5G MEC-based Intelligent Computation Offloading in Power Robotic Inspection

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***Abstract*—Power robotic inspection plays a critical role in the realization of real-time visualization and perception of substation in power grid. 5G mobile edge computing (MEC) has emerged as a promising solution to provide the large bandwidth, wide connectivity, and proximate computing capabilities for the computation offloading of power robotic inspection with stringent delay requirements. This article proposes a 5G MEC-based intelligent computation offloading framework in power robotic inspection to cope with multi-dimension entity heterogeneity, environment dynamics, and inspection delay guarantee. Specifically, the proposed framework and the implementation procedures of computation offloading are firstly elaborated, and the research challenges are outlined. Then, we propose an artificial intelligence (AI)-enabled multi-dimension collaborative optimization algorithm of route planning and task offloading to address the low-latency computation offloading problem under queue stability constraint. A case study is provided to verify the superiority of delay and queue backlog performance through simulation results.**

***Index Terms*—Power robotic inspection, 5G MEC, route planning, task offloading, artificial intelligence, computation offloading**

I. Introduction

Power robotic inspection combines infrared thermography, high-definition video, and dual view technologies to realize the visualization and perception of substation in power grid. It can timely find device fault such as oil leakage, equipment discharge, foreign matter adhesion in power line, and overheating of primary electrical equipment [1]. During inspection, power inspection robots collect a large quantity of images and videos, and generate various computation tasks that need to be processed timely for power inspection services such as fault diagnosis and abnormal alarm. However, the centralized cloud computing paradigm suffers from the communication bottleneck and cannot meet the strict delay requirements of task processing [2].

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With the development of 5G and mobile edge computing (MEC), power robotic inspection based on 5G MEC has received extensive attentions from academia and industry. On the one hand, 5G supports application scenarios of enhanced mobile broadband (eMBB), massive machine-type communications (mMTCs), and ultra-reliable low-latency communications (URLLCs), and can realize the secure isolation of power inspection services from public network services through network slicing and service level agreement (SLA). On the other hand, based on containerization and virtualization, edge computing resources of MEC are abstracted into adjustable resource pools with different granularities to support real-time response of power inspection task processing [3]. 3GPP further standardizes the integration architecture of 5G core network and MEC in 3GPP TS 23.501. It specifies standard data diversion methods including uplink classifier (UL CL), multi-anchoring IP, and local area data network (LADN) to support edge-side task processing and reduce end-to-end delay.

In 5G MEC-based power robotic inspection, computation offloading is the key technology to realize real-time task processing by combining the large bandwidth and wide connectivity capabilities of 5G as well as proximate computing capability of MEC [4]. Computation offloading enables resource-constrained inspection robots to offload computation-intensive tasks to MEC servers through 5G, which is fundamental to heterogeneous robotic systems.

In order to further reduce the end-to-end delay, the core of computation offloading is inspection route planning and task offloading. Therefore, we study the collaborative optimization of route planning and task offloading to achieve scalable, flexible and intelligent power robotic inspection. Some scholars have studied computation offloading optimization of power robots. In [5], Asad *et al.* proposed a reward-based feedback mechanism for resource sharing among robots, which aims to minimize the transmission delay by facilitating deadline-aware computing. In [6], Yu *et al.* developed an energy-sensitive model and proposed a modified genetic algorithm-based strategy to optimize task offloading in robotic network. However, these studies require accurate mathematical model of inspection route and statistical characteristics of data arrival, which are unsuitable for the power robotic inspection scenarios with severe electromagnetic interference, dynamic changes of environmental information, and high computation complexity. In addition, due to the mobility of power inspection robots, the available communication resources and computation resources within the communication range of robot are constantly changing [7]. As a result, it is difficult to obtain accurate global state information. Artificial intelligence (AI) with strong learning ability provides an effective solution for power robotic inspection. It enables intelligent computation offloading for 5G MEC-based power robotic inspection under large optimization dimensions, incomplete environmental information and high robot mobility.

In this paper, we propose a 5G MEC-based intelligent computation offloading framework in power robotic inspection. First, the proposed framework and the implementation procedures of computation offloading are elaborated, and the research challenges are outlined. Then, we formulate a low-latency computation offloading problem, and propose an AI-enabled multi-dimension collaborative optimization algorithm of route planning and task offloading to solve it. Next, a case study is provided to verify the superiority of computation offloading performance through simulation results. Finally, we conclude this paper, and put forward insights on future research directions of power robot inspection computation offloading.

II. 5G MEC-based Intelligent Computation Offloading Framework in Power Robotic Inspection

A. Architecture

The metal particles in gas insulated switchgear discharge under strong electric field which threatens the insulation safety of the electric equipment. When there is a discharge defect, the ions, atoms, molecules and other particles of the material inside the electrical equipment will be excited from a low energy state to a higher energy state under the action of electric energy or heat energy. When the particle is deexcited back to the low energy state, it will release photons and form the multispectral signals. Therefore, in the power transformer and distribution substations, power inspection robots can be equipped with visible light, ultraviolet, and Infrared cameras to collect multispectral information of electrical equipment operation status and perform online equipment monitoring. With the assistance of edge intelligence, robots can also perform real-time fault detection, localization, and alarming which substantially reduces manpower input, improves power system automation level and fine management ability.

We propose a 5G MEC-based intelligent computation offloading framework to guarantee the strict delay requirements of power inspection services under heterogeneous resources and highly dynamic environment as shown in Fig. 7. Particularly, we develop a multi-timescale collaborative optimization architecture of route planning and task offloading. Based on the service demands and incomplete information, route planning and task offloading decisions are jointly optimized to reduce end-to-end computation task offloading delay. AI technologies are explored to realize intelligent computation offloading. The power inspection service demands and major architecture entities are elaborated below.

Inspection Service Demand: Inspection services pose strict demands on video resolution, image resolution, inspection area, delay, bandwidth, and packet error rate. The inspection area of a typical 1000 kV substation spans around 96,000 m^2, which contains thousands of inspection points. Inspection requires video resolution of 1920*1080 and image resolution of 640*480. To support advanced inspection functions such as real-time fault diagnosis and abnormal alarm, reliable bandwidth and delay guarantee is required for massive data transmission [8]. Generally, the communication delay for transmission is required to be less than 500 ms, and the transmission rates of 1080P video and infrared thermal imaging data are required to be around 384 kbps to 4 Mbps.

Power Inspection System: Power inspection system combines software modules including task layer, application layer and system layer and hardware modules such as data acquisition system, data analysis system, master station data interaction interface and station human-computer interaction interface. It supports routine inspection, special inspection, regular inspection, and abnormal three-phase temperature difference alarm. Specifically, in routine inspection, an inspection robot automatically plans inspection routes, records inspection data based on predefined parameters such as inspection point, start time, and inspection cycle, and finally uploads the collected data to the power inspection system for advanced inspection functions.

Power Inspection Robot: Power inspection robot has the functions of autonomous navigation, positioning, charging, and power inspection. It implements substation inspection according to preset routes, and combines high-definition video, infrared thermal imaging, ultrasonic protection, and laser autonomous navigation to accurately identify the readings of various instruments and equipment status information [9]. For example, a CSG inspection robot is equipped with a 30x optical zoom camera and 640*480 resolution infrared thermal image sensor, which can achieve a positioning accuracy less than 1 cm, a long-distance detection of 100 m, and scanning with a 360-degree angle of view.

5G MEC: Power inspection robot offloads the collected data to MEC servers through 5G. The MEC consists of MEC servers, local MEC management platform, and regional MEC management platform. The servers perform data cleaning, preprocessing, calculation, and feedbacks the results to the inspection robot and system [10]. The local MEC management platform coordinates and dispatches the computing, storage, network, and other infrastructure resources in a transformer district to support local data preprocessing. The regional MEC management platform supports advanced data analysis through resource coordination among different transformer districts.

B. Implementation of 5G MEC-based Intelligent Computation Offloading

The implementation scenario of 5G MEC-based intelligent computation offloading is shown in Fig. 8. There exist multiple inspection points in substation, and the robot has to traverse all inspection points through route planning. During inspection, the robot continuously collects equipment and environment data including high-definition video, infrared thermal imaging, electromagnetic interference, channel gain, and available base stations (BSs), and stores them in its local buffer as a data queue. The stored data are either processed locally or offloaded to MEC servers through 5G BSs. Due to the robot mobility,

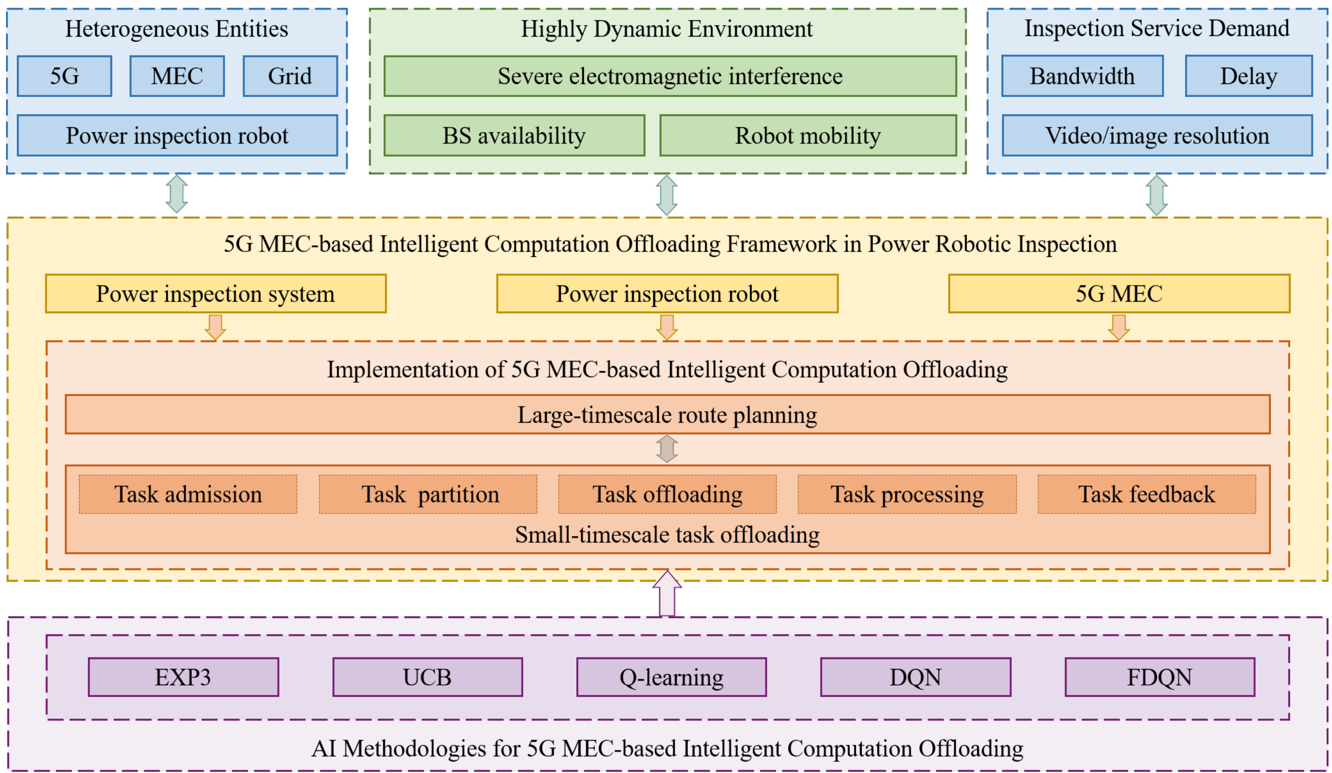


Fig. 1. The proposed 5G MEC-based intelligent computation offloading framework in power robotic inspection.

the available BS set is dynamically varying. Particularly, as the robot moves from one inspection point to another one, some previously available BSs are disconnected when the robot moves out of their communication ranges. Apart from BSs, other network states such as electromagnetic interference, channel state information, and server computation resources are also time-varying. Therefore, the robot has to decide which 5G BS and MEC server should be selected for task offloading to minimize the end-to-end delay.

The implementation process of power robotic inspection includes route planning, task admission and partition, task offloading, as well as task processing and feedback. Route planning is optimized in large timescale, i.e., every epoch, while task admission and partition, task offloading, as well as task processing and feedback are optimized in small timescale, i.e., every time slot. The details are explained as follows.

Route planning: Route planning determines the next inspection point from the current one. Then, a robot traverses all the inspection points and performs power inspection along predefined routes from one inspection point to another one. It is intuitive to avoid repeated inspection routes to further reduce the total inspection distance and improve inspection efficiency.

Task admission and partition: Task admission determines the portion of data that enter into the buffer queue of the robot. It is necessary to avoid the large volume of raw data flooding the limited buffer. Afterwards, the data stored in the queue are partitioned into two separate queues, as shown in Fig. 9. One is the local-computation queue processed locally by the robot, and the other is the task-offloading queue processed remotely by MEC servers. The balance between local-computing queue and task-offloading queue needs to be dynamically adjusted by optimizing task partitioning strategies.

Task offloading: Task offloading determines the 5G BS and co-located MEC server for task offloading and processing. Since multiple BSs with different link conditions and computing capabilities are available, both communication and computation combinations have to be decided by the robot with limited BS-side information. When the robot learns that the delay performance of the selected BS is poor or the selected BS becomes unavailable due to mobility, it will switch to another previously available BS or a newly appeared one. A switching cost evaluated in terms of delay occurs because of BS switching and task computation migration. An example is shown in Fig. 8 and Fig. 9. In Case 1 of Fig. 9, the robot selects BS 2 for task offloading in slot t, and the data are offloaded from the task-offloading queue of the robot to the buffer queue of BS 2. In the next slot, the robot moves out of the coverage of BS 2, and switches to BS 3 for task offloading, as shown in Fig. 8. The data are offloaded from the task-offloading queue of the robot to the buffer queue of BS 3, as shown in Case 2 of Fig. 9.

Task processing and feedback: The data stored in the local-computation queue are processed locally by the robot and uploaded to the power inspection system. The data stored in the buffer queue of BSs are processed by MEC servers and the results are fed back to robots and system based on service demands.

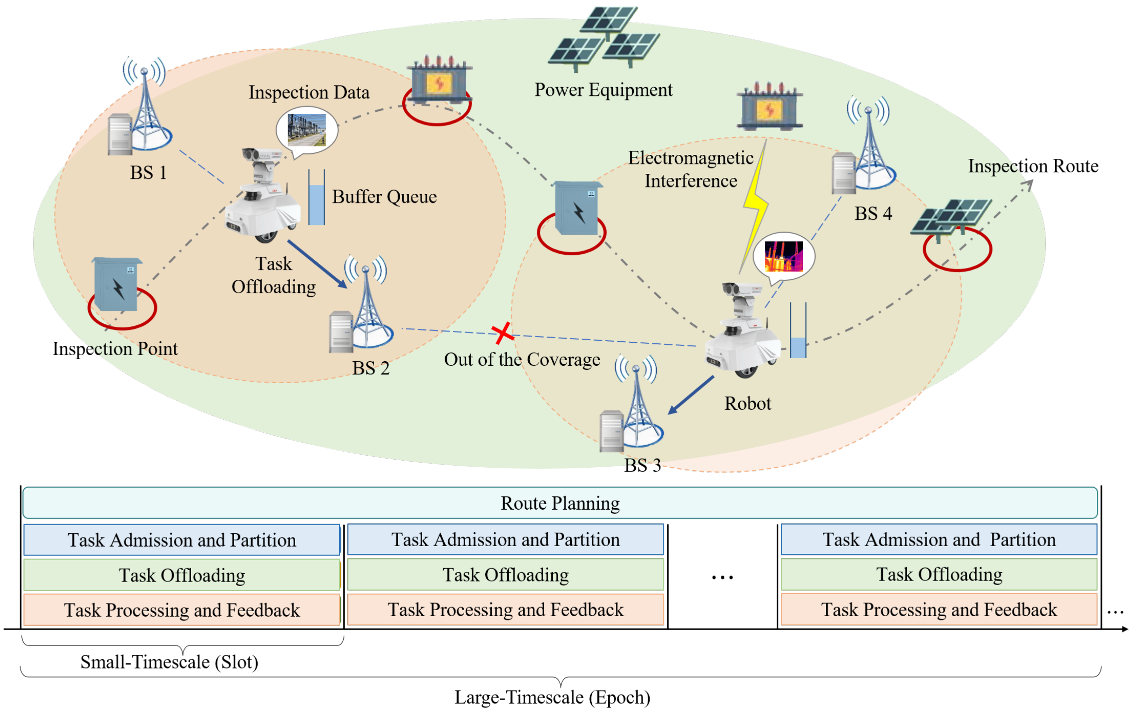


Fig. 2. The implementation scenario of 5G MEC-based intelligent computation offloading.

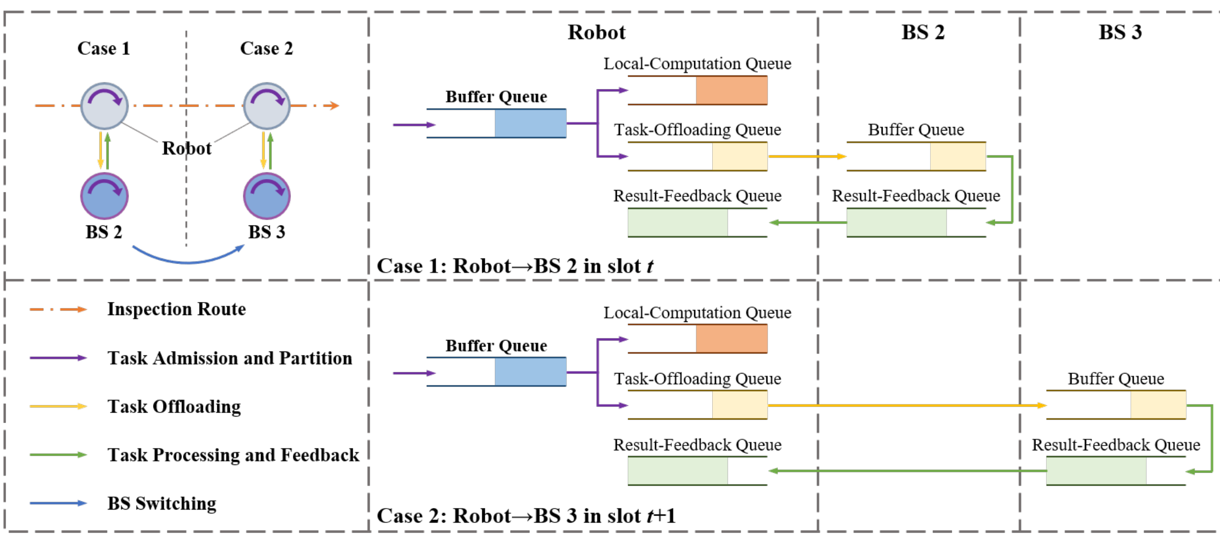


Fig. 3. The implementation procedure of 5G MEC-based intelligent computation offloading.

C. Research Challenges

To realize 5G MEC-based intelligent computation offloading in power robotic inspection, several critical research challenges have to be addressed.

Coupling between large-timescale route planning and small-timescale task offloading: The large-timescale route planning affects the total inspection distance and available BSs and MEC servers for small-timescale task offloading. On the other hand, the small-timescale task offloading affects the total end-to-end delay and needs to be jointly optimized with large-timescale route planning.

Unavailability of BS-side information: The BS-side information including BS load profile, available computation resources, and server operation state is generally unknown to the inspection robot. Furthermore, due to robot mobility and electromagnetic interference caused by partial discharge of high-voltage substation and gas insulated switchgear, the channel state information is time varying. How to collaboratively optimize route planning and task offloading without BS-side information is a great challenge. Traditional graph-based optimization approach requires to traverse all states, which leads to extremely high computation complexity in multi-dimension and multi-timescale decision-making.

Delay performance guarantee: The end-to-end computation offloading delay is determined by both inspection delay and task offloading delay. Moreover, the task offloading delay is determined by the last finished task, which is further affected by task size and server computing capability. The coupling between long-term data queue backlog stability of robot with short-term delay minimization puts another dimension of challenge on computation offloading optimization. For instance, offloading few tasks with smaller sizes may reduce delay but increases data backlog.

III. AI-enabled Multi-dimension Collaborative Optimization Algorithm of Route Planning and Task Offloading

Route planning and task offloading need to be collaboratively optimized in an online fashion without the perfect knowledge of BS-side and environment-related information. Reinforcement learning in AI can effectively deal with online random decision-making problems by constantly interacting with dynamic environment and learning from empirical performance [11]. It has the advantages of strong environmental adaptability and fast feedback convergence. Typical reinforcement learning algorithms include exponential-weight algorithm for exploration and exploitation (EXP3), upper confidence bound (UCB), Q-learning, deep Q-network (DQN), and federated deep Q-network (FDQN). Particularly, the fundamentals of Q-learning and UCB are introduced below [12].

Q-learning leverages Q value, i.e., state-action value, to evaluate and optimize strategy without the requirement of environment state transition model. Therefore, it is suitable for solving the route planning problem with complex electromagnetic interference where the environment state transition probability cannot be modeled directly [13]. UCB is a lightweight learning algorithm to solve sequential strategy optimizing problem, which evaluates a candidate option with the combined power of its empirical performance estimate and the estimate confidence interval. The advantage of low-complexity implementation makes it suitable to address task offloading problem [14].

By combining reinforcement learning algorithms, i.e., Q-learning and UCB, with queue awareness, we propose an AI-enabled multi-dimension collaborative optimization algorithm of route planning and task offloading to address the computation offloading problem. A two-timescale model is adopted. The large timescale, i.e., epoch, is defined as the inspection routing time for the robot moving from one inspection point to another one, the duration of which depends on the route planning decision optimized at the beginning of each epoch. Each epoch can be partitioned into several small-timescale intervals with a fixed time duration, i.e., time slot. Task offloading decision is optimized at the beginning of each slot. Without loss of generality, it can be assumed that the set of available BSs and the channel state information are unchanged within one slot.

Objective: The optimization objective is defined as the delay required for processing all the inspection data. It depends on both the inspection delay and task offloading delay, while the latter one is the sum of BS switching delay, data transmission delay, computing delay, and feedback delay. Considering the comparatively small size of feedback data, the feedback delay can be ignored.

Route planning constraint: It ensures that only one route is inspected in each epoch and the inspection procedure ends only if all inspection points have been traversed.

Task offloading constraint: In each time slot, the robot can only select one BS within its communication range for task offloading.

Queue stability constraint: The long-term average backlog of the robot-side data queue should not exceed a predefined threshold.

The framework of the proposed algorithm is shown in Fig. 10. A virtual queue is constructed to quantify the long-term performance deviation of queue backlog from the predefined threshold. Based on Lyapunov optimization, the queue stability constraint is transformed into minimizing virtual queue backlog. Therefore, the short-term route planning and task offloading decision optimization can be decoupled from the long-term queue stability constraint by transforming the original optimization problem into minimizing the upper bound of drift-plus-penalty in each slot. Specifically, the upper bound of drift-plus-penalty is derived as the weighted sum of delay and the product of virtual queue backlog and throughput, i.e., the amount of offloaded inspection data.

Based on the optimization variables involved, the joint optimization problem is transformed into a large-timescale route planning subproblem and a small-timescale task offloading subproblem.

Large-timescale route planning: The large-timescale route planning subproblem is modeled as a Markov decision process (MDP) problem, and its key elements include state space, action space and reward. State space is defined as the inspection point of the robot at the beginning of the current epoch and histroical channel information. Action space is defined as the set of candidate inspection options. The large-timescale reward consists of two parts. The first part is the delay required for processing all the inspection data offloaded in an epoch multiplied by weight V. The second part is the product of virtual queue backlog and the throughput at the end of an epoch. V trades off delay minimization and queue stability. The proposed algorithm leverages Q-learning to address the transformed large-timescale route planning problem. It quantifies each inspection route with Q value where a large Q value indicates that the inspection route has superior performances in delay and queue backlog stability. At the beginning of each epoch, the robot selects the next inspection point based on the Q values and ϵ-greedy algorithm. At the end of each epoch, the robot updates Q values based on the large-timescale reward and the potentially maximum Q value in the observed next state.

Small-timescale task offloading: The small-timescale task offloading subproblem is modeled as a multi-armed bandit (MAB) problem, and its key elements include player, arm and reward. Player is defined as the inspection robot. Arm is defined as the set of available BSs for the inspection robot,

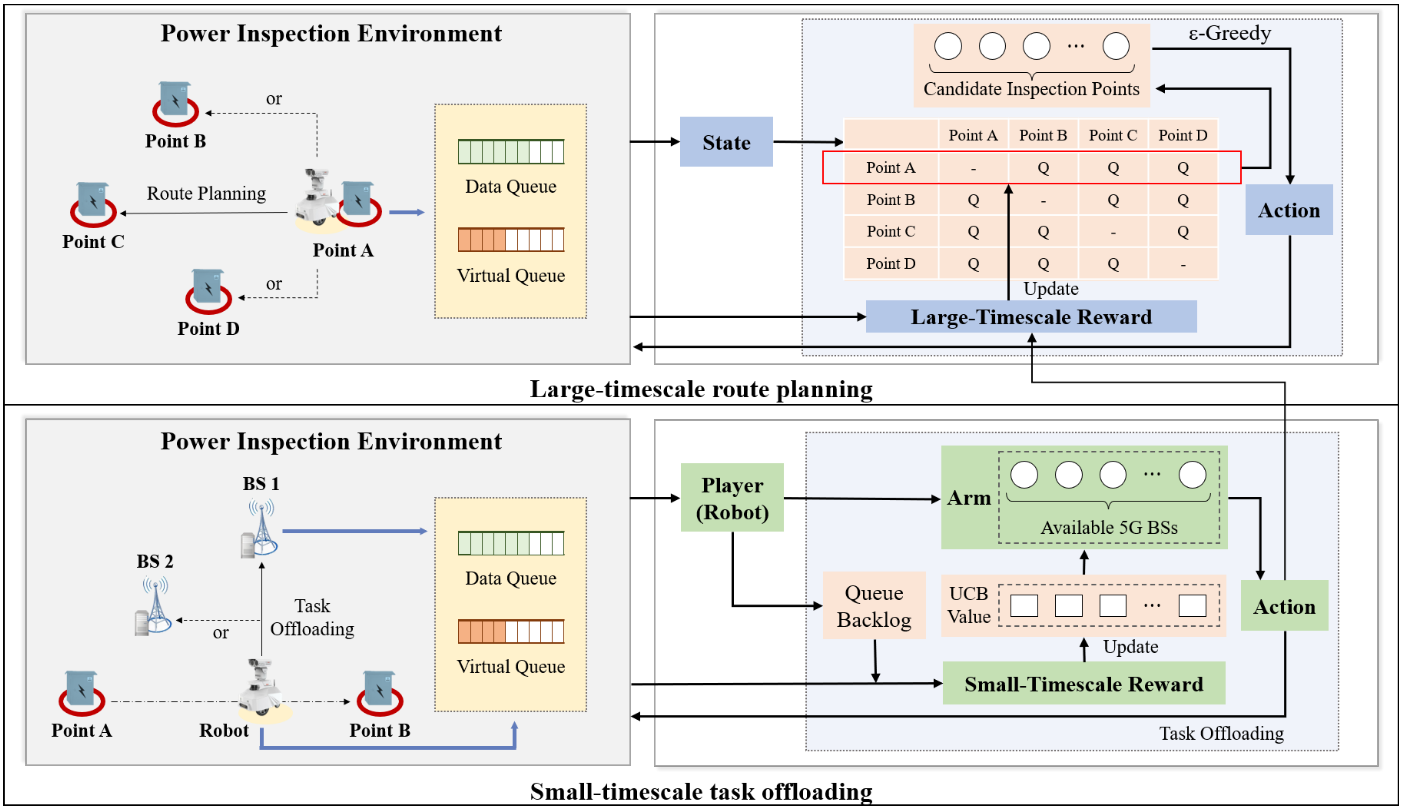


Fig. 4. The framework of the proposed algorithm.

which would vary across epochs due to robot mobility. The small-timescale reward consists of two parts. The first part is the delay for processing the inspection data in the current slot multiplied by V, which is fed back by the selected BS. The second part is the product of virtual queue backlog and the amount of offloaded inspection data. The proposed algorithm leverages UCB to address the transformed small-timescale task offloading problem. At the beginning of each slot, the robot selects the BS with the largest UCB value, which is defined as the sum of the empirical performance estimate and the estimate confidence interval. The confidence interval is defined as the square root of a fraction where its denominator is the number of times that the BS is selected, and its numerator is the logarithm of slot t multiplied with a queue backlog-related exploration weight ω. Specifically, ω is inversely proportional to queue backlog. Besides, the confidence interval of the firstly available BS is set as positive infinity to ensure that it is selected at least once. At the end of each slot, the robot updates the empirical performance estimate, confidence interval, exploration weight and UCB value based on the queue backlogs and the small-timescale reward. The upper bound confidence is updated at each slot. The proposed algorithm has fast convergence speed and strong learning performance to adapt with inter-epoch dynamics.

The proposed algorithm can achieve queue awareness in three folds. First, since it integrates Q value with the virtual queue backlog, the route with severe electromagnetic interference and poor task offloading performance is quantified with a small Q value and has less probability to be selected, thereby enabling queue stability. Second, since the small-timescale reward is involved with virtual queue backlog and the throughput, the large virtual queue backlog enforces the robot to select a BS with large transmission rate to reduce queue backlog, thereby maintaining data queue stability. Last but not least, with the queue backlog-related exploration weight, the robot prefers to explore the BS with potentially superior performance when its queue backlog is small and prefers to exploit the BS with historically optimal performance when the queue backlog is severely deviated from the threshold. Therefore, the tradeoff between exploration and exploitation is dynamically balanced without severe queue backlog fluctuation.

The specific implementation process of the proposed algorithm is shown in Fig. 11, which is described as follows.

Step 1: Initialization. Initialize large-timescale state space, action space, Q value and small-timescale available BS set.

Step 2: Large-timescale route planning.

Step 2.1: Route planning action drawing. Inspection robot draws a route planning action based on the ϵ-greedy method and Q values.

Step 2.2: Small-timescale task offloading. Based on the drawn route, the robot performs small-timescale task offloading optimization.

Step 2.2.1: Available BS set updating. The robot updates the available BS set.

Step 2.2.2: Task offloading action drawing. The robot selects the BS with the largest UCB value for task offloading.

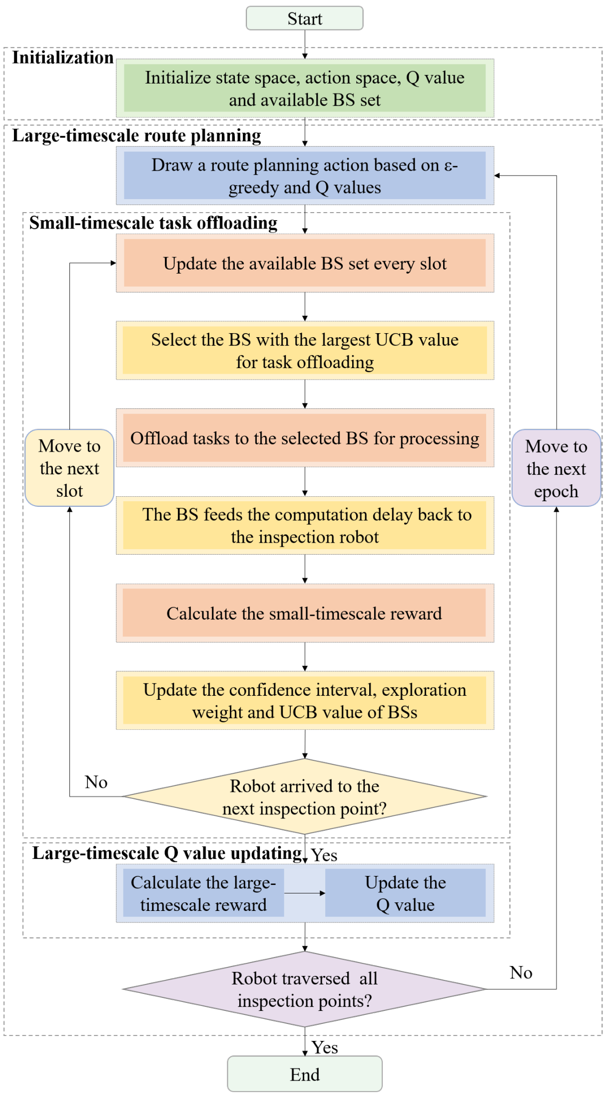


Fig. 5. The flowchart of the proposed algorithm.

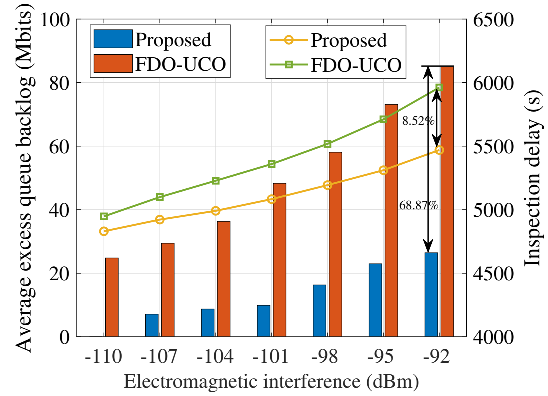
Step 2.2.3: Task offloading action execution. The robot offloads tasks to the selected BS.

Step 2.2.4: Small-timescale reward calculation. The robot calculates the small-timescale reward based on the computation delay fed back by the BS, virtual queue backlog, and the throughput.

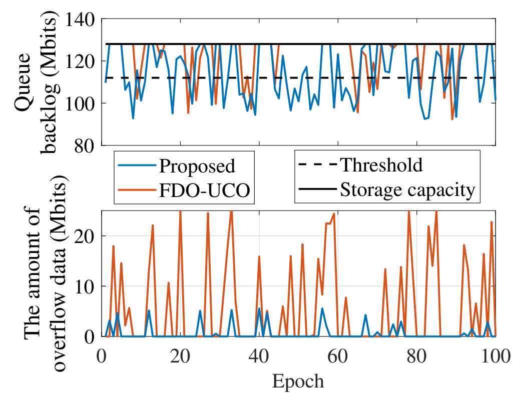
Step 2.2.5: UCB value updating. The inspection robot updates the empirical performance estimate, confidence interval, exploration weight and UCB value of BSs.

Step 2.3: Large-timescale Q value updating. When the inspection robot reaches the selected inspection point, it calculates the large-timescale reward and observes the next state. Then, it updates the Q value and enters the next epoch. Repeat step 2 until all inspection points have been traversed.

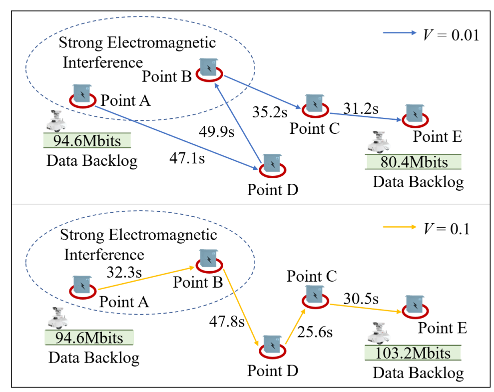
The complexity of the proposed algorithm includes the complexity of large-scale routing planning and that of small-scale task offloading. The former one is linearly proportional to the numbers of inspection points and epochs while the latter one is also linearly proportional to the numbers of time slots



(a) The average excess queue backlog and inspection delay performance.



(b) The queue backlog and the amount of overflow data performance.



(c) The influence of different weights on the inspection robot.

Fig. 6. Performance improvement of the proposed algorithm.

and available MEC servers.

IV. A Case Study

In the case study, we investigate the effectiveness improvement of the AI-enabled multi-dimension collaborative optimization algorithm of route planning and task offloading. A 1 km $\times$ 1 km power robotic inspection area with 100 inspection points and 10 5G BSs is considered. The power inspection robot moves at a speed within [2,6] m/s. The slot length is 100 ms. BS switching cost is set as 5 ms. The robot transmission power is 20 dBm, and the transmission bandwidth is 1 MHz. The route planning and task offloading decisions are jointly optimized to reduce end-to-end computation task offloading delay. Specifically, the joint optimization problem is transformed into two subproblems on different timescales based on Lyapunov optimization, which are solved by Q-learning and UCB respectively. The fixed detection order scheme-UCB based computation offloading algorithm (FDO-UCO) [15] is utilized for comparison, which cannot optimize route planning and ignores the queue stability constraint.

Fig. 12 (a) shows the average excess queue backlog and inspection delay versus electromagnetic interference. The excess queue backlog is defined as the amount of data backlog exceeding the predefined threshold. With the increase of electromagnetic interference from -110 dBm to -92 dBm, compared with FDO-UCO, the proposed algorithm can reduce 68.87% average excess queue backlog at the cost of only 8.52% inspection delay increment. The reason is that in addition to task offloading optimization, the proposed algorithm also optimizes the route planning to avoid the areas with strong electromagnetic interference and ensure the queue stability, which may result in detour and increase the inspection delay.

Considering the buffer capacity of the inspection robot is limited in the real-world implementation, data overflow occurs when the queue backlog exceeds the buffer capacity. Given that the inspection robot has a limited buffer capacity of 120 Mbits, Fig. 12 (b) shows the queue backlog and the amount of overflow data versus epoch. Compared with FDO-UCO, the proposed algorithm reduces the queue backlog and the amount of overflow data by 16.43% and 82.84% due to the endowed queue awareness.

Fig. 12 (c) shows inspection routes under different V, where the blue and yellow lines represent the inspection routes starting from inspection point A to point E when $V = 0.01$ and $V = 0.1$, respectively. When the weight increases from 0.01 to 0.1, the inspection delay decreases from 163.4 s to 136.2 s while the queue backlog increases from 86.8 Mbits to 98.5 Mbits. The reason is that with V increasing, the proposed algorithm puts more emphasis on inspection delay minimization which enforces the robot to select the shorter path. However, the strong electromagnetic interference between point A to point B results in poor data transmission performance and queue backlog increment.

V. CONCLUSION

In this article, we proposed a 5G MEC-based intelligent computation offloading framework in power robotic inspection, where a multi-timescale collaborative optimization architecture of route planning and task offloading was developed to deal with the heterogeneous resources and highly dynamic environment. An AI-enabled multi-dimension collaborative optimization algorithm of route planning and task offloading was proposed to minimize the inspection delay under queue backlog constraint. Simulation results show that compared with FDO-UCO, the queue backlog is reduced by 15.56%. The proposed algorithm can achieve well-balanced tradeoff between inspection delay and queue backlog under strong electromagnetic interference.

In future research, the proposed framework can be expanded by involving cloud-edge-end collaboration and advanced security technologies. First, edge computing is flawed by insufficient scalability, limited computing and storage resources. How to integrate the advantages of cloud computing and edge computing to achieve cloud-edge-end collaborative computation offloading for inspection delay performance improvement remains an open issue. Second, the 5G MEC-based computation offloading requires the power inspection robot to access to the public network, which leads to task data exposed in an untrusted and opaque environment. The stable operation of the power system is seriously endangered due to the security problems such as data interception and tampering caused by illegal attacks on the 5G MEC server. Therefore, it is necessary to combine advanced security technologies such as blockchain and trusted computing to further improve the data integrity and security in power robotic inspection.

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