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Particle Swarm Optimization Based Fire Risk Valuation Model: Shopping-Mall

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Abstract

In view of the shortcomings of the existing small-scale shopping mall fire prediction models, the effectiveness and scalability of the prediction results, a BP neural network prediction model is constructed to improve the prediction accuracy by considering a variety of fire risk factors. On this basis, the convergence speed of the BP neural network is accelerated with the help of the particle swarm optimization (PSO) algorithm. Then, a mixed multi-factor shopping mall fire risk grade prediction model based on a PSO based back-propagation (PSO-BP) neural network model is proposed. The constructed prediction model can simultaneously consider climate factors (daily maximum temperature, daily average temperature, 24-h precipitation, continuous drought days, sunshine hours, daily average relative humidity, and daily average wind speed), landform factors (altitude, slope, slope direction, soil water content), combustible factors (vegetation type, combustible water content, ground cover load), and human factors (density of population, distance from human activity area). Based on the actual data and field measurement data collected by the sensor network of the shopping mall (Lahore, Pakistan), the validity of the proposed model was verified by a group of experiments. The results show that the model based on the training data set and the test samples can effectively predict the fire risk level; the computational complexity of the model is significantly lower than that of the BP neural network model alone.

Keywords

Shopping Mall Fire Risk, Fire Factor, BP Neural Network, PSO, Multi Fire Risk Grade Prediction Model

1. Introduction

When it comes to helping people make their way around large, unfamiliar facilities, signage systems are invaluable. The capacity of building inhabitants to navigate from one point to another is enhanced by an appropriately designed signage system [1]. Additionally, emergency exits and safe zones can be quickly located with the use of signage. Positioning signs in "optimal" places is a major difficulty in designing signage systems for efficient and safe way finding. Manually placing signs in large, complex buildings with several entrances and exits is a difficult, cumbersome, and time-consuming design endeavor. Manually accounting for the vast number of possible way finding scenarios while taking into account different (often competing) design objectives like directing occupants along the shortest route (for example, in an emergency), avoiding redundancy of signs, optimizing the visual catchment area of a sign relative to decision points, etc. is nearly impossible. Traditional signage evaluation and design rely primarily on designers' intuition and experience.

In particular, fires occurring in buildings directly affect the lives of occupants and cause secondary and tertiary indirect damage including various infrastructures. Among the 423,317 domestic fire accidents in the last 10 years (2011-2020), fires occurring in residential and industrial facilities accounted for 265,365, accounting for 63% of the total number of fires [2]. To this end, it is necessary to examine the causes that affect the fire risk of buildings, check the indicators vulnerable to risk, and establish appropriate non-structural and structural measures [3]. Influenced by natural or human factors, there are hundreds of thousands of building fires in the world every year, and the affected injuries reach millions. Since the 1980s, the number of complex building fires has gone up every year. This is because global warming keeps getting worse and more extreme weather events are happening. Complex building fires burn mall places, destroy building resources, release a lot of greenhouse gases in a short amount of time, hurt the environment a lot, and have a big impact on the long-term development of buildings [4] [5]. Complex buildings fire risk grade prediction is an important technical means to reduce the occurrence of shopping malls fires and has important application value [6].

The occurrence of complex buildings fires is affected by many shopping malls. The risk of fire occurrence varies greatly in different regions due to climate, terrain, vegetation type, human factors, etc. [7] [8]. At present, relevant research mainly provides large-scale, medium-term, and long-term buildings fire risk rating predictions based on meteorological, remote sensing, and other data, such as fire risk rating predictions in days or months. However, there are few short-term building fire risk prediction research studies for specific regions. The prediction models proposed in previous studies have different fire risk factors, and different models have their inherent scope of application. It is difficult to exactly and timely forecast the fire risk level [9] [10]. In recent years, with the progress of artificial intelligence (AI) technology, the real-time data acquisition system based on sensor networks can use intelligent methods to build a multi-factor building fire risk rating forecast model and carry out accurate and real-time small-scale prediction, which is of great significance for effectively protecting shopping malls resources in key areas of building fire prevention and control and saving malls fire prevention and control funds [11] [12] [13]. In this article, we comprehensively consider the following factors:

- Climate factors, complex buildings, and human factors, and there are 16 building fire factors in three categories.
- The author proposes and validates experimentally a mixed multi-factor shopping malls fire risk prediction model, a particle swarm optimization-based back propagation (PSO-BP) neural network, by combining a PSO technique and a BP neural network model.
- We show the range of information interactions that individuals are capable of doing.
- When the local optimum weight is high, even a modest increase in population can speed up the evacuation process.
- For the purpose of simulating the large-scale outdoor evacuation problem in real scene and providing reference for the emergency plan following geological disaster, a PSO-BP technique is developed.

The remainder of the paper is organized as follows. The fundamental PSO and BP are described in detail in Section 2. In Section 3, we will go through the specifics and methodology of the PSO-BP hybrid in greater detail. In Section 4, we show how well the new algorithm performs using the shopping mall benchmark functions and results analysis. We draw some final findings and offer some final thoughts in Section 5.

2. Related Work

In order to evaluate the fire risk of hospitals, Rahmani *et al.* [14], NFPA has formed indicators according to three elements (fire interference, hospital protection, and interface between fire brigade and hospitals). From the perspective of buildings, owners and occupiers, Brzezińska *et al.* [15] formulated a fire risk assessment strategy considering multiple interests based on four indicators (business, life, environment and attributes). Frantzich *et al.* [16] once separated the individual fire risk suffered by residents from the social risk caused by large-scale fire, forming an indicator. With the development of the Internet, the popularization of mobile devices, and the expansion of SNS, the amount of digital information has grown exponentially. A term that appeared around 2010 has become an important technology concerned by many countries in the world in just a few years [17]. An example of the application of big data technology to building fire risk management is that the New York City Fire Department (FDNY) calculated the fire risk score of buildings by using the "Fire cast 2.0" model of big data and AI technology to formulate countermeasures for fire. The data (indicators), together with the building structure, material and location, have taken into account the number of deaths and losses caused by the building spacing and building characteristics. However, due to the limitations of New York City's manpower and budget, there are only more than 30,000 buildings among more than 33,000 fire safety inspection objects, accounting for about 10% [18]. In China, Park *et al.* [19] have processed the fire statistical data, which is realized on the big data fire prediction platform. Kim *et al.* [20] use the fire statistical data, through the analysis of relevant big data, to develop a model for predicting the risk degree of the fire scene, which mainly depends on the finalized statistical data for research.

Signage system assessments in buildings are difficult to perform. Expert opinion, experience, paper prototypes, and post-occupancy reviews are the norm when it comes to evaluating and designing signage [21]. The use of spatial analysis tools to quantify the visibility and inter-visibility related features of a building plan or proposed signage system is an advanced method [22]. Experts can "walk around" a 3D virtual model of the building to assess the viability of suggested sign placements and layouts [23]. In order to assess the efficacy of 2D evacuation sign designs, the authors in [24] developed a way finding simulation. The fundamental flaw of this approach is that it oversimplifies human vision and hence ignores issues of readability and detection in the signs used.

By delving into five different soft computing approaches within artificial neural networks (ANNs), Al-Janabi *et al.* [25] planned a module that would be the record effective way of predicting forest fires. Using geographical analysis, an expert-based virtual walk-through, and an agent-based simulation, we can evaluate several facets of way finding using signs. A virtual reality (VR) walk-through conducted by professionals who simulate navigation from the viewpoint of possible residents could be helpful in providing a qualitative valuation of way finding performance (e.g., hesitation points). While lay participants often experience "momentary suspension of disbelief" when navigating in simulated settings with a low level of feature and realism, this phenomenon may be overcome with the help of an expert who guides the walkthrough [26]. However, it has been observed that as population density rises, people's average journey times slow down. With the use of the Maxwell-Boltzmann distribution, Henderson *et al.* [27] derived the connection between forward velocity and several parameters involved in the evacuation process. Liu *et al.* [28] proposed the floor design of the building is abstracted into a network plan in the "queuing network" building evacuation simulation model. The queueing network is modeled using a Markov process [29] in the simulation language.

Due to its simple structure, strong nonlinear mapping ability, good self-learning capacity, and high-precision approximation of arbitrary functions [30] [31] [32] [33], the BP neural network has become one of the most popular neural network models. To acquire knowledge from its training data, the BP neural network algorithm employs a gradient descent technique. It uses error back-propagation to train the network nodes' weights and offsets with the aim of decreasing the square of the output error [34]. Slow learning speed, easy fall into local minima, and poor stability are some of the issues that arise with this technique when the

BP neural network topology (number of layers, number of nodes in each layer) is complicated [35] [36].

3. Methodology

In order to speed up the convergence of the standard BP neural network algorithm, we suggest a BP neural network algorithm based on PSO, which is integrated into the BP neural network model. To be more precise, the BP neural network's connection weights and thresholds are replaced with the particle swarm position vector at each layer. The PSO-BP neural network method model is established by continuously iterating the algorithm to create ideal population particles, which are then decoded and transformed into the optimal solution and used as the connection weights and thresholds of the BP neural network for global optimization. Using an enhanced BP neural network based on the PSO algorithm, a short-term prediction model of forest fire threat is developed. The PSO-BP neural network model improves upon the model established using a conventional BP neural network by addressing its weaknesses in the areas of training time, stability, and the likelihood of falling into local minima. When real data is fed into a model, it may make more precise predictions (in this case, assign a fire risk rating) in a shorter amount of time. Therefore, the following criteria were set and indicators were selected to meet the goals of this study by considering the factor selection principle and the ease of access acquisition among related search terms of the representative keywords:

- Relevance: It should be an indicator that affects the fire risk of buildings.
- Representativeness: must be able to represent the analysis results of representative keywords and related search terms.
- Availability: statistics of building units must be ensured or calculable.
- Continuity: The data shall be updated and produced continuously at regular intervals.
- Understandability: Be simple, clear and easy to understand.
- Directionality: The evaluation should be consistent with positive or negative effects.
- Comparability: It can be compared over time and shall be applicable to all buildings

3.1. Variable Selection

Taking the collected relevant search terms as the object, the article studies the relevance, representativeness, usability, continuity, comprehensibility, directionality and comparability, and selects the indicators. Based on the principles of generality, completeness and availability, the selected risk factors can not only comprehensively reflect the relevant situation of building fire, but also collect quantitative data of relevant risk factors in the study area. Referring to the existing work, this study selects 16 factors within 4 components fire related variables such as building characteristic, economy, climate factor, and fire protection to build a PSO-BP model, as shown in **Table 1**.

Table 1. Components and variable codes that were utilized in the forecasting model.

Components	Variable code	Variable name
Building characteristic	x_1	Building use
	x_2	Building structure
	x_3	Building scale
	x_4	Building deterioration
	x_5	Building density
	x_6	Gas usage
	x_7	Electricity usage
Economy factor	x_8	Occupant
	x_9	Fire vulnerable people
	x_{10}	Arson
	x_{11}	Road condition
Climate factor	x_{12}	Daily average temperature
	x_{13}	24 h precipitation
Fire protection	x_{14}	Fire protection facility
	x_{15}	Fire officer
	x_{16}	Noncombustible material

It can be seen from Table 1 that the 16 variables are divided into four dimensions. A complete and comprehensive description of various factors leading to building fire can effectively predict the occurrence of shopping mall fire. In order to improve the scalability of the prediction model (which can be applied to regions under different climatic conditions), some variables selected in this study may have some correlation for a specific region, such as soil water content and fuel water content; daily average temperature, 24 h precipitation etc. However, these variables and the correlation between them may be quite different for different regions. For example, the soil water content and the combustible water content may be similar in different regions due to different geological conditions after rainfall, while the combustible water content may be quite different. The correlation between these variables and regional topography, geological conditions, climate, and other factors is not within the scope of this research.

3.2. Data Source

The data for this study are from the sensor data collected by the building fire prevention experimental station in the study area and the field measurement results. The data was collected from January to December 2018. In order to analyze the availability and performance of the PSO-BP model, 8760 groups (each group includes 16 variable values) were randomly selected from the collected data as the data set. For each group of data, in combination with the real-time building fire risk meteorological grade forecast results, shopping mall fire prevention experts are invited to manually proofread the fire risk grade, which is divided into five different grades. 256 groups of data marked with fire risk grades are randomly selected as the training set, and 1752 groups of data are used as test samples to train the prediction model. The other 1752 groups of data are used as test sets to test the validity of the model.

The specifications for the many factors that can cause a fire have varying acceptable ranges. A higher value for some factors correlates with a higher fire risk, whereas a lower value for other parameters has the opposite effect. On the other hand, the hidden layer of the BP neural network model used in this study uses the Sigmaid function as the activation function, and the value range of this function is [0, 1]. In view of the above problems, this study first normalized the data. That is, the values of each parameter are mapped to the [0, 1] interval, and the greater the value is, the greater the fire risk is. The minimum maximum transformation method is used to normalize different parameters [37] [38]. For indicators with higher values and higher fire risks (*i.e.*, x_1, x_2, x_4, x_5, x_7, x_9, x_{14}, x_{15}), and the normalization method for indicators with higher values and lower fire risks (*i.e.*, x_3, x_6, x_8, x_{11}, x_{13}, x_{16}) is as,

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

$$y = \frac{x_{\max} - x}{x_{\max} - x_{\min}} \tag{2}$$

where, y is the value after normalization; x is the original value of a parameter; $x_{\max}$ represents the maximum value in the parameter value set; $x_{\min}$ denotes the minimum value in the parameter value set.

For the 16 selected variables, if they are quantitative indicators, use equation (1) or (2) to calculate. If it is a qualitative indicator, the fire risk shall be described qualitatively and then converted into a quantitative value by referring to the analytic hierarchy process (the 1 - 9 evaluation method by [39]). According to the distribution characteristics of the vegetation in Lahore shopping mall, the vegetation types are divided into four categories: weeds, shrubbery, mixed mall, and artificial mall, in order of fire risk. The quantitative values corresponding to the above four qualitative methods are 4, 3, 2, and 1, respectively. After obtaining the quantitative value, use formula (1) to normalize the corresponding variable value.

3.3. PSO-BP Model

To improve the BP neural network model, the PSO algorithm is implemented in [40] [41] [42]. In computer science, a PSO algorithm is an example of a swarm intelligence optimization method. This proposed method is inspired by the occurrence of bird predation. By searching the area surrounding the bird closest to the food, it gets closer and closer to the best solution. Particles' trajectories are represented in the algorithm by their fitness values, velocities, and coordinates (birds). When it comes to global optimization, the PSO method excels. With the particle swarm position vector serving as a stand-in for the connection weights and thresholds at each layer of the BP neural network, this research provides a novel approach of encoding the network's inner workings. The algorithm is continuously iterated in order to produce the best possible particle population. The PSO-BP neural network algorithm model is established after the decoding is transformed into the optimal solution and then utilized to determine the BP neural network's global ideal connection weight and threshold.

Figure 1 depicts the steps involved in building a PSO-BP neural network model. At the outset, a basic BP neural network with four layers (two of which are hidden) is built. The particle swarm's starting position and speed can be set using a neural network. For a BP neural network, each particle stands in for a node in the hidden layer, and each swarm of particles represents a particular combination of connection weights and thresholds. Following decoding, the BP neural network model is obtained. The neural network model is built by iteratively updating the particle swarm's speed and location to approximate the ideal solution. The calculation equation for particle fitness value F is as,

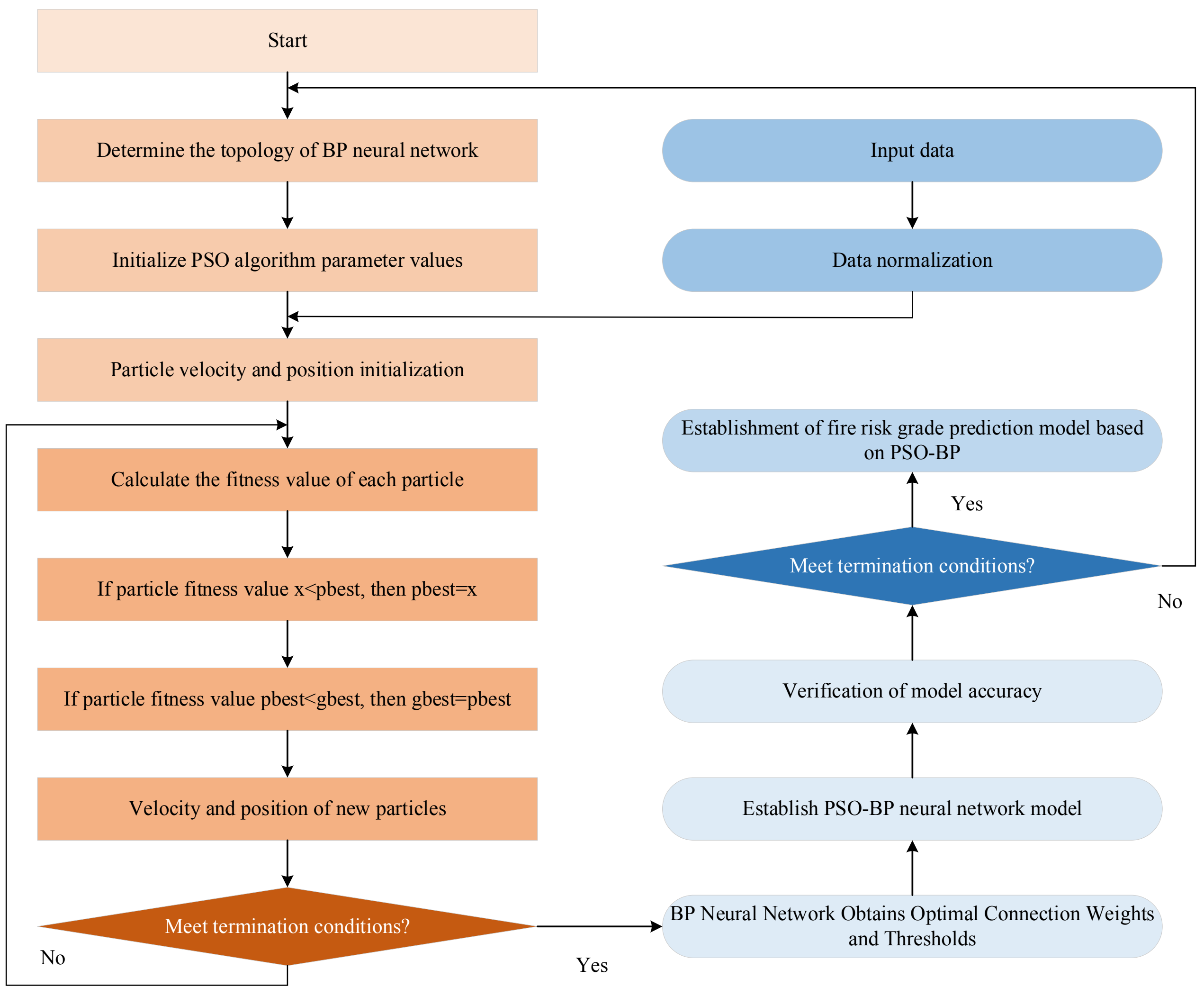

Figure 1. Flowchart of establishing BP neural network model by PSO.

$$F = \sum_{i=1}^{N} \text{abs}\left(y_i - t_i\right) \tag{3}$$

where, y_i signifies the experiential value of sample i; t_i denotes the predicted value of trial i; N characterizes the number of models; abs is an absolute value function.

On this basis, the velocity and position of elements are updated continuously until the iteration error reaches the set precision (e) or the number of repetitions reaches the preset maximum number of iterations (N_{num}). When the iteration terminates, the ideal solution is the particle with the lowest fitness. Decode the PSO-obtained optimal population particles, then determine the BP neural network's ideal connection weight and threshold.

4. Results Analysis and Comparison

4.1. Results

According to section 3.2, the data is divided into training data sets, test samples, and test data sets. The first 25 groups of data in the training data set are shown in Table 2 (each column is a group of data). To build the training data set, each column (a complete set of input data x_1 - x_6) is marked with the corresponding fire risk grade (dependent variable y) by soliciting the opinions of building fire management experts. When training the model, the first step is to use the pre-processing method described in section 3.2 to normalize the data that the model will use.

Table 2. Example of PSO-BP model training dataset.

Variable		Training data																								
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Independent	x_1	27	27	27	27	33	33	33	33	22	22	22	22	17	17	17	11	11	11	11	6	6	6	6	6	27
	x_2	22	18	17	16	25	22	23	20	16	15	16	17	11	10	11	12	6	7	6	6	2	1	0	1	18
	x_3	10	3	5	17	23	10	9	13	1	15	8	28	9	2	1	30	15	8	1	7	18	2	7	16	9
	x_4	5	8	12	17	3	1	8	14	7	4	9	10	1	4	9	4	9	15	4	6	10	1	11	9	5
	x_5	18	5	14	10	15	12	8	10	6	7	17	4	9	7	14	18	5	14	10	15	12	8	10	6	7
	x_6	42	30	28	35	68	60	29	32	25	51	38	44	54	39	24	73	38	23	24	32	30	31	25	31	36
	x_7	5	3	1	8	10	3	7	6	4	1	11	8	4	5	2	5	3	1	8	10	3	7	6	4	1
	x_8	350	50	120	280	160	220	100	80	300	90	150	30	95	140	70	450	70	120	380	160	220	100	80	300	90
	x_9	20	15	8	30	45	15	30	50	12	25	18	55	21	13	19	20	15	8	30	45	15	30	50	12	25
	x_{10}	2	3	1	4	2	1	4	3	1	4	2	2	3	4	1	2	3	1	4	2	1	4	3	1	4
	x_{11}	14	10	9	12	19	17	9	8	7	16	9	14	16	13	6	20	10	6	6	7	7	7	6	7	8
	x_{12}	4	4	1	2	1	1	3	4	1	1	1	3	4	4	3	8	9	3	1	3	3	10	9	8	2
	x_{13}	36	28	26	35	68	60	29	32	25	51	35	40	50	35	22	60	35	23	20	32	30	31	25	31	36
	x_{14}	10	20	11	18	8	5	6	14	16	12	4	9	8	23	10	10	20	11	18	8	5	6	14	16	12
	x_{15}	10	20	11	18	8	5	6	14	16	12	4	9	8	23	10	10	20	11	18	8	5	6	14	16	12
	x_{16}	10	20	11	18	8	5	6	14	16	12	4	9	8	23	10	10	20	11	18	8	5	6	14	16	12
Dependent	y	3	4	3	2	5	5	3	2	1	4	3	3	4	2	1	4	4	2	1	3	2	3	1	2	3

Through training data, build the PSO-BP prediction model and make predictions. In order to ensure the effectiveness of the prediction model, in the process of building the PSO-BP model, this study gradually increases the number of hidden layer nodes with reference to the method in [43]. First, the model is trained through training set data. After the training process converges, the prediction error is tested according to the test sample. When the test sample verifies that the prediction error is less than a certain stop training threshold (δ), stop the training process or start a new round of training. Through the above methods, the precision of the prediction model is gradually improved. Finally, the number of hidden layer nodes is determined to be 23, and the training threshold is stopped $\delta = 0.150$.

4.2. Analysis

Using MATLAB software and according to the method described in section 4.1, the parameters of a BP neural network model are determined and the PSO-BP neural network model is established through training data sets and test samples. On this basis, the PSO-BP neural network model is used to predict the fire risk grade. After inputting the test data as shown in **Table 3** (randomly selected from the test data set), 15 groups of test data are calculated in the model to obtain the fire risk rating.

Table 3. Example of PSO-BP model training dataset.

Variable codes	Test data														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
x_1	33	22	17	11	6	19	28	28	37	38	6	18	22	26	21
x_2	24	18	11	5	1	8	18	24	32	33	2	12	18	17	16
x_3	12	3	5	2	11	3	0	0	12	3	6	3	1	5	22
x_4	4	8	10	3	5	5	4	2	0	3	0	5	9	11	0
x_5	17	4	9	7	14	8	12	12	13	13	10	13	6	8	6
x_6	41	31	24	26	39	25	12	18	35	20	38	16	28	26	34
x_7	11	8	4	5	2	4	1	3	4	3	4	2	8	1	4
x_8	145	35	90	145	65	97	95	135	128	69	121	83	95	115	255
x_9	18	55	21	13	19	19	23	16	24	46	24	24	53	9	12
x_{10}	2	2	3	4	1	3	4	4	2	3	2	2	2	1	1
x_{11}	9	8	6	6	10	6	4	8	13	7	9	2	8	9	7
x_{12}	1	3	1	1	2	1	1	2	3	3	3	2	3	2	1
x_{13}	41	31	24	26	39	26	13	26	53	25	26	24	25	24	43
x_{14}	4	9	8	23	10	22	28	29	13	12	22	23	11	14	15
x_{15}	4	9	8	23	10	14	12	8	2	3	3	4	9	9	14
x_{16}	4	9	8	23	10	12	4	16	13	12	19	5	8	7	17

Table 4 shows that the actual prediction of fire risk grade is one grade lower than what was marked in the test data set. This shows that the PSO-BP model works. With reference to the method in the literature [44], SPSS V.18.0 software and the multifactor logistic regression analysis method are used to set x_1 - x_{16} as an independent variable and y as a dependent variable to build a fitting model. The stepwise regression method is used to get rid of variables that don't matter, and then the risk factors of building fires are looked at. The results showed that the six factors of daily maximum temperature (x_1), daily average temperature (x_2), 24 h precipitation (x_3), sunshine hours (x_5), daily average relative humidity (x_6), and moisture content of combustibles (x_{13}) had great influence on the incidence of building fire, and the results were consistent with the literature [45].

4.3. Comparison

In order to better understand how the proposed machine learning algorithm based on PSO compares to other models used to predict complex building fires, we have compiled our findings in **Table 5**. Root means square error (RMSE), mean square error (MSE), and mean absolute error (MAE) are all measures of accuracy. PSO is another popular machine learning algorithm. Using swarm intelligence, this type of algorithm is able to learn and perform well in global optimization.

Table 4. Comparison between predicted results and marked results of fire risk rating.

Test Data Group	Fire risk level	Mark fire risk grade
1	4	4
2	2	2
3	1	1
4	1	1
5	2	2
6	2	2
7	5	5
8	1	2
9	1	1
10	2	2
11	1	1
12	3	3
13	3	3
14	3	3
15	1	1

Table 5. A review of preexisting models and a comparison to the PSO for predicting buildings fires.

Techniques	Ref.	RMSE	MAE	MSE
Support vector machine	[46] 2007	63.5	502	4042
PSO	[47] 2013	63.45	454	4020
Message passing neural networks	[48] 2016	63.8	652.2	4076.4
Radial basis function	[49] 2019	68.1	887.9	4638.2
Convolution neural network	[50] 2020	68.3	673.9	4665.5
PSO-BP	This work	68.4	670.5	4690.2

In direction to verify the efficiency of the PSO-BP model and analyze its performance, firstly, the neural network connection weights and thresholds are randomly produced, and the PSO-BP and the basic BP neural network model are trained, respectively, through training set data and test samples. Among them, the maximum number of iterations N_{num} in the model-training process is set to 50. Secondly, the trained PSO-BP model and BP neural network model are used for prediction based on test set data. For BP neural networks and PSO-BP, the training model process is repeated 10 times, and the prediction is carried out based on the test data set. On this basis, compare the time complexity of different methods in the training model process and the accuracy of the prediction results of the constructed model. The root mean square error is used to calculate the forecast error of each module. The prediction error (P_{RMSE}) of the model is:

$$P_{RMSE} = \sqrt{\frac{\sum_i \left(p_i - l_i\right)^2}{N}} \tag{4}$$

where, p_i is the prediction grade of the i^{th} sample; l_i is the fire risk grade marked in the test data adopted by the i^{th} prediction sample; N is the number of predicted samples. The comparison results for different methods are shown in **Table 6**.

It can be seen from **Table 6** that compared with the BP neural network model, the PSO-BP model has fewer iterations and a shorter training time. In 10 operations of the PSO-BP model, the accuracy rate of prediction results is slightly higher than that of the BP model and higher than the accuracy rate of prediction results of the multifactor logistic regression model described in section 4.2 (the prediction error of the logistic regression model is 0.32475). The fluctuation range of PSO-BP model prediction accuracy is lower than that of the BP model, reflecting higher robustness. The prediction error of 10 prediction results of the prediction model is lower than the stop training threshold (δ), which shows that the prediction model has good scalability. This is because the neural network model that has not been optimized by the PSO algorithm will enter the flat area of the error surface during the training process, resulting in slower convergence speed or even falling into a local minimum, resulting in training failure. The

Table 6. Comparison of 10 running results of two models.

Models	Execution label	Iterations	Error/$\times 10^{-1}$	Time/s
BP neural network model	1	269	0.14876	14.0136
	2	271	0.14703	14.1280
	3	243	0.14978	12.6824
	4	197	0.13967	10.2800
	5	220	0.14693	11.4760
	6	262	0.14327	13.6808
	7	194	0.14560	10.1448
	8	222	0.14870	11.5592
	9	220	0.13972	11.4760
	10	230	0.14641	12.0168
PSO-BP model	1	243	0.13217	12.6824
	2	215	0.13345	11.2160
	3	186	0.12465	9.6872
	4	175	0.13284	9.1360
	5	137	0.13516	7.1600
	6	207	0.12765	10.7896
	7	162	0.13400	8.4808
	8	157	0.12993	8.2000
	9	179	0.12985	9.3440
	10	205	0.13318	10.6856

usability of the prediction model can be improved by using test samples. The introduction of a PSO algorithm can speed up the approximation of parameters to the optimal solution in the process of training the model, thus improving the effectiveness of the model. Thus, the PSO-BP model is more practical.

5. Conclusions

In order to improve the accuracy of building fire risk assessment, this paper proposes a shopping mall fire risk assessment model based on PSO-BP neural network and uses shopping malls (Lahore, Pakistan) fire risk data from 30 different shopping malls to conduct simulation experiments. 16 building fire-related factors including building characteristic, economy factor, climate factor, and fire protection were determined as prediction parameters. On this basis, the improved BP neural network based on a PSO algorithm is used to make a short-term prediction of building fire danger called the PSO-BP model. The PSO-BP model makes up for the problems of the BP neural network model, such as its easy fall into local minimum, poor stability, and uncertain training duration. The PSO-BP model can produce results faster and more accurately. According to the PSO-BP model algorithm and MATLAB software, a prototype system of fire risk grade prediction in the study area has been established. After testing, the prototype system can better analyze and process the data of 16 fire risk factors, predict the corresponding fire risk grade, and provide a basis for fire management in the study area. The model can also be extended to shopping mall farms with relevant data conditions.

The prototype system of fire risk grade prediction in the study area established in this study is a small-scale system for building classes. In the shopping mall fire risk prediction, the prediction accuracy can be improved, and with the real-time update of data, the real-time prediction can be carried out. In the future research work, more building fire risk-related factors will be introduced, and more accurate prediction models will be used to further improve the prediction performance of small-scale shopping mall fire ratings.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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