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Modeling for predicting the thermal protective and thermo-physiological comfort performance of fabrics used in firefighters' clothing

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Abstract

Standardized test methods are available for measuring the thermal protective as well as thermo-physiological comfort Performance of fabrics used in firefighters' clothing. However, these tests are usually fabric destructive in nature, time consuming, and/or expensive to carry out on a regular basis. Hence, the availability of empirical models could be useful for conveniently predicting the thermal protective and thermo-physiological comfort performances from the fabric properties. The aim of this study is to develop individual models for predicting thermal protective and thermo-physiological comfort performances of fabrics. For this, different single- and multi-layered fabrics that are commercially used to manufacture firefighters' protective clothing were selected, and the fundamental properties of these fabrics (weight, thickness, thermal resistance, air-permeability, evaporative resistance, and water spreading speed) were measured using the standard test methods developed by the International Organization for Standardization (ISO) or the American Association of Textile Chemists and Colorists. The thermal protective performance of these fabrics was measured by the ISO 9151:2016 test method under 80 kW/m^2 flame exposure. The thermo-physiological comfort performance of fabrics was determined by the ISO 18640-1:2018 test method and a statistical model. Thereafter, the key fabric properties affecting the thermal protective and thermo-physiological comfort performances of fabrics were determined statistically. It has been found that thermal and evaporative resistances are the key fabric properties to affect the thermal protective performance, whereas the fabric weight, evaporative resistance, and water spreading speed are the key properties to affect the thermo-physiological comfort performance. By employing these key fabric properties, Multiple Linear Regression and Artificial Neural Network (ANN) models were developed for predicting the thermal protective and thermo-physiological comfort performances. Through a comparison of the predicting performance parameters of these models, it has been found that ANN models can more accurately predict the performances of fabrics. These models can be implemented in the textile industry and academia for effectively and conveniently predicting the thermal protective and thermo-physiological comfort performances only by utilizing the key fabric properties.

Keywords

firefighters' clothing, fabric properties, thermal protective performance, thermo-physiological comfort performance, Multiple Linear Regression, Artificial Neural Network

Thermal protective clothing worn by firefighters provides them with protection from fire hazards while on duty.[1,2] Fabrics used in this clothing are generally thick, semi-air-permeable, and/or air-impermeable in order to provide a high level of protection to firefighters from different heat exposures.[2–4] As a consequence, these fabrics impede the metabolic-heat, liquid-sweat,

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and/or sweat-vapor transfer from firefighters' bodies to their ambient environment, which ultimately lowers the thermo-physiological comfort of firefighters and increases their heat strain.[3] Hence, it is important to experimentally measure both of these contradictory aspects – thermal protective and thermo-physiological comfort performances of the fabrics – in order to understand the interrelationship between them.[5,6] For this purpose, various test methods have been developed by the International Organization for Standardization (ISO).[7–11]

In particular, the ISO 6942:2015 and ISO 9151:2016 test standards are used for measuring the thermal protective performance under radiant-heat and flame exposures, respectively.[7,8] The ISO 6942:2015 standard recommends to measure the protective performance under low (5–10 kW/m^2) and medium (10–40 kW/m^2) intensity radiant-heat exposures, whereas the ISO 9151:2016 standard recommends to measure the performance under high-intensity (80 kW/m^2) flame exposure only. Moreover, the ISO 11092:2014 and ISO 18640-1:2018 test standards are widely used for measuring the thermo-physiological comfort performance of fabrics using a sweating guarded hot plate and torso testers, respectively.[10,11] The ISO 11092:2014 standard mainly measures the thermal and evaporative resistances of the fabrics to understand their resistance toward the metabolic-heat and sweat-vapor transfer from firefighters' bodies to the ambient environment. However, the individual measurement of the thermal and evaporative resistances is unrealistic because the metabolic-heat, liquid-sweat, and/or sweat-vapor transfer occur simultaneously from the human body to the ambient environment and are coupled by phase change mechanisms, such as liquid evaporation or vapor condensation.[12–14] Considering this, devices like a sweating guarded torso test device – that can holistically measure the thermo-physiological comfort performance of the fabrics by considering the combined effect of metabolic-heat and sweat-vapor transfer through the fabric – have been developed and documented in the ISO 18640-1:2018 standard.[11]

Although the above-mentioned test standards has been used to measure the thermal protective and thermo-physiological comfort performances of fabrics, these tests are usually fabric destructive in nature, time consuming, and/or expensive to carry out on a regular basis.[15–19] Considering this, some researchers have developed heat transfer models by studying the mathematical interactions between fabric properties and performances.[20–22] However, the practical application of these mathematical heat transfer models for predicting the performances may be limited due to their complexities. Therefore, a few researchers have developed empirical Multiple Linear Regression (MLR) and/or Artificial Neural Network (ANN) models to predict the thermal protective performance from a set of fabric properties (these fabric properties significantly affected the performance) under flame, radiant-heat, and/or hot surface contact exposures. In addition, it has been found that ANN models can more accurately predict the protective performance in comparison to MLR models.[17,18,23] Although these researchers have developed the individual models for predicting the protective performance under each exposure, the universal application of these models together for different exposures highly increases the complexity of the prediction, comparability, and/or holistic understanding of the thermal protective performance of fabrics. Hence, an ANN model is required to measure and holistically understand the thermal protective performance of fabrics under an exposure and intensity that simulates the real working scenario of firefighters. Furthermore, no models are available to date for conveniently predicting the thermo-physiological comfort performance of fabrics.

In this study, the thermal protective performance of a set of fabrics was measured under flame and radiant-heat exposures at different intensities using standardized test methods; in addition, the thermo-physiological comfort performance of the fabrics was measured using the standard sweating guarded torso test and a statistical model. As a first objective of this study, it was necessary to identify a standard representative test method with a particular exposure and intensity that can holistically measure and classify the protective performance of the fabrics for further modeling. Next, the key fabric properties that affect the thermal protective and thermo-physiological comfort performances were identified. By employing these key fabric properties, MLR and ANN models were developed to predict the thermal protective and thermo-physiological comfort performances. Finally, two better-fitting high-performance models were identified for predicting the thermal protective as well as the thermo-physiological comfort performances.

Methods

Fabric selection and property measurement

For this study, six single- and 13 multi-layered fabrics – which were developed by conventional (weaving, finishing) and/or latest technology (nano nonwoven) – were selected (Table 1). These fabrics are commercially used in firefighters' station uniforms and turnout gear clothing. The fundamental properties of these fabrics (weight, thickness, thermal resistance, air-permeability, evaporative resistance, and water spreading speed) were measured using standard test methods developed by the

Table 1. Selected fabrics [Outer Layer (OL) faces thermal exposures; Middle Layer (ML) is sandwiched between OL and IL; and Inner Layer (IL) is in contact with wearers' skin]

Fabrics		Composition and/or construction
Single-layered	1	50% Meta-aramid/50% Fire Retardant (FR) viscose woven fabric
	2	34% Meta-aramid and Para-aramid/33% Lyocell/31% Modacrylic/2% Antistatic fibers
	3	93% Meta-aramid/5% Para-aramid/2% Antistatic Fibers
	4	93% Meta-aramid/5% Para-aramid/2% Antistatic Fibers
	5	55% FR modacrylic/45% FR cotton woven fabric
	6	FR cotton woven fabric
Multi-layered	7	Double woven fabric with meta-aramid face and para-aramid back (OL) + Polytetrafluorethylene (PTFE) coated membrane on a aramid nonwoven fabric with dots toward IL (ML) + 50% meta-aramid/50% FR viscose (IL) woven fabric (IL)
	8	Double woven fabric with meta-aramid face and para-aramid back (OL) + PTFE coated membrane on two aramid fabrics with dots toward OL (IL)
	9	Double woven fabric with meta-aramid face and para-aramid back (OL) + PTFE coated membrane on a aramid nonwoven fabric (ML) + Aramid regenerated nonwoven felt sewn with 50% meta-aramid/50% FR viscose woven fabric (IL)
	10	99% aramid/1% beltron woven fabric (OL) + PTFE coated on meta-aramid nonwoven fabric (ML_{layer1}) + Aramid spunlace fleece (ML_{layer2}) + 50% meta-aramid/50% viscose woven fabric (IL)
	11	Meta-aramid woven fabric with thread on backside (OL) + Polyurethane (PU) liner on meta-aramid nonwoven fabric (ML) + Aramid woven fabric (IL)
	12	64% FR viscose/35% meta-aramid/1% antistatic woven fabric (OL) + PU coated on 50% meta-aramid/50% FR viscose nonwoven fabric (ML) + 65% FR viscose/35% meta-aramid fabric (IL)
	13	64% FR viscose/35% meta-aramid/1% antistatic woven fabric (OL) + PTFE coated on 50% meta-aramid/50% FR viscose nonwoven fabric (ML) + 65% FR viscose/35% meta-aramid woven fabric (IL)
	14	Meta-aramid woven fabric (OL) + PTFE coated on 25% meta-aramid/25% para-aramid/50% basofil nonwoven fabric (ML) + Nonwoven meta-aramid quilted with 50% meta-aramid/50 FR viscose fabric (IL)
	15	75% meta-aramid/23% para-aramid/2% antistatic woven fabric (OL) + PTFE coated membrane on a aramid nonwoven fabric (ML_{layer1}) + Meta-aramid nonwoven fabric (ML_{layer2}) + 93% meta-aramid/5% para-aramid/2% antistatic woven fabric (IL)
	16	75% meta-aramid/23% para-aramid/2% antistatic woven fabric (OL) + PTFE coated membrane on a aramid nonwoven fabric (ML_{layer1}) + Meta-aramid nonwoven fabric (ML_{layer2}) + Meta-aramid nano nonwoven fabric (ML_{layer3}) + 93% meta-aramid/5% para-aramid/2% antistatic woven fabric (IL)
	17	Filament Twill Technology-based meta-aramid spun yarn and para-aramid filament yarn woven fabric (OL) + PTFE coated membrane on two aramid nonwoven fabrics (ML) + PTFE coated membrane on a aramid woven fabric (IL)
	18	Filament Twill Technology based meta-aramid spun yarn and para-aramid filament yarn woven fabric (OL) + PTFE coated membrane on a aramid nonwoven fabric (ML_{layer1}) + Meta-aramid nonwoven fabric (ML_{layer2}) + Meta-aramid nano nonwoven fabric (ML_{layer3}) + 93% meta-aramid/5% para-aramid/2% antistatic woven fabric (IL)
	19	Filament Twill Technology-based meta-aramid spun yarn and para-aramid filament yarn woven fabric (OL) + PTFE membrane on a aramid nonwoven fabric (ML_{layer1}) + Meta-aramid nonwoven fabric (ML_{layer2}) + 93% meta-aramid/5% para-aramid/2% antistatic woven fabric (IL)

ISO or the AATCC (American Association of Textile Chemists and Colorists) (Table 2).

Selection of a representative standard test method for measuring the thermal protective performance of fabrics

The thermal protective performance of the fabrics was measured under radiant-heat exposures at 10 and 40 kW/m^2 using the ISO 6942:2015 standard.[7] In addition, the protective performance was measured under the flame exposure at 80 kW/m^2 using the ISO 9151:2016 standard.[8] For both the methods, a copper sensor was directly placed behind the back side of a fabric specimen (i.e., toward the side of the specimen that is in contact with wearers' skin) and the front side of the specimen (i.e., toward the side of the specimen that faces the fire hazard) was exposed to the

Table 2. Fundamental properties of the selected fabrics

Fabrics	Properties: Weight[a] (g/m^2)	Thickness[b] (mm)	Thermal resistance – R_{ct} [c] (°K·m^2/W.10^{-3})	Air-permeability[d] (cm^3/cm^2/s)	Evaporative resistance – R_{et}[e] (m^2·Pa/W)	Water (sweat) spreading speed[f] (mm/s)
1	197.0	0.4	12.9	148.6	3.0	2.8
2	243.7	0.6	8.9	90.0	2.5	4.3
3	154.7	0.3	9.7	502.2	2.4	6.7
4	229.8	0.4	9.4	91.4	3.3	6.8
5	367.3	0.7	13.0	44.3	3.6	0.5
6	366.8	0.8	12.9	43.0	4.7	0.8
7	609.9	3.9	79.7	0	20.2	0.8
8	547.5	3.9	80.0	0	15.8	0.5
9	673.8	4.9	127.7	0	25.4	0.3
10	635.2	3.2	82.7	0	15.6	3.3
11	592.1	3.9	95.4	0	23.9	1.9
12	587.8	2.1	46.6	0	9.4	0.6
13	599.8	2.3	49.3	0	10.0	0.5
14	493.0	2.3	71.0	0	16.8	4.3
15	520.5	2.1	61.8	1.0	12.2	2.6
16	514.8	2.2	65.6	0.8	13.0	3.4
17	568.1	3.0	83.3	0	12.8	3.2
18	496.7	2.1	64.2	0.8	14.2	3.0
19	490.4	1.9	60.0	1.1	13.2	2.3

[a]Measured by ISO 3801:1977.
[b]Measured by ISO 5084:1996.
[c]Measured by ISO 11092:2014.
[d]Measured by ISO 9237:1995.
[e]Measured by ISO 11092:2014.
[f]Water spreading speed of the fabric layer in contact with wearers' skin was measured by AATCC 195.

radiant-heat (generated from a radiant-heat panel) or flame (generated from a Meker burner). During the exposure, the time (in seconds) was required to increase (from the starting temperature of the sensor at ~25–28°C) the temperature of the sensor by 24°C (T24) was measured through software. Notably, T24 values of three specimens of each fabric were measured and then averaged. This averaged T24 value was interpreted as the thermal protective performance of the fabric. Through statistical comparison of the T24 values under different exposures and intensities, a representative standard test method (at a particular exposure and intensity that can simulate the real working scenario of firefighters) was identified for the holistic measurement and further modeling of the protective performance of fabrics. As described in earlier research,[24,25] a fabric with a high T24 value was inferred as the high thermal protective performance-based fabric in comparison to a fabric with a low T24.

Thermo-physiological comfort performance measurement of fabrics

The thermo-physiological comfort performance of the fabrics was measured using the ISO 18640-1:2018 standard test method[11] and a statistical model provided by Annaheim et al. in 2016[26] (i.e., Equation (1)). This method includes an upright standing heated cylinder with a surface area of 0.43 m^2, representing a human trunk/torso. The upper and lower sides of the torso are guarded in order to prevent any heat loss from it. Furthermore, perspiration is imitated by the release of deionized water through 54 evenly distributed nozzles on the cylinder surface. A fabric specimen was clipped around the sweating guarded torso (the surface temperature of the torso was kept at 35°C) that was placed in a climatic chamber with controlled air temperature (20 ± 0.5°C), relative humidity (50 ± 5%), and air velocity (1 ± 0.1 m/s). During the test, the thermal resistance of the fabric (R_{ct} in m^2.K/W) was measured during a dry phase (without sweating) and the initial cooling rate (IC in °C/h) was obtained during an activity phase consisting of a metabolic-heat production of 125 W and a sweat rate of 100 g/h [corresponding to a human physical activity of 5 Mets (290 W/m^2), and a sweat rate of 230 g/m^2/h]. Based on R_{ct} and IC, comparative Time to Heat Stress (cTHEST in minutes) was calculated for fabrics (Equation (1)). Notably, cTHEST values of three specimens of each fabric were calculated and then averaged. This averaged cTHEST value was interpreted as an indicator for wearing comfort and thermo-physiological impact of the fabric. Here, a high value of cTHEST indicates a high thermo-physiological comfort performance for the fabric.[26] Furthermore, cTHEST values have been validated based on human subject trials including similar physical activity as applied during the activity phase of the sweating guarded torso methodology (induced by walking on a treadmill) in environmental conditions of 40°C air temperature and 30% relative humidity.[26] Time to reach a core body temperature of 38.5°C, starting from thermo-neutral status (i.e., core body temperature of 37.0 ± 0.5°C), was compared to the cTHEST of four fabrics. Contextually, a significant linear relationship has been detected [the coefficient of determination (R^2) is 0.84]; thus, Annaheim et al.[26] concluded a powerful relevance of the cTHEST for the assessment of thermo-physiological comfort performance of fabrics

$$\text{Time to exceed core body temperature of } 38.5^\circ\text{C or cTHEST} = 0.68 \times IC - 0.067 \times R_{ct} + 119.39 \tag{1}$$

Modeling approaches for predicting the thermal protective and thermo-physiological comfort performances of fabrics

Empirical modeling techniques were used to predict the thermal protective and thermo-physiological comfort performances of fabrics. Different fabric properties were used as input parameters for predicting the thermal protective or thermo-physiological comfort performance. Contextually, it is notable that too many and/or mutually dependent input variables (e.g., fabric properties) could disturb the empirical models and lead to the error in predicting the output variable (e.g., thermal protective performance, thermo-physiological comfort performance). Therefore, key fabric properties for protective and comfort performances were identified and used as input variables in the empirical models. In this study, MLR and ANN modeling methodologies were used for predicting the performance.[17,23] These models were compared based on their predicting performance parameters [coefficient of determination (R^2), Root Mean Square Error (RMSE), and p-value] to identify the better-fitting high-performance models to predict the protective and comfort performances. A model with high R^2, low RMSE, and p-values of <0.05 was inferred as the better-fitting high-performance model. The following sections present the procedure to identify the key fabric properties affecting the performances and the modeling methodologies of the MLR and ANN models.

Procedure to identify the key fabric properties affecting the thermal protective and thermo-physiological comfort performances of fabrics. To identify the key fabric properties, linear regression t-tests were conducted between the individual fabric properties (weight, thickness, thermal resistance, air-permeability, evaporative resistance, or water spreading speed) and performance (thermal protective or thermo-physiological comfort performance) using the SPSS Statistics 23 Data Editor developed by IBM Corporation, USA. The p-values obtained from the t-tests were analyzed to identify the fabric properties that significantly affected the performance. Significance tests were carried out at the significance level of 0.05. Contextually, it is notable that the set of significant fabric properties identified could also be mutually dependent. To identify the most significant property, the correlation coefficient (r) was calculated between each mutually dependent fabric property and the performance. The fabric property with the highest r value was identified as the most significant fabric property among all the mutually dependent fabric properties. The significant fabric properties identified based on the p-values and/or r values were inferred as the key fabric properties affecting the performance. The '+' or '–' sign of the T-stat value obtained from the t-test indicated the positive or negative association between a key fabric property and the performance, respectively. This association was further justified based on the theories of textile science (e.g., fabric thermal insulation, liquid spreading speed) as well as heat and mass transfer (e.g., convective or radiative heat transfer, sweat-vapor/liquid transfer) through porous fabrics.

MLR and ANN modeling methodologies

MLR modeling. MLR modeling was used to predict the thermal protective or thermo-physiological comfort performances from the key fabric properties (obtained from the previous section) using the IBM SPSS Statistics 23 software. The generic form of MLR models used is shown in Equation (2), where, C is the identically distributed constant normal error, $\beta_1 \ldots \beta_n$ are the regression coefficients that determine relative strength of the respective key fabric properties, and $(KFP)_1 \ldots (KFP)_n$ are key fabric properties. Notable inherent limitations of the MLR model are that, firstly, it assumes the linear relationship between all input (key fabric properties) and output variables (thermal protective or thermo-physiological performance), which may not always be the case; and, secondly, this model should not be used to predict an output variable beyond the range of the input variables employed in the model[17,19,27–30]

$$\text{Performance} = C + \beta_1 \times (KFP)_1 + \beta_2 \times (KFP)_2 + \ldots \beta_n \times (KFP)_n \quad (2)$$

ANN modeling. The ANN is a powerful data modeling tool that could capture and represent any kind of relationship between input (key fabric properties) and output (thermal protective or thermo-physiological comfort performance) variables.[23,27–32] Two ANN models were developed for predicting the thermal protective and thermo-physiological comfort performances of fabrics using the MATLAB® R2015b software.

In this study, Multi Layer Perceptron (MLP) architecture was employed, as MLPs are universal function approximators and commonly used to create mathematical models by regression analysis. After setting different values for hyper-parameters (e.g., the number of hidden layers and neurons, choice of activation functions) and different training algorithms (e.g., gradient descent, Levenberg–Marquardt), a three-layered (input layer, one hidden layer, and output layer) feed-forward (one of the specialized versions of feed-forward network, i.e., fitnet) back-propagation (Levenberg–Marquardt back-propagation method) ANN model was employed (Figure 1). Generally, a challenge in using the feed-forward back-propagation ANN model is to decide the number of neurons in the hidden layer. If the neurons are too few in the hidden layer, the model is usually unable to differentiate between complex patterns, and it might lead to a linear estimate of the actual relationship between the input and output variables, whereas if the neurons are too many, the model follows a noise in the data set, and it might lead to an inaccurate output.[29] To choose the optimum number of neurons in the hidden layer, the ANN models were trained with different numbers of neurons, and the best predictive ANN models were found with 10 hidden neurons. Different measures and criteria – such as performance plot, error histogram, and regression plot – were consulted for deciding that the trained model is not over fitted or the trained model has generalized well. After a model was trained, we looked at the performance plot, which showed a decrease in Mean Square Error (MSE) as the model became trained.

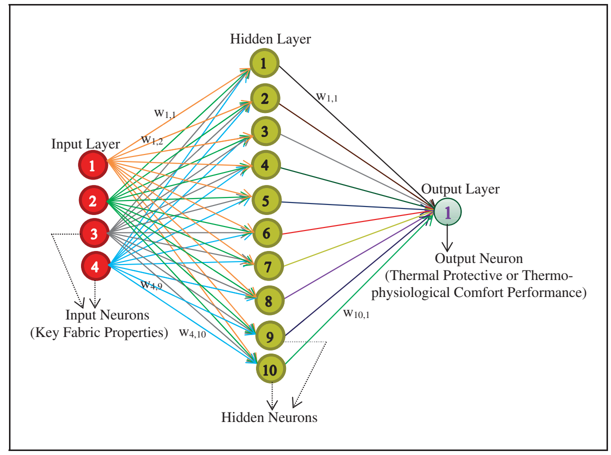

Figure 1. Schematic diagram of the three-layered feed-forward back-propagation Artificial Neural Network model with 10 hidden neurons (as an example: four input neurons, 10 hidden neurons, and one output neuron are used).

In this three-layered feed-forward model, each layer of the neural network contained connections to the next layer (e.g., from the input to the hidden layer), but there were no connections back. All the neurons in a particular layer received a signal from the neurons of the previous layer. The signal received was then multiplied by a weight factor known as a synaptic weight (w). Next, the weighted inputs were summed up and passed to a transfer function to generate the output in a fixed range of values. This output was then transferred to the neurons of the next layer. As the model used back-propagation supervised training, the final outputs predicted were always compared with the actual output. Through this comparison, the back-propagation training algorithm calculated the prediction error and adjusted the synaptic weight of layers backward from the output to the input layer. Eventually, the error signal decreased iteratively and the model got closer to producing the desired final output. The hyperbolic tangent sigmoid transfer function (Equation (3)) was assigned as an activation function in the hidden layer, and the linear function (Equation (4)) was used in the output layer. These specific functions can easily be applied with all types of data and provide the best performance for an ANN model.[27] In Equations (3) and (4), x is the weighted sum of inputs to a neuron and $f(x)$ is the transformed output from that neuron.

In this study, MATLAB randomly assigned 70% of data (i.e., significant fabric properties and performance) for the training, 15% of data for the validation, and the remaining 15% of data to test the predicting performance of the ANN models. Contextually, it is notable that these ANN models were trained on a small data set. Thus, these models might be unstable and may not be generalized for predicting the thermal protective or thermo-physiological comfort performance of all types of fabrics.

$$f(x) = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{3}$$

$$f(x) = x \tag{4}$$

Results and discussion

Thermal protective performances (T24) of the fabrics under flame and radiant-heat exposures at different intensities are shown in Table 3, and the relationships between the thermal protective performances for these exposures and intensities are shown in Figure 2. The coefficient of determination (R^2) >0.9 indicated a high interrelation between the thermal protective performances predicted at these exposures and intensities. This linear correlation suggests that the heat absorption and degradation energy generated by the samples are comparable for all of these exposures and intensities. The values obtained at 80 kW/m^2 flame exposure test were selected as a representative standard test method for measuring, classifying, and modeling the thermal protective performance of fabrics in this study. This is because the flame test can holistically simulate the combined effect of flame, radiant-heat, and hot gasses instead of considering the radiant-heat exposure only; also, firefighters could be at a greater risk when exposed to high-intensity heat.[33–35] In addition, Table 3 presents the thermo-physiological comfort performances (cTHEST) of the fabrics. In this study, an inverse relationship was detected for T24 and cTHEST (Table 3). This outcome was expected as fabrics with high T24 values or high protective performance generally allow limited metabolic-heat exchange, which results in low cTHEST values or low comfort performance.

Models for predicting the thermal protective and thermo-physiological comfort performances of fabrics

In order to develop the models, firstly, the key fabric properties affecting the thermal protective and thermo-physiological comfort performances are identified and tabulated (see the *Key fabric properties affecting the thermal protective and thermo-physiological comfort*

Table 3. Thermal protective and thermo-physiological comfort performances of fabrics

	Thermal protective performance			Thermo-physiological comfort performance
	Radiant-heat test		Flame test	sweating guarded torso test and statistical model (Equation (1))
Fabrics	T24 at 10 kW/m^2 (s)	T24 at 40 kW/m^2 (s)	T24 at 80 kW/m^2 (s)	cTHEST (min)
1	24.4	5.5	4.3	124.4
2	23.6	7.1	4.5	123.6
3	22.1	6.3	3.6	128.0
4	24.4	6.9	4.0	128.0
5	27.1	7.8	5.9	119.2
6	26.6	7.1	5.7	121.0
7	64.2	23.2	17.7	118.5
8	46.1	19.2	14.9	115.5
9	81.8	39.1	24.6	114.0
10	54.9	18.8	16.0	116.2
11	60.0	21.4	19.7	114.8
12	52.9	18.8	14.5	116.7
13	47.7	16.1	14.1	115.6
14	45.9	16.6	14.6	119.3
15	44.4	15.0	14.2	122.2
16	45.5	15.8	15.2	118.8
17	66.1	22.1	16.0	116.7
18	52.4	17.3	13.4	118.0
19	50.6	15.8	12.7	121.7

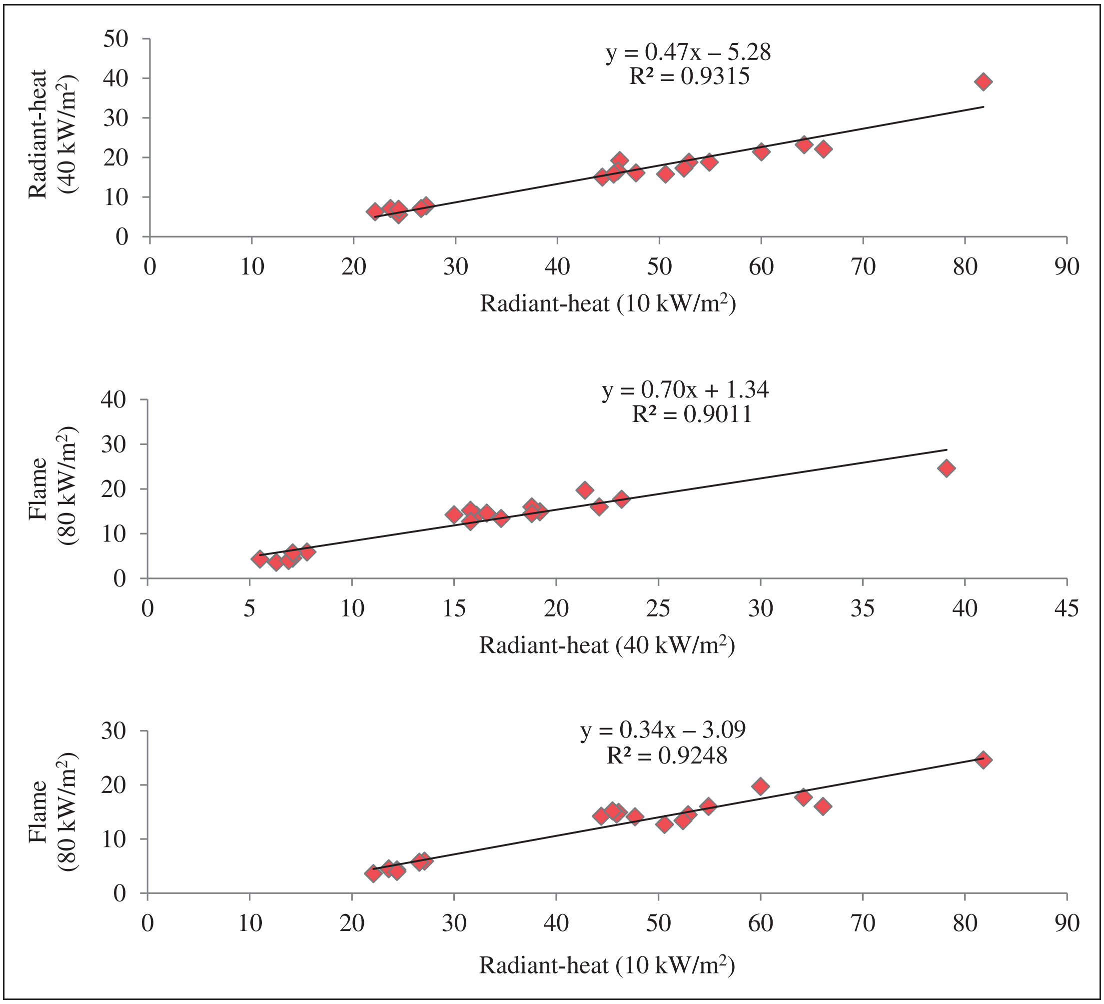

Figure 2. Relationships between the thermal protective performances under flame and radiant-heat exposures at different intensities.

performances of fabrics section). By using these key fabric properties, the MLR and ANN models are developed for predicting the thermal protective and thermo-physiological comfort performances (see the *MLR and ANN models for predicting the thermal protective and thermo-physiological comfort performances of fabrics* section). By comparing these MLR and ANN models, two better-fitting high-performance models are inferred for predicting the thermal protective and thermo-physiological comfort performances.

Key fabric properties affecting the thermal protective and thermo-physiological comfort performances of fabrics. The results obtained from statistical analysis to select key fabric properties are presented in Table 4. As per Table 4, weight, thickness, and thermal resistances were found to significantly affect both the thermal protective

Table 4. Results of the *t*-tests

Fabric properties	Performance			
	Thermal protective		Thermo-physiological comfort	
	p-value	*T*-stat	*p*-value	*T*-stat
Weight	0.0001	10.96	0.0001	−8.50
Thickness	0.0001	6.42	0.001	−4.16
Thermal resistance	0.0001	18.14	0.0001	−5.12
Air-permeability	0.006	−3.11	0.001	3.94
Evaporative resistance	0.0001	12.83	0.0001	−4.62
Water spreading speed	0.05	−2.31	0.0001	4.49

Table 5. Correlation coefficient of mutually dependent fabric properties

	Correlation coefficient (r)	
Mutually dependent fabric properties	Thermal protective	Thermo-physiological comfort
Set 1		
Weight	0.94	–0.90
Thickness	0.84	–0.71
Thermal resistance	0.98	–0.78
Set 2		
Air-permeability	–0.61	0.70
Evaporative resistance	0.95	–0.75

and thermo-physiological comfort performances, because their p-values are lower than 0.05. As these three fabric properties are mutually dependent,[36,37] the correlation coefficient (r) between each of these fabric properties and the performances was calculated in order to identify the most significant parameter (see Set 1 in Table 5). It was found that thermal resistance ($r = 0.98$) and weight ($r = 0.90$) were the most significant properties for thermal protective and thermo-physiological comfort performances, respectively. Here, the positive (+) T-stat value revealed a positive/direct correlation between thermal resistance and thermal protective performance, whereas the negative (−) T-stat value revealed a negative/indirect relationship between weight and thermo-physiological comfort performance (Table 4). Actually, a fabric with high thermal resistance traps a lot of dead air within its structure and/or possesses high thickness. This situation lowers the convective, radiative, and/or conductive heat transfer through the fabrics and enhances the thermal protective performances of the fabrics.[6,38] In this context, Schmid et al.[39] also found that thermal resistance is a key fabric property to affect the thermal protective performance, especially under flash fire exposure. In addition, a fabric with high weight could exert a physical burden on firefighters. A high-weight fabric might be thicker as well, and that impedes the metabolic-heat and sweat-vapor transfer from firefighters' bodies to the ambient environment. This situation could lower the thermo-physiological comfort performance of fabrics.[40]

From Table 4, it is also notable that two mutually dependent fabric properties, such as air-permeability and evaporative resistance (generally a fabric with high air-permeability results in low evaporative resistance) significantly (p-value < 0.05) affect the thermal protective and thermo-physiological comfort performances. However, the evaporative resistance can most significantly affect the performances, based on the highest r values (r for thermal protective performance $= 0.95$; r for thermo-physiological comfort performance $= 0.75$) in Set 2 of Table 5. Furthermore, it is clear from Table 4 that evaporative resistance is directly ('+' T-stat value) and indirectly ('−' T-stat value) related to the thermal protective and thermo-physiological comfort performances of the fabrics, respectively. Actually, a fabric with high evaporative resistance usually possesses fewer pores within its structure. This situation lowers the transmission of convective heat through the pores of the fabric and enhances the thermal protective performance of the fabrics. Contradictorily, a fabric with fewer pores might have more conductive heat transfer, depending upon the properties of the fibers used in the fabric, and this could result in low protective performance.[38,41] Furthermore, evaporative resistance could restrict the evaporative heat transfer from firefighters' bodies to the ambient environment. Eventually, a fabric with high evaporative resistance could restrict the metabolic-heat and sweat-vapor transfer from firefighters' bodies to the ambient environment. This situation ultimately lowers the comfort performance of the fabrics.

As this study focused on the thermal protective performance of only dry fabrics, it is clear from Table 4 that water spreading speed is not a significant property in this case. However, this property is significant for the thermo-physiological comfort performance of fabrics. Basically, a fabric (i.e., applied in the sweating guarded torso methodology) with high water spreading speed could quickly distribute the liquid-sweat within the fabric layer next to wearers' skin or other fabric layers, and then it could easily evaporate. This situation results in the enhanced thermo-physiological comfort performance of the fabrics.

Overall, Table 6 summaries the key fabric properties identified for the thermal protective and thermo-physiological comfort performances based on the p-values (<0.05) and/or r values (the highest r values for a particular set of fabrics in Table 5).

MLR and ANN models for predicting the thermal protective and thermo-physiological comfort performances of fabrics

MLR models. By implementing the key fabric properties (Table 6) in the MLR modeling methodology described in the *MLR and ANN modeling methodologies* section, the models developed for predicting the thermal protective and thermo-physiological comfort performances are presented in Equations (5) and (6),

Table 6. Key fabric properties for the thermal protective and thermo-physiological comfort performances (✓ = key fabric properties, × = non-key fabric properties)

Fabric properties	Key fabric properties for the performance	
	Thermal protective	Thermo-physiological comfort
Weight	×	✓
Thickness	×	×
Air-permeability	×	×
Water spreading speed	×	✓
Thermal resistance	✓	×
Evaporative resistance	✓	✓

respectively, where R_{ct} is thermal resistance, R_{et} is evaporative resistance, W is weight, and WSS is water spreading speed

$$\text{Thermal Protective Performance} = 3.13 + 0.14 \times R_{ct} + 0.14 \times R_{et} \tag{5}$$

$$\text{Thermo} - \text{physiological Comfort Performance} = 126.32 - 0.02 \times W + 0.64 \times WSS - 0.05 \times R_{et} \tag{6}$$

ANN models. For both thermal protective and comfort performance, ANN models were developed based on the key fabric properties (Table 6). The coding of these software programs for ANN models is presented in Appendices 1 and 2.

Comparison between MLR and ANN models. The prediction performance of the MLR and ANN models developed is presented in Table 7. Both prediction model approaches were found to provide statistically significant results. However, the ANN models reached higher coefficient of determination (R^2) values than the MLR models for both the prediction of thermal protective and thermo-physiological comfort performances. Moreover, the prediction errors (RMSE) of the ANN models are lower than that of the MLR models. In summary, the ANN models performed better than the MLR models for predicting the thermal protective and thermo-physiological comfort performances in terms of the precision and accuracy. As ANN models can capture and represent any kind of relationship between the key fabric properties and performances, they outperformed the MLR models.

Nevertheless, the precision and accuracy of the ANN model for predicting the thermal protective

Table 7. The R^2, Root Mean Square Error (RMSE), and p-values of the Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models

Predicting performance parameters of models	Models			
	Thermal protective performance		Thermo-physiological comfort performance	
	MLR	ANN	MLR	ANN
R^2	0.95	0.99	0.86	0.94
RMSE	1.38	0.71	1.70	1.53
p-value	0.0001		0.0001	

performance is higher than that of the ANN model for predicting the thermo-physiological comfort performance (by comparing the R^2 and RMSE values of the ANN models of thermal protective and thermo-physiological comfort performances). A possible reason for this difference in precision and accuracy could be related to heat and/or mass (sweat or moisture) transfer phenomena occurring through the fabrics while evaluating the thermal protective and thermo-physiological comfort performances of fabrics (using the methods described in the *Thermo-physiological comfort performance measurement of fabrics* and *Selection of a representative standard test method for measuring the thermal protective performance of fabrics* sections). While combined and complex heat and mass transfer (liquid-sweat as well as sweat-moisture-vapor) phenomenon occurs through the fabrics in the case of thermo-physiological comfort performance evaluation a more simplified phenomenon of heat transfer only is applied in the case of thermal protective performance evaluation. Due to these differences in heat and/mass transfer phenomena, different numbers and types of key fabric properties affect these two performances (Table 6). This difference in the numbers and types of key fabric properties leads to the difference in precision and accuracy of the ANN models developed for the protective and comfort performances. As comparatively fewer key fabric properties were involved in the development of ANN model for thermal protective performance, this model could generate fewer errors while predicting the protective performance. Finally, the precision and accuracy of the ANN model for thermal protective performance is higher than the ANN model for thermo-physiological comfort performance.

Summary and conclusion

The standardized test methods available for measuring the thermal protective and thermo-physiological comfort performances are usually fabric destructive in nature, time consuming, and/or expensive to carry out on a regular basis. Considering this, the present study aimed at developing empirical models for conveniently predicting the protective and comfort performances from fabric properties. For this, properties and performances of a set of fabrics used in firefighters' clothing were measured using the standardized test methods. Thermal protective performance was measured in terms of time to increase the wearers' skin temperature by 24°C under different heat exposures (radiant-heat and flame) and intensities faced by firefighters in a fire hazard. In addition, the thermo-physiological comfort performance of fabrics was measured in terms of comparative time to generate heat stress on wearers.

It has been found that the thermal protective performances of fabrics under exposures of $10\,kW/m^2$ radiant-heat, $40\,kW/m^2$ radiant-heat, and $80\,kW/m^2$ flame are linearly correlated. This suggests that heat absorption and degradation energy generated by the fabrics are comparable under these exposures and intensities. It can also be concluded from this study that the performance values obtained in the $80\,kW/m^2$ flame exposure test could be a representative to holistically measure, classify, and model the protective performance of fabrics.

It has been found that thermal and evaporative resistances are the key fabric properties to directly affect the thermal protective performance. Also, weight and evaporative resistance were identified as the key fabric properties to indirectly affect the thermo-physiological comfort performance, whereas the water spreading speed of the fabric that is in contact with the wearers' skin was identified as the key fabric property to directly affect the comfort performance. Also, this study clearly found that thermal and evaporative resistances are positively related to the protective performance, while these two properties are negatively related to the comfort performance of the fabrics. This confirms a need for optimizing the protective and comfort performances for a particular thermal exposure by controlling the fabric properties.

By implementing the key fabric properties and performance values, the MLR and ANN models are developed for predicting the thermal protective and thermo-physiological comfort performances of fabrics. As per the finding from this study, ANN models are recommended to use for more accurately predicting the protective and comfort performances of fabrics.

Contextually, it is notable that the ANN model developed for predicting the thermal protective performance was based on the experimental performance values obtained for the dry fabrics only. As firefighters sweat a lot while working, this sweat/moisture could also affect the thermal protective performance of fabrics.[41,42] In addition, existing microclimate air gaps between the clothing and firefighters' bodies can substantially influence the protective and comfort performances of fabrics.[3,43] In the future, it is recommended to develop ANN models considering the sweat/moisture and microclimate air gaps for more accurately predicting the protective and comfort performances of fabrics as well as whole clothing in consideration with clothing features, such as fit, size, and closures. Furthermore, a fabric with very high thermal protective performance results in very low thermo-physiological comfort performance. As these performances are inversely related, the development of a categorization tool in the future based on the protective and comfort performances could help in finding the best balance between these performances for the necessary protection. This type of tool could guide clothing manufacturers' and/or fire stations' clothing procurement managers to select an appropriate fabric for the clothing based on their end-uses – namely to select a fabric having high thermal protective performance with the maximum possible thermo-physiological comfort performance for a particular thermal exposure.

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As an authors' note, the thermal protective and thermo-physiological comfort performances were obtained by testing the fabrics in simulated, controlled environments to improve reproducibility. These environments represent accepted simulations of emergency conditions or scenarios to assess the physiological impact (standardized test methods). As real heat and fire exposure conditions are uncontrolled and random regarding intensities, the presented results may not be applicable to all real exposure conditions.

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Appendix 1: MATLAB program for the Artificial Neural Network model to predict thermal protective performance

```
% input training data i.e. Key Fabric Properties (KFP) for thermal protective performance.
  input = [12.9 8.9 9.7 9.4 13 12.9 79.7 80 127.7 82.7 95.4 46.6 49.3 71 61.8 65.6 83.3 64.2 60; 3 2.5 2.4 3.3 3.6 4.7 20.2 15.8 25.4 15.6 23.9 9.4 10 16.8 12.2 13 12.8 14.2 13.2];
  % target training data for thermal protective performance.
  target = [4.3 4.5 3.6 4 5.9 5.7 17.7 14.9 24.6 16 19.7 14.5 14.1 14.6 14.2 15.2 16 13.4 12.7];
  % choosing a training function
  trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation.
  % creating a fitting network
  hiddenLayerSize = 10;
  netp = fitnet(hiddenLayerSize,trainFcn);
  % setting up the division of data for training, validation, testing
  netp.divideParam.trainRatio = 70/100;
  netp.divideParam.valRatio = 15/100;
  netp.divideParam.testRatio = 15/100;
  % training the network
  [netp,tr] = train(netp,input,target);
  % testing the network
  y = netp(input);
  % assessing the performance of the trained network. The default performance function is mean squared error.
  performance = perform(netp,target,y)
  % saving the trained network
  save netp;
  % loading the trained network
  load netp;
  % calculating the root mean square error
  rmse=sqrt(performance);
  % viewing the network
  view(netp);
  % using the regression analysis to judge the network performance
  [m,b,r]=postreg(y,target);
  % entering the new input
  newinput = [64.2; 14.2];
  % predicting the output corresponding to new input
  newoutput = netp(newinput)
```

Appendix 2: MATLAB program for the Artificial Neural Network model to predict thermo-physiological comfort performance

```
% input training data i.e. Key Fabric Properties (KFP) for thermo-physiological comfort performance.
  input=[197 243.7 154.7 229.8 367.3 366.8-609.9 547.5 673.8 635.2 592.1 587.8 599.8 493-520.5 514.8 568.1 496.7 490.4; 2.8 4.3 6.7 6.8 0.5 0.8 0.8 0.5 0.3 3.3 1.9 0.6 0.5 4.3 2.6 3.4 3.2 3 2.3; 3 2.5 2.4 3.3 3.6 4.7 20.2 15.8 25.4 15.6 23.9 9.4 10 16.8 12.2 13 12.8 14.2 13.2];
  % target training data for thermo-physiological comfort performance.
  target=[124.4 123.6 128 128 119.2 121 118.5 115.5 114116.2 114.8 116.7 115.6 119.3 122.2 118.8 116.7 118 121.7];
  % choosing a training function
  trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation.
  % creating a fitting network
  hiddenLayerSize = 10;
```

```
netcp = fitnet(hiddenLayerSize,trainFcn);
% setting up the division of data for training, validation, testing
netcp.divideParam.trainRatio = 70/100;
netcp.divideParam.valRatio = 15/100;
netcp.divideParam.testRatio = 15/100;
% training the network
[netcp,tr] = train(netcp,input,target);
% testing the network
y = netcp(input);
% assessing the performance of the trained network. The default performance function is mean squared error.
performance = perform(netcp,target,y)
% saving the trained network
save netcp;
% loading the trained network
load netcp;
% calculating the root mean square error
rmse=sqrt(performance);
% viewing the network
view(netcp);
% using the regression analysis to judge the network performance
[m,b,r]=postreg(y,target);
% entering the new input
newinput = [496.7; 3;14.2];
% predicting the output corresponding to new input
newoutput = netcp(newinput)
```