An Empirical Analysis of Thermal Protective Performance of Fabrics Used in Protective Clothing
Sumit Mandal¹ and Guowen Song²,³*

1. Department of Human Ecology, University of Alberta, Human Ecology Building, Edmonton, Alberta T6G 2N1, Canada
2. Department of AESHM, Iowa State University, IA 50011, USA
3. College of Textile Engineering, Tianjin Polytechnic University, Tianjin, 300387, China

*Author to whom correspondence should be addressed. Tel: +1-780-492-0706; fax: +1-780-492-4821; e-mail: gwsongsx@gmail.com
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ABSTRACT
Fabric-based protective clothing is widely used for occupational safety of firefighters/industrial workers. The aim of this paper is to study thermal protective performance provided by fabric systems and to propose an effective model for predicting the thermal protective performance under various thermal exposures. Different fabric systems that are commonly used to manufacture thermal protective clothing were selected. Laboratory simulations of the various thermal exposures were created to evaluate the protective performance of the selected fabric systems in terms of time required to generate second-degree burns. Through the characterization of selected fabric systems in a particular thermal exposure, various factors affecting the performances were statistically analyzed. The key factors for a particular thermal exposure were recognized based on the t-test analysis. Using these key factors, the performance predictive multiple linear regression and artificial neural network (ANN) models were developed and compared. The identified best-fit ANN models provide a basic tool to study thermal protective performance of a fabric.

KEYWORDS: artificial neural network (ANN); empirical analysis; fabric properties; modeling; multiple linear regression (MLR); predictive models; protective clothing; thermal exposures; thermal protective performance

INTRODUCTION
Protective clothing of firefighters/industrial workers is required to provide them effective protection from various thermal exposures, namely flame (convection), radiant-heat (radiation), and hot surface (conduction). It is imperative for the textile/clothing industries as well as for the academic research to evaluate the thermal protective performance of textile fabrics used in the protective clothing under flame, radiant-heat, and hot surface exposures (Benisek and Phillips, 1979; Perkins, 1979; Stull, 1997; Song et al., 2004; Mandal and Song, 2012a; Gholamreza and Song, 2013; Lu et al., 2013). Therefore, many national and international organizations [e.g. American Society for Testing and Materials (ASTM), National Fire Protection Association, International Organization for Standardization (ISO)] have developed the standard laboratory-simulated methods for the accurate evaluation of thermal protective performances of fabrics in flame, radiant-heat, and hot surface exposures;
however, these experimental methods are expensive in operation, destructive, and difficult to carry out on a routine basis (Benisek and Phillips, 1979; Stull, 1997).

By evaluating the thermal protective performances of fabrics using the standardized experimental methods, many researchers empirically analyzed the interactions between fabric properties and performances; based on this understanding, a few researchers have also derived the empirical models to predict the performances without conducting any expensive and cumbersome laboratory experiments (Shalev and Barker, 1984; Lee and Barker, 1986; 1987; Sun et al., 2000; Song et al., 2004; Torvi and Threlfall, 2006; Song et al., 2008; Mandal and Song, 2011; Song et al., 2011; Mandal and Song, 2012b,c; Mandal et al., 2013). Song et al. (2004) and Song et al. (2008) used mathematical techniques to estimate the performance in convective flame exposures; similarly, Torvi and Threlfall (2006) applied a mathematical technique for reckoning the performance in the combined flame and radiant-heat exposures. These studies yield information about the mathematical interactions between fabric properties and performances; however, the practical applications of these mathematical models for calculating the performance may be limited due to their complexities. Furthermore, Lee and Barker (1987), Shalev and Barker (1984), and Sun et al. (2000) derived the statistical regression relationships between fabric properties (specifically, weight, thickness) and performances in the flame and radiant-heat exposures, and they found a positive relationship between these properties and the performances. Recently, Song et al. (2011) and Mandal and Song (2011) statistically established that fabrics having high weight, high thickness, and layered structure provide more effective protection to firefighters and/or industrial workers, especially in flame, radiant-heat, and/or hot surface exposures. Through statistical correlation analysis, Lee and Barker (1986) further found that moisture regain of the protective textile fabrics is an important property to consider because the presence of moisture may lower the performance of textile fabric system under flame/radiant-heat exposures. In addition, Mandal et al. (2013) statistically inferred that fabric compressibility and stability are the properties having a significant effect on the performance in hot surface exposures. Basically, a fabric with high compressibility and stability reduces the amount of thermal energy absorption inside the fabric structure and increases the thermal energy transmission through the fabric; consequently, the performances of the textile fabrics become lower (Mandal and Song, 2012b). In summary, many researchers statistically studied the performance with respect to fabric features under flame, radiant-heat, and/or hot surface exposures; here, it was found that there is a complex subjective interaction between different fabric features and performance (Shalev and Barker, 1984; Lee and Barker, 1986; Lee and Barker, 1987; Sun et al., 2000; Mandal and Song, 2011; Song et al., 2011; Mandal and Song, 2012b; Mandal et al., 2013). Recently, Mandal and Song (2012b,c) made a further effort to derive statistical models between fabric features and performance. They established the models between properties of fabric systems (namely, thickness, air permeability, thermal resistance) and thermal protective performances in flame, radiant-heat, and hot surface exposures using multiple linear regression (MLR) methodology. These MLR models could be used to predict the performance of textile fabric systems. However, prediction error percentages of these models were very high; thus, these models do not predict the performance accurately. In this context, many researchers have also challenged the inherent prediction accuracy of MLR models in different research fields (agriculture, applied chemistry, textile, etc.), especially where accurate forecasting is a prime concern (Pynckels et al., 1995; Arupjoyti and Iragavarapu, 1998; P. K. Majumdar and A. Majumdar, 2004; Murrells et al., 2009; Zaefizadeh et al., 2011; Mandal and Song, 2012c). They suggested that models developed by artificial neural network (ANN) could provide better prediction accuracy than MLR models. They found that ANN model development is an appropriate methodology for wide range of applications. This application is prominent especially in building predictive models of processes where many input factors (features of fabric systems) contribute to the eventual outcome (performance), despite having little knowledge about the exact relationships or interactions between the input and output (Murrells et al., 2009). The strength of ANN methodology lies in its ability to represent complex relationships, and learning these relationships directly from the data being modeled (Pynckels et al., 1995). Due to all this, many applications of ANN have also been reported in the textile and clothing field (Pynckels et al., 1995; Fan and Hunter, 1998; P. K. Majumdar and A. Majumdar, 2004; Beltran et al., 2006; Hui and Ng,
In this study, an empirical analysis of the thermal protective performance of textile fabric systems under flame, radiant-heat, and hot surface exposures is conducted. Thermal protective performances of fabric systems are measured in the laboratory. The importance of different factors on performances is statistically examined; the key factors are identified to establish the performance predictive ANN and MLR models. A statistical analysis is undertaken to compare the developed ANN and MLR models in order to check the validity of the prediction of thermal protective performance; in turn, the best-fit model for prediction of thermal protective performance is proposed.

**MATERIALS AND METHODS**

**Materials selection and physical properties evaluation**

Different fabrics (A–F that are commercially available and commonly used in thermal protective clothing) were selected based on their physical features (Table 1). Using these fabrics, various fabric systems (single, double, triple) with different configuration were developed; these fabric systems are: A (Fabric-A), B (Fabric-B), AC (Fabric-A + Fabric-C),
AE (Fabric-A + Fabric-E), AF (Fabric-A + Fabric-F), FA (Fabric-F + Fabric-A), AFC (Fabric-A + Fabric-F + Fabric-C), AFD (Fabric-A + Fabric-F + Fabric-D), AFE (Fabric-A + Fabric-F + Fabric-E), and FAD (Fabric-F + Fabric-A + Fabric-D). The features of these fabric systems (A-FAD) are shown in Table 2. According to Table 2, it is evident that AF (or AFD) and FA (or FAD) fabric systems have same features; however, the placement of moisture barrier is different in these fabric systems. As moisture may generate in thermal exposures, especially in a hydrocarbon-fueled flame exposure, the placement of moisture barrier can significantly influence the thermal protective performances of fabric systems depending upon the modes of heat transfer. As a consequence, both AF and FA fabric systems were constructed for the study.

**Test conditions and approaches**

The thermal protective performances of the three specimens of each selected fabric systems were determined. The selected fabric specimens were preconditioned in a standard atmosphere (21°C temp. and 65% relative humidity) for 24 h. To evaluate the performance, the laboratory simulations of the flame, radiant-heat, and hot surface thermal exposures were created according to the modified ISO 9151:1995, ASTM E 1354:2013, and ASTM F 1060:2008 standard, respectively (ISO 9151:1995, 1995; ASTM E 1354:2013, 2013). During the thermal exposure, the thermal energy transmitted through the specimens was measured at every 0.1 s by a skin simulant sensor. This skin simulant sensor can closely represent a human body; additionally, this sensor is rapid and accurate in measurement under highly intensive long duration thermal exposures (Torvi, 1997). From the measured thermal energy, the time required to generate second-degree burn injury was calculated using a burn prediction software that is programmed according to the Henriques’ Burn Integral (HBI) model (ASTM F 1930:2013, 2013).

**Flame exposure test**

In this study, the modified ISO 9151:1995 standard was used to evaluate the thermal protective performance of the selected fabric systems under the flame exposure (Fig. 1). In the original ISO 9151:1995 standard, a horizontally oriented specimen of the fabric system (14 × 14 cm) is subjected to an incident heat flux of 80 kW m⁻² from the flame of a gas burner placed beneath it. The heat passing through the specimen is measured by means of a small copper calorimeter on top of and in contact with the specimen. The time, in seconds, required to raise the temperature at (24 ± 0.2)°C in the calorimeter is recorded; the mean result for three test specimens is calculated as the ‘heat transfer index (flame)’. In the presently used modified ISO 9151:1995 standard, a specimen of the fabric system (10 × 10 cm) was mounted on a support frame by placing the outer layer downwards. Then, flame was exposed on the outer layer of the specimen at 84 kW m⁻² using a 38-mm-diameter Meker propane gas burner, and the specimen was separated from the flame source before and after the test run using a transverse shutter. The thermal energy transmitted through the specimen during the flame exposure was measured by a skin simulant sensor placed in an insulation board behind the exposed specimen. The measured thermal energy in terms of heat flux was recorded, and the time required to generate the second-degree burn was predicted using the HBI burn prediction software.

<table>
<thead>
<tr>
<th>Features</th>
<th>Fabric systems</th>
<th>Single-layered</th>
<th>Double-layered</th>
<th>Triple-layered</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>A</td>
<td>B</td>
<td>AC</td>
</tr>
<tr>
<td>Thickness (mm)</td>
<td></td>
<td>0.46</td>
<td>0.67</td>
<td>1.54</td>
</tr>
<tr>
<td>Air permeability (cm³ cm⁻² s⁻¹)</td>
<td>17.1</td>
<td>0</td>
<td>13.9</td>
<td>12.5</td>
</tr>
<tr>
<td>Thermal resistance (K m² W⁻¹)</td>
<td>0.073</td>
<td>0.074</td>
<td>0.117</td>
<td>0.169</td>
</tr>
</tbody>
</table>

Air permeability and thermal resistance were measured according to ASTM D 737:2004 and ASTM D 1518:2011, respectively.

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**Table 2. Developed fabric systems**

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**Footnotes:**


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**References:**

- Torvi, 1997
- ASTM F 1930:2013
- ASTM F 1060:2008
- ASTM E 1354:2013
- ASTM D 737:2004
- ASTM D 1518:2011

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**Table 2. Developed fabric systems**

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**Footnotes:**

Radiant-heat exposure test

In this study, the thermal protective performances of specimens of selected fabric systems (15×15 cm) under radiant-heat exposures were evaluated according to the modified ASTM E 1354:2013 standard (Fig. 2). In the original ASTM E 1354:2013 standard, a horizontally oriented specimen of the fabric system (10×10 cm) is subjected to an incident radiant-heat flux of 0–100 kW m⁻² generated by electric spark placed on top of it. The ignitability, heat release rates, mass loss rates, effective heat of combustion, and visible smoke development of the specimen in certain duration is measured using an oxygen consumption calorimeter. In the presently used modified ASTM E 1354:2013 standard, a radiant-heat flux of 50 kW m⁻² was created using a cone-shaped electrically heated coil (5000 W, 240 V). Beneath the heated coil, a specimen of the fabric system (15×15 cm) was horizontally mounted; and a transverse shutter was used to protect the fabric specimen from the heat source before and after the test. A skin simulant sensor was placed behind the radiant-heat-exposed specimen to measure the thermal energy.

1 Laboratory-simulated flame exposure test using the modified ISO 9151:1995 standard.

(heat flux) transmitted through the specimen during the exposure. The measured heat flux values from the sensors were recorded, and the recorded database was used to evaluate the second-degree burn time using the programmed HBI software.

**Hot surface exposure test**

In order to evaluate the thermal protective performance of specimens of the selected fabric systems under hot surface exposure, the modified ASTM F 1060:2008 standard was used (Fig. 3). In the original ASTM F 1060:2008 standard, a specimen of the fabric system (10 × 15 cm) is horizontally placed in contact (contact pressure is 3 kPa) with a standard hot surface (temperature is up to 316°C). The amount of heat transmitted by the specimen is measured by a copper calorimeter placed on top of the specimen; this calorimeter is mounted in an insulating block with added weight. Finally, the measured heat is compared with the human tissue tolerance (pain sensation or a second-degree burn) and the obvious effects of heat on the specimen (physical damage and degradation) are noted. In the presently used modified ASTM F 1060:2008 standard, a specimen (10 × 15 cm) was horizontally placed on an electrolytic copper-based hot surface plate; subsequently, a 1 kg load of insulated board with skin simulant sensor was put on the mounted specimen. In this test configuration, the temperature of the hot surface plate was controlled at 400°C. During the hot surface exposure, thermal energy transmitted through the specimen was measured by the sensor; and the measured thermal energy was further processed in the programmed HBI software to evaluate the second-degree burn time.

**Procedures for data analysis and modeling**

The measured performance values from the above mentioned flame, radiant-heat, and hot surface exposure tests were tabulated (tabulated values are shown in Table 3 of the Results and Discussion section). The selected fabric assembly features (Table 2) and the tabulated performance values (Table 3) were normalized between −1 to +1; the average of the each normalized data set was set to zero. This normalization process reduces the redundancy in the data set by pulling out the abnormal contributors. The normalized aspect (thickness, air permeability, thermal resistance, or performance) $X_{i,norm}$ is calculated by equation 1, where, $X_i$ is the value of a selected aspect, $X_{i,avg}$ is the average value of that particular aspect, $X_{i,min}$ is the minimum value of that aspect, and $X_{i,max}$ is the maximum value of that aspect. In this study, $t$-test was carried out between normalized affecting factors (fabric features: thickness, air permeability, and thermal resistance) and performance values using the STATCRUNCH software (a statistical software developed by programmers and statisticians led by Webster West of Texas A&M University, USA). The association between each factor and performance was inferred based on the sign (+ or −) of the $T$-stat. value obtained from the $t$-test. Relationship plots were developed between each factor and thermal protective performance, and the
coefficients of determination ($R^2$) of the developed plots were calculated; the $R^2$ value with proximity to 1 for a particular plot was inferred as a strong association between the respective factor and thermal protective performance. $P$ values obtained from the $t$-test for each factor were also analyzed. If the $P$ value for any factor was <0.05, this factor was identified as the key affecting factor for performance. All the identified key factors were further used to develop the MLR and ANN models for predicting the performance. In the present study, 60% of the original data set (key factors and performance) were used for the development of the models, 20% data were set aside for cross validation of the models, and the remaining 20% data were used to evaluate the predicting performance of the models. The developed MLR and ANN models were later statistically compared based on their predicting performance parameters [$R^2$, root mean square error (RMSE), $P$ values]; this comparison process identified the best-fit high performance models to predict the thermal protective performance. The best-fit high-performance models were further used in saliency tests to understand the relative importance of key factors on thermal protective performance. In the following section, the modeling methodology of MLR and ANN are elaborately discussed.

\[ X_{i,j,\text{norm}} = \frac{X_{i,j} - X_{i,j,\text{avg}}}{\text{Maximum}[(X_{i,\text{max}} - X_{i,\text{avg}}), (X_{i,\text{avg}} - X_{i,\text{min}})]} \]  

(1)

**MLR modeling**

In this study, standard MLR models were developed to predict the performance using the key factors obtained from the $t$-test analysis. This modeling was carried out using the STATCRUNCH statistical software. A generic form of the developed MLR models is shown in equation 2, where, $C =$ identically distributed constant normal error, $KF_1$, ..., $KF_n =$ key factors, $\beta_1$, ..., $\beta_n =$ regression coefficients that determine relative strength of the respective key factors. In this regard, a notable inherent limitation of these MLR models is that they should not be used to predict the performances beyond the range of key factors’ values employed to develop the models (P.K. Majumdar and A. Majumdar, 2004; Murrells et al., 2009; Zaefizadeh et al., 2011).

\[
\text{(Performance)}_{\text{flame/radiant-heat/hot surface}} = C + \beta_1 \times (KF)_1 + \beta_2 \times (KF)_2 + \ldots + \beta_n \times (KF)_n
\]  

(2)

**ANN modeling**

The used ANN was a powerful data modeling tool that captured and represented any kind of relationship between the input (key factors obtained from the $t$-test) and output (performances). In the ANN models, three layers were used—input layer, hidden layer, and output layer. These models were developed using the MATLAB 7.0.1 software (a numerical computing and fourth-generation programming language software developed by MathWorks, USA). For developing the models, an important point to consider was that ANN can have different architectures; thus, it was important to develop a suitable and stable model. Keeping this view in mind, various ANN architectures were deployed and investigated considering one hidden layer. Through this investigation, it was found that a three-layered feed-forward back propagation ANN model (with one hidden layer) can be a universal technique to model a complex linear function (Fig. 4).

**Table 3. Performance (second-degree burn time in seconds) under flame, radiant-heat, and hot surface exposures**

<table>
<thead>
<tr>
<th>Exposures</th>
<th>Single-layered</th>
<th>Double-layered</th>
<th>Triple-layered</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>AC</td>
</tr>
<tr>
<td>Flame</td>
<td>2.87</td>
<td>12.3</td>
<td>12.0</td>
</tr>
<tr>
<td>Radiant-heat</td>
<td>4.49</td>
<td>7.62</td>
<td>11.5</td>
</tr>
<tr>
<td>Hot Surface</td>
<td>1.32</td>
<td>2.91</td>
<td>4.94</td>
</tr>
</tbody>
</table>
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. Here, all the neurons in a particular layer received a signal from the neuron existed in the previous layer. The received signal was then multiplied by a weight factor known as synaptic weight. Next, the weighted inputs were summed up and passed through 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 models used back propagation supervised training form (the gradient descent with momentum constant), the predicted final outputs were always compared with the actual output; through this comparison, the back propagation training algorithms calculated the prediction error and adjusted the synaptic weight of various layers backward from the output to the input layer. This weight adjustment process worked based on a delta rule and decreased the error signal iteratively; eventually, the model got closer and closer to produce the desired final output [delta rule is shown in equation 3, where, \( W(n) \) is the weight connecting between two neurons at the nth iteration, \( \Delta W \) is the weight correction applied to the \( W(n) \) at the nth iteration, \( E \) = predicted error signal at the nth iteration, \( \eta \) = learning rate parameter constant]. The hyperbolic tangent sigmoid transfer function (equation 4) was assigned as an activation function in the hidden layer, and the linear function (equation 5) was used in the output layer. These specific functions were used because they can easily be applied with all types of data set and can provide the best performance for an ANN model (Hui and Ng, 2009). In the equations 4 and 5, \( x \) is the weighted sum of inputs to a neuron and \( f(x) \) is the transformed output from that neuron. In this regard, a challenge on the development of feed-forward back propagation ANN model was to decide the number of neurons in the hidden layer. If the neurons were too few in the hidden layer, the model was unable to differentiate between complex pattern, and it might lead to a linear estimate of the actual relationship between the inputs and output; whereas, if the neurons were too many, the model followed a noise in the data set, and it might lead to an inaccurate output (Murrells et al., 2009). In order to choose the optimum neurons in the hidden layer, the feed-forward ANN models were trained with 2–10 neurons, and the best predictive ANN models were identified with five hidden neurons (Fig. 4).

\[
\Delta W(n) = -\eta \left[ \frac{\partial E}{\partial W(n)} \right] \tag{3}
\]

\[
f(x) = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{4}
\]

\[
f(x) = x \tag{5}
\]
RESULTS AND DISCUSSION
The performances of the selected fabric systems (in terms of second-degree burn time) under the exposures are shown in Table 3. Obviously, the performances of the triple-layered fabric systems are higher than the single- and double-layered fabric systems; the air layers and trapped air provided by the triple-layered fabric systems contributes to the performances. It is also evident that both A and B are single-layered fabrics with almost same thermal resistance; however, their performances are different under the same exposures. As demonstrated in Table 2, Fabric-A has a high air permeability; hence, the structure of Fabric-A is highly porous than Fabric-B. This highly porous structure may develop the convective thermal energy transmission, which can lower the performance. Notably, Fabric-B is an air-impermeable Epic® fabric developed by Nextec Applications Inc., USA. This Fabric-B has encapsulated fiber finishing; due to this finishing, the porosity of Fabric-B is obscured and it had a restricted thermal energy transmission through its structure, specifically for mass transfer. This restriction resulted in better protective performance for Fabric-B. Table 3 also shows that the performances of AF and FA fabric systems are generally lower than AC and AE fabric systems. This phenomenon can be explained by the presence of moisture barrier in the AF and FA fabric systems. Although the functionality of these barriers was to provide protection from the moisture generated in a thermal exposure, it has been observed that these polyurethane based moisture barriers with low melting temperature were prone to degrade or burn while testing in an intensive thermal exposure. Due to this degradation, the structural integrity of the AF and FA fabric systems got damaged. This degraded or damaged condition of fabric systems caused the rapid transfer of thermal energy through the fabric systems towards wearers’ bodies, which ultimately lowered the performance. Actually, during the specific exposure, both configurations showed the degradation. Specifically, for FA fabric system, as this moisture barrier immediately come in contact with the high heat exposures, the structural integrity of the FA fabric system becomes vulnerable than AF fabric system. Furthermore, the t-test was carried out between the fabric properties (Table 2) and performance (Table 3) under each thermal exposure; the results of the t-test (T-stat., P values) are shown in Table 4.

Table 4. t-Test results

<table>
<thead>
<tr>
<th>Exposures</th>
<th>Features of fabric systems</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Air permeability</td>
</tr>
<tr>
<td>Flame</td>
<td>T-stat. -0.85</td>
</tr>
<tr>
<td></td>
<td>P value 0.42</td>
</tr>
<tr>
<td>Radiant-heat</td>
<td>T-stat. -0.80</td>
</tr>
<tr>
<td></td>
<td>P value 0.45</td>
</tr>
<tr>
<td>Hot surface</td>
<td>T-stat. -1.43</td>
</tr>
<tr>
<td></td>
<td>P value 0.19</td>
</tr>
</tbody>
</table>

In Table 4, the negative T-stat. values indicate a negative association between air permeability and second-degree burn time under flame, radiant-heat, and hot surface exposures. This is because a multiphase (a solid and a gaseous air phase) fabric with high air permeability transfers more thermal energy than a low air-permeable fabric; the transmitted thermal energy ultimately lowers the performance by generating quick burns on wearers’ bodies (Perkins, 1979). In this context, Shalev and Barker (1984) explained that the thermal energy transmission modes through fabrics under various exposures are quite different. In the flame exposures, thermal energy imposes on the fabric’s surface and blows through it; thus, thermal energy convection occurs through the fabric. On the other hand, thermal energy directly penetrates through the fabric in the radiant-heat exposures (Torvi, 1997; Chitrphiromsri and Kuznetsov, 2005). The thermal energy transmission is true for convective flame exposure, and to a lesser extent for radiant-heat exposure; however, this thermal energy transmission is not visible in the conductive heat transfer as occurred in hot surface contact. It has been identified that the fabrics get compressed under hot surface contact; due to this compression, the gaseous air phases inside the fabrics reduce and solid fiber phases predominate; as a result, the thermal properties of fabric system alter, the thermal energy transmission increases, and fabric performance becomes lower (Mandal et al., 2013). Interestingly, Torvi (1997) developed thermal energy balance equations for a fabric in flame exposures using the apparatus shown in Fig. 1; the thermal energy balance equations on the exposed [fabric thickness (x) = 0] and inner...
[equivalent to fabric thickness \((x) = L_f\)] boundary of the fabric are shown in equations 6 and 7, respectively. From these equations, it can be inferred that the incident thermal energy on the fabric surface under flame exposure can be a combination of convective-heat \((q_{\text{conv}})\) and radiant-heat \((q_{\text{rad}})\), and the thermal energy balance depends upon the thermal properties of the fabric [thermal conductivity \((k)\), density \((\rho)\), specific heat \((C_p)\)], temperature of the fabric \((T)\), the energy generated by the thermochemical reaction within the fabric in per unit volume \((G_{\text{chem}})\), radiant-heat transfer from the tested fabric to the sensors \((q_{\text{air, rad}})\) and/or conductive/convective-heat transfer from the tested fabric to the sensors \((q_{\text{air, cond/conv}})\).

\[
\rho(T)C_p(T)\frac{\delta T}{\delta t} = G_{\text{chem}} - \frac{\delta}{\delta x}(q_{\text{conv}}) - \frac{\delta}{\delta x}(q_{\text{rad}}) \quad (6)
\]

\[
\rho(T)C_p(T)\frac{\delta T}{\delta t} = G_{\text{chem}} - \frac{\delta}{\delta x}(q_{\text{air, rad}} + q_{\text{air, cond/conv}}) - \frac{\delta}{\delta x}(q_{\text{rad}}) \quad (7)
\]

Furthermore, the positive T-stat. values in Table 4 point out that the association between fabric thickness, thermal resistance, and second-degree burn time is positive (Figs 5 and 6). According to Figs 5 and 6, it is also evident that \(R^2\) values between the thickness/thermal resistance and second-degree burn time are close to 1 (all \(R^2\) values are >0.65); thus, it can be inferred that a strong positive relationship exists between the thickness/thermal resistance and second-degree burn time under all types of thermal exposures. Additionally, it is apparent that all the \(R^2\) values are different under various types of thermal exposures, and the \(R^2\) values are maximum in the case of radiant-heat exposure; thus, it can be concluded that the thickness and thermal resistance have different level of positive effect on second-degree burn time under different thermal exposures, and this positive effect is maximum in radiant-heat exposure. From these findings, it can be stated that a fabric with high thickness and thermal resistance results in higher second-degree burn time or performance and can provide a better protection. This is mainly because the structure of thicker fabrics tends to comprise more still or dead air than thinner fabrics; this dead air acts as thermal insulator and enhances the performance of the fabrics (Perkins, 1979; Sun et al., 2000; Mandal and Song, 2012b). Furthermore, given the same thickness, the fabrics with high thermal resistance trap more still or dead air inside their structures than the fabrics with low thermal resistance, depending upon the fabrics’ engineering parameters (fabric counts, weave constructions and design); the more trapped air in the high thermal resistance fabrics results in high thermal protective performance (Sun et al., 2000; Song et al., 2011; Mandal et al., 2013).

It can also be notified from Table 4 that the \(P\) values of fabric air permeability are considerably >0.05 under all types of thermal exposures. This demonstrates air permeability is not a significant factor for the second-degree burn time or performance. Furthermore, the \(P\) values of fabric thickness under flame and radiant-heat exposures indicate that the thickness is a highly significant fabric property for effective protection under
flame and radiant-heat exposures. However, the fabric thickness does not show highly significant protection under a hot surface exposure because its $P$ value is slightly $>0.05$. Additionally, the $P$ values of fabric thermal resistance under flame, radiant-heat, and hot surface exposure indicate that thermal resistance is a highly significant fabric property for effective protection under flame, radiant-heat, and hot surface exposures. Based on the $P$ values analysis, it can be inferred that the thickness and thermal resistance are the key factors to affect performance under each thermal exposure. By considering these key factors, the MLR models of fabric performance under flame, radiant-heat, and hot surface exposures were developed and are presented in equations 8–10, respectively. Furthermore, the developed ANN models (with five neurons in the hidden layer) under these exposures are investigated. The $R^2$, RMSE, and $P$ values of the developed MLR and ANN models are shown in Table 5.

Table 5. The $R^2$, RMSE, and $P$ values of the developed MLR and ANN models

<table>
<thead>
<tr>
<th>Thermal exposures</th>
<th>Models</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>$P$ values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flame</td>
<td>MLR</td>
<td>0.85</td>
<td>3.04</td>
<td>0.0077</td>
</tr>
<tr>
<td></td>
<td>ANN</td>
<td>0.94</td>
<td>1.10</td>
<td></td>
</tr>
<tr>
<td>Radiant-heat</td>
<td>MLR</td>
<td>0.88</td>
<td>1.47</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>ANN</td>
<td>0.97</td>
<td>1.06</td>
<td></td>
</tr>
<tr>
<td>Hot Surface</td>
<td>MLR</td>
<td>0.60</td>
<td>3.69</td>
<td>0.0088</td>
</tr>
<tr>
<td></td>
<td>ANN</td>
<td>0.63</td>
<td>3.33</td>
<td></td>
</tr>
</tbody>
</table>

Table 5 presents that the prediction models are valid as all of the $P$ values are $<0.05$. In a comparison between the MLR and ANN models under all exposures, it can be identified that the $R^2$ value of MLR models are lower than the ANN models; hence, the predictability of the ANN models works better than the MLR models. Moreover, the prediction errors (RMSE) by the ANN models are much lower than the MLR models. In summary, the ANN models perform better than the MLR models for protective performance prediction in terms of the precision and accuracy. Thus, it is worthwhile to use the ANN models for predicting the performance of the fabric systems under all types of thermal exposures. Furthermore, these developed ANN models are used to analyze the relative importance of the key factors on performance of fabric systems under all types of thermal exposures. For this, a saliency test is conducted by eliminating only one designated key factor from a developed ANN model at a time. In this test, the increase in RMSE value in the saliency test compared to the developed model is considered as the indicator of importance of the eliminated key factor; the eliminated factor that generates
The highest RMSE is inferred as the prime key factor for performance. The results of the saliency tests for all the developed models are shown in Table 6. Based on Table 6, it is notable that the thermal resistance of fabric systems dominates over the fabric thickness; thus, the thermal resistance is a prime key factor to affect the performance under all types of thermal exposures. It is also notable that the percentage (%) increase in RMSE is generally maximum in the case of radiant-heat exposure and minimum in the case of hot surface exposure; this difference happened due to different modes of thermal energy transfer in these exposures.

**CONCLUSIONS**

In this study, it has been identified that the layered fabrics possess higher thermal protective performance than the nonlayered fabrics under flame, radiant-heat, and hot surface exposures; on the other hand, the performance is low in the highly porous fabric, if the airflow is nonrestricted through its structure. The study also shows that the location of moisture barrier in the layered fabric is critical in thermal protective performance. Additionally, a highly air-permeable fabric allows the thermal energy transmission through its structure; therefore, it lowers the protective performance. Here, the thermal energy transmission mainly depends upon the thermal properties of the fabric: thermal conductivity, density, and specific heat. Moreover, it can be concluded that the fabric thickness and thermal resistance are key factors affecting the performance provided by fabric systems when exposed to flame, radiant-heat, and hot surface.

With these key factors, the MLR and ANN models are developed on the thermal protective performance. The results indicate that the ANN models outperformed the MLR models in predicting the performance; here, the three-layered feed-forward back propagation ANN models with five neurons in the hidden layer are suggested as the best-fit models to effectively predict the thermal protective performance. By using the ANN models, it can be concluded that the thermal resistance primarily affects the performance. This study can help to engineer an optimized performance-based fabric for better occupational health and safety of firefighters/industrial workers. In future, more factors affecting the thermal protective performance can be investigated; and the optimization techniques of ANN models can also be explored.

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**DISCLAIMER**

The findings and conclusions in this paper are those of the authors and do not necessarily represent the views of the National Institute for Occupational Safety and Health.

**REFERENCES**


