the most important contributor and the second is porosity. We tested correlation between thickness and planner weight, which is significant with coefficient 0.600. It seems that both models are applicable and can be used to find thermal resistance of fabric.

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