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Green public building water supply and drainage and fire protection design

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Abstract. In order to improve the rationality of green public building water supply and drainage and fire protection design and reduce the cost of system design, a method of green public building water supply and drainage and fire protection design based on wolves convolutional neural network algorithm is proposed. Firstly, the model of green public building water supply and drainage and fire fighting system is analyzed, and the models of high pressure water mist fire hydrant system and rainwater drainage system are given respectively; Secondly, the convolutional neural network algorithm is introduced to optimize the green building water supply and drainage and fire protection design. At the same time, in order to improve the performance of convolutional neural network algorithm, the parameters are optimized by wolves algorithm. Finally, through simulation experiments, the advantages of the proposed method in convergence accuracy and design cost can be shown.

Key words. Wolves algorithm, Convolutional neural network, Green public building, Drainage and fire.

1. Introduction

With the rapid development of China's economy, there are more and more green public building water supply and drainage and fire protection design projects, but there are no corresponding norms and standards of water supply and drainage and fire engineering design, especially fire design, and the conventional fire design method can not meet the requirements. In the green public building drainage and fire system design, the fire system is seen as a whole through the fire performance of the design. Consider the project fire safety strategy in a whole. The safety assessment of green public building evacuation and rescue system, fire smoke extraction system, fire detection system, fire extinguishing system, emergency lighting and evacuation command system, green public building drainage system and so on has been done. On this basis, the project for drainage and fire engineering are designed.

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In this paper, a green public building drainage and fire design method based on wolves convolutional neural network algorithm is proposed for green public building drainage and fire system design. The rational optimization of the design process of green public building water supply and drainage and fire control system is realized. The simulation results verify the effectiveness of the algorithm.

2. System model

Fire protection systems include high pressure water mist fire hydrant systems, automatic fire extinguishing systems and fire extinguisher systems. In view of the construction of green public buildings for a long time and relatively limited space of the green public building, more entrances and exits connected to the ground, adverse rescue and other characteristics, disaster relief areas can be set up in the range of 300m in front and back of the lowest point of green public building, and relief area is provided with high pressure water mist fire hydrant system for protection. In the case of fire in green public building, ventilation, communication and electricity and other chambers shall be provided with automatic fire extinguishing equipment.

2.1. High pressure water mist fire hydrant system

High-pressure water mist pump unit is located in the F13 horizontal channel of the green public building, and the water pump tank is located next to rescue channel near the right-line F13 link channel. It consists of regulating water tank (including liquid level display and control cabinet), water tank inlet filter, replenishment solenoid valve, safety relief valve, pressure sensor, valves, frames and connecting pipe. High pressure water mist fire hydrant is mainly constituted by high pressure manual ball valve, water mist spray gun, seismic radial pressure gauge and other components.

The length of the first floor is 2.8m. The installation distance of the spray gun is 25m. Fire fighting on the first floor is the most unfavorable. The cooling fire can be taken for the adjacent two floors at the same time, that is, three sets of sprinkler start at the same time. The flow of the spray gun is calculated as follows:

$$q = k\sqrt{10P}\,. \tag{1}$$

In the formula, k is the flow coefficient of the spray gun, and P is the working pressure of the spray gun. The design flow of the spray gun is $q = \ 3.2 \times\sqrt{10 \ \times 10} \ = 32\ L/\min$.

The flow of the system is calculated as follows:

$$\begin{aligned} Q_s &= K \times Q_j = \ 1.1 \times 32 \times 3 \\ &= 105.6L/\min = 6.34m^3/h \end{aligned} \tag{2}$$

High pressure water mist pipe is DN25 stainless steel seamless steel pipe, which uses a circular arrangement, according to the most unfavorable branch pipe network calculation. The loss of the head of the fire pipe is calculated by sections based on the Darcy-Weisbach formula according to the flow of the pipe section. Frictional head loss is calculated as follows:

$$\Delta h_1 = 2.252 \cdot k \frac{f L \rho Q^2}{d^5} \,. \tag{3}$$

$$Re = 21.22 \frac{Q\rho}{du} \,. \tag{4}$$

In order to ensure the safe operation of the fire fighting system, a pressurized water supply pump is set up in front of the high pressure water mist pump unit to regulate water supply for the water tank of the pump unit. The 12m3 pressurized water tank is located in front of pressurized water pump for booster pump suction. The pump is provided with a 3m3 regulating water tank on the upper part of the pump unit for its suction. The installation height of the pressurized water tank and regulating water tank is 1m and 1.5m respectively. The installation height of fire hydrant box is 1m. The head loss in the pump room is calculated by 10kPa. If the pressure of the spray gun is greater than or equal to 10MPa, then the lead of the high-pressure water mist fire pump group can be calculated as follows:

$$\begin{aligned} H &\geq -1.5 + 1 + 1 + 100 + 36.874 \\ &= 137.374 \; bar \approx 13.73MPa \end{aligned} \tag{5}$$

2.2. Rainwater drainage system

The rainstorm intensity formula is used to calculate the rainfall as below:

$$q = 2424.17 \times \frac{1 + 0.553 lgT}{(t + 11.0)^{0.668}} \,. \tag{6}$$

$$t = t_1 + m t_2 \,. \tag{7}$$

In the formula, the designed rainfall intensity is q, and the designed rainfall recurrence period is T, and the rainfall duration is t. The ground collecting time is t_1. The rain-flow time within tube (canal) ist_2. The delaying coefficient is$m$, and the designed flow of rainwater is calculated as follows:

$$Q_R = \psi \cdot q \cdot F \,. \tag{8}$$

In the formula, runoff coefficient isψ, and drainage area is$F$. The catchment area of the open section of the inlet side can be calculated as$F = 0.55 \; hm^2$. Then the designed flow of rainwater can be calculated as$Q_R = 259.4L/s$.

3. Convolutional neural network based on wolves algorithm

3.1. Convolutional neural network

The convolutional neural network (CNN) [8] is designed by Schipholt, a network of probability density estimates. The core concept of CNN is the "winner-taking strategy" that uses multiple probability estimates and learning to compete. It is a classifier version of the Bayesian strategy combined with the Parzen window, a nonparametric estimate of the probability density function (PDF (s)) method. Different from the traditional radial basis function (RBF) network and multi-layer feed-forward network, the neural network training process can be based on statistical principles of data processing data. Because CNN is based on PDF estimation rather than iterative function approximation, it has a high training speed and good generalization ability. According to the Bayesian method, the classification of unknown input vectors is based on historical data, rather than the parameters of the model, such as mean and standard deviation. The Bayesian classifier can be configured as follows:

$$P(C_i|x) = \frac{f(\chi|C_i) * P(C_i)}{f(x)} \,. \tag{9}$$

Where, $P(C_i|x)$ is the posterior probability, which indicates the probability of input x that belongs to the category$i$. For any classification problem, calculate the posteriori probability of class i and divide the input x with the largest $P(C_i|x)$ into class$i$. The calculation of $P(C_i|x)$ is the prior probability $P(C_i)$ obtained from the historical data, and the category conditional probability $f(\chi|C_i)$can be approximately estimated according to the Parzen window. Then the nonparametric estimator form based on the Gaussian probability density function can be obtained as follows:

$$f(x|C_i) = \frac{1}{(2\pi)^{n/2}} \left[\frac{1}{m} \sum_{j=1}^{m} e^{-\left(\frac{1}{2\sigma^2}\right)\left[\left(x - x_{c_{ij}}\right)^T \left(x - x_{c_{ij}}\right)\right]} \right] . \tag{10}$$

Where, m represents the number of patterns in class C_i, $x_{c_{ij}}$ is the jth mode in class C_i, and $\sigma$is the smoothing parameter. CNN has a four-tier structure that contains nodes and can map input types to discrete categories, as shown in Figure 1. The structure of each layer of CNN is described as follows:

Layer 1: Input layer and input unit. The input layer does not perform any computational processes, and its role is to assign the input elements to the convolution layer;

Layer 2: Convolution layer. After receiving the training samples from the input layer, the nodes of the convolution layer can be calculated as:

$$\exp\left[\frac{(x_T * x) - 1}{\sigma^2}\right] . \tag{11}$$

Where, x_T is the training data pattern, x is the unknown pattern for a given category, and σ is the smoothing factor.

Layer 3: Convergence layer. Each node in the layer calculates the convergence value of the output value in the convolution layer. The calculation is as follows:

$$S_L = \sum_{i=1}^{C} exp\left[\frac{(x_T * x) - 1}{\sigma^2}\right]. \tag{12}$$

Where, the total number of categories is$C$.

Layer 4: Output layer. The nodes in the output layer based on the Bayesian rule may determine the category of each input pattern$x$. The form is as follows:

$$\sum_{i=1}^{C} exp\left[\frac{(x_T * x_i) - 1}{\sigma^2}\right] > \sum_{j=1}^{C} exp\left[\frac{(x_T * x_j) - 1}{\sigma^2}\right]. \tag{13}$$

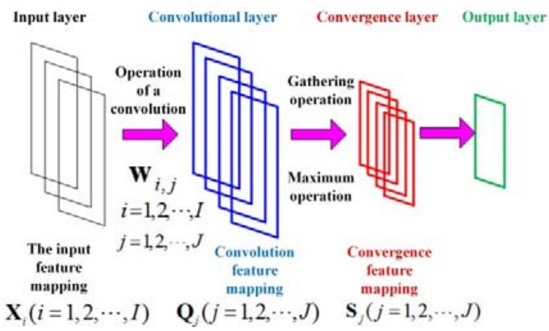

Fig. 1. CNN Structure

3.2. Optimization for parameters of wolves algorithm

The wolves live in a well-defined social life. Artificial wolf is divided into leader wolf, discovery wolf and fierce wolf according to different functions. They unite their cooperation and hunt cooperatively. Each artificial wolf in the wolves algorithm represents a solution. The information sharing, discovering unknown environment and self-organization character are taken to achieve wolves hunting by artificial wolves through the perception of the wolf to the prey odor concentration [14].

Discovery wolf in accordance with the formula (8) updates the position, through random walk, to find the optimal solutions for their leader wolf; Artificial fierce wolf in accordance with the formula (9) raids into the leader wolf. If the prey odor perceived by artificial fierce wolf on the way is greater than that of the leader wolf, the fierce wolf will replace leader wolf and initiates the call, or artificial fierce wolf raids as before. When the distance from artificial fierce wolf's position to the leader wolf is less than a certain threshold, the wolves continuously update the position according to formula (10), and launch stalking, and update the leader wolf constantly according to the prey odor concentration. When the termination condition is satisfied, the optimal solution is given out, otherwise the walking behavior is repeated. The artificial wolf position update formula is as follows:

$$X_{id}^{p} = X_{id} + step_a^d \times \sin(2\pi \times p/h)\,. \tag{14}$$

$$X_{id}^{K+1} = X_{id}^{k} + step_b^d \times (g_d^k - X_{id}^k)/\left|g_d^k - X_{id}^k\right|\,. \tag{15}$$

$$X_{id}^{K+1} = X_{id}^{k} + \lambda \cdot step_c^d \times \left|g_d^k - X_{id}^k\right|\,. \tag{16}$$

The standard convolutional neural network algorithm is very sensitive to the initial optimization center. If the initial optimization center is unreasonable, the convolutional neural network algorithm is easy to fall into the local optimal solution, which leads to the over-segmentation or under-division of the optimization process. In order to solve this problem, this paper chooses the wolves algorithm to optimize the convolutional neural network algorithm. Specific steps are as follows:

Step 1: The optimization process is converted to $M \times N$ points, and the gray value of each point is calculated to get the feature vector set to be optimized, and perform initial noise reduction.

Step 2: Initialize the number of the individuals of the wolves population N, the maximum number of iterations *kmax*, the scale factor of the discovery wolf α, the maximum number of walks *Tmax*, the population update scale factor R, and so on.

Step 3: The best individual is chosen as the leader wolf, and other than the leader wolf in the Snum, artificial wolf serves as the discovery wolf and implements wandering behavior until a wolf feels the prey odor concentration *Yi* greater than the wolf perceived prey odor concentration *Ylead* or maximum number of walks is reached.

Step 4: Fierce wolf raids. If the prey odor concentration *Yi*> *Ylead*, which is perceived by the fierce wolf on the way, then *Yi*= *Ylead*, and the fierce wolf will replace the leader wolf to initiate call behavior; if *Yi*< *Ylead*, then the fierce wolf continues to raid until the distance from the prey is less than the threshold *dnear.*

Step 5: The position of the artificial wolf that participates in the siege is updated according to the formula (15).

Step 6: Pick out the nearest artificial wolf to replace leader wolf and to complete the update on the wolf. The scale factor will be updated according to the population to update the wolves. The artificial wolf far away from the prey will be condemned.

Step 7: To determine whether the maximum number of iterations is reached, outputting the leader wolf's position if the requirement is met, or going to step 2 if not.

Step 8: The initial optimization center is obtained according to the position of the leader wolf, and the fuzzy membership degree and the optimization center are calculated according to the formula (16), and the fuzzy membership matrix is updated to generate a new optimization center matrix.

Step 9: According to the optimization center, the optimization process is segmented, and the segmentation result of the optimization process is given out.

4. Experiment analysis

4.1. Algorithm performance test

In this paper, when the nonlinear function approximation performance experiment is carried out, the function shown in formula. (20) is used as the objective function.

$$y = \sin(\pi x/3) + 3 \times e(1 - x^2) \times \sin(x^2) \tag{17}$$

Table 1. Algorithm performance test

Training function	Algorithm	Convergence time/s	Convergence steps	Mean-square error
Traingdm	Momentum BP algorithm	15.3130	5891	0.000999987
Traingda	Adaptive learning rate algorithm	13.4850	5086	0.000999145
Traingdx	Adaptive learning rate algorithm	3.7970	1175	0.000999529
Trainrp	resilient BP algorithm	4.4220	1354	0.000999917
Trainscg	SCG algorithm	1.4680	140	0.000999383
Traincgf	Fletcher-reeves algorithm	1.2970	79	0.000984893
Traincgp	Polak-Ribiere algorithm	1.3750	88	0.000993376
Traincgb	Powell-Beale algorithm	1.2030	63	0.000985458
Trainoss	One-step secant algorithm	1.6090	150	0.000998862
Trainbfg	BFGS algorithm	1.1090	45	0.000878124
Trainlm	Present algorithm	0.8280	6	0.000389785

By comparing several typical improved neural network algorithms, the results are shown in Table 1. The error criterion is: the target error mse (mean square error) is calculated as shown in formula (18):

$$mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 \,. \tag{18}$$

Through experiments, it is shown that the convergence speed of this algorithm is usually the fastest and the precision is higher for function approximation network with hundreds of weights. The less mean square error compared with other improved neural network algorithm can be obtained by using the trainlm training function, but this algorithm needs more memory space than other algorithms. So this algorithm is not suitable for large scale network. When the elastic neural network algorithm is used for function approximation, the approximation performance decreases with the decrease of the target error, but the storage space is relatively small. The adaptive learning rate algorithm and the momentum neural network algorithm have the slowest convergence and the storage space is relatively small. Compared with the quasi-Newton algorithm and this algorithm, the approximation performance of conjugate gradient algorithms for small and medium-sized networks are worse for function approximation. But the approximation performance of conjugate gradient algorithms for large-scale network can be compared with this algorithm. Especially when the network size is larger, the advantage of the SCG algorithm in the conjugate gradient algorithm is more obvious, and it can be the best choice. BFGS algorithm is similar to this algorithm, the storage space is smaller than that of this algorithm, but the amount of computation increases exponentially with the network size, so it is not suitable for large-scale network. The amount of memory and calculation required for one-step secant algorithm is between the gradient algorithm and BFGS.

With the trainlm training function, the changes of the error of network training process in this algorithm is shown in figure 1 when the number of hidden nodes is 19. It can be seen that after the network is initialized, only after 6 iterations, the target error is achieved. In the process of training, the target error decreases with the increase of training times, until it reaches the desired error 0.001. Based on this algorithm, nonlinear function approximation effect diagram of the neural network can be seen in figure 2.

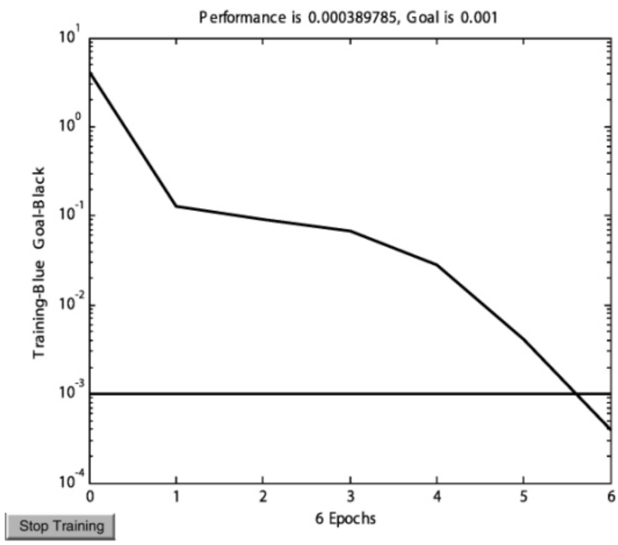

Fig. 2. Changes of the error of network training process in this algorithm

4.2. Drainage and fire protection system cost analysis

The network training curve of this algorithm is shown in figure 2. Convergence speed is quick. The actual output shown in Table 3 corresponds to the expected output of Table 2.

Using the sample 7 of Table 2 as a test sample to test the trained network, the actual output is 5058 yuan, with the difference of 6 yuan from actual cost of 5052 yuan. The error is very low, in line with actual requirements.

Table 2. Normalized training samples and expected outputs

Sample no.	Raw material grade	Steel consumption	Quality requirements	Tool consumption	Cost
Sample 1	9	6521	9	34.03	6281
Sample 2	9.4	9492	9.5	39.21	6620
Sample 3	8.7	6445	8.8	31.85	6003
Sample 4	8.4	4.68	8.5	30.64	5821
Sample 5	9.1	6783	9.2	36.21	6453
Sample 6	6	3806	6	30.36	4882
Sample 7	7.4	3817	7.3	31.25	5052

Table 3. Test output

Sample no.		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7
Cost control	This algorithm	6279	6618	6005	5823	6452	4887	5053
	BP algorithm	6293	6652	6152	5896	6521	4982	5143
	Convolutional neural network	6268	6638	6056	5864	6492	4831	5006

5. Conclusion

In this paper, a method of green public building water supply and drainage and fire protection design based on wolves convolutional neural network algorithm is proposed. The green public building water supply and drainage and fire control system model is analyzed. The convolutional neural network algorithm is introduced to optimize the green building and water supply and drainage design. At the same time, in order to improve the performance of the convolutional neural network algorithm, the parameters of this algorithm are optimized by wolves algorithm, and the optimization of water supply and drainage and fire design method of green public building is realized. The problem in this paper is: The algorithm has further optimized space for computational complexity.

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