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Prediction of thermal protection performance and empirical study of flame-retardant cotton based on a combined model

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Thermal protection performance (TPP) is an important index to evaluate the performance of firefighting clothing. The purpose of this work is to build a model to predict the TPP values of fabrics with fewer variables. Two properties of flame-retardant cotton were tested with TPP values under different air gaps, and the correlations between these properties were also analyzed. A combined model was established by integrating multivariate nonlinear regression model and gradient boosting regression tree model. Then the combined model was compared with these two single models. The results showed that the correlation coefficients between gram weight and thickness of fabric and TPP value were 0.833 and 0.837, respectively, indicating a strong correlation. The correlation coefficient between air gap and TPP value was 0.304, indicating a weak correlation. In predicting the thermal protective performance of flame-retardant cotton, this study employed a multivariate nonlinear regression model, a Gradient Boosting Regression Tree (GBRT) model, and a combined model. After comparing various evaluation metrics, it was finally decided to adopt the combined model for predicting the thermal protective performance values of flame-retardant cotton. This method improved the prediction accuracy of thermal protective performance, facilitating the promotion and application of the combined model. Furthermore, when exploring the thermal protective performance of flame-retardant cotton, the use of fewer variables to establish the prediction model can not only significantly simplify the complex structure of the model but also greatly enhance the analysis efficiency, ensuring the efficiency and precision of the research process.

KEYWORDS

flame-retardant cotton, thermal protection performance, multivariate nonlinear regression, gradient boosting regression tree, combined model

1 Introduction

Firefighters frequently work in high temperatures while performing their duties and are subject to a variety of thermal hazards, such as flash fires, intense thermal radiation, hot gases, hot objects, hot liquid splashes and hot steam, etc. The heat flux can be as high as 200 kW/m^2 (Su et al., 2016; Udayraj et al., 2017). Therefore, fire protection clothing must have good flame retardant, heat insulation and heat stability (Xu et al., 2020).

TPP experiment and burning dummy experiment are two commonly used methods to evaluate the thermal protection performance (TPP) at present. TPP experiment is simple and low cost, but it is limited to measure the TPP of small fabric samples. The burning dummy experiment can simulate the second and third degree of human burns and their distribution to evaluate the TPP of clothing, but it has high technical requirements, high cost and complex operation (Li et al., 2015).

Factors influencing the thermal protective performance of fabrics include weight per unit area, thickness, air permeability, and air gap. Li et al. (2008) conducted TPP experiments with 13 fabrics that can be used for the outer layer of firefighting suits and found that there was a linear positive correlation between fabric thickness, areal density, and thermal protective performance, with thickness having a more significant impact on thermal protective performance. Liu et al. (2018) tested the thermal protective performance of different fabrics and found a positive correlation between areal density, thickness, and TPP values. Zong et al. (2009) compared and studied materials such as aramid, polysulfonamide, and flame-retardant cotton fabrics for outer layers and found that the thermal protective performance of various fabrics increased with their areal density and thickness. Based on previous research, it can be concluded that there was a positive correlation between fabric thickness, weight per unit area, and thermal protective performance, and that the thermal protective performance of fabrics increased with increasing thickness and weight per unit area (Yang et al., 2014).

Most of the studies that have been carried out to predict the TPP of fabrics through properties of fabrics. Table 1 lists the various prediction models for TPP, which can be categorized as numerical model, neural network model and fitted model. As can be seen from Table 1, (Onofrei et al., 2014; Ghazy, 2014; Su et al., 2018) established numerical models for predicting the TPP of clothing. Although the numerical model had a high accuracy, there were many difficulties to measure the parameters (including impact jet between the steam nozzle and the fabric, blood perfusion rate between the dermis and subcutaneous tissue, etc.). Cui Z. and Zhang W. (2008), (Mandal and Song, 2014; Mandal et al., 2018a; Mandal et al., 2021a; MÜGe et al., 2019) established neural network models that can predict the TPP of fabrics, while (Mandal et al., 2018a) also established a model to predict the thermal physiological comfort performance. However, the accuracy of machine learning is contingent upon the sample size, with higher numbers of samples yielding greater precision. Besides, (Mandal et al., 2021b; Xu et al., 2020; He et al., 2020) built fitting models to predict the TPP of fabrics. Crown et al. (2002), Xu et al. (2020), He et al. (2020) established fitting models to predict the TPP of clothings. Furthermore, most of the above scholars predicted the TPP of fabrics and garments through gram weight, thickness, air gap, thermal resistance, etc. Bates and Granger first proposed the system of combinatorial prediction theory, which combined different prediction models to reduce the prediction errors caused by parameters or models (Andrawis et al., 2011).

Investigating the performance of flame-retardant cotton is of great importance in improving product quality and meeting market demands. Studying the TPP of flame-retardant cotton is not only in line with current trends in environmental protection and sustainable development, but also contributes to the advancement of green and safe protective materials. In order to improve the prediction accuracy, this work used a combined model that integrating the strengths of multivariate nonlinear regression and gradient boosting regression trees to more effectively capture nonlinear relationships and multidimensional features in complex data.

2 Materials and methods

2.1 Flame-retardant cotton fabric

Cotton fabrics are favored by people due to their good moisture absorption, breathability, skin-friendliness, and comfortable wearing experience. However, cotton fibers have a limited oxygen index of only 17%–19%, making them flammable and highly combustible, which limits the application range of cotton fabrics. Therefore, it is extremely necessary to conduct flame-retardant finishing on cotton fabrics (Yang et al., 2012).

Flame-retardant cotton is a type of new fire-resistant material made by adding flame retardants or using flame-retardant modification technology to 100% cotton fabric (Jin et al., 2020). It is a type of fabric that is difficult to ignite, and once removed from the source of ignition, it will automatically extinguish and not reignite. It belongs to the category of post-finishing flame-retardant fabrics. The principle behind its flame-retardant properties is that when the flame retardant encounters high temperatures or heat, it rapidly generates gases that hinder the combustion process, reducing the released thermal energy and preventing the combustion from continuing, thereby actively contributing to the flame retardancy of the fabric (Yang et al., 2012). The sample diagram of flame-retardant cotton fabric is shown in Figure 1.

Flame-retardant cotton materials have found widespread applications in various fields such as industrial safety, personal protective clothing, thermal insulation in transportation, and household textiles due to their superior fire-retardant and thermal insulation properties. They not only significantly enhance safety but also improve the comfort of use (Yang, 2015). With the continuous increase in safety requirements from all sectors of society, the application prospects of flame-retardant cotton materials are exhibiting even broader development opportunities.

Fire-fighting clothing follows the standards of "Firefighter's Protective Clothing for Fire Fighting", consisting of four layers: flame-retardant outer layer, waterproof and breathable layer, thermal insulation layer, and comfort layer. Each layer performs specific functions of flame retardancy and high-temperature resistance, waterproofness and breathability, thermal insulation, and comfort, collectively enhancing thermal protective performance (Zhou, 2021). In this study, the flame-retardant cotton fabric was used as the outer layer of fire-fighting clothing to effectively exert its flame-retardant properties.

TABLE 1 Thermal protection performance prediction models.

Year	Literature source	Model Type	Scope of application	Parameters
2014	Onofrei et al. (2014)	Numerical models	TPP of clothing	Temperature, air gap, thickness, density, thermal conductivity, specific heat capacity
2014	Ghazy (2014)	Numerical model	TPP of clothing	Heat shrinkage
2018	Su et al. (2018)	Numerical model	TPP of clothing	Impact jet between the steam nozzle and the fabric, steam flow in the fabric caused by the pressure gradient
2019	Su et al. (2018)	Numerical model	TPP of clothing	air gap, specific heat capacity of skin tissue, density of skin tissue, blood perfusion rate for dermis and subcutaneous tissue, blood temperature, average metabolic heat production of human body
2008	Cui and Zhang (2008a)	Neural network model	Thermal protection properties of fabrics	Fabric weight, thickness, structure, warp density, weft density, warp count, weft count, LOI, damaged length
2014	Mandal and Song (2014)	Neural network model	Fabric TPP	Thermal resistance, thickness
		Fitting model		Thermal resistance, thickness
2018	Mandal and Song (2014)	Neural network model	Thermal protection properties and thermal physiological comfort properties of fabrics	Weight, thickness, thermal resistance
2019	MÜGe et al. (2019)	Neural network model	Fabric TPP	Fabric structure, weight, warp and weft density, thickness LOI, water vapor resistance
2021	Mandal et al. (2021b)	Neural network model	Fabric TPP	Thermal resistance, evaporation resistance
2002	Crown et al. (2002)	Fitting model	Clothing thermal protection properties	Air gap, TPP value
2018	Mandal et al. (2018b)	Fitting model	Thermal protection properties and thermal physiological comfort properties of fabric	Weight, thickness, thermal resistance
2019	Xu et al. (2020)	Fitting model	Fabric thermal protection properties	Thickness, weight, air gap
2019	Xu et al. (2020)	Fitting model	Clothing thermal protection properties	Thickness, weight, air gap, shrinkage
2020	He et al. (2020)	Fitting model	Thermal protection properties of clothing and fabrics	Maximum attenuation factor for second-degree burn of clothing, thickness of air layer under clothing, heat exposure time
2021	Mandal et al. (2021b)	Fitting model	Fabric thermal protection properties	Thermal resistance, evaporation resistance

FIGURE 1
The sample diagram of flame-retardant cotton fabric.

2.2 Fabric TPP experiment

The TPP test is currently the most commonly used test method to measure the thermal protection properties of fabrics. In this work, a thermal protection performance tester (model type: DR255) was used to measure TPP value of flame-retardant cotton fabrics. The experiments were carried out according to the *Protective clothing—Thermal protective performance test method* (Textile Protection and Comfort Center, 2019). During the experiment, the total heat flux was set to 84 kW/m^2, and the sample size was 150 mm × 150 mm. The TPP value is the total heat flux multiplied by the time to cause second degree burn, and the higher the TPP value, the better the TPP values (Shalev and Barker, 1984; Stoll and Chianta, 1968). Figure 2 shows the schematic diagram of the TPP experimental device.

According to previous studies, convective heat transfer begins to occur when the air gap exceeds 6.4 mm in the TPP tests (Deng et al., 2018). Therefore, in this experiment, spacers of 3.2 mm and 6.4 mm were made to create different air gap layer thicknesses to measure the thermal protection properties of the fabrics. Table 2 shows the performance of fabrics and TPP experimental results.

The samples used in the experimental results presented in this study, as well as those from the experiments conducted by other researchers, were all flame-retardant cotton materials. The key differences lie in the weight, thickness, and air gaps of the experimental samples. The purpose of selecting these samples was to expand the data set in order to improve the accuracy of the gradient boosting regression tree (GBRT).

3 Results and discussion

3.1 Correlation analysis between fabric properties and TPP value

From the previous studies, it is known that the prediction of fabric's thermal protective performance involves factors such as gram weight, thickness, air gap, and thermal resistance. In this experiment, gram weight, thickness, and air gap were used to predict the TPP value. The Pearson correlation analysis method was employed to analyze the correlation between fabric's gram weight, thickness, air gap, and thermal protective performance (TPP). The calculation formula of correlation coefficient is shown in Formula 1: (Zhou et al., 2023):

$$r = \frac{\sum_{i}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i}^{n}(x_i - \bar{x})^2 \sum_{i}^{n}(y_i - \bar{y})^2}}, \tag{1}$$

where r is the correlation coefficient. The calculated results are shown in Table 3. The correlation coefficients between gram

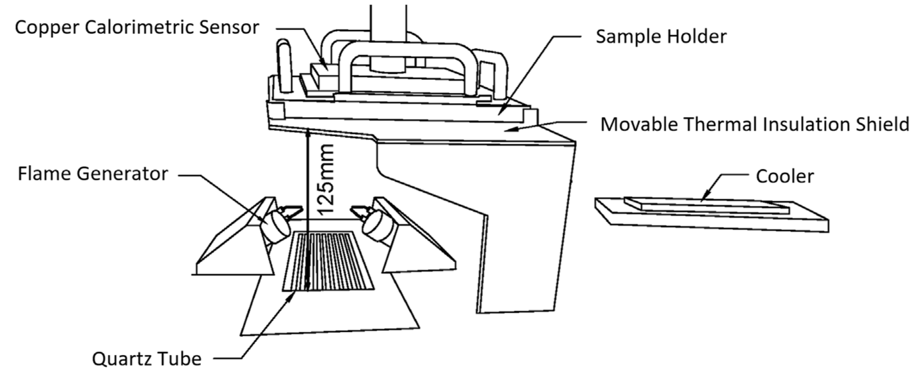

FIGURE 2
TPP experimental device.

weight and thickness of fabric and TPP value were 0.833 and 0.837 respectively, both greater than 0.8, indicating that gram weight, thickness and TPP value had high linear correlations. The r between air gap and TPP value was 0.304, indicating that there was a weak linear correlation between air gap and TPP value. Meanwhile, gram weight, air gap and thickness were positively correlated with the TPP value, indicating that the TPP value would increase with the increase of these variables. Correlation analysis of each variable showed that the r between gram weight and thickness was 1 and that there was a perfect positive linear correlation.

3.2 Regression analysis and prediction model

3.2.1 Influence of air gap on TPP

Figure 3 shows the TPP values of flame-retardant cotton with different air gaps. It was evident that the TPP values with various weights decreased when the air gap was 9.6 mm. This is because the air's ability to act as a thermal insulation is weakened when the air gap is more than 6.4 mm (Deng et al., 2018; Talukdar et al., 2010; Torvi et al., 1999). As the air gap continued to increase, the heat decreased, and the thermal protective performance increased (Deng et al., 2018). Subsequently, as the air gap continued to increase up to 16.0 mm, the TPP gradually improved. With the further increase of air gap, a large amount of smoke and tar were found to be produced. A significant amount of hot gas, hot tar, smoke, etc. was released when the flame-retardant cotton came into contact with the heat source and the flame-retardant gas and flame retardant in the fabric were exhausted (Zong et al., 2009). Therefore, the thermal protective performance decreased when the air gap was 19.2 mm.

Correlation analysis showed that the r between TPP values and air gaps was 0.304, indicating that there might be a nonlinear relationship between them. In this experiment, with the increase of air gap, the TPP first increased and decreased, and then increased and decreased again. The TPP values of fabrics with gram weight of 220 g/m^2, 260 g/m^2 and 320 g/m^2 under different air gaps were fitted by polynomial. Formula 2 is the TPP fitting equation for fabrics with a weight of 220 g/m^2, Formula 3 is for 260 g/m^2, and Formula 4 is for 320 g/m^2:

$$z_1 = -0.0034x_1^5 + 0.165x_1^4 - 2.764x_1^3 + 18.445x_1^2 - 36.654x_1 + 352, \tag{2}$$

$$z_2 = -0.004x_1^5 + 0.174x_1^4 - 2.486x_1^3 + 12.373x_1^2 - 5.465x_1 + 388.47, \tag{3}$$

$$z_3 = -0.0072x_1^5 + 0.338x_1^4 - 5.520x_1^3 + 36.013x_1^2 - 69.915x_1 + 439.21, \tag{4}$$

where x_1 is the air gap, z_1 is the TPP value with a gram weight of 220 g/m^2, z_2 is the TPP value of 260 g/m^2, and z_3 is the TPP value of 320 g/m^2.

Figure 4 shows the comparison between the measured TPP values and the predicted TPP values of the above three models. It can be seen from the figure, the R^2 of the three models were 0.754, 0.913, and 0.984, respectively. Therefore, these three models can respectively predict the TPP value of flame-retardant cotton of 220 g/m^2, 260 g/m^2 and 320 g/m^2 in the air gap between 0 and 19.2 mm.

3.2.2 Multivariate nonlinear regression

Through the above analysis and previous studies, it can be seen that there was a high linear correlation between gram weight and thickness and TPP (Mandal and Song, 2014; Sawcyn and Torvi, 2009; Torvi and Dale, 1999). Hence, a model can be established to relate TPP to weight, thickness, and air gap, as shown in Formula 5:

$$z_4 = ax_1^5 + bx_1^4 + cx_1^3 + dx_1^2 + ex_1 + fx_2 + gx_3 + h, \tag{5}$$

where x_1 is the air gap (mm), x_2 is the thickness (mm) and x_3 is the gram weight (g/m^2). Substituting data from Table 1 into model (5), yielded a = −0.005, b = 0.234, c = −3.769, d = 24.029, e = −45.119, f = 0.193, g = 402.12, h = 127.694.

Figure 5 shows the comparison between the measured values and the predicted values of the multivariate nonlinear regression model. It can be seen from the figure that most of the relative errors between the predicted values and the measured values were less than 5%, and the model had a good fitting effect (R^2 was 0.932). Therefore, model (5) can predict the TPP value of flame-retardant cotton between 0 and 19.2 mm.

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TABLE 2 Fabric properties and TPP results.

No.	Source	Gram weight (g/m^2)	Thickness (mm)	Gap size (mm)	Second-degree burn time (s)	TPP value ($kW \cdot s/m^2$)
1	Experiments of this work	220	0.454	0	4.2	352.8
2		220	0.454	3.2	4.1	344.4
3		220	0.454	6.4	4.8	400.4
4		220	0.454	9.6	4.3	361.2
5		220	0.454	12.8	4.5	373.8
6		220	0.454	16	4.6	386.4
7		220	0.454	19.2	4.5	378
8		260	0.551	0	4.6	389.2
9		260	0.551	3.2	5.1	428.4
10		260	0.551	6.4	5.6	467.6
11		260	0.551	9.6	4.9	411.6
12		260	0.551	12.8	5.2	434
13		260	0.551	16	5.7	478.8
14		260	0.551	19.2	5.2	436.8
15		320	0.682	0	5.2	439.6
16		320	0.682	3.2	5.2	434
17		320	0.682	6.4	6.1	515.2
18		320	0.682	9.6	5.7	478.8
19		320	0.682	12.8	5.7	476
20		320	0.682	16	6.5	543.2
21		320	0.682	19.2	5.9	495.6
22	Zhai et al. (2018)	310	0.66	0	5.25	441.1
23	Zong et al. (2009)	343	0.76	0	6.3	528
24		109.2	0.56	0	4.4	364
25		352.4	0.86	0	6.3	532
26		164.6	0.43	0	4.2	352
27	Cui and Zhang (2008b)	220	0.67	0	5.3	445.2
28	Liu et al. (2018)	400	0.89	0	6.7	562.8
29		285	0.62	0	5.3	445.2

3.3 Gradient boosting regression tree (GBRT)

Gradient boosting regression tree is a type of ensemble learning algorithm, whose core lies in that each tree learns from the residuals of all previous trees, uses the negative gradient value of the loss function in the current model as an approximation of the residuals in the progressive tree algorithm, and then fits a regression tree (Friedman, 2001).

TABLE 3 Correlation coefficients between TPP values and variables of flame-retardant cotton.

	Gram weight	Thickness	Air gap	TPP
Gram weight	1	1.000[a]	0.000	0.833[a]
Thickness	1.000[a]	1	0.000	0.837[a]
Air gap	0.000	0.000	1	0.304
TPP	0.833[a]	0.837[a]	0.304	1

[a]Correlation is significant at 0.01 level (two-tailed).

Gram weight, thickness and air gap were set as input parameters and TPP value was set as output parameter. 70% of the data was randomly chosen for training of the model, 15% of the data was for validated, and the remaining 15% was for tested. When the model parameters were set as default, the training set R^2 was 0.999 and the test set R^2 was 0.862, and overfitting occurred. The parameters known to have great influence on the accuracy of GBRT model are maximum depth of regression tree (max_depth), maximum number of iterations (n_estimators), subsample and learning rate (Song, 2019).

Due to the small number of data set samples, the single random chance results in too small data for model training, and it is impossible to obtain data information comprehensively (Liu et al., 2021). Cross-validation is often used when data sets are small. The principle of K-fold cross-validation was used to divide the whole data sample set into K groups, taking the K-1 group in the data set as the training set in turns, and the remaining 1 group as the test set. A corresponding score will be obtained for each model training, and the average score value will be calculated as the model evaluation standard (Arlot and Celisse, 2010).

In order to avoid overfitting and the appearance of local optimal solutions, random search was first used to narrow the search scope, and grid search and cross-validation were then used to automatically find the optimal of hyperparameters. After adjustment, max_depth = 16, n_estimators = 220 and subsample = 0.2 were set finally. The training set R^2 as 0.983 and the test set R^2 as 0.931. Figure 6 shows the comparison of the predicted and measured GBRT values. The figure shows that the model fitted well (R^2 = 0.953). The average relative error between predicted values and measured values was less than 5%, and only three predicted values had relative error greater than 5%.

3.4 Combined model

3.4.1 Establishment of combined model

Model combination is a method of weighting the prediction results of different models according to a certain proportion to obtain a brand-new prediction data that combining all the results (Wu et al., 2022). It improves the accuracy of multi-step prediction by combining several models with different domains and high variability to achieve complementary prediction results. In Section 2.2 and 2.3, a multivariate nonlinear regression model as well as a gradient boosting regression tree model were developed to predict the TPP of fabrics, respectively. In order to improve the accuracy of the prediction results, a combined model was used to predict the TPP, and the model can be expressed as shown in Formula 6:

$$z_6 = w_1 z_4 + w_2 z_5 \tag{6}$$

where z_6 is the predicted TPP value obtained by the combined model, z_4 is the predicted value obtained by the multivariate nonlinear regression model, z_5 is the predicted value obtained by the gradient boosting regression tree, w_1 and w_2 are the weights of the multivariate nonlinear regression model and the gradient boosting regression tree in the combined model respectively.

Figure 7 shows the establishment process of the weighted combined model. Firstly, multivariate nonlinear regression and gradient boosting regression tree were used to build the prediction models. Secondly, weights were assigned to these two single models. Finally, a combined model was established.

3.4.2 Determination of weight coefficients

The key to the combined model is to determine the weight coefficient in the model. In this work, the inverse variance method was used for weight assignment. The formula of the inverse variance method is as follows:

$$w_i = \frac{S_i^{-1}}{\sum_{i=1}^{k} S_i^{-1}}, \tag{7}$$

where S_i is the variance of a single model. S_1 and S_2 are the variances of the prediction results of the multivariate nonlinear regression model and GBRT respectively. Here, S_1 was 5079.7 and S_2 was 7355.6 after calculation. By substituting S_1 and S_2 into Formula 7, w_1 was 0.41 and w_2 was 0.59. So the weighted combined model was shown in Formula 8.

Figure 8 shows a comparison of the predicted values from the combined model and the actual measured values, R^2 value of 0.958, indicating a good fit.

$$y_6 = 0.41 y_4 + 0.59 y_5 \tag{8}$$

3.5 Model evaluation

In this analysis, root mean square error (RMSE), mean relative error (MRE) and determination coefficient R^2 were used to evaluate the models. The RMSE can directly quantify the prediction error (LeCun et al., 2015). The formulas for root mean square error (RMSE), mean relative error (MRE), and R^2 are shown in Formulas 9–11:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_k - z_i)^2} \tag{9}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{z_k - z_i}{z_k}\right| \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(z_k - z_i)}{\sum_{i=1}^{n}(z_k - \bar{z})} \tag{11}$$

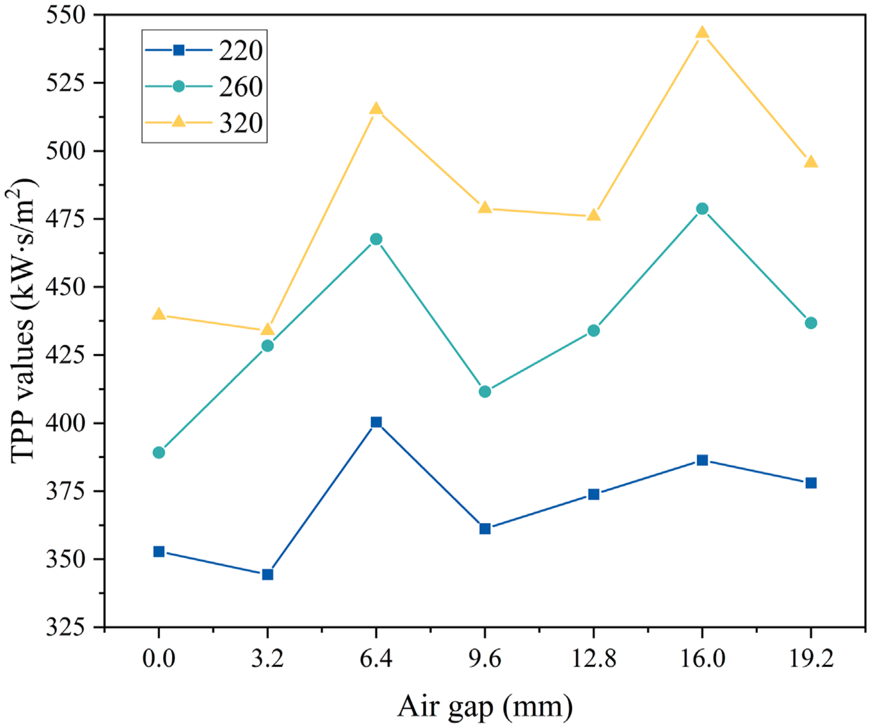

FIGURE 3
TPP values of flame-retardant cotton with different air gaps.

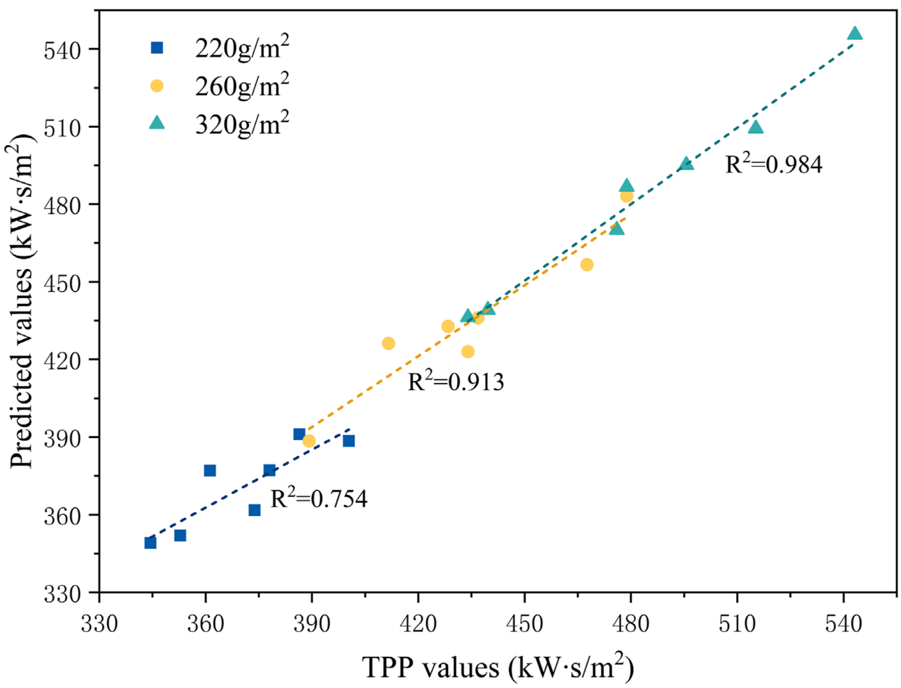

FIGURE 4
Comparison of measured values and predicted values.

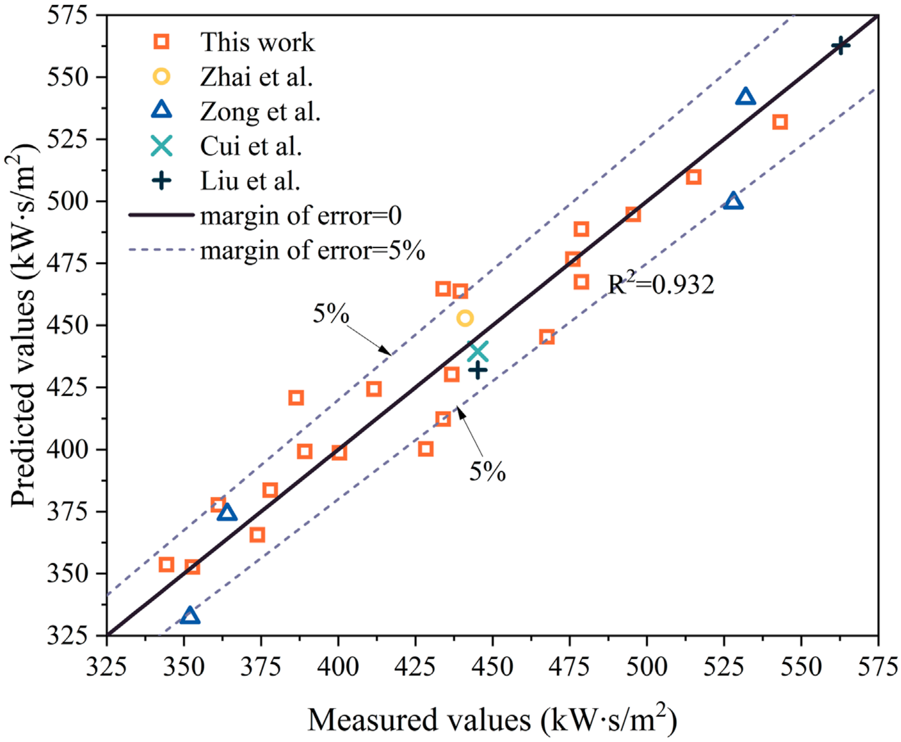

FIGURE 5
Measured values versus predicted values from multivariate nonlinear regression model.

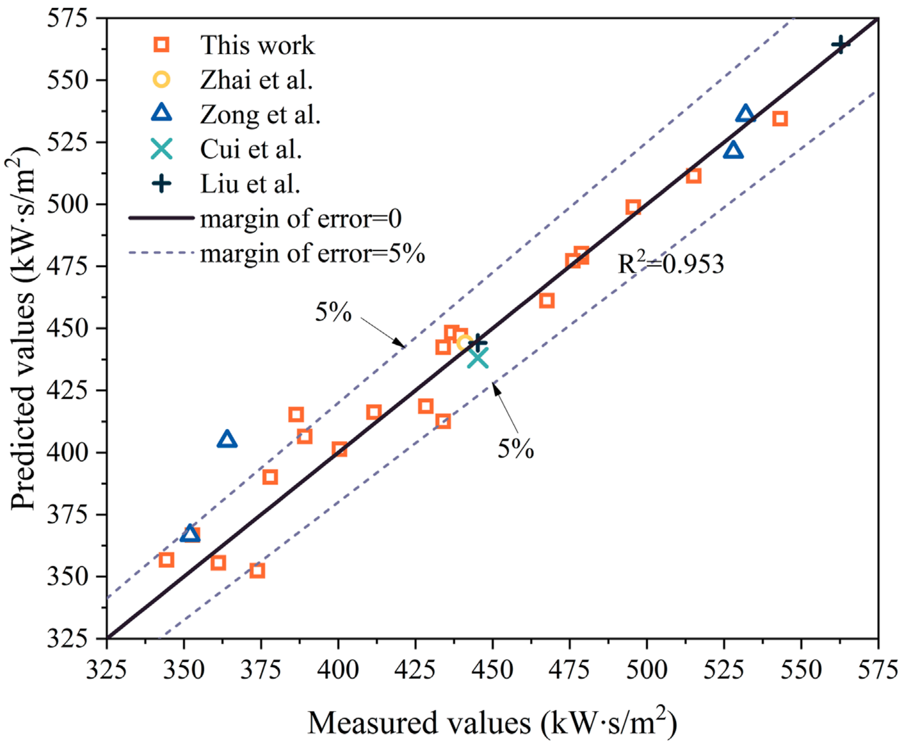

FIGURE 6
Comparison of measured values and predicted values by GBRT.

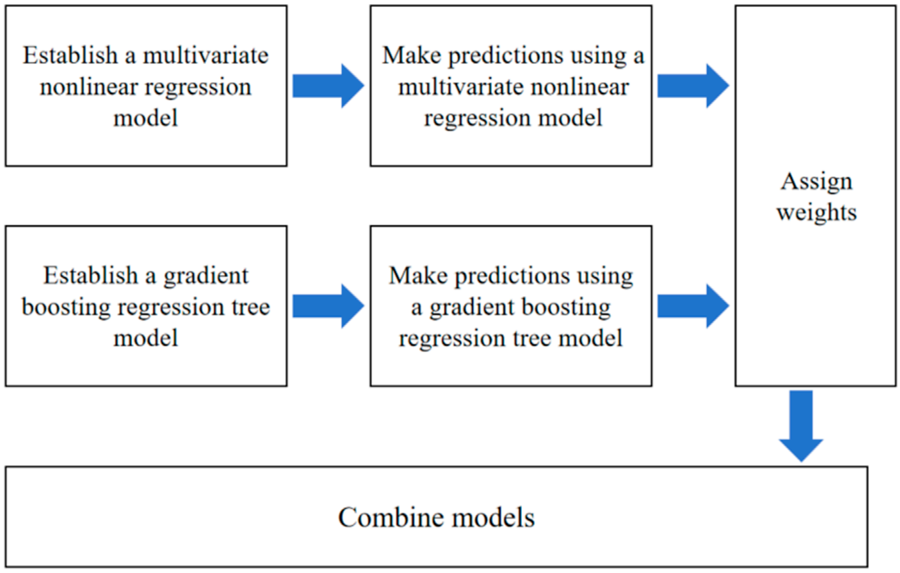

FIGURE 7
Establishment process of the combined model.

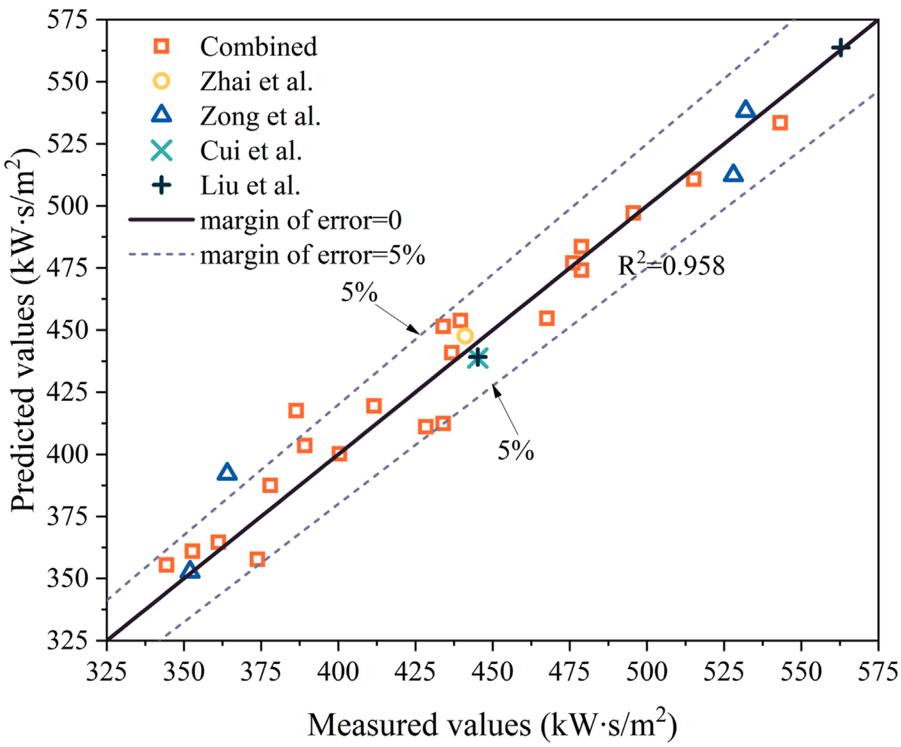

FIGURE 8
Measured values versus predicted values of the combined model.

where z_k is the measured value, z_i is the predicted value, n is the total number of the measured values, and $\bar{z}$ is the average value of the actual value.

Table 4 shows the values of these three evaluation indexes. Judging from the R^2, the fitting effect of the combined model was optimal (R^2 = 0.958). According to MRE, the average relative error of the combined model was the smallest. Compared with the RMSE, it can be seen that the root-mean-square error of the combined model was smallest. According to all these evaluation indexes, the

TABLE 4 Model evaluation indexes.

	Multivariate nonlinear regression	GBRT	Combined model	Instructions (combined model vs other models)
R^2	0.932	0.953	0.958	R^2 increases by 0.026 and 0.005
MRE	12.763	9.607	9.856	The error was reduced by 0.54% and 0.04%
RMSE	15.926	13.235	12.587	The error was reduced by 3.339 and 0.648

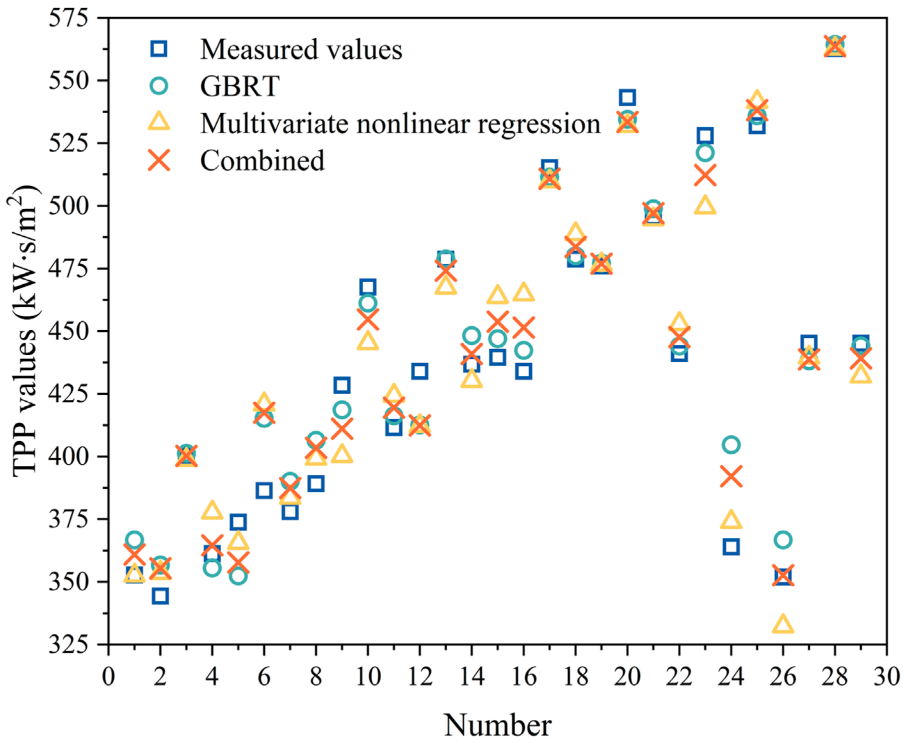

FIGURE 9
Comparison of prediction results of the three models.

combined model was optimal in predicting the TPP of flame-retardant cotton.

Figure 9 shows the comparison between the measured TPP and the predicted results of the three models. It can be seen that both of the two single models predicted the TPP relatively well. However, the multivariate nonlinear regression model was better than the GBRT in some prediction results, while the latter model was better in other prediction results. Comparing the combined model with the single models, it can be seen that the combined model took the advantages of the multivariate nonlinear regression model and the GBRT model. Hence, the prediction results of the combined model were better than these of the single models on the whole.

Figure 10 shows the relative errors of the prediction results of the three models. It can be seen that the relative errors of the multivariate nonlinear regression model and the combined model were all less than 9%, and the average relative errors were 2.99% and 2.36% respectively. Most of the relative errors of the GBRT were less than 9%, and its average relative error was 2.40%. However, some of the relative errors between the measured value and the predicted value of the GBRT was greater than 10%, and the accuracy of some predicted results was not high. Compared with the average relative error of the three prediction models, the combined model had a best prediction effect.

On the whole, the GBRT model and the combined model were good in predicting TPP values. However, according to the above analysis, the GBRT prediction results included a predicted value with a relative error of up to 11.18%. According to the root-mean-square error formula, the RMS error is more sensitive to outliers than the mean absolute error. Compared with the RMS errors of the three models, the combined model had a smallest error. When predicting the TPP of flame-retardant cotton, it is necessary to ensure that the relative errors between the predicted values and the measured values are small in addition to ensuring that the overall accuracy is high. According to the model evaluation indexes, the fitting effect of the combined model was best and the error was smallest. Therefore, model (8) can predict the TPP of flame-retardant cotton with air

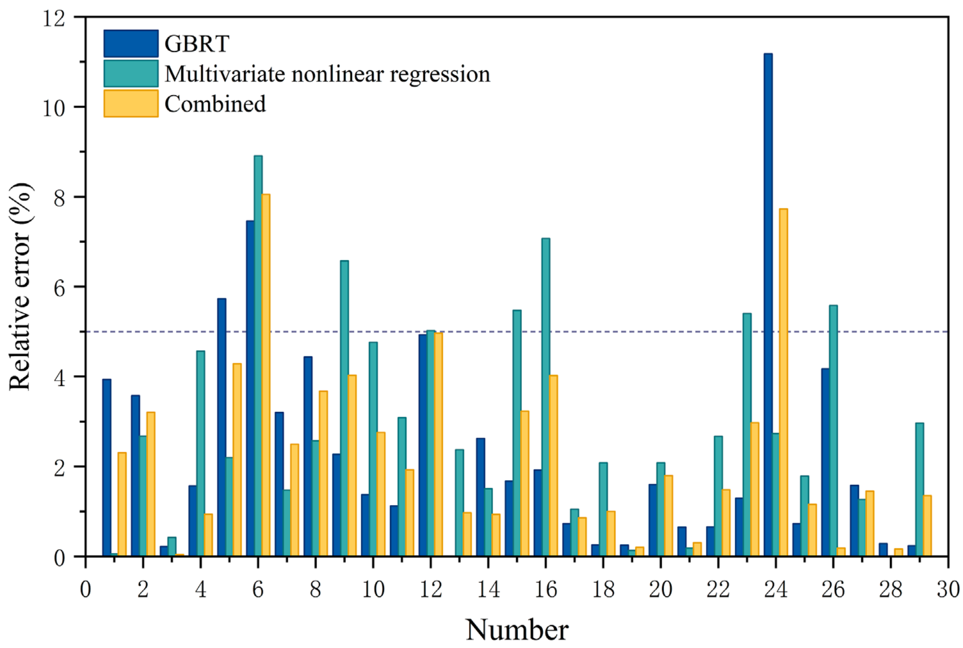

FIGURE 10
Relative errors of predicted values of the three models.

gap between 0 and 19.2 mm. The combined model was conducive to application.

4 Conclusion

This work analyzed the correlations between gram weight, thickness, air gap, and thermal protection performance (TPP). Multivariate nonlinear regression model, gradient boosting regression tree model and combined model were established and compared. The following conclusions were drawn:

(1) There were strong linear correlations between gram weight, thickness, and TPP value, as indicated by the correlation coefficients between these three variables being larger than 0.8. There was a slight linear correlation between the TPP value and air gap, as indicated by the correlation coefficient of 0.304.
(2) In the multivariate nonlinear regression model and GBRT model, most of the relative errors between the predicted values and the measured values were less than 5%.
(3) The inverse variance method was used to construct a combined model for predicting the TPP value. The R^2, MRE and RMSE of the combined model were superior to single models, By integrating the strengths of both models, the combined model enhanced the prediction accuracy of thermal protective performance, facilitating a wider application.
(4) In investigating the thermal protective performance of flame-retardant cotton, this study utilized a limited number of variables to establish the prediction model. This approach significantly streamlined the model's complexity while dramatically improving analysis efficiency, ensuring both efficiency and precision.

However, there were certain limitations in the exploration of flame-retardant cotton fabrics in this work. The methodology presented was specifically tailored for flame-retardant cotton fabrics and has not been validated for other types of fabrics. Future research could explore the applicability of this approach by incorporating data from additional fabric types.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

SZ: Conceptualization, Methodology, Writing–original draft. KM: Funding acquisition, Project administration, Resources, Writing–original draft. LW: Software, Validation, Visualization, Writing–review and editing. ZZ: Data curation, Methodology, Writing–original draft. XY: Conceptualization, Investigation, Resources, Writing–review and editing. JZ: Data curation, Methodology, Resources, Writing–original draft. HL: Conceptualization, Supervision, Writing–review and editing.

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Conflict of interest

Authors KM and JZ were employed by Wenzhou Darong Textile Instrument Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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