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Ubiquitous Heterogeneous Network Topology Optimization Control of DC Converter Station

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Abstract. *To ensure that UHV DC converter stations work in a safe and stable manner, topology optimization control is very important. Currently, most algorithms use heuristic rules to reduce the number of candidate searches, but only obtain suboptimal solutions in some sense. In this paper, a topology optimization algorithm based on convolutional reinforcement learning is proposed for heterogeneous networks in UHV DC converter stations. In a nutshell, the algorithm conducts a simulation through a deep neural network-guided Monte Carlo tree search, and the findings of the tree search then reinforce the neural network's learning. Furthermore, the algorithm is a real-time algorithm, and the solution can be continuously improved as computing resources increase. The simulation experiments show that compared with the heuristic algorithm, the proposed algorithm has better reliability and can adapt to dynamic environment and network changes without restarting the algorithm.*

Keywords: Heterogeneous network, Topology control, DRL, Monte Carlo tree search.

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1. **Introduction.** Considering a variety of power equipment in the converter station, the complex equipment information, and the close association between secure operation of the DC transmission system and the equipment status, panoramic surveillance of various power equipment should be conducted to guarantee security and stabilization of the UHV DC converter station [1]. However, the networks of the converter station are heterogeneous, because the mode of data transmission varies from different power devices and

multiple networks are required for coordinated transmission. If the topology of heterogeneous networks is improperly connected, dynamic imbalance of data access to the network will occur, resulting in poor data transmission performance and lower network reliability. Therefore, it is necessary to optimize the topology of the heterogeneous networks, improving the network topology and thus the transmission performance.

In recent years, topology optimization of heterogeneous networks has been widely concerned. Based on the reliability-based structural topology optimization, In Literature [2], a method based on random gradient is proposed to calculate the failure probability of every few optimization iterations through effective sampling strategies. Literature [3] proposed a new adaptive distributed topology control algorithm to ensure that the networks were connected in the event of node failure. Literature [4] proposed a tree-based algorithm to build a tree topology for the multi-hop wireless network. Advantage of the tree topology was to realize efficient data transmission and aggregation through non-leaf nodes in the tree [5]. The throughput of heterogeneous networks is the main criterion to evaluate the pros and cons of the established network model. Currently, some of network topologies established for efficient data transmission have been constructed [6, 7, 8]. The performance of the above-mentioned topologies of heterogeneous networks shows the great impact of topology quality on data transmission, especially in some real networks [9]. Some network topologies also consider data security and transmission efficiency [10, 11, 12]. Literature [13] put forward an energy-saving topology control algorithm (named EDTC), which built a robust backbone topology with the maximum spanning tree algorithm, and reintroduced some edges into the topology, making the network life cycle of the algorithm twice as long as the existing algorithm. However, the time delay problem caused by large search volume is not considered. Therefore, the network topology should be constructed according to the needs of the specific network, need to meet as much as possible a variety of network types and network transmission performance.

Although the topology optimization methods mentioned above take into account the data transmission quality and security, the optimization process is time-consuming, when the topology changes. This can not meet the data transmission requirements of the power industry. Finding the topology with optimal reliability in the heterogeneous networks of UHV DC transmission system is essentially a combinatorial problem [14]. Literature [15] proposed a minimum spanning tree topology optimization method, which used heuristic rules to decrease the quantity of candidate searches and seek for sub-optimal answers in a way. However, this method still failed to meet the requirements for rapid, real-time and reliable reconstruction of the communication network that fails. Furthermore, because the search space is too large for all possible topological configurations, it becomes more complicated to optimize network configuration with exhaustive search.

Deep reinforcement learning (DRL) is performing better and better in network allocation, resource optimization and wireless control in communication field [16]. Literature [17] propose a new convolutional neural network architecture named DNetUnet, which combines U-Nets with different down-sampling levels and a new dense block as feature extractor. Literature [18] designed an early warning mechanism to help the agent identify a proper action time, which effectively improves the fault tolerance and robustness of the method. Most of the existing algorithms do not take advantage of the characteristics of network models to heuristically reduce the number of potential candidate searches. To solve this problem, this paper applies reinforcement learning to topology control, and proposes a topology control algorithm based on deep reinforcement learning (DRL-TC). It uses a framework combining deep reinforcement learning and Monte Carlo Tree Search (MCTS) to build networks according to predefined routing topology. First, convolutional neural network (CNN) is trained to measure the transmission flow of the partly established topology and guide the MCTS to continue searching the more possible parts of the search space. In turn, MCTS search findings enhance CNN learning, which contributes to more satisfactory prediction results in the next iteration. The contributions of this paper include:

(1) An innovative and general DRL-TC algorithm is proposed, which can determine the approximate optimal topology of heterogeneous networks from a reliability perspective in cases where domain-specific knowledge beyond topological rules is not required.

(2) The algorithm is an at-a-time statistical algorithm that can adapt to environmental dynamics (including possible network anomalies) and reconfigures the network accordingly.

(3) The proposed DRL-TC algorithm obtained by simulation results is faster than other heuristic algorithms in the optimization calculation.

2. System Modeling and Related Issues.

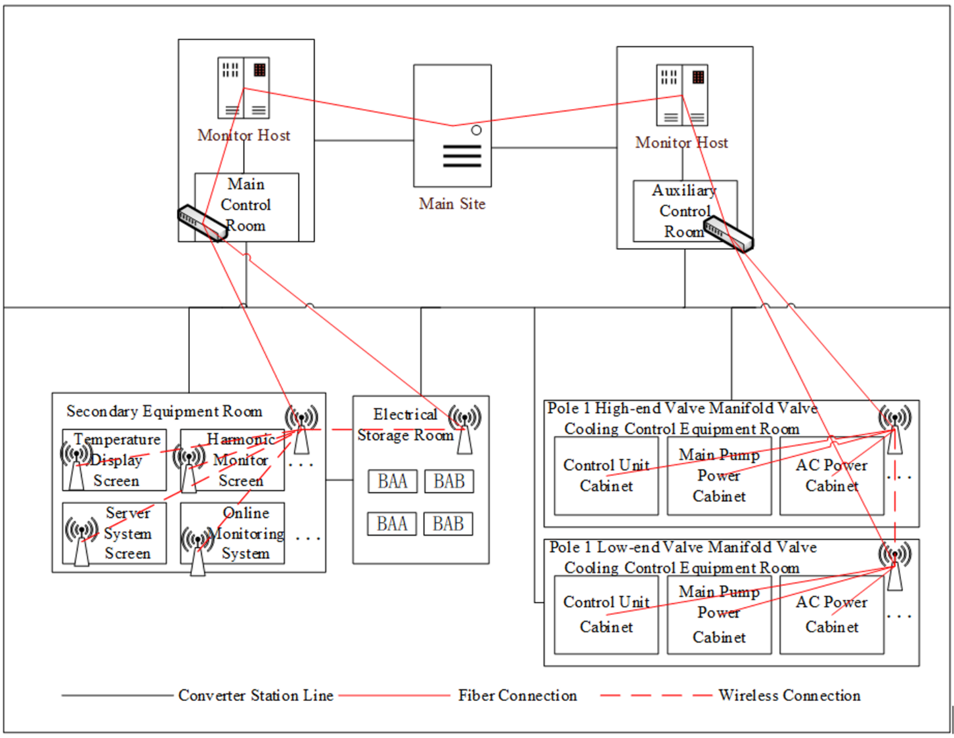

FIGURE 1. Heterogeneous network diagram of converter station

2.1. Heterogeneous Network Model.

Since the network of UHV DC converter station is heterogeneous (as shown in Figure 1), the network topology should be optimized to settle the dynamic imbalance matter that occurs when data flow accesses the internet and that is caused by the unreasonable topological link. Thus, the communication requirements of the network can be met.

For the heterogeneous network model, as shown in Figure 1, the heterogeneous network is modeled as a tree structure (Figure 2), which is composed of a master station v_0 and $N-1$ data transmission nodes $v_1, v_2, ..., v_{N-1}$, where each node has a unique path to the master station v_0. The symbols used in the network model are shown in Table 1.

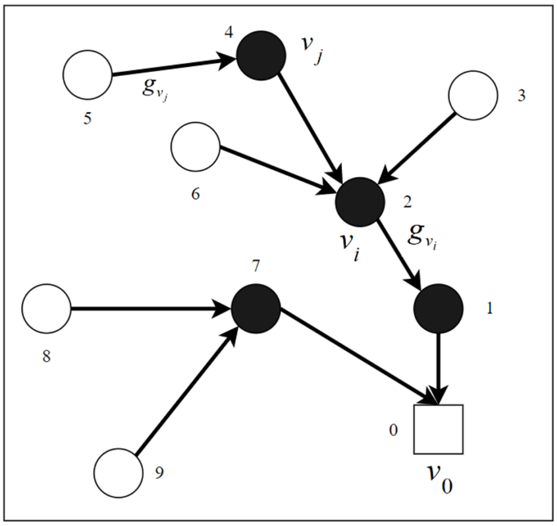

FIGURE 2. Heterogeneous network tree structure

TABLE 1. Symbols used in network models

Symbol	Meaning
v_0	Main station
v_i	Node
$C(v_i)$	Child node v_i
$\delta(U)$	A set of edges pointing to U
R_{v_i}	Data generated at node v_i
g_{v_i}	Data aggregated at node v_i
$a(\cdot)$	Aggregate function
$\varepsilon_{v_i}^{P}$	Processing time consumed per bit
$\varepsilon_{v_i}^{Tx}$	Transmission time consumed per bit
ρ	Power amplification constant
d_{v_i,v_j}	Euclidean distance between v_i and v_j
E_{v_i}	Total traffic of node v_i
e_{v_i}	Transmission flow per round
x_{v_i,v_j}	Binary variable pointing to edge(v_i, v_j)

In each round when the data is collected, the node v_i, $i \in \{1, 2, \dots, N-1\}$ needs to forward g_{v_i} data to its parent node. Calculate the value of g_{v_i} by Equation (1) shown as follows:

$$g_{v_i} = R_{v_i} + a\left(\sum_{v_j \in C(i)} R_{v_j}\right) \tag{1}$$

Where, R_{v_i} is the data generated by v_i itself; the data set $\sum_{v_j \in C(i)} R_{v_j}$ is originated from the child nodes of v_i, and $a(\cdot)$ is the aggregation function. In this paper, the transmission traffic of transmission model shown in Equation (2) is utilized, in which the node transmission traffic related to the topology is mainly composed of data processing and the time consumed for transmission:

$$e_{v_i} \quad = \quad \left(\varepsilon_{v_i}^{P} + \varepsilon_{v_i}^{\mathrm{Tx}}\right) g_{v_i} \tag{2}$$

Where, $\varepsilon_{v_i}^{P}$ and $\varepsilon_{v_i}^{Tx}$ are the time per bit consumed by data processing and transmission at the node v_i, respectively. Their values depend on the distance to the parent node, as shown by Equation (3):

$$\varepsilon_{v_i}^{\mathrm{Tx}} \quad = \quad \rho d_{v_i,v_j}^{2} \tag{3}$$

Where, d_{v_i,v_j} is the Euclidean distance between node v_i and its parent node (or master) v_j, and ρ is the power amplification constant in the link budget that considers the shadow fading effect.

2.2. **Problem Descriptions.** Denote the total transmission flow of node v_i as E_{v_i}. $E_{v_i} = \infty$, assuming that the master station v_0 is unlimited. In this paper, the lifetime of a heterogeneous network is defined as the minimum transmission flow of all nodes according to the total rounds. The maximization of this lifetime can be expressed as:

$$\text{maximize}_{\{x_{ij}\}} \quad \min_{v_i \in V} \left[\frac{E_{v_i}}{e_{v_i}}\right] \tag{4}$$

$$\sum_{(v_i,v_j)\in\delta(S)} x_{v_i,v_j} \geq 1, \forall S \in V \backslash \{v_0\} \tag{5}$$

$$\sum_{(v_i,v_j)\in\delta(v_i)} x_{v_i,v_j} \quad = \quad 1, \forall v_i \in V \backslash \{v_0\} \tag{6}$$

$$x_{v_i,v_j} \in \{0,1\}, \forall v_i, v_j \in V \tag{7}$$

where, $\delta(S)$ is the set of edges $\{(u,v) : u \in S, v \notin S\}$. If v_i is a subset of v_j, $v_i = 1$, otherwise 0. Constraint condition Equation (5) guarantees the connection among all nodes, while constraint condition Equation (6) guarantees that only one node can be transferred to the parent node at a time. The optimization problem in Equation (4) is an NP-hard problem [15]. To reduce the number of candidate searches, a real-time DRL-TC algorithm is proposed, which can focus on the more possible part of the search space, of which computing resources are limited, and approach the optimal solution with improved computing ability.

3. Topology Optimization Algorithm Based on Deep Reinforcement Learning.

3.1. **Reinforcement Learning.** Reinforcement learning means that the actions are learnt and taken in a dynamic environment to maximize reward signals. In step t, the agent performs actions in a context and receives observation results of the environmental state through an immediate reward r_t. The policy can be deemed as a set of deterministic actions that depend on the state s_t, or a kind of stochastic policy that uses a set of probabilities of actions. A series of states and actions are collectively defined as the trajectory motion τ, and the discount sum of all reward values r_t collected along a trajectory is called reward, as shown in Equation (8):

$$R(\tau) = \sum_{t=0}^{T} \gamma^t r_t, \quad \gamma \in [0,1] \tag{8}$$

where, γ is the discount factor. The value function and policy function are shown in Equation (9) and Equation (10):

$$Q^\pi(s,a) \triangleq E\left[\sum_{\tau=t}^{N} r_\tau \mid s_t = s, a_t = a\right] \tag{9}$$

$$V^\pi(s) \triangleq E_h\left[\sum_{\tau=t}^{N} r_\tau \mid s_t = s\right] \tag{10}$$

Reinforcement learning focuses primarily on finding a strategy that maximizes the expected return, and usually adopts the approximation value function. In the deep learning method adopted by this paper, CNN is utilized to approximate the policy function and value function.

3.2. **Monte Carlo Tree Search.** To fit CNN as a function approximator, a training dataset composed of states, policies, and values should be provided. Training datasets are efficiently collected in the more possible part of the search space via MCTS (as shown in Figure 3). Each node of the search tree is represented by a tuple as $(s, a, M(s,a), \pi(s), Q^\pi(s,a))$, where s is the state of the heterogeneous network, a is the action selected by s, $M(s,a)$ the total visits to (s,a)on the search tree, $\pi(s)$ the prior probability of valid actions predicted by the CNN, and $Q^\pi(s,a)$ the state action value, which refers to the expected reward for taking the action a since the state s, and is calculated by Equation (9).

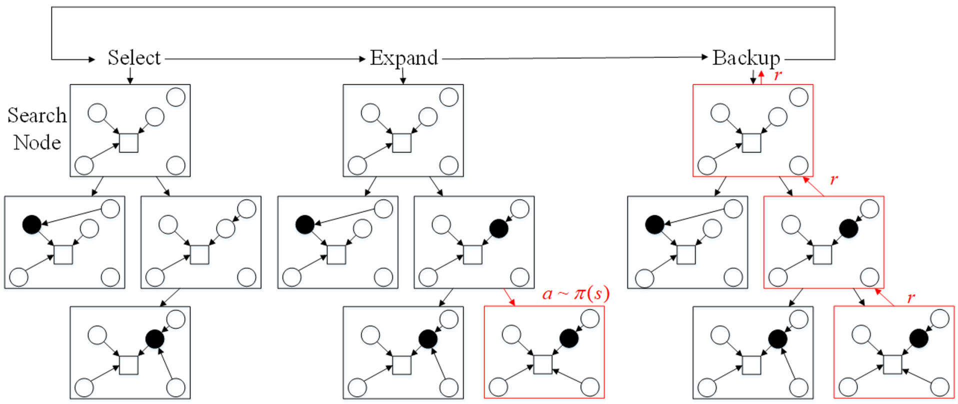

FIGURE 3. The process of MCTS

At each search step $t < N$, Choose the action with the highest confidence, as shown in Equation (11):

$$a_t = \arg\max_a \left(Q^\pi(s,a) + c\pi(s,a)\frac{\sqrt{M(s)}}{1 + M(s,a)}\right) \tag{11}$$

where $M(s) \triangleq \sum_{b\in A} M(s,b)$ represents the number of visits in the states, which takes no into account the actions; c is a hyperparameter that manages the search level. When the search ends $(t < N)$, the rewards are granted, and the root state of all the visited states and the actions performed are transmitted back along the search path, in which the value of Q^π is updated accordingly by the average value of the nodes. MCTS is expounded in algorithm 1 in details (as shown in Table 2).

TABLE 2. MCTS subroutine of DRL-TC algorithm

Algorithm 1: Monte Carlo tree search subroutine

Input: CNN $f_\Theta(s)$; Number of visits: $M(s,a)$; Prior probability: $\pi(s)$; State-action value: $Q^\pi(s,a)$;
Output: number of visits M;

    exit condition for the recursion
if s is the final state, **then**
    return r
end if
    Extend a new search page
if s is not visited, **then**
    $\pi(s), V(s) \leftarrow f_\Theta(s)$;
    Get all valid actions of state s;
    Renormalize $\pi(s)$ for all valid operations;
    $M(s) \leftarrow 1$;
    return $V(s)$;
end if
    Calculate UCBs
Initialize $U \leftarrow \phi$;
for all valid actions a **do**
    $U(s,a) \leftarrow Q^\pi(s,a) + c\pi(s,a)\frac{\sqrt{M(s)}}{1+M(s,a)}$;
end for
    Select an action and perform recursive search in next state
$a \leftarrow \mathrm{argmax}_a\, U(s,a)$;
$s \leftarrow T(s,a)$;
Recursively search for a new state$V(s) = MCTS(s)$;
    Update tree state
$Q^\pi(s,a) \leftarrow \frac{M(s,a)Q^\pi(s,a)+V(s)}{N(s,a)+1}$;
$M(s,a) \leftarrow M(s,a) + 1$;
$M(s) \leftarrow M(s) + 1$;
return $V(s)$

3.3. **Deep Convolutional Neural Networks.** The random strategy $\pi(s)$ determines the distribution of effective actions in a state. According to the stochastic policy, the system produces the state and the trajectory $h(s_t) = s_t, a_t, ..., s_{N-1}, a_{N-1}, s_N$ from state s_t to terminal state s_N. The value function $V^\pi(s)$ is devoted as the anticipated reward for all possible choices starting from states. It is calculated by Equation (10).

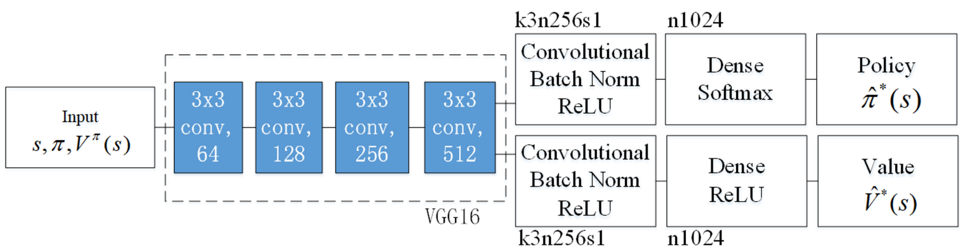

FIGURE 4. Description of the structure of CNN

This paper uses CNN $f_\Theta(s)$ (denoted as Θ) to approximate the optimal value function $V^*(s) = \max_\pi V^\pi(s)$ and the optimal policy $\pi^*(s)$. As described in Figure 4, the input of CNN is the training dataset $\{(s, \pi(s), V^\pi(s))\}$. In order to maintain the feasibility of multi-layer neural network training and significantly improve the representation ability of CNN, this paper adopts the deep Vgg16 module for feature extraction. The CNN is then divided into two branches of the convolutional layer, namely softmax used for policy and value functions and the fully connected layer for ReLU activations, respectively. In each state, policies and values predicted by CNN $(\pi(s), V^\pi(s)) = f_\Theta(s)$ contain the prior data that directs MCTS to gather states with high rewards and collects in turn the CNN training dataset.

Once the CNN $(\pi(s), V^\pi(s)) = f_\Theta(s)$ is trained, this paper starts from the root state $s_0 = 0$, and selects in order the actions at $a_t \sim \pi(s_t)$ from the policies predicted by the CNN, as well as updates the $s_{t+1} = T(s_t, a_t)$ until the complete tree is traversed. Construction of such topology is a stochastic process that converges to a solution, when the CNN is trained at sufficient iterations.

3.4. **Self-configured DRL-TC Algorithm.** The function of self-configuration and self-optimization, called as SON (Self Organizing Network), can better adapt to the flat and flexible network structure, and thus has received widespread attention. In this paper, the DRL-TC algorithm is able to adjust to the dynamic environmental changes. For example, when nodes are abruptly added or removed, some actions will be valid or invalid according to the topology rules. In a new round of MCTS, the policy π of a state returned by the CNN will renormalize all valid actions. Therefore, the new prior policy $\pi(s)$ that reflects network changes remains related to historical information. MCTS collects the new training dataset that is then used to update the CNN. Assuming that the network changes more slowly than the training, the DRL-TC algorithm is able to track dynamic network changes and reconfigure the topology accordingly. Algorithm 2 describes the complete process of the proposed DRL-TC (shown in Table 3).

4. **Experiment Simulation.**

4.1. **Experiment Simulation.** To verify the validity the DRL-TC algorithm, a simulation test is performed upon the heterogeneous network of a ±1100 kV converter station. The heterogeneous network consists of a master node and 12 nodes. 500 to 1000 bits of perceptual data are uniformly generated in each round of transmission. In this paper, all nodes have enough time to transmit data in a round. The data transmission flow of all nodes in each unit is set to $\varepsilon_{v_i}^P = 5$ Mbit/s, and set the power amplification factor $\rho = 1$.

In each iteration, $N_e = 10$ training sets from the MCTS are collected at $N_m = 100$ in each state. Batch size is B=16, and learning rate is $\alpha = 10^{-6}$. In this paper, the ADAM optimizer is used to train the CNN. After each iteration, 100 network topologies are constructed using the CNN and the mean value is taken to verify the validity of the algorithm.

4.2. **Simulation Results.** First, this paper demonstrates the accuracy of the DRL-TC algorithm. In Figure 5, the solid line represents the network delay time for 100 policies returned by the CNN after each iteration of training. Table 4 gives the comparison results of the DRL-TC algorithm and three heuristic algorithms: star topology, random topology, and minimum spanning tree (MST) topology. Among them, the star topology displays the longest network delay time, while the random topology's network delay time is relatively shorter in average but remarkably different. The MST topology reduces the network delay time again by shortening the entire transmission distance. The DRL-TC algorithm

TABLE 3. DRL-TC Algorithm proposed

Algorithm 2: DRL-TC Algorithm Proposed

Input: iterations: N_i; episodes: N_e; search trees: N_m; batch size: B; learning rate: α;
Output: $f_\Theta(s)$;
Training set $E \leftarrow \phi$;
for i **form** 1 **to** N_i **do**
  $s \leftarrow 0$
  for e **form** 1 **to** N_e **do**
    $M \leftarrow \phi$
    for m **form** 1 **to** N_m **do**
      $MCTS(s)$
    doend for
    Normalize the number of visits $M(s)$ from $MCTS(s)$
    $E \bigcup (s, M(s), V)$
    if s is the final state, **then**
      Get reward r, and update V of all s in iteration e
    else
      Select a state $a \sim M(s)$
      $s \leftarrow T(s, a)$
    else if
  end for
  disorganize data setE;
  Train CNN $f_\Theta(s)$, with batch size B and learning rate α
end for

proposed in this paper outperforms these heuristic methods in a large part, with a shorter period of time for convergence.

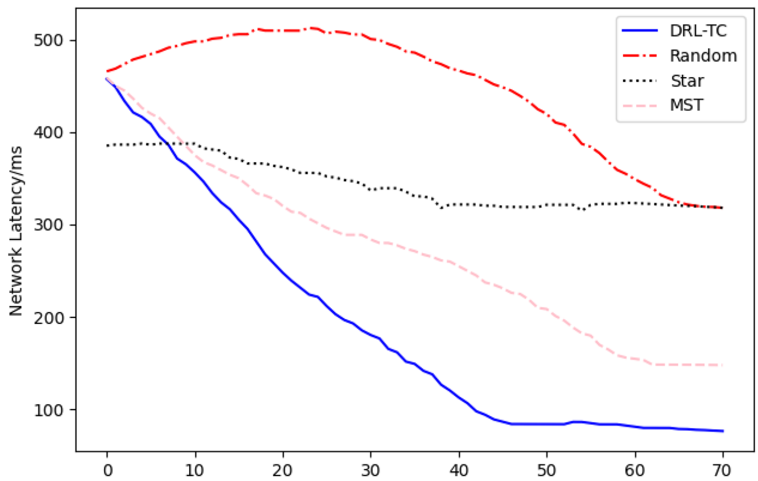

FIGURE 5. Accuracy of the proposed DRL-TC algorithm

Figure 6 reveals that DRL-TC can adapt to suddenly changing heterogeneous network, and average network delay time after each training iteration. In the first iteration, DRL-TC traverses the search space randomly because CNN get no prior information of the state value. The algorithm converges to a very high-confidence solution after about 50 iterations. Then, after a particular heterogeneous node is disabled and disconnected, the

Table 4. Performance comparison between DRL-TC algorithm and three heuristic methods

Topology	10	20	30	40	50	60	70
Random topology	281.2	291.1	257.4	280.5	282.2	275.3	282.9
Star topology	183.9	186.9	186.9	186.9	186.9	186.9	186.9
Minimum spanning tree topology	236.9	236.9	236.9	236.9	236.9	236.9	236.9
DRL-TC	359.9	235.8	186.5	148.6	148.6	148.6	148.6

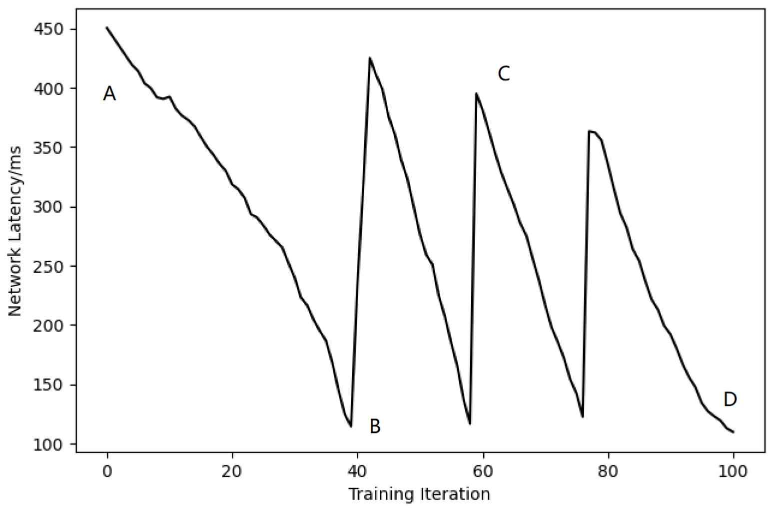

Figure 6. Evolution of the training process

DRL-TC begins to reconfigure the network, while the new topology is still related to the historical data (C in Figure 6). Another advantage of the algorithm is thus obtained, adapting to changes in the network without restarting.

4.3. **Network's Performance Verification.** To verify the topology optimization performance of the proposed method, we executed the simulation in QualNet software. The heterogeneous network adopted in the simulation is as in Figure 2. In the simulation, Node 3 as shown in Figure 8 is sudden failed. The simulation result is shown in Figure 7.

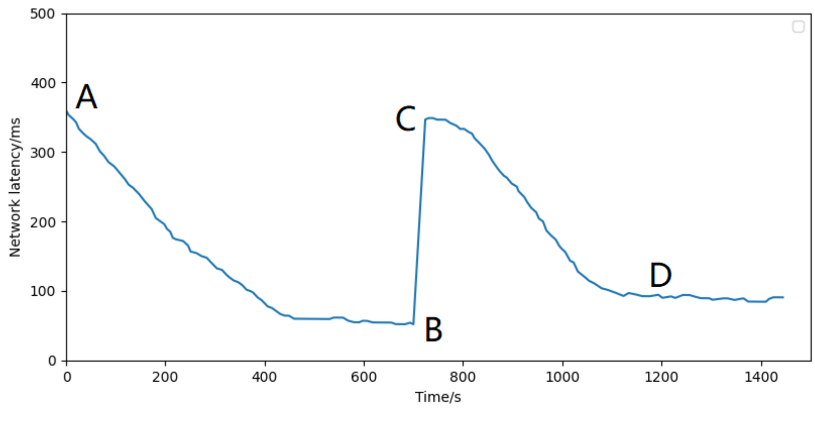

Figure 7. Simulation results of dynamic adaptation to the environment

From Figure 7, we can find out that. When the system is just started (as stage A), it shows a high delay time, and then gradually converges to a stable solution with time, and starts to run stably with a short delay time. At about 700 seconds, Node 3 is sudden failed (as stage B). And then the system exhibits a sudden increase in latency(as stage C). The proposed method dynamically optimizes the topology again. Then it gradually returns to the steady state(as stage D).In summary, the proposed algorithm can adapt to environmental dynamics and reconfigures the network accordingly. The process of topology optimization is shown in Figure 8.

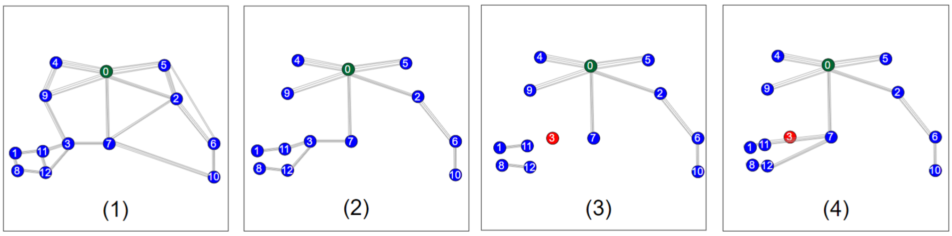

FIGURE 8. Node failure topology optimization

5. **Conclusions.** In this paper, a general and novel topology control algorithm based on DRL is proposed for heterogeneous networks. The algorithm uses a framework combining deep reinforcement learning and Monte Carlo tree search. Deep convolutional neural networks are trained to predict the transmission traffic of partially established topologies and guide MCTS to carry out the remaining steps in more promising areas of the search space, enhancing CNN learning. Experimental results show that this algorithm can adapt to sudden changes of heterogeneous networks, and can converge to a solution faster than other heuristic algorithms, and does not need to start from scratch when network conditions change. In addition, the convergent solution has higher confidence. The reliability of structure is becoming an important index of modern structure design. The topology optimization design based on reliability should be a future research direction. Furthermore, with the improvement of computing resources, this paper predicts that DRL-MCTS will appear in other promising topological control applications in self-organizing and fully automated networks of the IoT in the 5G era.

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