Optimal application of multi-agent environmental decision-making model in the replication and relocation of traditional villages in areas prone to geological hazards--- taking wengcao village, a traditional village in Guzhang county, western Hunan as an example

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Abstract. Wengcao Village, listed in the fourth batch of traditional villages in China, is a remote Miao village which built in a landslide-prone risk, and always at the risk of geological hazard-prone area. In order to solve the contradiction between the protection of traditional villages and the economic development of traditional villages, on the basis of environmental behavior, spatial behavior and complex theory, the author combined with the investigation. For the first time, a four-dimensional collaboration model of expert supervision, enterprise leadership, government guidance, and public participation was creatively proposed to ensure the replication and relocation of traditional villages. Aim to ensure the smooth progress of the replication and construction of traditional villages, the current popular neural network prediction model and reinforcement learning multi-agent model are combined to build a replication and construction decision model and its optimize to avoid possible future risks.

1. Introduction
In a certain area, population density is regulated naturally and consciously through the natural reproduction of the population[1]. This reproduction is restricted and regulated by two main factors: renewable land resources and population density. The concept of density limitation was originally
used to describe the self-regulation of biological populations [2], and was also used to explain the imbalance of resources caused by high-density or low-density human living environments. In this study, the concept of density limitation is used to describe the density of traditional villages in western Hunan. In addition, the lack of reasonable functional division of traditional villages, low travel efficiency and high labor costs are some of the most important reasons for poverty in these areas. According to this principle, the "three living spaces" proposed by the 18th National Congress of the Communist Party of China focuses on "building intensive and efficient production spaces [3], livable spaces and beautiful ecological spaces". For the Land and Resources Planning Bureau, the "Sansheng" space is not only paper works and murals, but also must be implemented, which is a more specific method of using traditional villages as a metaphor for implementation.

Wengcao Temple Village, located in Guzhang County, western Hunan, is one of the fourth batch of traditional villages in China, because the residents of the village have built a unique wooden residential structure [4]. The houses in the village are all built on the hillside, showing a unique style of wooden stilts. A certain number of wooden houses are arranged in an amazing way (Figure 1, 2). Due to the lack of land resources suitable for building houses, some villagers began to occupy cultivated land to build houses (Figure 3, 4), and some people cut down hillsides to build flat construction sites.

The construction area of the village is located in several debris flows and landslide areas, which is obviously not conducive to the long-term development of traditional villages. Recent news reports indicate that Sichuan, Guizhou and other mountain villages have suffered many casualties due to landslides and mudslides. Therefore, mountain villages established in areas with frequent geological disasters should be relocated as soon as possible to avoid greater losses. After field investigations, the principles and practical experience of design, hydrology, geology, landscape ecology, environmental science and engineering, and other multidisciplinary and interdisciplinary disciplines were analyzed and compared.

Over the years, the impact of modern civilization on Wengcao Village has prominently exposed rural economic development and environmental protection issues. Due to inconvenient transportation, lack of clinics, schools, roads and other infrastructure, and weak industrial structure, most villagers with low education level went to other places to make a living. After verification by many parties, we formulated the original relocation design plan of the village. As follows: The open space in the
southwest of the village is suitable for replication and reconstruction. Traditional villages (see Figure 5, 6) "Planning for replication and migration in different places"). This method of replication and reconstruction can also be called "off-site" relocation. Although this method is a migration, its strategic constraints and migration costs are completely different. This "off-site" location is only a few hundred meters from the original village.

![Figure 5. Plan for relocation and reproduction in different places (the revision comes from the design drawing of Design Institute of Hunan University).](image)

![Figure 6. Geographical coordinates of wengcao Village.](image)

From the perspective of the government and villagers, building a beautiful village may be desirable; or, planners may prefer to use the principles of urban planning to perform rural planning and other tasks. However, there are few documents that integrate government, enterprises, villagers and external talents (university intellectuals). In view of this reality, we have proposed a multi-dimensional cooperation model of expert supervision, corporate leadership, government guidance and public participation. In China, agricultural modernization, rural urbanization, and the realization of farmers’ rich lives are the same historical process [5]. In this process, the level of rural design, planning and construction is very important. By building modern livable villages, farmers in these villages can directly experience the benefits and convenience brought by modern civilization, cultivate modern professional agricultural awareness, improve the quality of modern tasks and products, promote economic development, narrow the gap between urban and rural areas, promote large, medium, Coordinated development of small cities, modern towns and traditional villages.

Through further comparison and analysis of these reconstructed and transformed villages, we have concluded that every successful village has a farsighted plan. Therefore, when we consider the relocation of poor villages, we should first advance the planning time, and create a plan that is 30 or even 50 years in scope.
2. The series of theories used in this article are as follows:

2.1. Complex adaptive system theory
Complex adaptive systems (CAS theory) can explain some of the characteristics and interaction mechanisms among the four dimensions of expert supervision, business leadership, government guidance, and public participation. Mainland scholar Qian Xuesen proposed a complex giant system theory, pointing out that the real world is a complex giant system [6]. Tang Yuanqiang introduced Mr. Qian Xuesen's "giant system theory" in detail in the paper [7].

2.2. Space environment behavior
The continued sustainability of the interaction between the subject and the environment eventually becomes an adaptation. We believe that people's adaptive adjustments to the environment are reflected where the subject's behavior occurs.

2.3. Proposal of four-dimensional interactive decision-making mechanism

2.3.1. Supervision of university experts and professors of village planning and construction. Mr. Wen Tiejun believes that rural issues need to be addressed with an upgraded version of agriculture. Geng Haiqing believes that the breadth and depth of public participation in decision-making must be increased to promote the level of decision-making institutionalization [8]. As a third party, professors and experts in relevant fields of universities have natural early warning capabilities. At a micro level, the architect's feelings are reflected in the construction of local buildings and the protection of local culture [9]. There are many outstanding works of classic country abroad that are completed on the basis of cooperation of many parties [10].

2.3.2. Rural construction enterprises with family and country feelings
A. Rural construction enterprises
In this paper, the enterprises supporting rural construction are collectively referred to as ‘rural construction enterprises’. They usually support agriculture with the model of urban enterprises feeding agriculture back [11-13]. The external manifestation is to absorb the employment of rural rich labour, purchase agricultural products or invest in agriculture. With the continuous improvement of the construction of rural infrastructure, the degree of rural industrialisation increases, which lays a solid material foundation for urban enterprises to invest in agriculture-related industries and win rich profits.

B. Rural enterprises and rural elites
Rural enterprises also belong to rural non-governmental organisations. They have the characteristics of rural economic cooperation and provide high-quality social services and public welfare culture for rural construction. The rural elites usually refer to the groups who have been wandering, have insight and courage and are willing to help change the rural appearance.

C. Third-party agricultural organisations
Third-party agricultural organisations usually refer to the relevant organisations, groups and institutions that give full play to the forces other than the government and enterprises to support rural construction. Relying on the unique functions of diversified organisations, groups and institutions, we can provide various forms of agricultural assistance to meet the needs of different levels of agriculture, rural areas and farmers. Due to the complexity of the actual situation, the specific and technical contents of rural construction assistance are quite different.

2.4. Government with modern service consciousness and concept as a guide
An enlightened and visionary service-oriented government will certainly support the relocation of ecologically fragile villages in underdeveloped areas.
2.5. Villager participation in village reproduction, reconstruction and assistance

The elite plays an irreplaceable role in the formation of national strategy or rural governance, but the wrong elite decision-making model will lead to irreversible serious consequences. For example, the "deforestation, reclamation and steel smelting" policy implemented in the 1950s led to serious ecological damage. Therefore, as a copy and relocation project beneficial to traditional villages, the participation of villagers is an important guarantee for completing the project according to quality and quantity.

3. Model construction and discussion

A multi-agent learning mechanism is an important means to control and make decisions in a complex system. In reality, almost all systems or models must learn or train themselves according to the input samples before practical application; subsequently, a system or model can thus remember or become familiarized with trained input patterns and then test and evaluate the unknown sample patterns. Therefore, learning algorithms is regarded as an important part of computing technology. In 1944, Hebb proposed the Hebb rule to change the connection strength of neurons, and the "learning algorithm" concept appeared for the first time. Recently, Ni Jianjun and Ren Li of Hehai University have demonstrated several agent applications [14] [15]. The main learning algorithms are the neural network learning algorithm, reinforcement learning algorithm, and so on.

3.1. Model construction

3.1.1. Illustrating agent functions

![General Framework of Agent Reinforcement Learning](image)

In the standard agent learning algorithm with the frame in the above Figure 7, the agent is mainly composed of three modules: state sensor (P), learner (L), and action selector (c): a state sensor (P) mainly denotes the agent's mastery of the social environment and natural environment, and K is the specific domain knowledge. The specific understanding of the environment or its agent can be expressed by the following formula 1:

$$P = (x_1, x_2, x_3, ..., x_n)(n > 1)$$  \[1\]

The status value sets is set to $S = \{s_1, s_2, ..., s_m\}$, and the action sets is set to $A = \{a_1, a_2, ..., a_k\}$. Each time $t$, the agent selects an action according to the policy and observes its reward $r_t$. The agent updates its Q value according to the following formula: $Q^*(s, a) = Q^*(s, a) + \alpha [r + \gamma \max Q^*(s', b)]$. Where $\alpha (0,1)$ is the learning rate, $\gamma (0,1)$ is the discount factor, $s$ and $a$ is the state and action of the agent at time $t$, respectively. $s'$ is the state of the agent at time $t + 1$, and $b$ is all the actions taken by the agent at time $s'$. The $Q^*$ reinforcement learning formula is as follows:

$$Q^*(s, \alpha) = R(s, \alpha) + \gamma \sum T(s, a, s') \max \{Q^*(s', \alpha') | s < S, \alpha < A\}$$  \[2\]

3.1.2. Multi-agent integration algorithm (The Bagging algorithm is used in this paper). The diversity of individual networks in integrated learning directly affects the integrated learning model. If the
The learning effect of each individual is the same, regardless of the integration strategy chosen, the generalization ability of the integration model cannot be improved, and the significance of integration does not exist. To improve the learning accuracy of individuals, different data sets (as shown in Figure 8) are usually used to train different individual networks and thus maximize the differences between individual learners. The common methods are: network structure adjustments, objective function adjustments, and changes in the number of neurons in the hidden layer to build a subdivided individual network, which are needed to obtain a larger decision-making integrated individual of a neural network.

The integration algorithm represented by Bagging is suitable for the four-dimensional interaction model, and each independent training set can be randomly selected. Because each individual network has no weight and can be trained in parallel, this algorithm can save time as shown in Figure 9.

3.1.3. Evaluation and Section of Decision-making Scheme. A better scheme is the integration evaluation sets which composed by each dimension in the Four-dimensions Co-operational System (as shown in Figure 10). In the multi-agent decision-making optimization model, it is not only to divide the classification accuracy of the integrated network composed of two or four individuals locally or globally, but also to ensure the individual differences in the decision-making network. Hence, the individual independent classification accuracy within the decision-making network will affect the evaluation and selection of the decision-making planning, and the individual differences are shown in formula 3:

$$A_{\alpha}(P_{i}) = \frac{N_{\alpha}(P_{i})}{N_{i}} \tag{3}$$

In the formula, the algorithm contains the number of individual samples $N_{\alpha}(P_{i})$ as hidden layer nodes $P_{i}$ (a neural network can correctly divide all training sets into two categories), and $N_{i}$ also contains the number of all training samples.

In general, a multi-objective function is used to evaluate the adaptability of a single individual to avoid any deviation caused by a single evaluation index. This method ensures the diversity of decision-making dimensions. To avoid consistency in the evaluation results due to the same evaluation set being used for individual classification accuracy and integrated classification accuracy, which can potentially reduce the correlation between two evaluation indexes, the classification accuracy of multidimensional individuals is arranged from large to small; the objective function of the fitness value can be expressed as formula 4:

$$f_{1}(P_{i}) = \alpha(1-\alpha)^{i_{1}(P_{i})} \tag{4}$$

Where, $i_{1}(P_{i})$ is the correct classification rate of the individual $P_{i}$ on the training set. The classification rate of the single dimension of the decision is arranged in order from large to small, $\alpha \in (0,1)$ and $\alpha = 0.5$.

The integrated classification accuracy is mainly used to evaluate the classification performance of the whole decision network, which generally occurs using the conclusion method of the algorithm. By
using this method, we can reduce the impact of a small output on the determination of the sample category. At the same time, we can sum the response output of each dimension by category, and finally decide the category that has the largest response; then, we can divide the sample into this category. If the output of each individual network is less than the threshold sample, then we may sum the original output values of all individuals and use the maximum value to identify their categories.

Thus, the accuracy of the integrated classification of the single dimension $r_i^j$, which corresponding to the decision is obtained, as shown in formula 5:

$$A_r(P_i^j) = \frac{N_r(\Theta^j_i)}{N_r}$$  (5)

Where, $N_r$ is the number of samples in the evaluation set, and $N_r(\Theta^j_i)$ is the number of correctly classified evaluation samples. The classification accuracy $f_2(P_i^j)$ of the integration on the evaluation set $\Theta^j_i$ obtained from a certain decision dimension $L$ is the sequence number $t_2(P_i^j)$ from the largest to the smallest. The modified adaptive function value is shown in formula 6:

$$f_2(P_i^j) = \alpha(1 - \alpha)t_2(P_i^j)$$  (6)

Independent classification of individual network differences. In the multi-agent co-evolutionary learning algorithm based on a neural network, in addition to calculating the accuracy of the classifier and subdividing the differences of individual networks, the individual networks with large differences should be preserved. This also means that in the four-dimensional collaborative decision-making model mentioned previously, when there is a large divergence of views, the most divergent views will be retained to formulate the best optimization for the final decision. At this moment, the differential evaluation index of fine-tuning adaptability evaluation should be introduced. In other words, an integrated differentiation is used to calculate the differences in output vectors of individual networks. In this paper, Yao and Chandra's PFC method (Pairwise Failure Credit) is used to evaluate the difference [16] as shown in formula 7:

$$f_3(P_i^j) = \frac{\sum_{j=1,2} \sum_{M-i}^M h_{ij}^j}{M - 1}$$  (7)

In the formula, $h_{ij}^j$ is the Hemingway distance, which is characterized by the difference between the two networks, and $f_3$ is the evaluation index of the difference between individual networks. The local optimal value is replaced by the fitness value of individual network $r_i^j$, and the integrated performance of neural network is formed to confirm finally. The specific values are the union of several objective function values, as follows 8:

$$\forall \in[f_1(P_i^j)f_2(P_i^j)f_3(P_i^j)]$$  (8)

3.1.4. Decision optimization evaluation strategy of multi-objective fitness. The strategy adopted in this section is the Pareto optimal evaluation of individual multi-objective fitness. The algorithm adopts the League selection strategy, calculates the crowding distance of individual fitness, adopts a crowding strategy, and maintains the diversity of individual population; at the same time, the algorithm also adopts an elite retention strategy.

3.2. Algorithm and pseudo code

3.2.1. Algorithm of Individual Agent

% The single Agent-Q-learning algorithm
Initialize $\Theta(s, a)$ arbitrarily
for all episode do
    Initialize $s$.

```matlab
% The single Agent-Q-learning algorithm
Initialize $\Theta(s, a)$ arbitrarily
for all episode do
    Initialize $s$.
```
A. Overall steps of the multi-agent learning algorithm based on convolution:

Step 1. The DRSC algorithm is used to determine the initial structure of the neural network, the sample distribution is used to determine the width of the radial basis, and then bootstrap sampling is used to obtain t training subsets. DRSC is used to determine the initial structure of the neural network on each subset. As the initial local optimal strategy \( \Theta^* = \{ P_1^*, P_2^*, ..., P_t^* \} \) is set for each single dimension decision pool, decision factors \( L \) are randomly generated as the initial group, and the maximum evolution algebra is set as \( G_c \); the current algebra is \( g_c = 1 \).

Step 2. The optimal value of each decision scheme in each decision dimension (called an individual fitness value in a neural network) is calculated, and the elitist retention strategy (local optimal decision scheme) is adopted. In this case, if \( f_i t_i^* > f_i t_i \) in the individual network (also referred to as the local optimal strategy in a single decision dimension) will update the elite set \( \Theta^* = \Theta_i^* = \{ P_1^*, P_2^*, ..., P_t^* \} \) and its adaptive value.

Step 3. According to the Pareto optimal selection strategy, each sub network generates a new individual \( L \) (which can be understood as the local optimal decision scheme after the continuous optimization of the decision dimension).

Step 4. Using the two-point crossover genetic algorithm, each random number \( r_i^l \) is generated by a certain individual (there will be different schemes in each dimension). If the crossover rate is greater than the randomly generated number, then the first individual \( l \) is selected in the sub network for the crossover operation, and the point location is selected randomly.

Step 5. Mutation operators are used to perform mutation operations on individuals in subnet works.

Step 6. If \( g < G_c \) and the termination condition of \( g = g + 1 \) is not met, return to step 2; otherwise move to step 7.

Step 7. Select the final elite set \( \Theta^* = \{ P_1^*, P_2^*, ..., P_t^* \} \) as the final neural network integration (specifically, from the local optimal scheme to the global optimal scheme).

B. Pseudo Code of Algorithm: modify Co-NNF Conclusion Generation Method (HOC) [17]

Input: output matrix of each individual network for a certain evaluation sample \( y_i \)

\( y_i = (y_{i1}, y_{i2}, ..., y_{in})^T \quad i=1,2,3,...,M \)

1. For \( i = 1 \) to \( M \) {
2. \( y_i^F = (y_{i1}^F, y_{i2}^F, ..., y_{in}^F)^T \) (search for the components in individual network output \( \preceq \varepsilon \) )
3. If \( y_i^F = 0 \), then
4. \( y_i^F = (y_{i1}^F, y_{i2}^F, ..., y_{in}^F) \) (selecting output components in individual network \( \preceq \varepsilon \) )
5. \( y_i^F = 0 \) (will output component if \( \varepsilon = 0 \), and only if \( \varepsilon \) )
6. \( y_i' = y_i^F \) (merge the above two sets)
7. Otherwise \( y_i' = y_i \)
8. }
9. \( s_i = (s_{i1}, s_{i2}, ..., s_{in})^T = \sum y_i', \quad i=1,2,3,...,M \) (sum the output vectors of all individual networks in the network)
10 \ maxs = \max(\mathbf{\hat{s}}_1, \mathbf{\hat{s}}_2, \ldots, \mathbf{\hat{s}}_M). \text{ If } \maxs = 0, \text{ in other words, all individual networks will go to step } 11 \text{ for the output components of the sample } \mathbf{\alpha} = \mathbf{\hat{s}}; \text{ otherwise, } \mathbf{cl} = \arg\max(\mathbf{\hat{s}}_1, \mathbf{\hat{s}}_2, \ldots, \mathbf{\hat{s}}_M), \text{ go to step } 13.

11 \ S = \sum_{i=1}^{M}(\mathbf{\hat{s}}_i) = \sum_{i=1}^{M}(\mathbf{\hat{s}}_1) (\text{sum the initial network output vectors by superposition})

12 \ \mathbf{cl} = \arg\max(\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_M)

13 \ Identification and determination of sample \mathbf{cl} \ class.

Output: \mathbf{cl}

3.3. Discussion

The basic principle of reinforcement learning is that if the actor's behavior receives a positive reward (reinforcement signal) from the environment, the actor's future trend of action will be strengthened. On the contrary, the action trend of the agent will be weakened. It also has the best application in actual complex system decision-making. The combination of reinforcement learning methods and neural network collaborative algorithms has different assumptions and results for different researchers and research purposes. This quaternary interactive decision-making mechanism should state that at least two decision makers are jointly responsible.

Usually, multi-dimensional interactive decision-making mechanism can solve complex unstructured problems. The decision result should conform to the principle of Pareto optimality. The quality of decision-making is affected by the different decision dimensions, the relationship between decision-making groups and the decision rules adopted by the multi-dimensional interaction mechanism.

4. Conclusions

Through the construction and optimization of the multi-agent model, the decision simulates the whole process of village relocation. The results show that it is feasible to retain the old village and the relocated village. The meaning is as follows:

Prevented geological disasters such as large and small landslides, and avoided the potential risk of villagers continuing to dig hillsides to build houses on open soil

The old traditional villages will continue to retain their original characteristics and attract domestic and foreign tourists to visit and experience village life.

The new traditional villages will be copied because they are not prone to geological disasters and are more suitable for people in the village.

Establish a multi-agent decision-making model of operational reinforcement learning to jointly promote the construction of traditional villages. The model can be used as a basis for the reform, expansion and relocation of traditional villages in other places.

This study can provide a reference for the planning and construction of other non-traditional villages.

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Conflicts of Interest

The authors declare no conflicts of interest.
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