Planning and Design of Elderly Care Space Combining PER and Dueling DQN

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***Abstract*—With the continuous development of the aging phenomenon in society, people's attention to the planning of elderly care spaces is increasing. Currently, many scholars have used various spatial planning models to plan and design elderly care spaces. However, the resource utilization rate and comfort of the elderly care spaces designed by these models are low, and the models still need to be optimized. This study first integrates the Prioritized Experience Replay mechanism with the Dueling deep Q-network algorithm, and constructs a spatial planning model based on the fused algorithm, to use this model to plan elderly care spaces reasonably. The study first conducts comparative experiments on the fusion algorithm, and the outcomes indicate that the fusion algorithm has the best prediction performance, with a minimum prediction error rate of only 0.9% and a prediction speed of up to 8.7bps. In addition, the denoising effect of the algorithm is the best, and the performance of the algorithm is much higher than that of the comparative algorithm. Further analysis of the spatial planning model based on this algorithm shows that the average time required for elderly care space planning is only 1.3 seconds, and the comfort level of the planned elderly care space reaches 98.7%, the resource utilization rate reaches 89.7%, and the planned elderly care space can raise the living standard of the elderly by 67.7%. From the above information, the spatial planning model raised in the study can validly enhance the resource utilization and comfort of elderly care spaces, and raise the living standard of the elderly.**

Keywords*—Elderly care space; planning and design; prioritized experience replay; dueling deep q-network algorithm; spatial planning

I. INTRODUCTION

With the continuous aggravation of the aging problem in society, the attention to the rationalization of elderly care space planning and design is constantly increasing [1]. Reasonable planning and design of elderly care spaces can create a comfortable, safe, and natural living environment for the elderly, improving their quality of life. In addition, it can also provide sufficient outdoor activity space for the elderly, promoting physical and mental health [2]. With the sustained growth of computer technology, numerous scholars have conducted research on spatial planning and design methods using intelligent algorithms and physical models [3-4]. However, these spatial planning and design methods still have problems such as slow spatial planning speed and low utilization of spatial resources, and optimization of planning models is needed. The Dueling Deep Q-Network (Dueling DQN) algorithm can improve its learning efficiency through Q-values, thereby accelerating spatial planning speed. The Prioritized Experience Replay (PER) mechanism can accelerate the convergence speed of the algorithm through its priority sampling method. In order to improve the spatial planning speed of the elderly care space planning model, enhance the resource utilization rate in the elderly care space, and ensure the quality of life and mental health of the elderly, this study organically combines the PER mechanism with the Dueling DQN algorithm, and constructs an elderly care space planning and design model based on the combined PER-Dueling DQN algorithm. The innovation of this study lies in optimizing the uniform sampling in the Dueling DQN algorithm through the priority sampling technique in the PER mechanism, in order to reduce the adverse effects of uniform sampling on the calculation accuracy of the Dueling DQN algorithm. The contribution of the research lies in the fact that through reasonable planning of elderly care spaces, it can improve the quality of life of the elderly, promote equal social welfare and public services, drive the development of the elderly care industry, and better cope with population aging.

II. RELATED WORK

With the rapid development of computer technology, many scholars have conducted research on spatial planning and design methods using intelligent algorithms and mathematical models. For example, Gu Y et al. raised a spatial planning model grounded on the least squares parameter estimation method to plan and design the state space of the simulated product portfolio. The model was tested in practical situations, and the outcomes indicated that the spatial planning time of the model was only 3.2 seconds [5]. SS VC et al. developed a space design model grounded on metaheuristic algorithm to address the problem of high memory resource utilization in current engineering space design models. The model was compared with traditional space design models, and the results showed that the model could reduce resource utilization by 23.1% [6]. In addition, to deal with the issue of high computational complexity in diffusion grounded spatial model planning, Karras T et al. raised a spatial design model grounded on fractional network preprocessing method, which was used for detection in practical situations. The outcomes indicated that the computational complexity of this model was reduced by 12.6% compared to traditional spatial planning models [7]. However, there are still problems with slow spatial planning speed and low utilization of spatial resources in the above spatial planning models, and the model still needs to be optimized [8].

Dueling DQN algorithm is an algorithm that can improve computational efficacy and steadiness by separating state value and dominance function [9]. This algorithm is commonly applied in various models due to its ability to validly reduce the quantity of parameters and high applicability. For example, Chi

J et al. designed a deep reinforcement training model grounded on the Dueling DQN algorithm to solve the matters of slow convergence speed and low training accuracy in the deep reinforcement training process. The model was compared with traditional models, and the outcomes indicated that the convergence speed of the model was improved by 19.5% [10]. However, there are still problems with poor learning efficiency and slow convergence speed caused by the uniform sampling mechanism in this algorithm [11]. PER mechanism can improve the convergence speed and learning efficiency of algorithms by sampling based on priority [12]. This mechanism is also commonly utilized in various areas to raise the convergence speed and computational precision of models [13].

To sum up, although many researchers have carried out studies on spatial planning models, these models still suffer from slow planning speed and low utilization of spatial resources, and further improvements are needed. Therefore, this study organically combines the PER mechanism with the Dueling DQN algorithm, and constructs a retirement space planning and design model based on the combined PER Dueling DQN algorithm, to use this model to plan retirement spaces reasonably and guarantee the living standard and mental health of the elderly.

III. Methods and Materials

A. Dueling DQN Algorithm Based on Per Optimization

Elderly care space refers to a social space that provides safe, comfortable, and convenient living and living environments for the elderly [14]. The main purpose of this space is to meet the material and spiritual needs of the elderly and help them maintain physical health [15]. With the continuous development of the aging phenomenon, people's attention to elderly care space is constantly increasing. Thoughtful design and strategic planning of spaces for elderly care can guarantee financial stability for individuals as they age [16]. However, many spatial planning models currently suffer from insufficient coordination and low utilization of spatial planning resources, and further optimization of the models is needed. The Dueling DQN algorithm is an improved Q-learning algorithm that can improve learning efficiency by decomposing Q-values and effectively handle complex spatial states and decision problems [17]. The basic process of this algorithm is shown in Fig. 1.

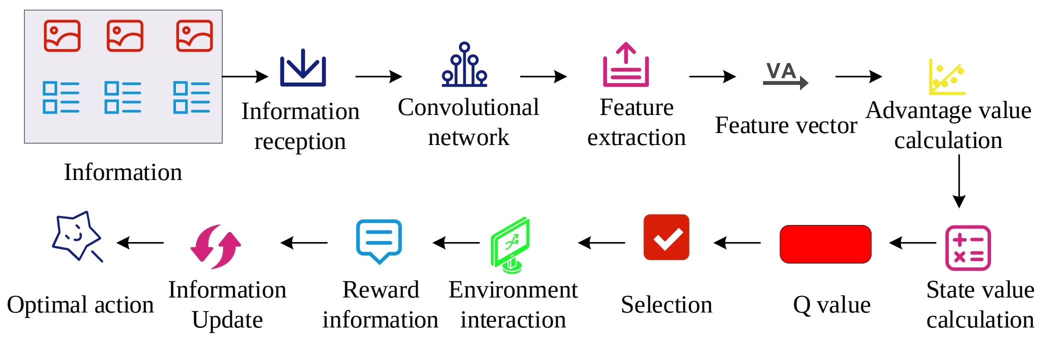


Fig. 1. Basic process of dueling DQN algorithm.

In Fig. 1, the algorithm first needs to receive input state information, which includes multiple images or chart data. Then, the convolutional network is applied to identify the features of the state information and generate feature vectors. Then, the evaluation network and target network in the dual network are used to calculate the value of state information and the advantage value of each action. The calculated state value and action advantage value are added to obtain the Q value of each action. Using the computed Q value, the best course of action is chosen, typically opting for the action with the highest Q value for implementation. After determining the execution action, it engages with its surroundings to acquire rewards and updated state data. The neural network's parameters undergo modification grounded on the obtained new state information and reward mechanism, so that the algorithm can find the optimal action execution. The calculation method of Q value is shown in Eq. (1).

$$Q(S,A,w,\alpha,\beta)= V(S,w,\alpha)+(A(S,A,w,\beta)-\frac{1}{|A|}\sum_{a\in A}A(S,\alpha,w,\beta)) \tag{1}$$

In Eq. (1), S means the information state, A means the action, w means the network parameters of the common part, α means the network parameters unique to the value function, β means the network parameters unique to the advantage function, $Q(S,A,w,\alpha,\beta)$ means the calculated Q value, $V(S,w,\alpha)$ means the value function part related to the state function, and $A(S,A,w,\beta)$ means the advantage function related to both the state and action. The calculation method of the state value function is shown in Eq. (2).

$$V(s)=f(s;\theta) \tag{2}$$

In Eq. (2), $V(s)$ means the action function in state s, f means the neural network used to calculate the state value, and θ means the parameters of the state value function used to optimize the neural network. The calculation formula for the action advantage function is shown in Eq. (3).

$$A(s,a)=Q(s,a)-V(s) \tag{3}$$

In Eq. (3), $Q(s,a)$ means the Q value of taking action a in state s, and V means the value function. When performing feature extraction operations in the convolutional layer, it is necessary to calculate the computational and parameter quantities of the convolutional layer in order to optimize the network structure and design a reasonable convolutional layer structure and parameters. The calculation method for the parameter quantity of the convolutional layer is shown in Eq. (4).

$$N = k \times k \times C_{in} \times C_{out} \quad (4)$$

In Eq. (4), N means the number of parameters in the convolutional layer, k means the size of the convolutional kernel, C_{in} means the number of input channels, and C_{out} means the number of output channels. The calculation method for the computational complexity of the convolutional layer is shown in Eq. (5).

$$N' = W_{out} \times H_{out} \times k \times k \times C_{in} \times C_{out} \quad (5)$$

In Eq. (5), N' means the computational complexity, and W_{out} and H_{out} mean the width and height of the output feature map. The optimal action can be found through the above calculation. However, due to the uniform sampling mechanism, the Dueling DQN algorithm may reduce its learning efficiency and effectiveness, and further optimization of the algorithm is needed. The PER mechanism is a commonly-used technique in reinforcement learning, which can improve the computational speed and learning efficiency of algorithms by prioritizing sampling the most valuable experiences for learning [18]. The basic structure of PER mechanism is in Fig. 2.

As shown in Fig. 2, the PER mechanism consists of five parts: experience pool, time difference error calculation, sampling probability calculation, sampling process, and policy update. The experience pool is a data storage pool that contains the experience data obtained by the algorithm during each interaction with the environment during reinforcement learning, including the current state, actions taken, rewards obtained, and next state. The calculation of time difference error refers to the calculation of the difference between the current Q value and the target Q value. The larger the Q value and temporal error of the experience, the higher the importance of the experience in algorithm learning. The sampling probability of each experience is calculated again, the sampling probability of each experience is calculated, and the experience with high sampling probability is prioritized for training by PER, thereby reducing unnecessary learning time and accelerating algorithm convergence to get the best solution. Finally, the Q value parameter or strategy parameter is adjusted based on the calculated sampling probability and time difference error to improve the algorithm's computation speed and learning efficiency. The calculation method of time difference error in this algorithm is shown in Eq. (6).

$$TD = Q(s,a) - (r + \gamma * V(s') - V(s)) \quad (6)$$

In Eq. (6), r means the immediate reward obtained from executing action a from state s, γ means the discount factor, and $V(s')$ and $V(s)$ mean the value estimation functions of the current state and the next state. The calculation method of sampling probability is shown in Eq. (7).

$$E[f(x)] = 1/m \sum_{i=1}^{m} f(xi) \quad (7)$$

In Eq. (7), m means the total number of sampling times, xi means the sampled samples, and $f(xi)$ means the function value of the samples. To improve the drawbacks of slow computation speed and low learning efficiency caused by uniform sampling methods in the Dueling DQN algorithm, this study utilizes the PER mechanism to optimize the Dueling DQN algorithm. The basic process of the optimized PER-Dueling DQN algorithm is in Fig. 3.

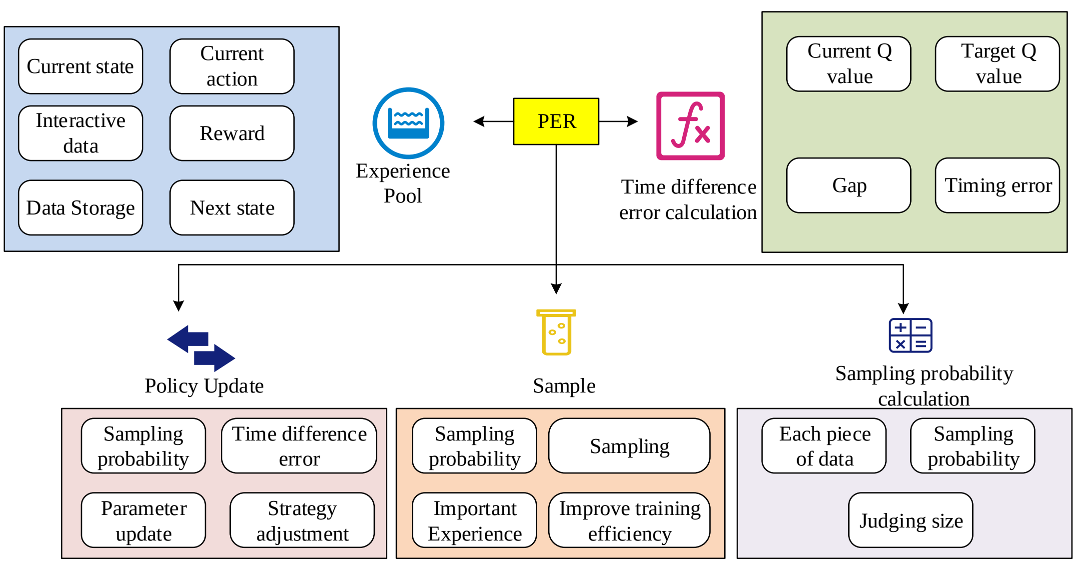


Fig. 2. Basic structure diagram of PER mechanism.

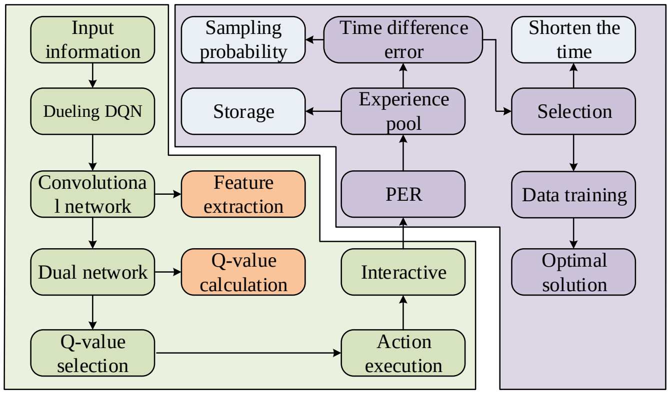


Fig. 3. Basic process of PER-dueling DQN algorithm.

As shown in Fig. 3, after receiving various input information, the PER-Dueling DQN algorithm first uses the convolutional network in the Dueling DQN algorithm to extract features, and then uses the dual network in the algorithm to calculate the Q value of each piece of information. The action with the highest Q value is chosen for execution. After the action is executed, when the algorithm interacts with the environment, the experience pool in the PER mechanism is used to store the experience obtained after each action interaction. The time discrepancy error and sampling likelihood of each action are computed, and the empirical data with high sampling likelihood and minimal temporal error are chosen for training. This approach minimizes unnecessary training duration and enhances both the computational speed and training efficiency of the algorithm.

B. *Retirement Space Planning Model Based on PER-Dueling DQN Algorithm*

In response to the problems of poor spatial planning effectiveness and long planning time in current elderly care space planning models, this study uses the PER-Dueling DQN algorithm proposed in the previous section to optimize the spatial planning model, aiming to raise the planning efficiency of the model and reduce the planning time of the model. The basic framework of the elderly care space planning model grounded on PER-Dueling DQN algorithm is shown in Fig. 4.

From Fig. 4, the model first needs to clarify the planning goals and objectives, namely the quality of life, medical security, and leisure activities for individuals after retirement. Secondly, it is necessary to evaluate the existing assets, income, and expenses of individuals or families to determine retirement funds. Then, based on the determined retirement funds, a suitable pension plan should be developed, including pension investment portfolio, pension insurance, and retirement pension plan. Then, the pension plan is followed, and corresponding adjustments are made according to the actual situation. Finally, spatial planning and design are carried out. The planning and design of elderly care spaces first need to collect relevant information about space use, management, and functions. Then, the collected information and planning objectives are input into the PER-Dueling DQN algorithm to find the optimal planning path, that is, the optimal spatial planning and design scheme. After finding the optimal design scheme, it is necessary to verify the scheme to determine its practical feasibility. Finally, the plan is recorded and a planning and design report is generated, which is submitted to relevant personnel for review and evaluation. If the evaluation is qualified, the elderly care space planning and design will be carried out according to the plan. If the evaluation is not qualified, the plan selection will be repeated until it is qualified. In spatial planning and design, it is necessary to calculate the volume of various objects in space, as well as the strength of objects and structures in space, in order to design the structures in space. The calculation method for the volume of various objects is shown in Eq. (8).

$$\begin{cases} V1 = c^3 \\ V2 = \pi r^2 h \\ V3 = 3/4\pi r^3 \end{cases} \tag{8}$$

In Eq. (8), $V1$ means the volume of the cube, c means the side length of the cube, $V2$ means the volume of the cylinder, r means the radius, h means the height, and $V3$ means the volume of the sphere. The strength calculation method for beam objects in space is shown in Eq. (9).

$$\begin{cases} \sigma = M\max/Wz \\ \tau = V''S''/Wit \end{cases} \tag{9}$$

In Eq. (9), σ means the maximum stress of the beam material, $M\max$ means the maximum bending moment, $V(s')$ and Wz mean the section modulus, τ means the material shear stress, V'' means the material shear force, S'' means the material gross section area, and Wit means the gross section moment of inertia. The calculation method for the strength of a pole in space is shown in Eq. (10).

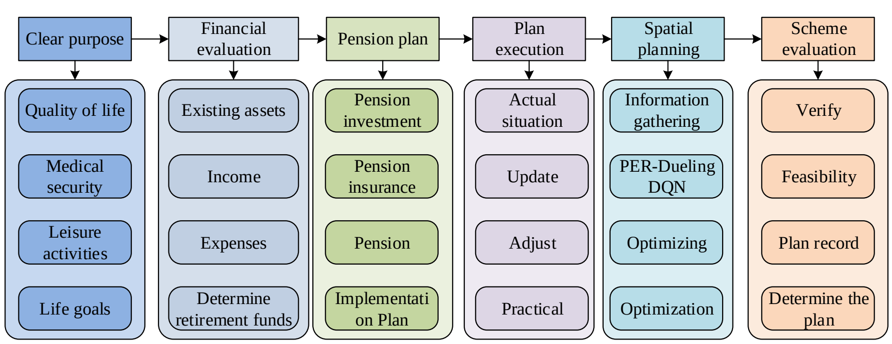


Fig. 4. Retirement space planning model based on PER-Dueling DQN algorithm.

$$\begin{cases} F1 = Pq / \varepsilon \\ F2 = \delta 1 / \delta 2 \end{cases} \quad (10)$$

In Eq. (10), $F1$ means the tensile strength of the rod, Pq means the yield strength of the rod, ε is the safety factor, $F2$ is the bending strength, δ is the bending moment, and $\delta 1$ means the bending moment resistance. In the planning of elderly care space, compound interest terminal value can help planners better plan elderly care funds. By selecting the initial investment amount and investment time reasonably, it ensures that the funding needs of the elderly care space are met. The calculation formula is shown in Eq. (11).

$$Fv = Pv \times (1+r)^n \quad (11)$$

In Eq. (11), Fv means the terminal value, Pv means the present value, r means the interest rate, and n is a term number. The application principle of PER-Dueling DQN algorithm in elderly care space planning is shown in Fig. 5.

In Fig. 5, in the planning and design of elderly care space, this algorithm first needs to receive the spatial data collected in the early stage, as well as the spatial planning purpose and requirements, and preprocess these data to denoise the data information. Then the eval network and target network in the PER-Dueling DQN algorithm, namely the evaluation network and target network, are initialized. Spatial information is input into the eval network to calculate the Q value of each action, that is, the Q value of each planning and design scheme. The action with the highest Q value is chosen for execution, and the current action, state, and the next state after completing the action are stored in the PER's experience pool. Once all actions have been executed and states recorded, the temporal difference error for each piece of data in the experience replay buffer is computed to establish its priority. The data with larger errors has higher priority. A batch of data is selected by priority from the experience pool and input into the eval network, where the current Q value is calculated. At the same time, these data are input into the target network to calculate the target Q value. The mean square deviation between the current Q value and the target Q value is used as the loss function. Based on this loss function, the parameters of the eval network are backpropagated and updated, and the parameters of the target network are synchronously updated. The above steps are repeated until the preset training coefficients are reached or the optimal solution is found, that is, the spatial optimal planning and design scheme. The optimal solution is output and recorded. The calculation method for the target Q value is shown in Eq. (12).

$$Y = \chi + \gamma Qt(s', \max a')Qe(s', a', \theta', \theta'') \quad (12)$$

In Eq. (12), χ represents the immediate reward, Qt is the target network, Qe represents the estimation network, θ' represents the parameters of the estimation network, and θ'' represents the parameters of the target network. Through the above process, the optimal planning and design scheme for the elderly space is obtained, in order to meet the material, spiritual, and social needs of the elderly, and help them maintain physical health, independent living, and mental vitality.

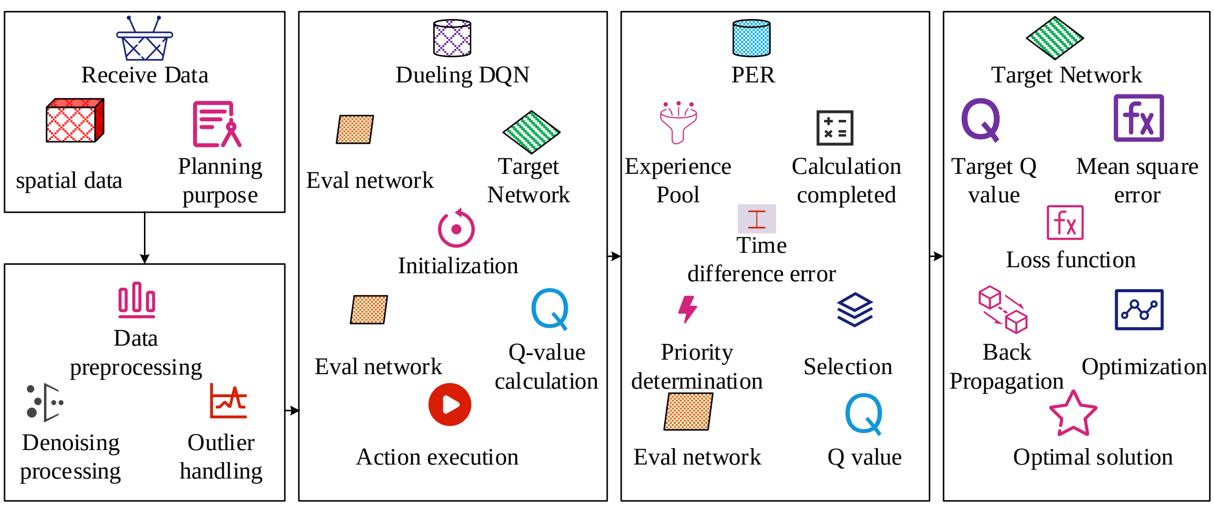


Fig. 5. Application principle of PER-dueling DQN algorithm.

IV. Results

A. Performance Analysis of PER-Dueling DQN Algorithm

In order to analyze the superiority of the prediction performance of the PER-Dueling DQN algorithm, this study conducted comparative experiments between the PER-Dueling DQN algorithm and the Genetic Algorithm-Back Propagation (GA-BP) algorithm, the Particle Swarm Optimization-Support Vector Machine (PSO-SVM) algorithm, and the Dueling DQN algorithm before optimization using the PER mechanism. The environment configuration during the experiment is in Table I.

TABLE I EXPERIMENTAL ENVIRONMENT CONFIGURATION

Experimental environment	Index	Style
Hardware environment	CPU	Intel Core i9
	EMS memory	64GB
Software environment	OS	Windows 10
	Python edition	Python 4.0

	Python environment	Anaconda 3

During the experiment, the ImageNet dataset was chosen as the experimental dataset, which contains 22000 categories of image data. The predictive performance of the four algorithms was analyzed through the above experimental environment configuration and experimental dataset. Firstly, the validity of the dataset was verified using k-fold cross validation. The dataset in ImageNet was evenly divided into (a, b, c, d, e) 5 parts, and four parts were used for testing. The remaining dataset was used for validation. The selection of the dataset was validated by testing each part of the dataset. The results are shown in Table II.

According to Table II, each dataset in the ImageNet dataset had a relatively low impact on the PER-Dueling DQN algorithm, indicating that the selection of this dataset was reasonable. The prediction performance of the four algorithms was compared, and the results are shown in Fig. 6.

TABLE II RESULTS OF RATIONAL TESTING OF DATA SETS

Training dataset	Test dataset	PER-Dueling DQN prediction accuracy	PER-Dueling DQN denoising accuracy
a,b,c,d	e	98.7%	93.2%
a,b,c,e	d	97.9%	92.8%
a,b,d,e	c	97.9%	92.7%
a,c,d,e	b	98.1%	93.1%
b,c,d,e	a	98.6%	93.5%

The red dashed line in Fig. 6 represents the areas where the predicted values differ from the actual values. From Fig. 6, among the four algorithms, only the PER-Dueling DQN algorithm had similar forecasted values to the true values. However, GA-BP algorithm, PSO-SVM algorithm, and Dueling DQN algorithm had different degrees of error between their forecasted values and true values after predicting the data, with Dueling DQN algorithm having the largest error between the forecasted values and true values. By comparing the prediction errors and speeds among the four algorithms, the results are presented in Fig. 7.

According to Fig. 7 (a), among the four algorithms, the PER-Dueling DQN algorithm had the lowest prediction error, only 0.9%, while the GA-BP algorithm, PSO-SVM algorithm, and Dueling DQN algorithm had prediction errors of 1.6%, 2.1%, and 3.2%, respectively. The prediction errors of the latter three algorithms were much higher than those of the PER-Dueling DQN algorithm. As shown in Fig. 7 (b), the average prediction speeds of PER-Dueling DQN algorithm, GA-BP algorithm, PSO-SVM algorithm, and Dueling DQN algorithm for data were 8.7 bps, 5.7 bps, 4.8 bps, and 2.1 bps, respectively. PER-Dueling DQN algorithm had the fastest prediction speed, while the unoptimized Dueling DQN algorithm had the slowest prediction speed, with a difference of 6.6 bps between the two. Finally, the denoising effects of the four algorithms were compared, and the results are shown in Fig. 8.

In Fig. 8, the PER-Dueling DQN algorithm had the best denoising effect among the four algorithms. After using this algorithm for denoising, the noise information in the data could be almost completely removed. However, after denoising the data, GA-BP algorithm, PSO-SVM algorithm, and Dueling DQN algorithm still contained a large amount of noise information. The denoising performance of the last three algorithms was inadequate, potentially leading to inaccurate predictions when forecasting future data. From the above experimental results, the PER-Dueling DQN algorithm raised in this study had the best denoising effect, the shortest prediction time, the lowest prediction error, and the best prediction effect. Therefore, this study uses the PER-Dueling DQN algorithm to construct a spatial planning model, in order to predict the various performance of elderly space planning through the excellent prediction effect of the PER-Dueling DQN algorithm. By adjusting the elderly space planning scheme based on the prediction results, the comfort and resource utilization of the elderly space can be improved.

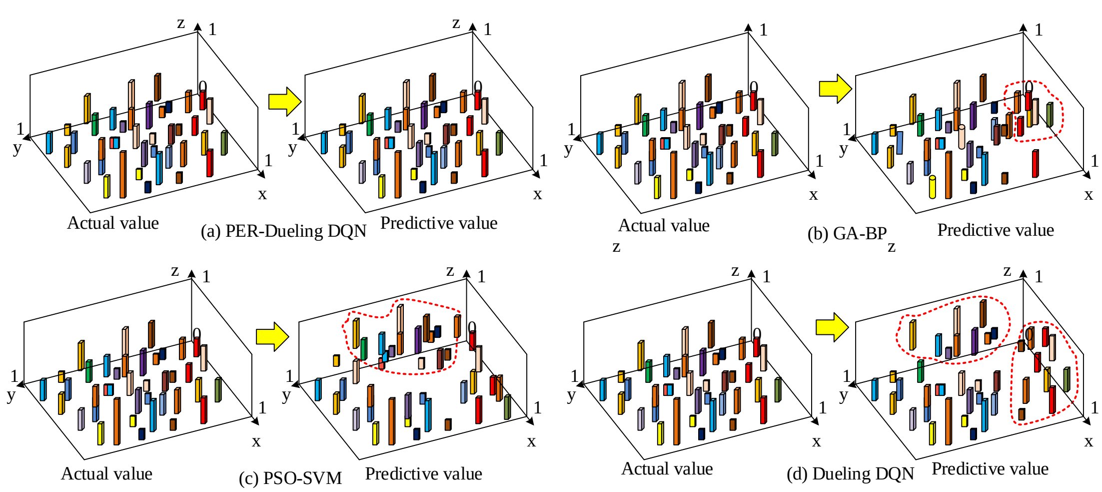
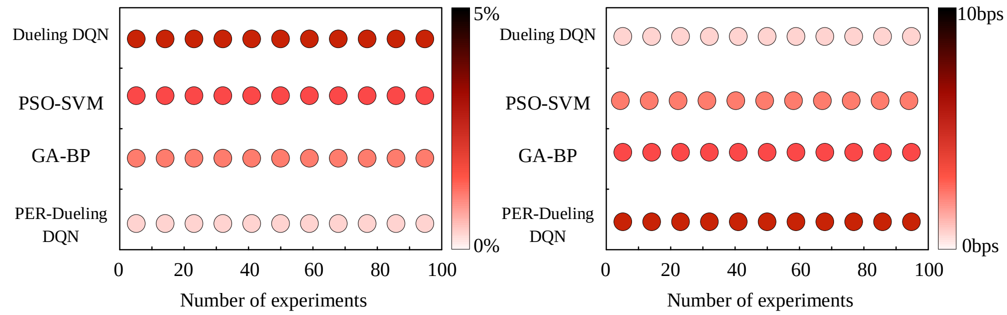
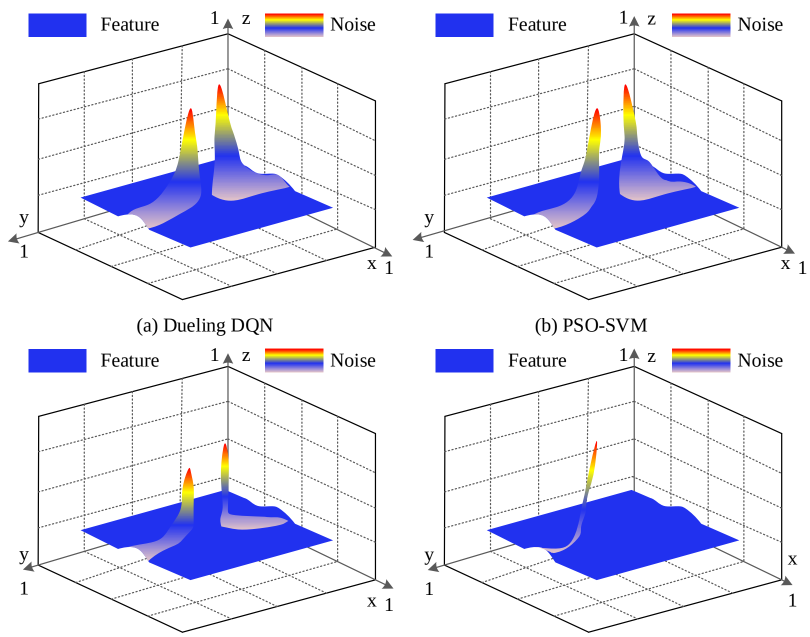


Fig. 6. Comparison of algorithm prediction performance.



(a) Prediction error (b) Predicting speed

Fig. 7. Comparison of algorithm prediction error and prediction speed.



(a) Dueling DQN (b) PSO-SVM

(c) GA-BP (d) PER-Dueling DQN

Fig. 8. Comparison of denoising effects of algorithms.

B. Empirical Analysis of PER-Dueling DQN Planning Model

After verifying the superiority of the prediction performance of the PER-Dueling DQN algorithm, the planning effect of the spatial planning model based on this algorithm was validated. The PER-Dueling DQN model was compared with commonly-used spatial planning models based on Convolutional Neural Networks Simulated Annealing (CNN-SA), Ant Colony Optimization Tabu Search (ACO-TA), and Discrete Grey Wolf Optimization (DGWO). During the experiment, a planning scheme for elderly care space in a certain family was selected as the source of the experimental dataset, which includes information on the size, scale, funding sources, and elderly care goals and needs of the elderly care space. The elderly space planning scheme was optimized using four models, the performance of the elderly space design scheme optimized by the four models was compared, and the advantage of the raised model was verified. Firstly, the planning time and spatial comfort of the four planning models were compared, and the results are shown in Fig. 9.

From Fig. 9 (a), the PER-Dueling DQN spatial planning model took an average of 1.3 seconds to plan the elderly care space, and the comfort level of the elderly care space designed by this model reached 98.7%. The spatial planning time of this model was short, and the planned space had a high comfort level, which was conducive to the living of the elderly. As shown in Fig. 9 (b), the average time taken by the CNN-SA spatial planning model for spatial planning reached 2.2 seconds, which was higher than that of the PER-Dueling DQN model. Moreover, the comfort level of the elderly care space planned by the CNN-SA model was 85.6%. From Fig. 9 (c) and Fig. 9 (d), the average time spent on spatial planning by the ACO-TA and DGWO spatial planning models was much higher than that of the PER-Dueling DQN model. The time spent by the ACO-TA and DGWO models was 2.9 seconds and 3.7 seconds, respectively. The comfort levels of the elderly care space planned by the two models were 78.9% and 68.6%, respectively. Comparing the safety and spatial resource utilization efficiency of the elderly care spaces planned by the four models, the results are shown in Fig. 10.

According to Fig. 10 (a), the PER-Dueling DQN spatial planning model had the highest safety of the elderly care space, reaching 98.3%, which can effectively ensure the safety of the elderly. The safety of the elderly care space designed by the CNN-SA model, ACO-TA model, and DGWO model was 90.2%, 82.6%, and 75.8%, respectively. The safety of the elderly care space planned by the latter three models was much lower than that of the PER-Dueling DQN model. From Fig. 10 (b), among the four models, the PER-Dueling DQN model had the highest utilization rate of spatial resources, reaching 89.7%, while the DGWO model had the lowest utilization rate of spatial resources, only 65.4%. Finally, the impact of elderly care spaces on the elderly was compared, and the data are in Table III.

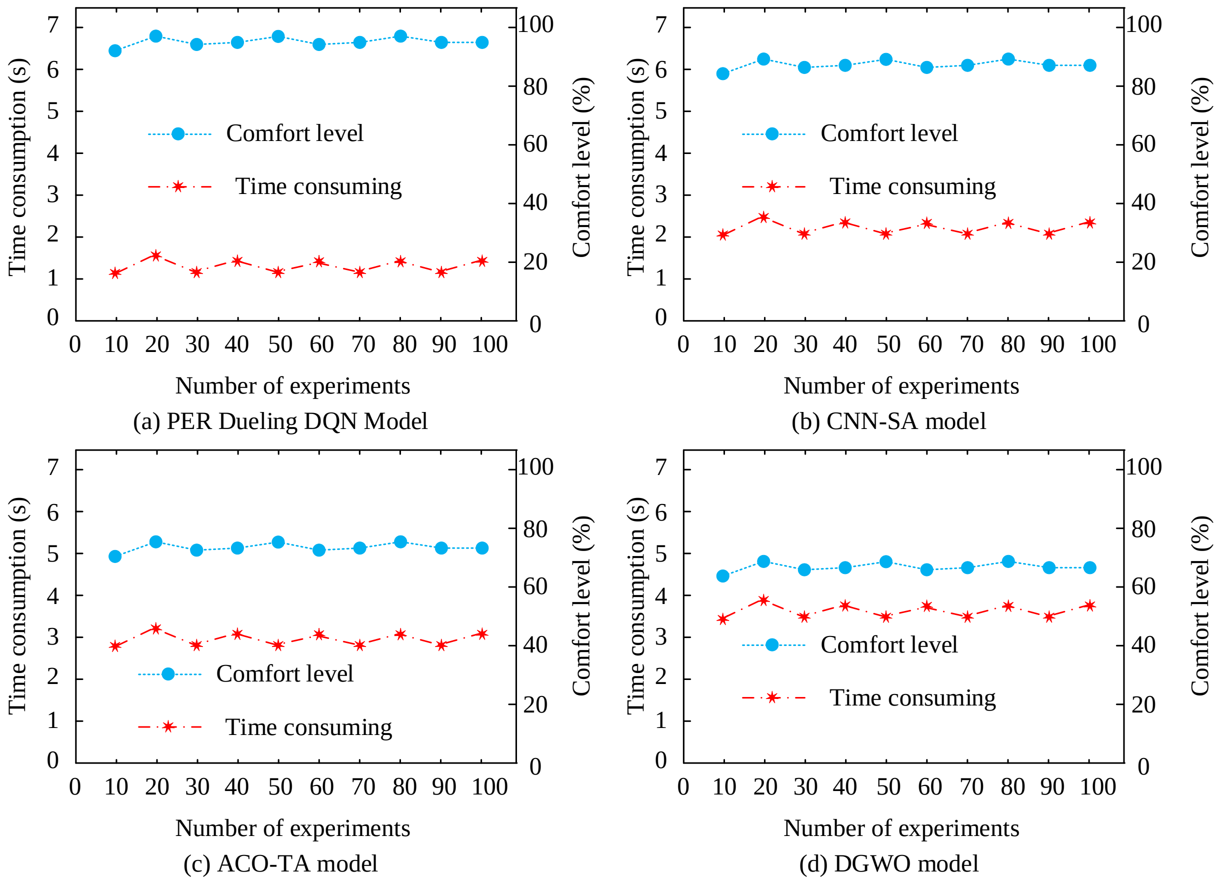


Fig. 9. Model planning time and spatial comfort.

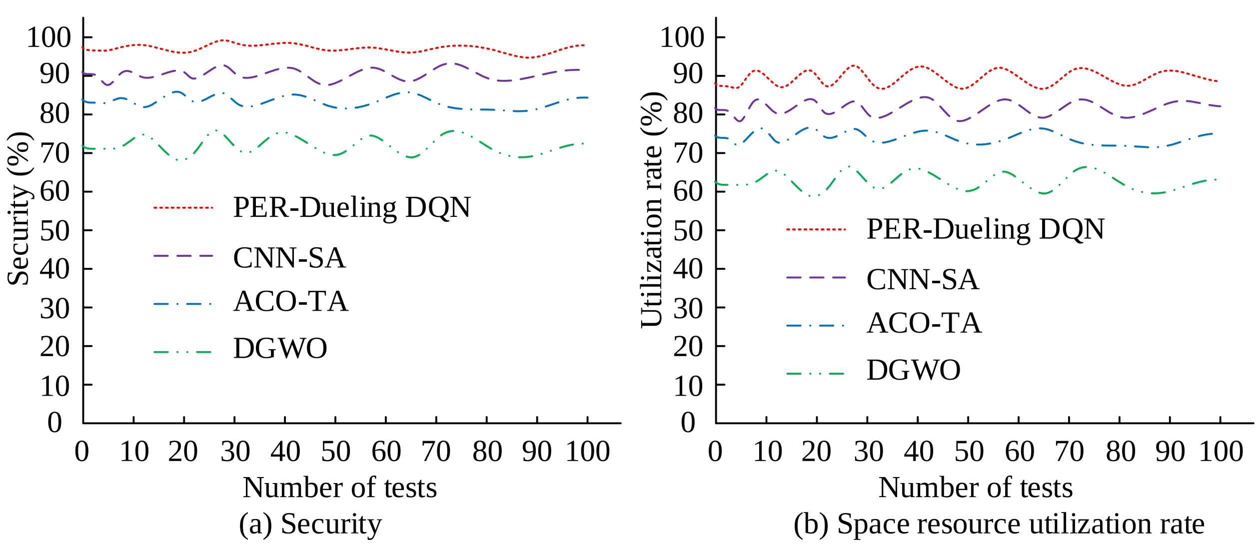


Fig. 10. Comparison of safety and resource utilization in elderly care spaces.

TABLE III ANALYSIS OF THE EFFECTS OF FOUR MODELS ON THE ELDERLY

Model		Quality of life	Mental health	Convenient living	Sense of happiness	Social skills
PER-Dueling DQN	Increase percentage	67.7%	82.4%	88.7%	90.3%	96.4%
	Meet expectations	Y	Y	Y	Y	Y
CNN-SA	Increase percentage	60.5%	74.7%	82.3%	85.8%	89.7%
	Meet expectations	Y	N	Y	N	N
ACO-TA	Increase percentage	50.3%	70.3%	78.7%	80.6%	82.7%
	Meet expectations	N	N	N	N	N
DGWO	Increase percentage	48.7%	68.5%	75.3%	73.8%	72.1%
	Meet expectations	N	N	N	N	N
Expected increase		>50.7%	>75.6%	>80.5%	>88.6%	>90.2%

According to Table III, after using four spatial planning models for elderly care space planning and design, only the PER-Dueling DQN spatial planning model could achieve the expected performance indicators of elderly care space for the elderly. After using the PER-Dueling DQN model, the planned elderly care space could raise the living standard of the elderly by 67.7%, mental health by 82.4%, convenience of life by 88.7%, happiness by 90.3%, and social skills by 96.4%, which was much higher than the expected improvement of 50.7%, 75.6%, 78.7%, 80.6%, and 82.7%. The elderly care space designed using the CNN-SA model could only raise the living standard and convenience of the elderly to the expected level, while other indicators were slightly lower than expected. Although the performance indicators of the elderly care space planned by the ACO-TA model and DGWO model improved, the improvement level of both models was far from meeting the expected requirements. Based on the above information, the PER-Dueling DQN spatial planning model proposed in this study can offer sensible planning and design for elderly care spaces, ensuring a high standard of living for the elderly and enhancing their physical health.

V. DISCUSSION

In response to the problems of poor spatial planning rationality and low spatial comfort in current elderly care space planning models, this study used the PER mechanism to optimize the Dueling DQN algorithm, proposed a PER-Dueling DQN algorithm, and constructed an elderly care space planning model based on this algorithm. To confirm the superiority of the model, comparative experiments were carried out on the optimization algorithm first. The study compared the PER-Dueling DQN algorithm with the GA-BP algorithm, PSO-SVM algorithm, and Dueling DQN algorithm. The results showed that among the four algorithms, the PER-Dueling DQN algorithm had the strongest denoising ability, and its prediction error was only 0.9%, far lower than the other three algorithms. The prediction speeds of PER-Dueling DQN algorithm, GA-BP algorithm, PSO-SVM algorithm, and Dueling DQN algorithm were 8.7 bps, 5.7 bps, 4.8 bps, and 2.1 bps, respectively. PER-Dueling DQN algorithm has the fastest prediction speed, which is similar to the experimental results of Bai Z team [19]. The reason for this result may be that the PER-Dueling DQN algorithm can improve the training speed and efficiency of the algorithm through the priority sampling method in the PER mechanism, thereby ensuring the denoising effect of the algorithm and improving its prediction accuracy. Further experimental analysis was conducted on the spatial planning models based on the PER-Dueling DQN algorithm, CNN-SA spatial planning model, ACO-TA spatial planning model, and DGWO spatial planning model. The results showed that among the four spatial planning models, the PER-Dueling DQN model had the shortest spatial planning time, only requiring 1.3 seconds, and the highest resource utilization rate of the elderly care space planned by the PER-Dueling DQN model reached 89.7%. The elderly care space planned by the PER-Dueling DQN model could raise the living standard of the elderly by 67.7%, improve their mental health by 82.4%, and increase their sense of happiness by 90.3%, which fully met the expected level of improvement. Although the other three models also improved, they could not all meet expectations, which is consistent with the results of Williams R A et al. [20]. The reason for the results may be that the algorithm in the PER-Dueling DQN model has excellent predictive ability, which can continuously optimize the space through the predicted results until the optimal result is reached, thereby improving the performance of the elderly care space.

VI. CONCLUSION

In order to solve the problem of low spatial planning rationality in current elderly care space planning, this study combined PER mechanism and Dueling DQN algorithm, and designed an elderly care space planning model based on the combined algorithm. The study first compared the PER-Dueling DQN algorithm with other related algorithms, and the results showed that the performance of the PER-Dueling DQN algorithm was superior to other algorithms. The elderly space planning model based on the PER-Dueling DQN algorithm could improve the quality of life, mental health status, and happiness of the elderly. From the above results, the suggested elderly care space planning model can effectively improve the comfort of the elderly care space, thereby ensuring the physical and mental health status and quality of life of the elderly. However, although the PER-Dueling DQN algorithm used in this study had excellent prediction performance, it contained many hyperparameters, making parameter tuning difficult. It had high computational complexity and required a large amount of resources. Moreover, in some complex or dynamically changing environments, the PER-Dueling DQN algorithm may not be able to effectively adapt and achieve optimal algorithm performance. In the future, automated parameter tuning techniques such as Bayesian optimization algorithm and genetic algorithm can be utilized to intelligently select and optimize hyperparameters of algorithms, reducing the difficulty and cost of parameter tuning and lowering computational complexity. Moreover, it can be combined with other reinforcement learning algorithms to form a hybrid algorithm, further improving the performance and stability of the algorithm.

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REFERENCES

[1] Bardaro G, Antonini A, Motta E. Robots for elderly care in the home: A landscape analysis and co-design toolkit. International Journal of Social Robotics, 2022, 14(3): 657-681.

[2] Rahmawati E A, Wahyunengseh R D, Mulyadi A W E. Evaluation of elderly-friendly open space and public service buildings in madiun city using importance performance analysis (IPA). JPPI (Jurnal Penelitian Pendidikan Indonesia), 2024, 10(3): 148-162.

[3] Amri I, Giyarsih S R. Monitoring urban physical growth in tsunami-affected areas: A case study of Banda Aceh City, Indonesia. Geojournal, 2022, 87(3): 1929-1944.

[4] Serat Z, Fatemi S A Z, Shirzad S. Design and Economic Analysis of On-Grid Solar Rooftop PV System Using PVsyst Software. Archives of Advanced Engineering Science, 2023, 1(1): 63-76.

[5] Gu Y, Zhu Q, Nouri H. Identification and U-control of a state-space system with time-delay. International Journal of Adaptive Control and Signal Processing, 2022, 36(1): 138-154.

[6] SS V C, HS A. Nature inspired meta heuristic algorithms for optimization problems. Computing, 2022, 104(2): 251-269.

[7] Karras T, Aittala M, Aila T, Laine S. Elucidating the design space of diffusion-based generative models. Advances in neural information processing systems, 2022, 35(5): 26565-26577.

[8] Li C, Conejo A J, Liu P, Omell B P, Siirola J D, Grossmann I E. Mixed-integer linear programming models and algorithms for generation and transmission expansion planning of power systems. European Journal of Operational Research, 2022, 297(3): 1071-1082.

[9] Chraibi A, Ben Alla S, Touhafi A, Ezzati A. A novel dynamic multi-objective task scheduling optimization based on Dueling DQN and PER. The Journal of Supercomputing, 2023, 79(18): 21368-21423.

[10] Chi J, Zhou X, Xiao F, Lim Y, Qiu T. Task Offloading via Prioritized Experience-based Double Dueling DQN in Edge-assisted IIoT. IEEE Transactions on Mobile Computing, 2024, 23(12): 14575-14591.

[11] Huang L, Ye M, Xue X, Wang Y, Qiu H. Intelligent routing method based on Dueling DQN reinforcement learning and network traffic state prediction in SDN. Wireless Networks, 2024, 30(5): 4507-4525.

[12] Zhang L, Feng Y, Wang R, Xu Y, Xu N, Liu Z. Efficient experience replay architecture for offline reinforcement learning. Robotic Intelligence and Automation, 2023, 43(1): 35-43.

[13] Zhou C, Huang B, Hassan H, Fränti P. Attention-based advantage actor-critic algorithm with prioritized experience replay for complex 2-D robotic motion planning. Journal of Intelligent Manufacturing, 2023, 34(1): 151-180.

[14] Carlsson H, Pijpers R, Van Melik R. Day-care centres for older migrants: spaces to translate practices in the care landscape. Social & Cultural Geography, 2022, 23(2): 250-269.

[15] Kikuta J, Kamagata K, Takabayashi K, Taoka T, Yokota H, Andica C, Aoki S. An investigation of water diffusivity changes along the perivascular space in elderly subjects with hypertension. American Journal of Neuroradiology, 2022, 43(1): 48-55.

[16] Boeing G, Higgs C, Liu S, Giles-Corti B, Sallis J F, Cerin E. Using open data and open-source software to develop spatial indicators of urban design and transport features for achieving healthy and sustainable cities. The Lancet Global Health, 2022, 10(6): 907-918.

[17] Cao J, Wang X, Wang Y. An improved Dueling Deep Q-network with optimizing reward functions for driving decision method. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 2023, 237(9): 2295-2309.

[18] Saglam B, Mutlu F, Cicek D, Kozat, S. Actor Prioritized Experience Replay (Abstract Reprint). Proceedings of the AAAI Conference on Artificial Intelligence. 2024, 38(20): 22710-22710.

[19] Bai Z, Fan X, Jin X, Zhao Z, Wu Y, Oenema O. Relocate 10 billion livestock to reduce harmful nitrogen pollution exposure for 90% of China’s population. Nature Food, 2022, 3(2): 152-160.

[20] Williams R A. From racial to reparative planning: Confronting the white side of planning. Journal of Planning Education and Research, 2024, 44(1): 64-74.