Edge Intelligent Networking Optimization for Internet of Things in Smart City

Ning Chen, Tie Qiu, Laiping Zhao, Xiaobo Zhou, and Huansheng Ning

Abstract

Massive devices connected through fifth-generation (5G) networks constitute a ubiquitous Internet of Things (IoT), providing diverse service applications in a smart city. A robust network topology structure against cyber-attacks is the foundation of highly reliable service quality, especially in next-generation networks or beyond 5G (B5G) networks. Existing methods apply neural networks with deep reinforcement learning methods to advance the network topology. However, the reduction of unique hardware resource constraints and the application of edge intelligent networking capability of terminal nodes are emerging challenges for robustness optimization of IoT with 5G and B5G networks. To address these problems, we design a distributed learning framework utilizing edge intelligence, improving smart terminal nodes' networking capability, which is deployed on ordinary computers instead of specialized hardware such as GPUs. The proposed framework leveraging multi-core CPU and intelligent edge methods decreases the training time and economic cost and takes full advantage of computer resources. Furthermore, the best performing framework considers the distributed communication model of edge computing and optimizes the network topology by taking advantage of smart terminal nodes' contributions. We show that the framework succeeds in various topologies and outperforms compared with other state-of-art algorithms in improving the robustness for IoT topology in smart cities.

Introduction

The robust network topology provide rich application services for the Internet of Things (IoT) [1] with the emerging technologies for fifth-generation (5G) and beyond 5G (B5G) networks. Nowadays, a stable adaptive robust topology is particularly important due to the complexity of application scenarios and the variability of network service requirements, such as intelligent agriculture [2], smart city [3], smart ocean [4], intelligent transportation [5], etc. Benefit for the high speed and bandwidth of 5G and B5G, massive smart sensor devices can be connected to form a highly heterogeneous complex IoT. Failure of some nodes causes the global network's chain collapse effect, which makes the global network unable to communicate. Therefore, designing reliable network topologies for 5G and B5G networks are drawn much attention from researchers. A variety of solutions have been proposed to improve network topology's robustness [6–8]. These algorithms share a common idea: the best optimum topology is searched by the evolution framework and takes more computing resources and time.

Robustness optimization of network topology represents improving the resistance to cyber-attacks, including self-failure, invasion attacks, disaster attacks, etc. Many existing algorithms evaluate performance with several types of attacks. Some proposed learning frameworks [3] utilize centralized architectures to optimize the networking for IoT in smart cities, which can dynamically and intelligently adjust the IoT topology to maintain high communication capability. However, these frameworks rely too heavily on specialized hardware such as GPUs and ignore smart terminal nodes' contributions to the IoT topology in a smart city. With the rise of edge computing technology with 5G and B5G [9], smart terminal nodes have an important influence on the whole network robustness, which is considered to optimize the IoT network topology.

Besides, classic solutions modify the links between devices connected while keeping the number of links the same. Hill Climbing algorithm [6] improves the resistance to cyber-attacks for IoT, but it is prone to be falling into local optimum. Simulated Annealing algorithm [7] changes the links of IoT in a probabilistic and can search the global optimum. Besides, through analyzing the formation of the local optimum, multi-population genetic algorithm [8] utilizes evolution computing to obtain the best solution. On the other hand, an intelligent learning algorithm (NN) [3] based on a neural network is proposed to reduce the computational overhead and accelerate the optimizing process.

Moreover, with the improvement of network nodes' hardware performance and the construction of 5G and B5G networks, smart terminal nodes can execute several computing tasks under the support of edge computing technology [1]. Therefore, a distributed training model of edge computing method is utilized to accelerate IoT topologies' optimization robustness. Given that the limitation of hardware computing resources, we deploy a distributed communication training model [10] to construct a robust IoT topology,

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which provides better data analysis and communication capacity services for applications in 5G and B5G networks.

In this article, we design a very different paradigm for the robustness optimization of network topology for IoT, referred to as edge computing communication methods. Instead of a single centralized neural network training model, we asynchronously execute distributed multiple models parallel with multiple instances of the network topology, which includes a global learning model and several edge local learning models [10]. Each learning instance is like an edge learning node, responsible for optimizing the local model and then communicating with the global model. The paradigm also decorates the models' data into a stationary process because each model experiences various states at each training step. Each model runs a deep reinforcement learning framework which is input different IoT topology data. This strategy enables more kinds of samples on the model with more edge nodes, which learn practical optimization approaches, accelerate the convergence, and improve performance.

Our proposed parallel distributed networking robustness optimization mechanism also offers practical benefits. Whereas previous approaches to machine learning [3] rely heavily on specialized hardware such as GPUs, our mechanism executes on a single machine with a standard multi-core CPU [10]. Besides, we run a distributed communication mechanism according to edge computing methods. Furthermore, we consider a general attack method to evaluate the performance of the algorithm [3, 8, 11], namely Degree Centrality. The best of the proposed method masters several state-of-art existing solutions. Nowadays, 5G technology can be applied to many scenarios of smart cities, i.e., intelligent transportation, smart drones, monitoring system, smart office, etc., as shown in Fig. 1. The server stores the topology of a smart city and converts it into a state vector. The global learning model has better networking optimization effectiveness than each edge local model [10]. Furthermore, we design an asynchronous communication mechanism for the global learning model and edge local learning model. The optimized edge local learning model will communicate with the global learning model during step interval based on the "optimization-first, communication-first" rule.

The rest of the article is organized as follows. We introduce the advanced researches and several fundamental conceptions about the networking optimization of 5G or B5G IoT topologies in a smart city. Then, we outline the framework. We present the technical details of our asynchronous learning model with the deep reinforcement learning method. Next, the simulation and experimental results are discussed. Finally, we conclude this article.

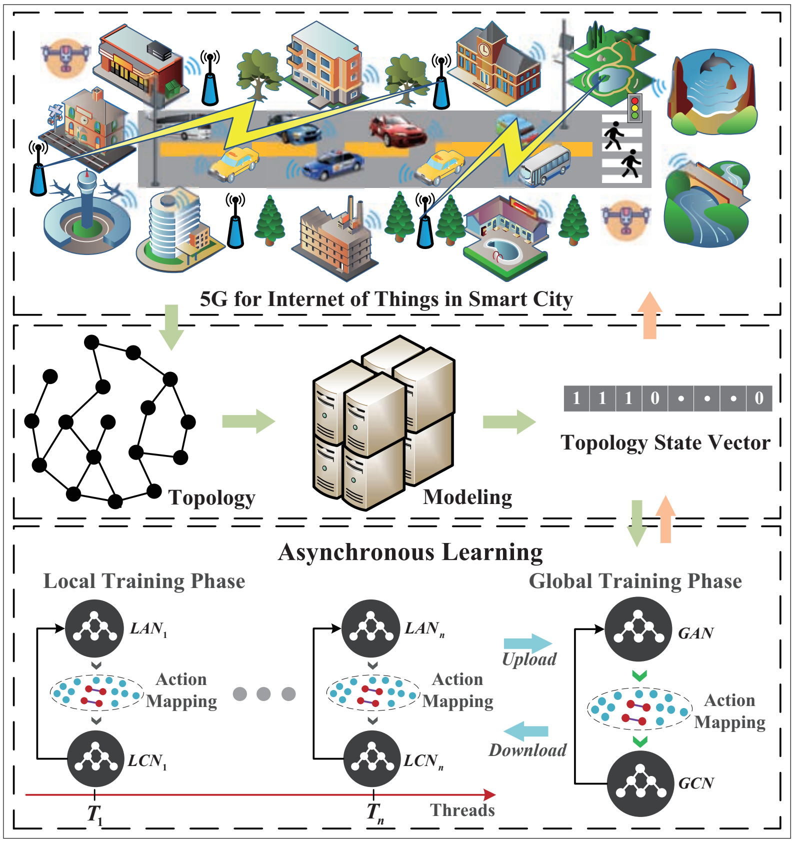

FIGURE 1. In a smart city, the topology of 5G and B5G for IoT can be modeled by servers and then converted to state vector. We input the topology state vector to the asynchronous learning model. In the local training phase, each thread T executes an exclusive deep reinforcement learning model. Individual topology optimization policies are obtained through the local actor-network LAN, action mapping operator, and local critic network LCN. Threads share the global learning phase, and global actor-network GAN and global critic network GCN update their parameters asynchronously through pulling each local training model.

Conceptions about Robustness Optimization

Initial Topology Construction. Scale-free network model [12] generally is strong robust against random attacks, which represent that nodes or links may be equally failed in networks and is fragile resistant to malicious attacks or intentional attacks, which means that important nodes or links may be prone to be failed in networks. We can order the important nodes by utilizing the degree centrality, betweenness centrality, etc. [3, 8]. To take full advantage of scale-free mode, researchers [3, 6, 8, 11] improve robustness against malicious attacks of network topologies constructed by scale-free model. However, in 5G and B5G IoT applications, there are some limitations when constructs the network topology:

1. The communication ranges of nodes or the distance between nodes cannot be infinitely long because each smart terminal node has limited energy to maintain long-distance communication services.
2. The number of nodes cannot be infinitely large since each node cannot apply all computing resources to provide a high quality of communication connection and ignore other tasks

Therefore, in this article, the network topology follows these constraints based on the scale-free policy.

Robustness Optimization. Herrmann *et al.* [6] used a greedy edge-swapping strategy to improve the network's ability to resist malicious attacks. To acquire the global optimum, Schneider *et al.* [11] proposed a probability-based edge swapping algorithm that avoids the local optimum solution. However, the computational overhead is high, and Qiu *et al.* [8] presented a multi-population

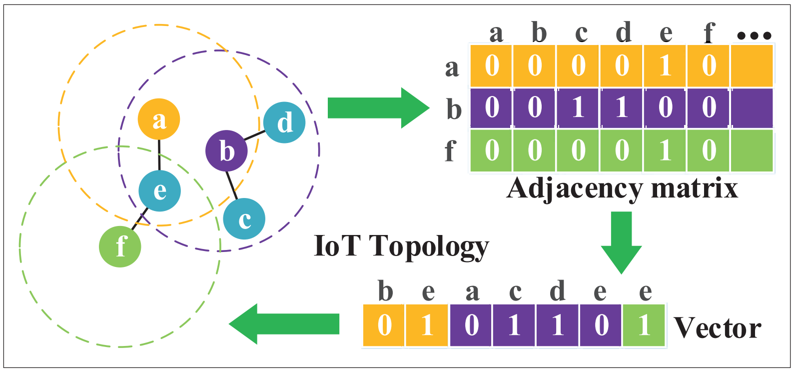

FIGURE 2. Network topology of 5G and B5G IoT firstly converts to an adjacency matrix, then we eliminate redundant information, and finally, we obtain the topology state vector s, which can completely represent the network topology of IoT.

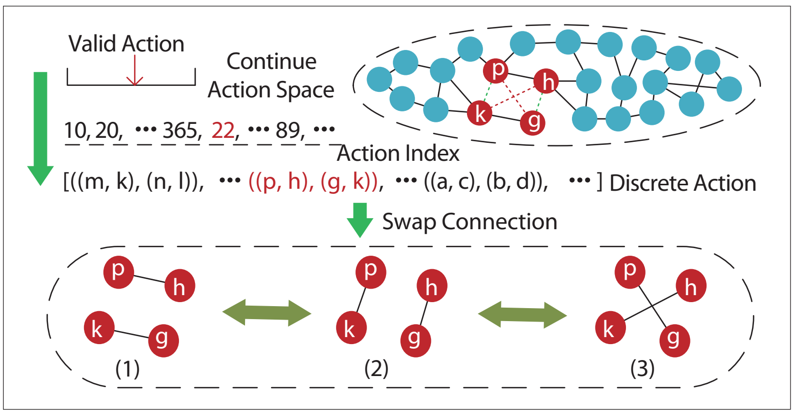

FIGURE 3. We select the action that can swap connections. Each selecting action should contain at least one alternative combination.

genetic algorithm that effectively increases the robustness of the IoT topology. For intelligently dynamically optimizing network topology, Chen *et al.* [3] proposed a dynamic networking optimization method with a neural learning network. However, both the relevance of sample data and supervised learning behavior reduce the robust optimization of network topology. Therefore, in this article, we propose an asynchronous distributed learning strategy with smart terminal nodes to accelerate the learning model's convergence and reduce the dependency on specialized hardware. We apply an edge computing communication method to connect the global learning model and edge local learning models. For measuring the robustness of networks, we utilize the popular metric [11] which statistics the remaining maximum connected component of the network topology after each attack.

Asynchronous Learning. Unlike the existing approaches [3] relying heavily on specialized hardware such as GPUs, Mnih *et al.* [10] propose asynchronous methods for deep reinforcement learning, which reduce half the time for training on a single multi-core CPU machine. Concerning updating parameters [13], the gradients $\nabla\theta$ are asynchronously sent to the shared global network model, which updates a global copy of the model. Meanwhile, the updated parameters are sent to local networks at fixed intervals. Each local network contains an actor-network *LAN*, which acts in the same topology vector *s* and a critic network *LCN* that evaluates the performance of policy generated by *LAN*. In this article, we set each local learning model as an edge intelligence node, which optimizes the local network topology, and the global learning model aggregates the parameters sent by local models. We utilize the asynchronous learning mechanism to improve the resistance to cyber-attacks and reduce IoT applications' computational overhead.

Preliminary

This section focuses on the construction of network topology for 5G and B5G IoT networks and the framework of deep reinforcement learning.

Environment State

The network topology of IoT applications connected by 5G and B5G is converted to a state vector as environment state *s* that inputs into each local learning network model. First, the topology is transformed into an adjacency matrix shown in Fig. 2. Then, we remove the non-neighbors' nodes from the adjacency matrix to eliminate the redundant topology information, which reduces the overhead of topology storage. For example, node *b* has neighbors *c*, *d*, and non-neighbors *a*, *e*. We only reserve the necessary nodes' information and remove the redundancy nodes, such as *f*. Finally, for node *b*, in the topology state vector *s*, we remain the neighbor nodes' connection information. Other nodes also convert to the state vector according to this criterion.

Deep Reinforcement Learning

Actor Network. This article applies a policy-based model-free reinforcement model, including actor-network (policy learning) and critic network (evaluation learning). Besides, to deal with the discrete action selected by actor-network, we design an action mapping operator to convert the continued action to an exclusive discrete action strategy, which can optimize the network topology with high resistance cyber-attacks. Through the input of environment state vector *s*, the actor-network trains the action selecting the policy, alters the connections of nodes for 5G and B5G network topologies.

Action Mapping Operator. Because the model of deep reinforcement learning [10] cannot completely address the robustness optimization for IoT network topology, which has discrete action instead of continuing action [14], such as robot arm control. As shown in Fig. 3, each action we select is valid. We note that the edge swapping operator only involves two-node pairs by analyzing the topology edge swapping strategy [6, 7]. For example, nodes *h*, *g*, *k*, *p* are selected as a valid action combination (*p*, *h*), (*g*, *k*). Before we change the connection, we need to make sure that the candidate actions are available valid. If there is more than one action combination, we select one action that makes the network topology more robust and finally executes the edge swapping strategy.

Critic Network. When we get an action policy, we evaluate the policy in the next step and predict the direction of the action policy learning in the future. The next topology state s_{t+1} and action policy are input the critic network, which can criticize the performance of the action policy.

Through the critic network evaluating, the action policy is adjusted to optimize 5G and B5G IoT topologies' robustness. Besides, the critic policy deployed in global learning and local edge models can improve the efficiency of action selection by reducing selecting actions.

Technical Details

In this section, we introduce the details of the proposed distributed learning model, including edge local training and global learning, as shown in Fig. 4. The distributed framework reduces computing resource overhead and improves optimization efficiency.

Local Training. Each core of the multi-core CPU runs an exclusive deep reinforcement learning model defined as the *worker* or local learning model. The initialization of parameters of models, including *workers* and global network, is the same. For *workers*, the same initial environment state s is assigned to them. As shown in Fig. 4, *worker* obtains an action selecting policy $\pi(s)$ and the evaluation $V(s)$ based on environment state s. Generally, due to the limitation of each core's computing power, local models can not complete tasks at the same time. Therefore, we update local and global parameters asynchronously. The local model *worker* shares parameters θ with the global network every few cycles. We should note that the local edge model *worker* that finishes the training task first communicates with the global model: first completion, first communication. Besides, each local edge model does not wait for each other to finish the task. However, each other waits for others until the final training is complete.

Global Learning. When local model *worker* has its parameters θ, the global network will pull *worker*'s parameters to assign its model. However, in this article, we assign the gradient of the parameters $\Delta\theta_i$ instead of simply assigning parameters [10]. The global network also executes the action policy $\pi(s)$ and policy evaluation $V(s)$. As shown in Fig. 4, the updates of global network is defined as $\theta + \eta\Delta\theta_i$, where θ is the parameter of global network and η is a discount factor which ranges (0, 1). If one local model *worker 1* has finished the task, then the global network updates its parameters based on $\theta + \eta\Delta\theta_1$. Then, to accelerate the speed of convergence and obtain the best solutions, we distribute global parameters θ to each local model *worker* so that the local model can train the best solution as fast as possible. Each local model *worker* continues training under this gradient and shares the parameters $\Delta\theta_i$ with the global parameters θ after a certain number of steps.

Objective Function. We discuss the details of the objective loss function of the asynchronous learning model. The objective loss function that the model minimizes contains three parts [14], policy loss L_π, evaluation loss L_v, and policy entropy L_{reg} which balances the output distribution to avoid the centralization of action sampling. In policy loss L_π, we introduce an advantage function [14] $a(s, a)$ to evaluate the performance of the action. Concerning evaluation loss L_v, we apply the reward value r based on the Q-learning model to describe the situation of the environment state s. For policy entropy L_{reg}, we calculate the entropy of the action policy $h(\pi(s))$. The three loss functions are added with regular factors defined as objective loss function L.

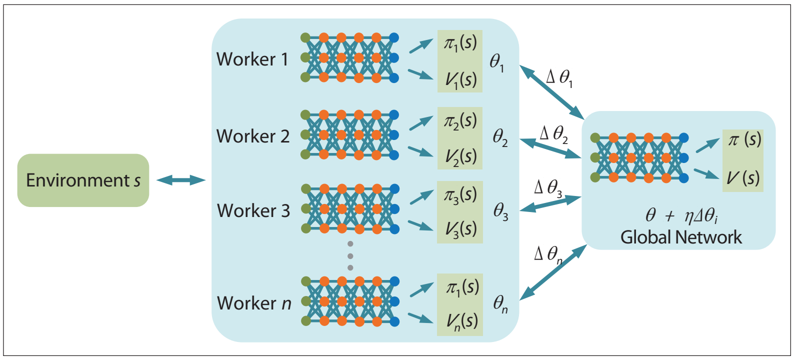

FIGURE 4. Each worker executes the action selecting policy $\pi_n(s)$ and evaluate the performance $V_n(s)$ of the policy π. The parameters of local networks and global networks are asynchronously shared.

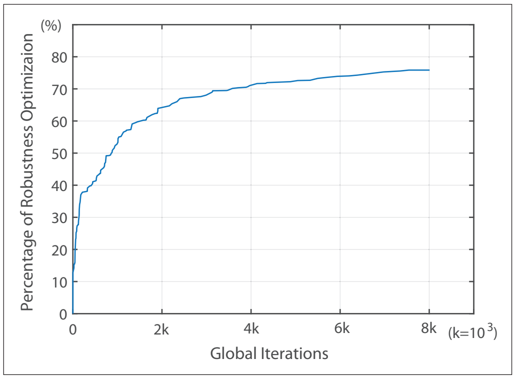

FIGURE 5. The robustness evaluation of global network in our algorithm.

Experiments

To better extract valid information of nodes for 5G and B5G IoT in a smart city, we utilize deep reinforcement learning framework [15] executed by python language to simulate experiments on multi-core CPU machine with Intel(R) Core(TM) i7-8700K CPU @ 3.70GHz. Note that we only apply 6 cores to simulate the proposed algorithm. The nodes of IoT are randomly deployed in a $500m * 500m$ sensing area. The communication range of each node is set to $200m$, which maintains enough neighbors. Many experiments assign the parameters of the proposed model. A robust network topology is constructed through the simulated experiments to provide a better quality of services for 5G and B5G network applications.

For the local training task, if each local network does not produce better results within 200 iterations, we terminate the local learning phase and restart the task. As shown in Fig. 5, we present the robustness evaluation of the global network for a 100-nodes topology with link density 2. As for the calculation of robustness, we consider the previously existing algorithm based on the maximal connected component [3, 8]}. The curve shows an improving trend with the growth of iterations. The maximal 75.85 percent is got at the 7545th iteration. The global learning model aggregates the model parameters provided by local learning models, which explore different learning directions according to the same environment. The global learning model has better

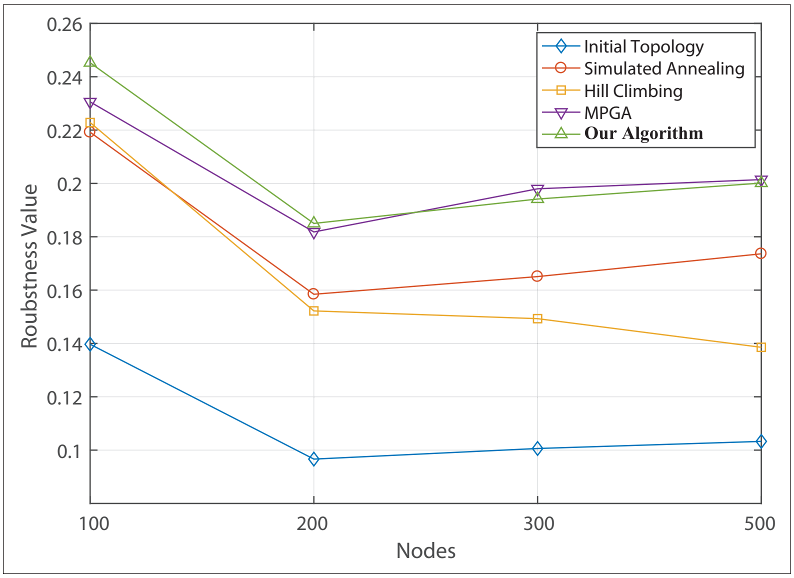

FIGURE 6. The comparison with other algorithms.

performance than local learning models because the global learning model obtains the most appropriate learning parameters by accessing all the environment's local learning situations.

We compare our algorithm with other state-of-art algorithms, including Hill Climbing [6], Simulated Annealing [7], and multi-populations genetic algorithm (MPGA) [8]. These heuristic methods have a disadvantage in computational overhead, which keeps the initial degree distribution unchanged. Figure 6 shows the optimization results in different sizes of IoT topology, which are 100, 200, 300, 500 nodes with link density 2. From Fig. 6, our algorithm has better performance than other algorithms. However, when IoT topology size is less than 300 nodes, our algorithm outperforms MPGA. In 300 and 500 nodes, the proposed algorithm and MPGA have little difference. Overall, the asynchronous learning algorithm can dynamically and intelligently optimize the networking robustness of IoT topologies.

Conclusion

This article proposes a novel asynchronous distributed learning networking optimization with smart terminal nodes for IoT in smart cities. We presented the local training and global learning phases, which rely on a multi-core CPU machine instead of specialized GPUs. Each local model can communicate with the global model to share the parameters that accelerate the speed of convergence for the learning model. The experiment results show that the robustness of IoT topology against cyber-attacks is enhanced significantly by the learning model. The model outperforms other state-of-art algorithms in resisting malicious attacks. For future research, we will explore distributed edge machine learning in the topology optimization of IoT for 5G and B5G networks.

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