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Design for landscape under the concept of folk art communication and green low carbon

Qing Wang[1]

Abstract. To improve the reasonability and high efficiency of garden landscape design, a low-carbon garden landscape design method based on Q reinforced differential neural network algorithm is put forward. First, an analysis is conducted in problems arising from the low-carbon garden landscape design, and an indicator system for low-carbon garden landscape design constituted by 7 elements including functional orientation and spatial arrangement etc is identified; then, the BP neural network algorithm is introduced to carry out the index prediction, and to improve performance of such neural network algorithm, the Q reinforced differential evolution algorithm instead of the original BP algorithm is adopted as a parameter optimization method for the neural network algorithm, thus achieving the performance improvement; finally, a simulation experiment is carried out, showing that the proposed method can effectively improve the index accuracy of garden landscape design and improve the design reasonability, and verifying effectiveness of such method.

Key words. Q reinforcement, Differential evolution, Neural network, BP algorithm, Garden landscape, Low carbon.

1. Introduction

Low carbon is, at present, the most popular design idea in art design. For urban garden landscape design, plant cultivation itself serves as an expression of the low carbon idea. Nowadays, the garden design in China is still facing the following problems:

1. Awareness of adaptation to local conditions is lacking in the process of garden design. Some gardens, before specific planning and design, have been endowed with natural and favorable terrain. However, most garden designers tend to neglect these original geographical/geomorphic features and cannot make a full and reasonable

[1]College of fine arts, University of Jinan, Jinan Shandong, 250022, China

use of local natural resources; on the contrary, they often complete their "imaginative" design by digging the mountain or transplanting, which not only increases the design cost but also aggravates the situation of increasing carbon emissions. 2. The building material selection is not reasonable. For garden design at present, there is trend of selecting chemical materials as the building material. However, such material, with short service cycle and poor renewability, is showing more and more disadvantages such as producing large amount of harmful gases. 3. Purposely seeking and following foreign design style, to a great extent, goes against the idea of "design originating from local". Garden design in each country has gone through a process of historical evolution, so the design style of different country and region has its own characteristics. Hence, blindly seeking for international popular elements and gathering different foreign styles into a garden with limited area will merely lead to an uncoordinated environment, as well as more resource waste and carbon emissions. 4. No significance is attached to plant selection and collocation. Relevant investigation reveals that plants of different types have different carbon sequestration capacity, so reasonable plant selection and collocation will promote the function of carbon absorption. Hence, the incorrect idea of "paving a great lawn in a garden" should be abandoned, and ground cover plants with higher ecological benefits should be selected for greening, which, being a low-carbon and economical design method, can effectively lower the cost incurred in post-stage nursing and management.

BP neural network model, which performs fairly well in its predictive function, enjoys an application potential in garden landscape planning evaluation. In this research, qualitative evaluation is combined with quantitative evaluation, and a BP neural network model with predictive function, which can effectively lower the error in evaluation for landscape planning scheme, is established to provide basis for scheme optimization.

2. Problem model description

2.1. Evaluation indicators for garden landscape planning

According to document literature, 14 key elements for garden landscape planning are screened out, and then 7 elements including function orientation, spatial arrangement, agricultural characteristics, traffic organization, scenic spots, service facilities and vegetation landscape are finalized as the evaluation indicators through investigation in the public and experts regarding their degree of attention. Evaluation indicators for garden landscape planning and their assignment standards are given in Table 1, and the evaluation criterions are: very bad: 0$\sim$2 scores; relatively bad: 2$\sim$4 scores; just so-so: 4$\sim$6 scores; good: 6$\sim$8 scores; very good: 8$\sim$10 scores.

Table 1. Evaluation indicators for garden landscape planning and their assignment standards

S/N	Evaluation indicators	Value-determined standards
1	Function orientation	Accurate function orientation, which meets the market requirements
2	Spatial arrangement	Reasonable spatial arrangement, with clear and diversified space forms
3	Agricultural characteristics	Distinct agricultural characteristics; landscape with full-bodied agricultural style
4	Traffic organization	Clear, unblocked and well-arranged traffic organization
5	Scenic spots	Reasonable landscape division, rich in attractions
6	Service facilities	Complete service facilities, which meet the requirement for garden development
7	Vegetation landscape	Rich vegetation landscape, with diversified species and communities
8	Impression evaluation	Subjective evaluation of experts according to experience

2.2. BP neural network model

BP network is a mathematic equation used to learn and store lots of input-output mode mapping relationship without prior description of such relationship. Topological structure of BP neural network model includes the input layer, hidden layer and output layer, as is shown in Fig. 1. Learning process of BP algorithm can be divided into forward propagation and back propagation. In the process of forward propagation, the information is propagated from the input layer to hidden layer, and then to the output layer. If the output layer fails to receive the expected output results, back propagation will be carried out, during which the error signal returns along the original propagation routine. The model weight adjustment adopts the learning algorithm of back propagation, and the network model adopts three-layer BP network, in which the input layer includes 7 nodes, namely function orientation, spatial arrangement, agricultural characteristics, traffic organization, scenic spots, service facilities and vegetation landscape. After calculation and adjustment, there are neurons in the hidden layer and one node in the output layer. For the purpose of impression evaluation, Sigmoid is adopted as the conversion function and the maximum training parameter is set as 9000, with training objectives of error less than 0.001, as well as a learning efficiency of 0.16 and a momentum factor of 0.7; other parameters all adopt the default value. The analysis is carried out under the help of DPS software.

However, BP neural network algorithm also has its problem in performance, namely local extremum optimization. In this paper, an optimization algorithm is proposed to replace the BP learning algorithm, and an improvement in such optimization algorithm is carried out to improve prediction performance of the neural network algorithm. Here, differential evolution algorithm is selected as the optimization algorithm.

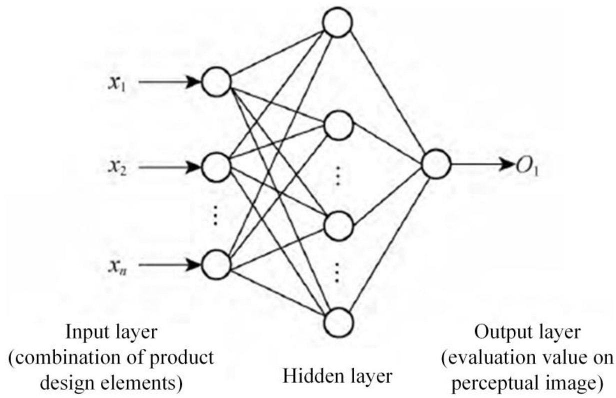

Fig. 1. Structure of neural network model

3. Q learning theory and DE algorithm

3.1. Q learning theory

Q learning is a kind of reinforced learning method, in which the environmental state change through a certain operation endows the operation with corresponding rewards (or punishment), thus pushing forward the operation towards a clear target direction. In practical application, it is difficult, under the state of s, to predict the rewards at s' in the future. In Q learning, merely the optimal action rewards are taken into consideration.

Select $S = \{s_1, \cdots, s_n\}$ as a state set of the agent under the given environment; $A = \{a_1, \cdots, a_n\}$ as the set of actions optional for the agent under the state of $s_i \in S$; $r(s_i, a_j)$ as immediate rewards for action a_j of the agent under the state of s_i; $\delta(s_i, a_j)$ as a transition function for action a_j of the agent under the state of s_i; γ as a discount factor for punishment on future reward delay, $\gamma \in [0, 1]$; $Q(s_i, a_j)$ as the overall rewards for action a_j of the agent under the stage of s_i. In this way, $Q(s, a)$ can be expressed as [11]:

$$\begin{aligned} Q(s,a) &= r(s,a) + \gamma \overset{*}{V} Q(\delta(s,a)) \\ &= r(s,a) + \gamma \max_{a'} Q(\delta(s,a), a') \,. \end{aligned} \tag{1}$$

In the formula, $\overset{*}{V}$ represents overall rewards obtained by the agent under the state of s.

A differential improvement method for Q learning algorithm is given below:

$$\begin{aligned} Q(s,a) \leftarrow & (1-\alpha) Q(s,a) + \\ & \alpha \times \left(r(s,a) + \gamma \max_{a'} Q(\delta(s,a), a') \right) \,. \end{aligned} \tag{2}$$

In the formula above, the main purpose is to achieve a progressive increase in Q-value of $Q(s,a)$ when action a is towards $\delta(s,a)$, thus ensuring a next action reward $r(s,a)$ greater than $Q(s,a)$ and an evolution towards an optimal direction. When $\alpha = 0$, it represents a suspension of the learning process, and $\alpha = 1$ represents that the agent merely considers the latest information. The discount factor γ determines the significance of future information; $\gamma = 0$ represents that the algorithm merely values the current rewards, while $\gamma = 1$ indicates that the algorithm focuses on higher long-term rewards.

3.2. Differential evolution algorithm

The DE algorithm, characterized by simple structure, quick convergence and high accuracy, enjoys extensive application. Assume that there are NP population vectors in the DE algorithm, the Gth population can be expressed as [8]:

$$P_G = \{\mathbf{X}_1(G), \mathbf{X}_2(G), \cdots, \mathbf{X}_{NP}(G)\} \tag{3}$$

In the formula, $\mathbf{X}_i(G)$, $i \in 1, \cdots, NP$ represents the population individual. The DE algorithm can be implemented through the following steps [9]:

Step 1 (initialization): For the $G = 0$th population, its individual $X_i(0)$ can be achieved through a uniform random action within the value range of $[X_{\min}, X_{\max}]$, in which:

$$\begin{cases} X_{\min} = \{x_{\min-1}, \cdots, x_{\min-D}\}, \\ X_{\max} = \{x_{\max-1}, \cdots, x_{\max-D}\}. \end{cases} \tag{4}$$

In the formula, D serves as the DE population dimension. Hence, the jth element of the $G = 0$th population individual i can be initialized by using the following formula:

$$x_{ij}(0) = x_{\min-j} + rand_{ij}(0,1) \times (x_{\max-j} - x_{\min-j}). \tag{5}$$

In the formula, $rand_{ij}(0,1)$, as a uniform distribution function in the interval $[0,1]$, can randomly initialize the crossover frequency probability in such interval.

Step 2 (variation): for standard DE variation, 2 population individuals ($\mathbf{X}_{rand-1}(G)$, $\mathbf{X}_{rand-2}(G)$) are randomly selected to produce new individual $\mathbf{V}_i(G)$ through vector superposition with the target individual $\mathbf{X}_i(G)$, namely that:

$$\begin{aligned} V_i(G) = & \mathbf{X}_i(G) + F_1(\mathbf{X}_{best}(G) - \mathbf{X}_i(G)) \\ & + F_2(\mathbf{X}_{rand-1}(G) - \mathbf{X}_{rand-2}(G)) \end{aligned} \tag{6}$$

In the formula, F is the scale factor ($F \in [0,2]$). A relatively simple variation mode is selected.

Step 3 (crossover): there are, in general, two crossover mode, namely binomial crossover and exponential crossover:

Binomial crossover: crossover between the donor vector $\mathbf{V}_i(G)$ and target vector $\mathbf{X}_i(G)$ is carried out to produce the new individual $\mathbf{U}_i(G)$. Its operation form is shown below:

$$u_{ij}(G) = \begin{cases} v_{ij}(G), & if\, rand_{ij} \le Cr\; or\; j = j_{rand} \\ x_{ij}(G), & otherwise \end{cases} \tag{7}$$

Exponential crossover: an integer n is randomly selected as the starting point of target vector $\mathbf{X}_i(G)$ in the interval $[1, D]$ to indicate the start of element exchange with the donor vector $\mathbf{V}_i(G)$. In the interval $[1, D]$, at the same time, another integer L is selected as number of elements contributed by the donor vector to the new individual vector. In this way, the exponential crossover can be expressed as:

$$u_{ij}(G) = \begin{cases} v_{ij}(G), & for\, j = \langle n \rangle_D, \cdots, \langle n + L - 1 \rangle_D \\ x_{ij}(G), & otherwise \end{cases} \tag{8}$$

In the formula, $\langle \cdot \rangle_D$ represents modular function of the modulus D.

Step 4 (selection): for minimization of the given target function $f(x)$, optimal selection mode in the DE algorithm can be expressed as:

$$\mathbf{X}_i(G+1) = \begin{cases} \mathbf{U}_i(G), & if\; f(\mathbf{U}_i(G)) \le f(\mathbf{X}_i(G)) \\ \mathbf{X}_i(G), & if\; f(\mathbf{U}_i(G)) > f(\mathbf{X}_i(G)) \end{cases} \tag{9}$$

4. Neural network parameter learning based on QDEMA algorithm

In the QDEMA algorithm, global optimization is achieved by Differential Evolution (DE algorithm), and local deep search by Differential Q Learning (DQL). Pseudo codes for the QDEMA algorithm are given in Table 1, and the algorithm steps are shown as follows:

Step 1 (initialization): initialize NP and population of the dimension D in the initial search range. The Q-table is initialized at relatively small numerical value. If the Q-value can reach its maximum value, namely 100, the corresponding Q-table value determined will be 1;

Step 2 (parameter self-adaptation): rewards and punishment measures for Q-table are mainly used to select appropriate scale factor F. The probability of $F = F_j$ can be calculated from the following formula:

$$P(F_j) = Q(s_i, 10F_j) \Big/ \sum_{l=1}^{10} Q(s_i, 10F_l). \tag{10}$$

To maintain Q-value adaptability of each row, a random numerical value r is selected in the interval $[0,1]$ and F_j is selected to meet the following conditions:

$$7\sum_{m=1}^{j-1} P\left(F=F_m\right) < r \leq \sum_{m=1}^{j} P\left(F=F_m\right)$$
$$\Rightarrow \frac{\sum_{m=1}^{j-1} Q\left(s_i, 10F_m\right)}{\sum_{l=1}^{10} Q\left(s_i, 10F_l\right)} < 1 \leq \frac{\sum_{m=1}^{j} Q\left(s_i, 10F_m\right)}{\sum_{l=1}^{10} Q\left(s_i, 10F_l\right)}\,. \tag{11}$$

Step 3 (DE operation): carry out the individual ranking and state assignment by using the DE algorithm, determine f_i as the newest target value of individual i, and then carry out normalization in f_i $\left(f_i \middle/ \sum_{j=1}^{NP} f_i\right)$; then implement the descending ranking, thus obtaining a ranking table graded as r, with a state of s_r; and finally repeat these steps in $r = 1 : NP$.

Step 4 (Q-table updating): if the individual s_i with a state of s_i, after executing the operation F_j, turns into a state of s_k, its target adaptive value will be increased. Hence, the positive reward formula for updating $Q\left(s_i, 10F_j\right)$ can be expressed as:

$$\begin{aligned} Q\left(s_i, 10F_j\right) = &\left(1-\alpha\right) Q\left(s_i, 10F_j\right) \\ &+ \alpha\left(reward\left(s_i, 10F_j\right) + \gamma \max_{F'}\left(s_k, 10F'\right)\right)\,. \end{aligned} \tag{12}$$

Or $Q\left(s_i, 10F_j\right)$ will adopt negative reward $-K$ for updating.

Step 5 (judgment in convergence): repeat the step 2-4 until the following conditions are satisfied: reach the limit for termination of iteration or meet the convergence accuracy.

5. Experimental analysis

In this research, 20 garden landscape planning schemes from a domestic city are taken as the examples, and 5 experts in landscape planning & design are invited to carry out the scoring simulation, in which scoring is in accordance with the evaluation standards listed in Chapter 2, and the average score is set as the final assignment. The results are shown in Table 2.

Table 3 shows the assignment results for garden landscape planning scheme in a domestic city which adopts the BP neural network algorithm and method proposed in this paper. It indicates that the model adopting the BP neural network algorithm and method proposed in this paper can more accurately fit the original data, and predicted value of the sample is very approximate to the actual value. However, method proposed in this paper can achieve higher evaluation accuracy than the BP neural network algorithm. Hence, with high prediction accuracy and excellent generalization ability, such proposed method, after appropriate setting, can be applied to scheme evaluation for garden landscape planning.

Table 2. Assignment for garden landscape planning scheme in a domestic city

Scheme No.	Function orientation	Spatial arrangement	Agricultural characteristics	Traffic organization	Scenic spots	Service facilities	Vegetation landscape	Impression evaluation
1	5.6	7.8	9.2	7.8	8.7	7.8	7.8	8.7
2	9.1	9.5	7.8	8.6	7.4	8.6	8.9	6.4
3	8.3	9.2	8.6	8.3	9.2	8.6	9.6	9.2
4	7.6	6.4	5.8	7.6	6.4	5.8	6.2	7.9
5	8.9	9.2	8.9	9.2	8.7	9.4	5.2	9.1
6	9.6	7.9	9.6	6.4	6.3	8.2	6.3	8.3
7	9.0	9.3	6.2	5.9	8.2	7.9	8.2	9.3
8	6.3	8.0	7.4	8.7	4.9	6.4	7.2	8.0
9	7.8	8.7	4.8	8.9	9.2	4.9	2.6	8.9
10	8.6	7.4	8.6	9.6	8.3	9.2	8.6	9.6
11	9.4	5.2	9.1	6.2	4.9	8.9	8.9	9.2
12	8.2	6.3	8.3	9.0	9.3	6.2	9.6	7.9
13	7.9	8.2	5.4	6.3	8.0	7.4	8.0	8.9
14	9.2	4.9	2.6	8.3	9.2	8.6	8.7	9.6
15	6.4	7.2	8.4	7.6	6.4	9.1	9.2	4.9
16	5.9	4.9	1.9	7.9	8.2	5.4	6.4	7.2
17	9.0	5.1	8.3	9.6	7.9	9.6	5.9	4.9
18	8.7	6.2	6.5	9.0	5.1	8.3	5.1	8.3
19	7.4	6.7	9.3	9.0	9.3	6.5	6.2	6.5
20	8.5	7.6	4.8	7.2	8.4	9.0	5.1	8.3

Table 3. Evaluation results of garden landscape planning scheme in a domestic city

Scheme No.	Original value	Predicted value by method proposed in this paper	Predicted value by BP	Scheme No.	Original value	Predicted value	Error (%)
1	7.6	7.5	7.2	11	9.0	9.2	9.4
2	9.2	9.0	9.3	12	8.1	8.0	8.5
3	8.4	8.3	8.7	13	6.7	6.8	6.2
4	8.8	8.6	8.4	14	8.8	8.7	8.4
5	9.0	9.1	9.3	15	6.9	6.7	6.7
6	9.5	9.3	9.2	16	7.5	7.6	7.3
7	8.4	8.5	8.7	17	9.4	9.2	9.0
8	7.4	7.6	7.6	18	8.6	8.7	8.2
9	7.0	7.2	7.5	19	7.8	7.7	7.6
10	8.7	8.8	8.6	20	8.2	8.4	8.5

There is a complicated non-linear relationship among function orientation, spatial arrangement, agricultural characteristics, traffic organization, scenic spots, service facilities, vegetation landscape and comprehensive quality of urban gardens. In such model, total score of a scheme can be obtained by inputting the expert's evaluation scores in each indicator, which overcomes the randomness, subjective uncertainty and cognitive fuzziness of manual evaluation, and, at the same time, ensures objectivity and accuracy of the evaluation results. Since there is a big difference in the experts' knowledge background and experience, which may affect accuracy of the prediction results, the number of experts should be increased to lower the potential error, thus ensuring accuracy of the original data. At the same time, massive and reliable samples are also a fundamental guarantee for prediction accuracy. In this research, the demonstration part is mainly aiming at the scheme for garden landscape planning in a certain city; in the future research, the sample size should be enlarged to improve the evaluation accuracy. With regard to the method proposed in this paper and the BP neural network algorithm, scientificity of the indicator system and accuracy of the evaluation standards, as well as neglecting important factors, will have a significant impact on the evaluation results. Hence, further research shall be necessary for such problems.

6. Conclusion

In this paper, a low-carbon garden landscape design method based on Q reinforced differential neural network algorithm is put forward, and an indicator system for low-carbon garden landscape design constituted by 7 elements including functional orientation and spatial arrangement etc is established; and then such proposed method is used to achieve optimization design of the indicator system. The experimental results show that the proposed method can achieve higher design accuracy and design reasonability. Emphasis for next research: (1) further improvement in the indicator system for low-carbon garden landscape design; (2) further improvement in performance of the prediction algorithm; (3) joint development with the design system.

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