AI-Enabled Deployment Automation for 6G Space-Air-Ground Integrated Networks: Challenges, Design, and Outlook

Sheng Wu, Ning Chen, Ailing Xiao, Haoge Jia, Chunxiao Jiang, and Peiying Zhang

Abstract

Combined with artificial intelligence (AI) technology, Space-Air-Ground Integrated Networks (SAGINs) play a crucial role in realizing the 6G vision of self-awareness, ubiquitous intelligence, and Internet of Everything (IoE). Compared with 5G, the 6G vision demands higher performance in key performance indexes (KPIs) such as peak data rate, user experience data rate, delay, coverage percentage, reliability, etc. And, the independent configuration and deployment of network functions through network deployment automation is essential for meeting these 6G KPIs. However, traditional deployment strategies lack flexibility and applicability, relying on manual intervention. To address this, we analyze the characteristics of various AI algorithms in 6G SAGINs and propose a federated learning (FL)-assisted deep reinforcement learning (DRL) framework, which jointly optimizes deployment strategies through local and global collaboration. Case studies verify the effectiveness of this approach in improving network deployment automation and ensuring related KPIs in data management, resource allocation, and other tasks. Finally, we discuss the significant challenges that AI will face in deploying 6G SAGIN settings.

Introduction

The sixth-generation mobile communication standard (6G) is anticipated to be a comprehensive improvement of 10 to 100 times compared with 5G. Furthermore, 6G vision has higher requirements in key performance indexes (KPIs) such as peak data rate (>100 Gb/s), user experience data rate (>10 Gb/s), delay (<1 ms), coverage percent (>99%), reliability (>99.999%), and other aspects [1]. The Space-Air-Ground Integrated Networks (SAGINs) is the key trend for enabling 6G deployment and realizing Internet of Everything (IoE) [2]. As shown in Fig. 1, 6G SAGIN is built upon terrestrial networks and expanded through satellite networks, encompassing space, air, land, ocean, *etc*., providing information guarantees for diverse user activities. In particular, the non-terrestrial networks (NTNs) [3], a 3rd Generation Partnership Project (3GPP) initiative, aim to integrate satellite and air communications with the terrestrial network, enabling broader coverage to meet user access requirements. Therefore, the future wireless communications technology will make transformative improvements in quality of service (QoS) and quality of experience (QoE). At that time, emerging technologies such as Connected and Automated Vehicles (CAVs), Internet of Things (IoT), Mobile Edge Computing (MEC), Social Networks, Intelligent Transportation Systems (ITS), Holographic Projection, Virtual Reality (VR), Extended Reality (XR), and so on will achieve breakthrough developments [4].

To meet the richer service and performance requirements in 6G SAGIN settings, it is necessary to achieve necessary breakthroughs in critical technologies based on existing wireless network architectures. Network deployment automation plays a crucial role in meeting the 6G KPIs [1]. Specifically, it is the automatic deployment of network functions and decisions according to the network environment without manual intervention. Through it, some network informatization strategies can be specified and implemented, thereby improving the overall efficiency and level of network management. For instance, 6G SAGINs will involve a significant amount of resources, including spectrum, energy, and computing resources. By intelligent resource allocation and management, network deployment automation can enhance resource utilization efficiency and reduce operating expenses (OPEX). Moreover, the deployment and switching of large-scale infrastructure are essential for 6G SAGINs. Through automated management, network deployment automation enables efficient, accurate, flexible, and reliable task decision-making and deployment. Furthermore, network deployment automation processes like data management, resource allocation, and task offloading will be widely utilized across all aspects of 6G SAGINs. Currently, many related research activities [2], [4], [5], [6], [7] are using various emerging technologies to support the development of 6G SAGINs, which also significantly promotes automation of network deployment. For instance, to support key

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services, Hou et al. [2] utilize diverse resources at the edge of 6G SAGINs to build low-latency and ultrareliable edge intelligence.

AI Boosts Network Automation Deployment

Notably, traditional network deployment automation faces the following challenges in 6G SAGIN settings: (1) It relies on predefined rules and lacks the ability to make intelligent decisions based on real-time network state and demand, resulting in inflexible and less adaptable deployments. (2) It is unable to self-tune and optimize performance based on historical data and feedback. Instead, it relies on manual intervention. (3) It is prevalent in manual configuration and management, including device configuration and network topology planning. This approach has low fault tolerance and struggles to handle large-scale network deployment requirements. (4) It is designed for specific scenarios and lacks universality and adaptability.

In recent years, artificial intelligence (AI) has been widely employed at all levels of network architecture and has significantly improved the level of network automation, which aligns with the trend of self-awareness and ubiquitous intelligence for the 6G vision [4]. Specifically, relative to traditional deployment strategies, AI-based network automation deployment methods have the following advantages. Firstly, they can rapidly analyze and process large amounts of network data, automatically completing deployment tasks based on preset rules, and improving deployment speed and efficiency. Secondly, these methods can automatically adjust and optimize network deployment schemes in response to real-time network environment changes and demand. Thirdly, they accurately identify and analyze network problems such as faults and security vulnerabilities, providing corresponding solutions to enhance the accuracy and reliability of deployment. Fourthly, they automate the management and configuration of network devices, offering scalable and large-scale deployment solutions. Lastly, these methods continuously learn and optimize the deployment process using historical data, providing intelligent decision-making to improve network performance and effectiveness. Therefore, AI algorithms demonstrate high efficiency, adaptability, accuracy, reliability, scalability, and intelligence in the network deployment automation process.

Motivation

Excitingly, DRL shows more promising prospects in various network decisions. Specifically, it utilizes deep neural networks (DNNs) to replace Q-tables in reinforcement learning (RL). Through DNNs, the agent can obtain a higherdimensional abstract feature representation, thereby improving the perception ability of the model. Second, the value function of each action is evaluated by the expected reward, and the current state is mapped to the corresponding action through a certain strategy. Based on this action, the environment generates a corresponding reward, which will guide the next positive action. The above process is repeated until the optimal strategy is reached. Therefore, DRL has more satisfactory perception and decision-making capabilities simultaneously, which will show promising potential in the automation process of 6G SAGIN deployment [8].

In addition, ubiquitous computing will lead to a surge of data, which will gradually expose issues

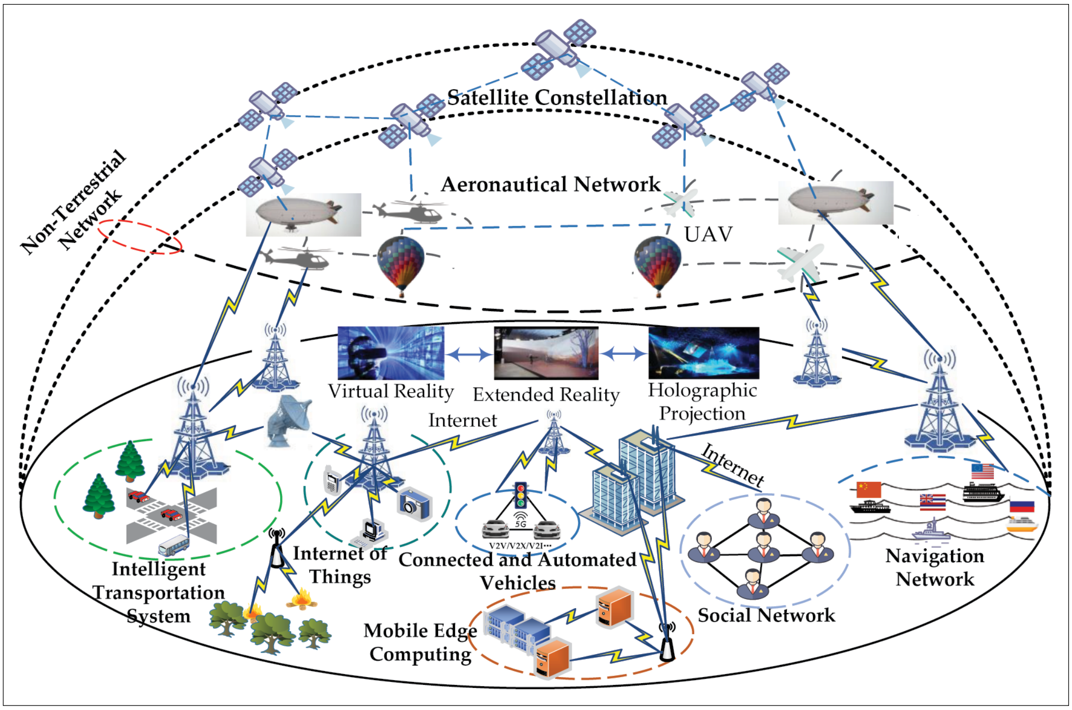

FIGURE 1. 6G space-air-ground integrated network architecture.

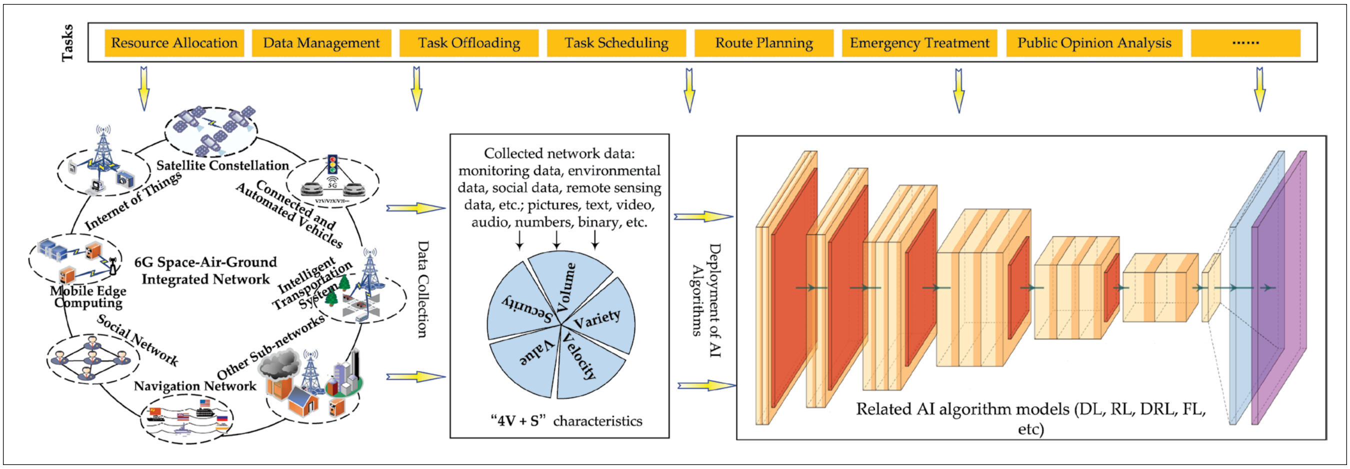

FIGURE 2. Deployment of AI algorithms in 6G space-air-ground integrated networks.

such as data privacy and real-time performance. Specifically, traditional AI-enabled applications need to upload all training data to a cloud server for unified training and send it back to update each local server [9]. This will lead to privacy breaches and inefficiencies in learning. It is worth mentioning that federated learning (FL) is widely employed to solve the phenomenon of data silos. On the premise that the data does not leave the local, parameters are shared for joint modeling, which not only ensures data privacy but also effectively alleviates training delay.

Therefore, *an AI paradigm that can not only ensure security and privacy but also ensure task decision-making performance is necessary for* 6G *SAGINs*. Therefore, the contributions of this work are summarized as follows,

1. We articulate the challenges of deployment automation in 6G SAGIN settings and summarize and analyze the pros and cons of the different AI techniques that are available.
2. For the "4V+S" feature of 6G SAGIN scenarios, we propose an FL-assisted DRL framework to support various automation processes. Through case studies the effectiveness of this approach in improving network deployment automation and ensuring related KPIs has been verified.

In what follows, we first present the fundamentals of AI algorithms and discuss their characteristics and deployments. Second, for the deployment automation of 6G SAGINs, we propose an FL-assisted DRL model and analyze and discuss its principles and related applications. Finally, we summarize this work and look forward to the future.

Fundamentals of AI Deployment

AI is a significantly broad science that consists of different fields such as machine learning (ML), deep learning (DL), RL, DRL, FL, *etc* [5]. In general, one of the main goals of AI research is to make machines capable of complex tasks, that is, to increase the automation of tasks. A schematic diagram of the AI algorithms deployed in 6G SAGINs is illustrated in Fig. 2.

Data Characterization in 6G SAGIN Settings

According to Statista, the number of connected IoT devices worldwide is expected to surge to 25.4 billion in 2030. In 6G SAGIN settings, edge computing, fog computing, and other mechanisms will deploy ubiquitous computing in booming IoT devices [10]. This will generate massive big data that exhibit "4V+S" characteristics, specifically,

1) Volume: With the advancement of the global seamless coverage process and the widespread deployment of AI in computing equipment, large volumes of data will be generated.

2) Variety: It is mainly reflected in data sources, types, and correlations. Specifically, data may originate from sensors, ITS, social networks, IoT, *etc.*, which leads to a variety of big data forms, such as structured data, semi-structured data, *etc*. In addition, data types are also a form of representation, such as image, audio, video, *etc*. Also, these data tend to show strong correlations, especially in social networks.

3) Velocity: Emerging technologies impose stricter requirements on the response speed of 6G SAGINs. In particular, related technologies such as VR, XR, and navigation have higher QoS requirements for latency. Specifically, it must be required to collect valuable information from massive data in a short time.

4) Value: Only a relatively small part of the massive data is of value. Therefore, mining valuable data for forecasting future trends and patterns, analyzing it through AI-related algorithms, and applying it to various fields can create more important value behind the data.

5) Security: With the popularization of computing and the evolution and development of AI technology, much more attention has been paid to data security in the process of data sharing. How to balance data sharing and data privacy will also be an essential challenge in 6G SAGINs.

Comparison of Different AI Algorithms in 6G SAGIN Deployment

As mentioned earlier, in 6G SAGIN settings, due to the ubiquity of computing, the amount of data will expand rapidly. Therefore, how to effectively utilize this information to provide support for network adjustment and decision-making is difficult to be solved. In turn, it leads to a series of network deployment automation issues, such as resource allocation, task offloading, path planning, *etc*. Moreover,

Moreover, relevant AI algorithms will serve as fundamental means in the deployment automation of 6G SAGINs.

AI algorithms	Advantages	Disadvantages
Deep Learning	(1) Fit arbitrary complex functions and complex nonlinear mappings; (2) Powerful representation ability in high-dimensional space; (3) Strong robustness and fault tolerance to noisy data.	(1) Long training time; (2) Rely on computing and storage resources, sufficient training data, and high hardware; (2) Occur gradient disappearance and slow convergence in deep layers; (3) Complex model design.
Reinforcement Learning	(1) Weak training data dependence, unsupervised learning; (2) Relatively fewer constraints, fewer parameters, and lower hardware requirements; (3) Adopt a trial-and-error learning strategy, and tend to the overall revenue.	(1) Weak generalization and portability; (2) In high-dimensional spaces rely on larger action and state spaces; (3) Complex specific reward function design; (4) Weak perception and representation.
Deep Reinforcement Learning	Combining the advantages of DL and RL at the same time: (1) Good perception and decision-making; (2) Better performance for problems in continuous or high-dimensional discrete action space; (3) Easier to converge.	(1) Complex specific reward function design; (2) Weak data privacy and protection.
Federated Learning	(1) Strong data privacy and protection; (2) All parties involved are equal; (3) Multi-party collaboration to build a shared model; (4) Higher learning efficiency by the distributed architecture.	(1) The global network is susceptible to the instability of local networks; (2) Lack of interaction with environments.

TABLE 1. A comparison of advantages and disadvantages of different AI deployments in 6G SAGINs.

relevant AI algorithms will serve as fundamental means in the deployment automation of 6G SAGINs. Therefore, how to scientifically, reasonably, and effectively manage, analyze, and mine the data of "4V+S" characteristics in 6G SAGINs to meet the needs of various intelligent applications will be important challenges for AI deployment [11].

At present, there is already some related research combined with AI that has been continuously trying to solve the challenges. For example, our previous work [12] leveraged DRL to deploy relevant models for resource allocation strategies of SAGINs, driving automation of network deployment. To solve the deployment problem of AI in mobile applications of future 6G networks, Letaief et al. [5] combine FL to provide a training paradigm of parameter sharing to deal with security and complexity issues satisfactorily.

In AI algorithms, ML is a technique that enables computer programs to acquire knowledge and experience automatically through data. DL is a form of ML that employs DNNs to simulate and solve intricate problems. RL is a method for agents to learn by interacting with their environment, aiming to maximize cumulative rewards through trial-and-error learning. Moreover, DRL combines the strengths of DL and RL, utilizing DNNs to enhance the agent's learning efficiency. FL, on the other hand, is a distributed learning approach that employs joint learning across multiple devices to train a global model while safeguarding the privacy of local data on each device. In such scenarios, different AI algorithms will present different advantages and disadvantages. According to experience and surveys, Table 1 presents the pros and cons of different AI techniques that are available.

Framework of AI-Enabled 6G SAGIN Deployment Automation

Based on the above analysis, different AI algorithms play different roles in the automation process of 6G SAGIN deployment. In particular, DRL will play a more dominant role in the dynamic network environment due to its good interaction performance and perception of the environment. In addition, the training mechanism of FL will better protect the data privacy of different sub-networks, thereby improving the security of the data. Therefore, based on the above reasoning and inspiration, we propose an FL-assisted DRL framework as shown in Fig. 3, which ensures the performance of task decision-making and data security, thereby further improving the deployment automation of network tasks.

In this section, we first introduce the principle analysis of the proposed framework for FL-assisted DRL. Second, its application on various network tasks to facilitate network deployment automation is introduced.

FL-Assisted DRL Framework

As mentioned above, in 6G SAGINs, there are different technical sub-networks associated with different user requirements. Each sub-network has specific local characteristics and service requirements. For example, the requirements for the delay in the intelligent transportation system are relatively strict; the aeronautical ad-hoc network has high mobility; the social network has high requirements for data security [13]. In addition, the security of information between different sub-networks is particularly important. When the centralized training strategy collects the global network deployment information, it collects all sub-networks information for unified training, which is not friendly to various intelligent applications. Since a huge security hole will be created, it also makes the problem more complicated and increases the learning time.

Therefore, considering the differentiated QoS requirements of different sub-networks and the security issues in the network deployment optimization process, an FL-based training paradigm is necessary. To better focus on the dynamics and heterogeneity of each sub-network, local servers and local DRL models are deployed in each sub-network to effectively interact with the sub-network environment. It is important to deploy a global server and a global DRL model on the global network. Specifically, the global model has the following functions:

- Collect federated actions and federated states, which are the combination of local actions and states of each subnet respectively, and will be used for training the global DRL model. In this way, it can effectively focus on the global characteristics of the network (inter-subnet).
- Parameter Aggregation. In the training paradigm of FL-assisted DRL, all distributed local models upload parameters to the global model. Without sharing local data, the global model aggregates all local parameters and shares the training parameters for collaborative optimization.

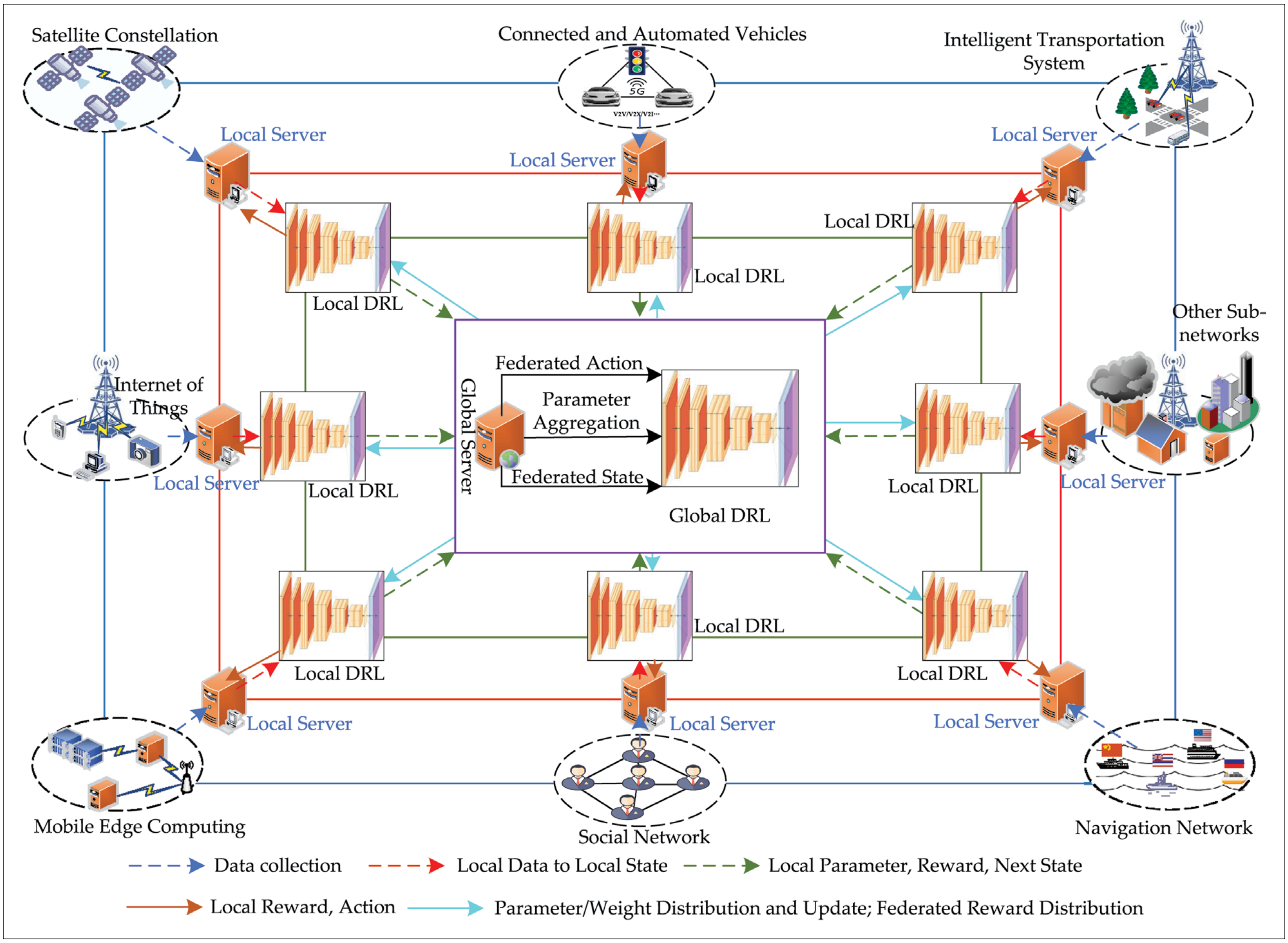

FIGURE 3. The proposed FL-assisted DRL framework for 6G SAGIN deployment automation.

- The global server distributes aggregated weights, federated parameters, *etc.* to each local model after optimizing training with shared weights.

Unlike the traditional learning architecture, the FL paradigm adopts a distributed architecture and only shares local training parameters. Therefore, it effectively protects the privacy of data, accelerates the deployment of distributed ML, and reduces the demand for resources such as computing and communication.

In the era of big data produced by 6G SAGINs, traditional ML and DL algorithms require a large amount of manually processed data as input. In particular, supervised learning often requires manual labeling of the data. Despite the emergence of a series of automated processing tools, the loss of human time cost has not decreased. As an object-oriented technique, the DRL algorithm alleviates the above problems while efficiently fitting complex objects. Specifically, it learns through the following modes:

- Extract States. The DRL algorithm automatically extracts environmental information to construct a feature matrix as a state input. It does not require specific manual processing and marking, and only needs to formulate extraction rules.
- Combine the powerful feature representation ability and nonlinear fitting ability of DNN, carry out forward feature processing and calculation, and then obtain the guide of current actions.
- Combine the reward mechanism and gradient descent and other strategies to optimize and update the parameters of the model. Specifically, the model will be optimized towards a gradient with a high reward value and a global optimum.
- Repeat the above process according to time slices and other methods to better pay attention to the dynamics of networks.

In summary, in the sub-network, the local model collects local data for learning and analysis to gain a grasp of the local environment and needs. The global model aggregates all uploaded local parameters, federation states, *etc.*, and performs iterative updates to better focus on the global characteristics of the network. Finally, the aggregation parameters and rewards are distributed to each local model. Therefore, the proposed framework not only ensures the security and privacy of local data but also pays better attention to the local characteristics of the local network and the global characteristics of the global network, which will effectively improve the performance of task decision-making.

Case Study: Taking the Industrial Internet of Things (IIoT)[1] as the background, the data management task is taken as an example. In [9], we adapt the FL-assisted DRL framework as shown in Fig. 3 to solve the problem of data management and learning with "4V+S" characteristics in IIoT.

[1] An important architecture in the era of Industry 4.0, where extensive IIoT devices will be continuously and frequently connected to the Internet of Things, and will generate data with the characteristics of "4V+S."

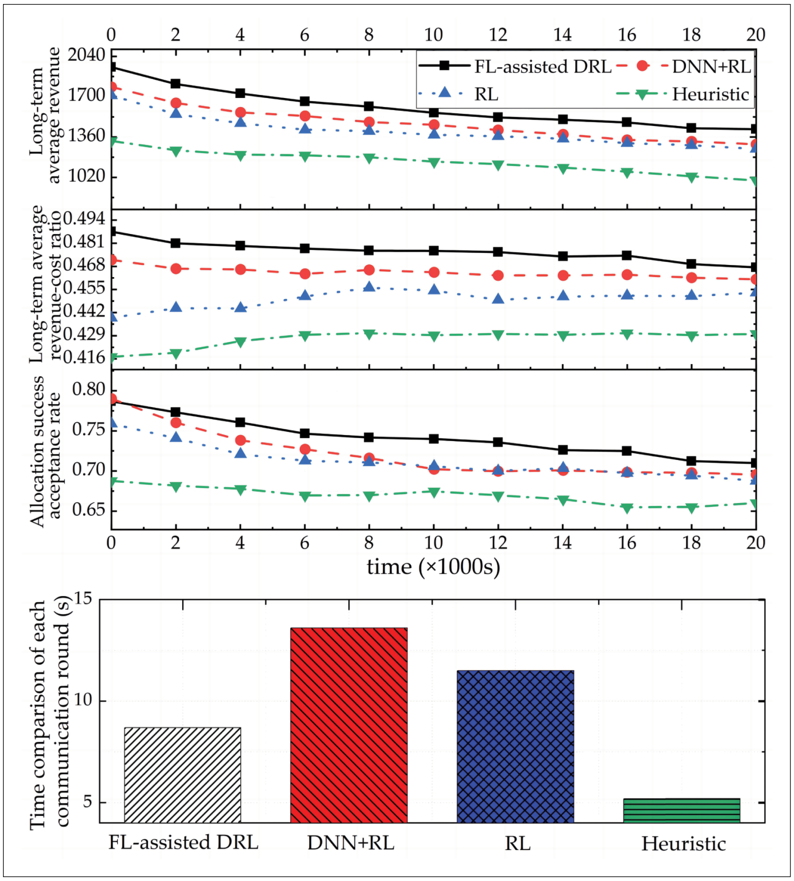

FIGURE 4. In [14], the comparison results of the proposed FL-assisted DRL model and existing works on different indicators. Three benchmarks are adopted separately: "Deep Neural Network (DNN) + RL", "RL" and "Heuristic" strategies. Evaluation indicators for long-term average revenue, long-term average revenue-cost ratio, and allocation success acceptance rate imply resource consumption, and the higher their values, the higher the resource utilization rate. Additionally, evaluation indicator time comparison of each communication round (*s*) implies completion time. For details, see [14].

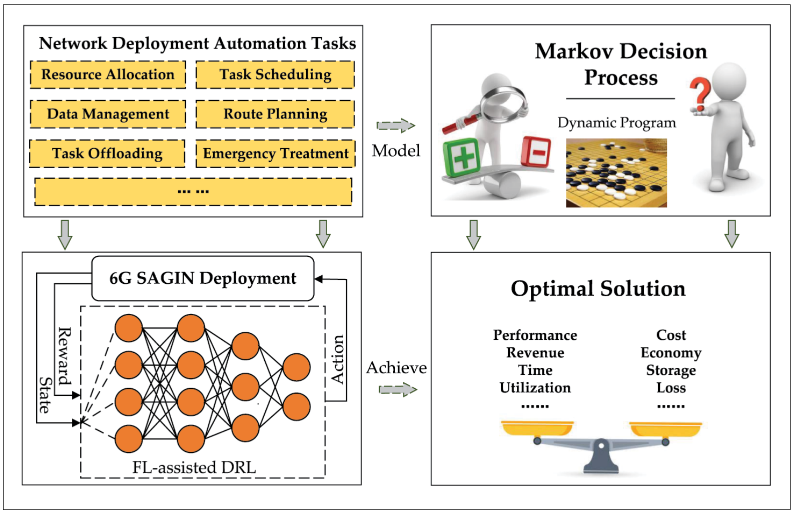

FIGURE 5. Network deployment automation facilitated by the proposed FL-assisted DRL model.

From all angles, all aspects of experiments are carried out. Through experimental analysis, it is determined that the framework is efficient in data management tasks on the premise of ensuring data security. Therefore, the proposed FL-assisted DRL framework effectively enhances the deployment automation process of data management for 6G SAGINs.

Taking SAGINs as the background, the resource allocation task is taken as an example. In [12], we adopt and deploy the architecture of distributed DRL for resource management decisions. The experimental results show that the DRL-based method can better interact with the environment, and the distributed architecture can better focus on local and global characteristics, thereby achieving better task performance. Inspired by FL, as discussed in [14], we propose an FL-based multi-domain virtual network embedding algorithm, which adopts the architecture of Fig. 3 to make resource allocation decisions for multi-domain physical networks. Specifically, the work utilizes the distributed paradigm, deploying a local server in each physical domain and a global server. In addition, GT-ITM was used to generate a simulation environment, and the simulation experiment was implemented based on Python. Heuristic, RL, and deep neural network (DNN) + RL strategies were selected as benchmarks for comparative experiments. Also, service requests arrive in time order based on Poisson distribution, with a start time of 22*s* and an end time of 20, 000*s*. The time unit is 1000*s*, and the change of indicators value for 20-time units is recorded. The pairwise comparison of the results can clarify the effectiveness of different strategies. As illustrated in Fig. 4, the final experimental results show that it can efficiently provide low-cost, high-revenue, and fast-response decision-making, and it is significantly better than other ML strategies. This work significantly reduces resource fragmentation and enhances learning efficiency and data privacy. Therefore, the proposed FL-assisted DRL framework effectively enhances the deployment automation process of resource allocation for 6G SAGINs.

AI-Enabled Network Deployment Automation

In addition, as illustrated in Fig. 5, tasks like resource allocation that can be modeled as Markov Decision Processes (MDPs) in 6G SAGINs can be effectively modeled by this framework. For example, data management, task offloading, etc. That is, the FL-assisted DEL framework has good generalization and generality.

1) Resource Allocation: Due to frequent service requests and task scheduling, limited resources (computing, bandwidth, *etc.*) pose challenges to the normal operation of the network. As the basic conditions for network operation, these requirements should be met with the least resource cost as much as possible to maintain the operation of different services and network functions. The FL-assisted DRL algorithm can observe the complex resource state in the network and calculate the optimal resource allocation strategy for indicators such as long-term benefits in the current view [12].

2) Data Management: In 6G SAGINs, the frequent access of massive IoT devices will generate a large amount of dynamic data. In particular, the privacy of data in the IIoT environment presents challenges. To effectively manage these data to mine the enormous value, and avoid the data being directly presented to a third party, the FL-assisted DRL framework will provide a reasonable solution [9].

3) Task Offloading: With the deep integration of the computing network and IoT, edge computing (EC) and MEC will flourish. The traditional method uploads the collected data to the computing center and returns the result to the device to guide its behavior after calculation and analysis. However, it is difficult to meet the demand for the delay only through the enhancement of communication capability. Using ubiquitous computing power, EC offloads computing-intensive or latency-sensitive tasks to edge devices to realize the entire process of data collection, processing, analysis, and decision-making. It avoids the task congestion of the core network while greatly reducing the delay. For limited edge resources, how to reasonably arrange the offloading strategy to achieve the goal of the shortest delay is the problem to be solved. In addition, the high-speed mobility of edge devices in MEC and the heterogeneity of computing tasks further pose challenges. Notably, it can likewise be modeled as an MDP process [15].

Besides, it is easy to reason that the FL-assisted DRL framework can be employed in various aspects of 6G SAGINs. Specifically, it can provide excellent decision support for various applications of the network under the premise of ensuring the data security requirements of each sub-network. Moreover, it illustrates that AI-enabled algorithms will drive the automation of 6G SAGIN deployments.

Conclusion and Future Outlook

In this work, we analyze the architecture and challenges of 6G SAGINs in detail. On this basis, we present the fundamentals of related AI algorithms and their different characteristics in network deployment automation. Furthermore, we propose an FL-assisted DRL model and discuss its principles and applications in network deployment.

Although the advantages of AI in 6G SAGIN settings are already obvious, in future work, there are still the following challenges to be solved:

Support of wireless communication technology and hardware equipment: It is expected that 6G will expand to the terahertz band, and hardware equipment that supports this signal will directly affect the deployment of AI algorithms. In addition, limited device resources (especially computing) will also limit the deployment and decision-making of AI algorithms. Therefore, an efficient hardware device to support future wireless communication scenarios is essential.

Integration of 6G new technologies: For 6G scenarios, a large number of emerging technologies will be produced. How to deploy generalized AI algorithms for specific characteristics is a key challenge to be solved.

Construction of simulation environment: The development of emerging communication technologies have contributed to the increasing complexity of network environments, including characteristics such as heterogeneity, dynamics, and self-organization. To promote the practicability of AI algorithms, researchers rely heavily on simulation experiment environments during

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the design and deployment phases of AI algorithms. In addition, AI algorithms are also prone to overfitting to a customized environment. Therefore, a simulation environment platform that integrates various algorithmic benchmarks and simulates realistic network environments is urgently desired.

Complexity of AI algorithms: Communication technologies represented by B5G and 6G will bring higher device access density, larger network cluster scale, and more ad-hoc coexistence. The deployment of complex AI algorithms may involve extensive physical node coverage, which will make the service response delay more serious and reduce the users' QoS and QoE. Therefore, a more lightweight AI algorithm deployment is an important issue.

Deployment of Explainable AI: Explainable ML, represented by Deep Fuzzy Neural Systems (DNFS), breaks the black-box model of traditional AI algorithms fitting data laws. Explainable AI algorithms will make the decision-making laws of the model more transparent to researchers, which is conducive to the diagnosis, analysis, and upgrading of products, and thus the effective collaboration between humans and machines.

Trade-off between redundancy and cost: A key feature of 6G SAGIN is its capacity to support Native AI, that is, 6G carries native AI and AI is spread throughout SAGIN. Through environment awareness and data support, deployment automation for SAGIN is enabled, and communication-sensing-computing integration will become an important technology for 6G SAGIN. In addition, in the future 6G SAGIN integrated with communication-sensing-computing, duplicate or redundant functions, processes, and resources can be deployed to enhance system reliability, fault tolerance, and resilience [6]. For instance, (1) establishing multiple backup communication routes to ensure resilient links in dynamic environments; (2) deploying redundant backup equipment resources to prevent service interruptions caused by node failures. However, these aspects of communication-sensing-computing bring additional resource costs in terms of AI load. For example, (1) Communication: redundant communication routes or functions result in increased data transmission overhead, requiring effective management and coordination of data flow by AI algorithms to avoid unnecessary redundancy; (2) Sensing: AI algorithms need to perceive changes in the surrounding environment in real-time to cope with potential node and link failures; (3) Computing: redundant functions and processes require additional computing resources, making AI algorithms responsible for managing and optimizing the network need to deal with increasing complexity; (4) Other aspects: AI models need to be continuously trained, maintained, and updated to adapt to redundant configurations in dynamic environments, affecting processing time and energy consumption. In summary, a good trade-off between redundancy and cost needs to be maintained in the future 6G SAGIN system.

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