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RESEARCH ARTICLE

Adaptive Smart Radio Environment (ASRE): New Paradigm for Wireless Communication Networks

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ABSTRACT Recent efforts have promoted Smart Radio Environment (SRE) to enhance the reception quality in high-frequency bands via reconfigurable intelligent surfaces (RISs) for supporting hyperconnectivity of Beyond 5G/6G Era. The functionality of SRE is based on the more degrees of freedom that come from electronically controlling the environment itself rather than transmitter and receiver. Accordingly, the spectral efficiency and the sum rate throughput can be enhanced by applying customized transformations to the electromagnetic radio waves. However, futuristic applications that are envisioned to be time-critical demand much more than what SRE can handle because that too much time is spent on sensing the environment and applying customized transformations. In this work, we propose a novel concept of adaptive SRE (ASRE), which intends to start from the semantic perception of a wireless environment to explore the learning and evolutionary mechanisms of SRE through the loop of recognition, adaptation, and proaction. In combination with the techniques known in artificial intelligence (AI), such as deep reinforcement learning, knowledge graph, etc., this technology can provide enhanced ultra-reliable low-latency communication (URLLC) services. Furthermore, the wireless environment is expected to become not just adaptive, but partially intelligent by predicting and utilizing the changes in the communication environment. To corroborate the rationality and superiority of ASRE, we also present simulation results related to the typical dynamic NLOS scenario. Finally, we highlight numerous open challenges and research directions.

INDEX TERMS Smart radio environment (SRE), reconfigurable intelligent surface (RIS), deep reinforcement learning (DRL), sensing, knowledge graph.

I. INTRODUCTION

The future wireless propagation environment will be a reconfigurable platform [1], which will not only control the signal propagation intentionally and deterministically but will also bring new possibilities for capacity and coverage enhancement [2]. Motivated by these considerations, the concept of "smart radio environment" was introduced in [3] and detailed in [1], which is aligned with recent advances in the design of reconfigurable intelligent surfaces (RISs). RISs consist of many anomalous controllable reflecting surfaces capable of changing the phase of the incoming electromagnetic waves. Therefore, smart radio environments provide more degrees of freedom by electronically controlling the environment itself rather than the transmitter and receiver and by turning the wireless medium into a software-reconfigurable entity, as shown in FIGURE 1.

Several studies have investigated the benefits of SRE. In [2], multiple repositionable dynamic RISs and coordinated ambient backscatter communication (ABCs) were used to extend geographical coverage and maximize the sum rate throughput for a given geographical region and spectrum. The heterogeneous deployment of SRE entities, namely Integrated Access and Backhaul (IAB) nodes, smart repeaters, RISs, and passive surfaces, is judiciously planned to minimize the total installation costs while simultaneously optimizing the network spectrum [4]. In [5], the system performance of RIS-assisted SREs was studied by adopting a simulation-driven approach and conducting a holistic evaluation of capacity and reliability aspects. In [6],

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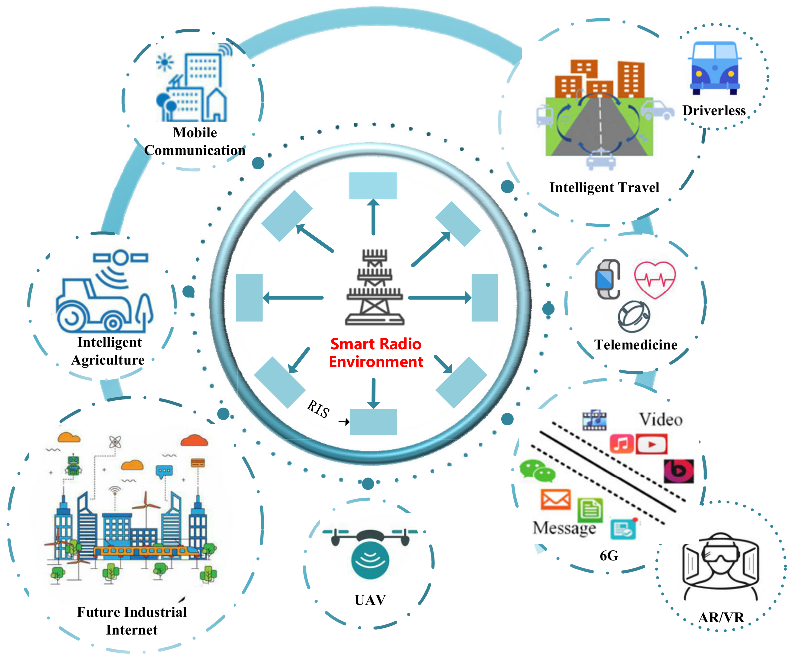


FIGURE 1. Smart radio environment.

a resource allocation framework was developed that explicitly accounted for the overhead associated with channel estimation and the configuration of the optimal RIS phase shifts. Existing research demonstrate that pertinent efforts mainly focus on networking environments that consist of stationary user equipment (UE), which completely overlooks the impact of user mobility on the channel gains. Accordingly, in a dynamic environment with user and scatters mobility, reassignment of the RIS parameters will take place frequently. One of the major challenges with the envisioned dense deployment of RISs in SRE is the efficient configuration of multiple RISs, which depends on the perception of the communication environments. The most well-known radio environment sensing method is radar [7], which operates by sending transmissions, typically a linear frequency-modulated continuous chirp, and correlating the reflected signals with the transmitted signal to obtain the delay and Doppler frequency. On the other hand, LiDAR [8], Vision [9], etc. are also used to sense the communication environment. However, perception and controlling the environment require a lot of time to process, which does not provide a latency of a millisecond order for URLLC services often represented by factory automation, telesurgery, and autonomous driving.

To address the aforementioned challenges and develop an efficient *configurable* strategy for SRE, we have enriched the smart radio environment concept with the harmony of sensing the environment and applying customized *reassignments* called ASRE. This concept intends to achieve optimized network deployment through environmental awareness and early inference prediction, which is essentially a ubiquitous wireless environment that supports personalized adaptation based on perceptual information (static environment information, dynamic wireless environment information, etc.) and wireless environment adaptation characteristics, as well as extends the perceptual intelligence of traditional SRE to cognitive intelligence. The key features of this study are summarized as follows:

- An adaptive SRE system is proposed utilizing a wireless intelligent control component (WICC), which not only controls sensors to obtain static and dynamic information of the wireless environment but also controls spatial electromagnetic radiation by using perceived information.
- This is the first time that triple parameterizations of wireless environments have been proposed, including controllable RISs parameterization, static parameterization, and dynamic uncontrollable parameterization. After the obtained data are fused, detailed information on the current wireless environment can be fed back in real-time, which can provide effective data support for the comprehensive decision-making of wireless connections.
- Based on the semantic understanding and adaptation mechanism of the wireless communication environment, ASRE constructs an open interface by introducing multiple mobile adaptive RISs, IAB nodes, and intelligent relays and dynamically constructs a heterogeneous wireless communication environment in combination with WICC to provide a mechanism to quickly handle user mobility and handover in response to changes in the wireless environment and business requirements.

- In combination with artificial intelligence (AI) techniques such as deep reinforcement learning and knowledge graphs, this technology can provide enhanced ultra-reliable low-latency communication (URLLC) services. Furthermore, wireless environments are expected to become adaptive and partially intelligent by predicting and utilizing changes in communication environments.
- Using this novel concept, we validated the beam prediction algorithm in a mobile cellular network including one base station (BS), one moving user equipment (UE), and a fully reflective RIS. The results proved the effectiveness of our proposed ASRE in terms of reducing the average switching delay by 41-50%. The proposed ASRE concept is compatible with the scenarios of (a) varying user densities, (b) different BS densities, and (c) different transmission bands.

The remainder of this paper is organized as follows. Section II explains the concept of the ASRE. In Section III, the important aspects of ASRE recognition in communication environments are discussed. In Section IV, we present an adaptation of the ASRE with multiple adaptive RISs, IAB nodes, and intelligent relays. In Section V, the proactive ASRE is detailed. Section VI discusses future challenges and research opportunities.

II. ADAPTIVE SMART RADIO ENVIRONMENT (ASRE) FOR WIRELESS COMMUNICATION NETWORKS

Unlike SRE, ASRE aims to achieve optimized network deployment through environmental awareness and early inference prediction. Therefore, we first built a spatiotemporal dynamic awareness system that can fuse sensed multidimensional wireless environmental information with an understandable and operational knowledge description. We then clarify the wireless environment adaptation mechanism of specific key performance indicators (KPIs) as well as the intelligent adaptation architecture, adaptation methods, and hybrid migration learning method. In addition, changes in the wireless communication environment can be predicted in advance according to a certain Knowledge Graph, using new information to realize the learning and evolution of the wireless communication environment. In this case, novel wireless connectivity is provided with high flexibility, capacity, robustness, and coverage by constructing an adaptive wireless communication environment characterized by the accurate identification of environmental changes, scientific adaptation, and proactive adaptation. Therefore, ASRE can sense and understand environmental disturbances, adapt to different changes in the environment, and evolve based on Knowledge Graphs and new knowledge. Its main characteristics are summarized as follows:

- The dynamic perception of the wireless communication environment follows the procedure described in Section III.
- The wireless environment adaptation architecture is based on multiple mobile adaptive RISs, IAB nodes, and intelligent relays, which follow the procedure summarized in Section IV.
- The co-evolution based on mixed transfer learning is summarized in Section V.

III. PARAMETERIZATION AND FUSION PERCEPTION OF VARIOUS ELEMENTS OF WIRELESS PROPAGATION ENVIRONMENT

In this section, parameterization and fusion perception of various elements of the wireless communication environment are introduced.

A. PARAMETERIZATION OF WIRELESS COMMUNICATION ENVIRONMENT

1) THE RICH INDOOR SCATTERING SCENES

First, all three types of entities that affect the wireless communication environment (i.e., the transceiver antenna, scattering environment, and programmable RIS unit) are described as dipoles or a set of dipoles with specific characteristics [10]. The scattering environment, introduced in the form of a coupling dipole, changes rapidly with the addition of dynamic effects, leading to rapid fading.

The wireless communication environment is then triply parameterized, including the controllable RIS parameterization, static uncontrollable channel parameterization, and dynamic uncontrollable channel parameterization. The triple parameterization of fading rich-scattering wireless channels is described as follows:

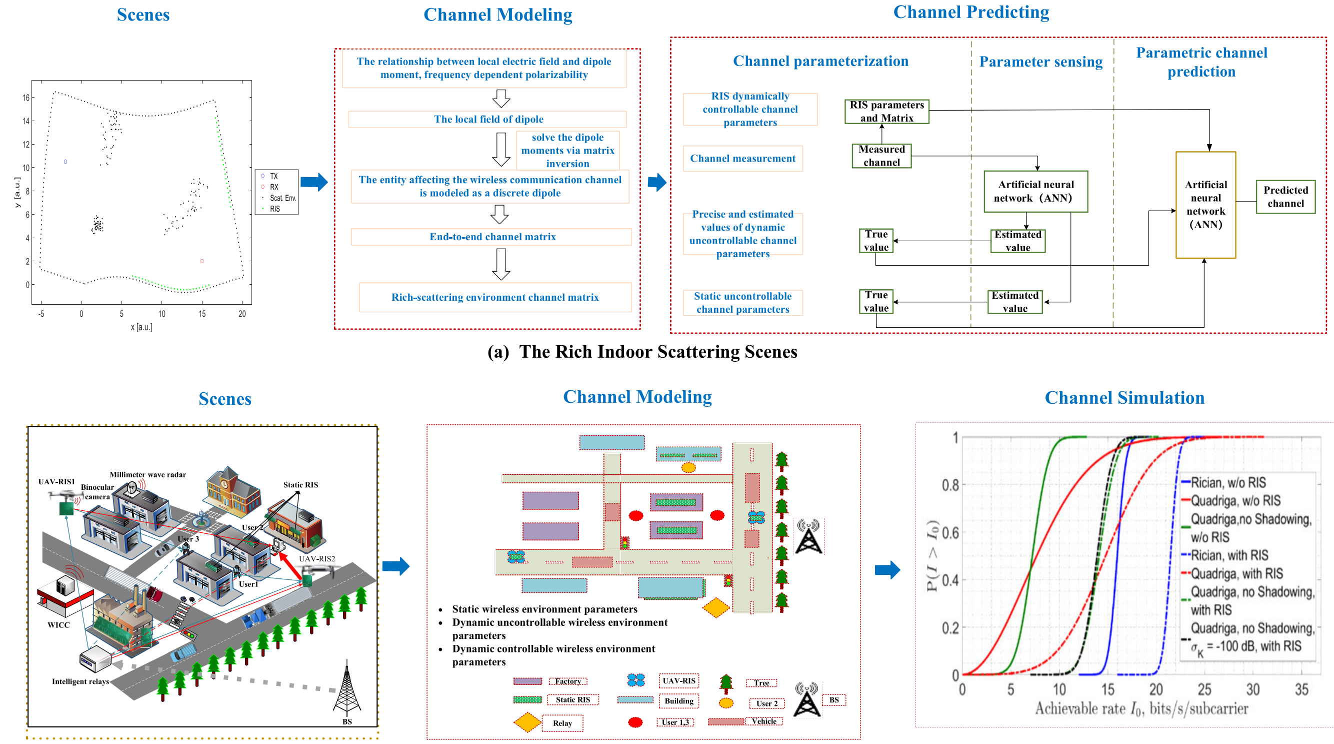
- Dynamic controllable wireless environment parameterization, such as RISs and IAB nodes.
- Dynamic uncontrollable wireless environment parameters such as the location of the receiver, location of moving objects, and orientation of rotating objects.
- Static wireless environment parameters, such as the location of the BS and wall.

A fully connected artificial neural network (ANN) is trained as an alternative inverse model [11]. Auxiliary field measurements were used as inputs for the ANN. The static and dynamic uncontrollable channel parameters are the outputs.

Finally, the RISs modeled by the dipole provide a controllable set of RISs parameters. Combined with static and dynamic uncontrollable channel parameters, the RISs parameterized wireless environment is converted into a physically compatible end-to-end channel matrix with a controllable fading level through an ANN. The parameterized modeling and prediction processes are illustrated in FIGURE 2(a). It involves learning a surrogate forward model to predict the channel as a function of the above triple-parameterization, estimating the static wireless environment parameters and uncontrollable perturbing parameters, and optimizing the RIS parameters (given the perturbing parameters) to achieve the desired shape of the wireless channel.

2) THE OUTDOOR OPEN SCENES

Consider a UAV/RIS-assisted multi-user wireless communication system, as shown in FIGURE 2(b). The system



(a) The Rich Indoor Scattering Scenes

(b) The Outdoor Open Scenes

FIGURE 2. Parameterization of wireless communication environment for (a) the rich indoor scattering scenes and (b) the outdoor open scenes.

consisted of N single-antenna users, a UAV carrying an RIS, and a base station. The Rician channel model is commonly used to model the NLoS channel without considering scene geometry, which contradicts the deterministic parameterization introduced by the RIS in intelligent wireless environments. At the same time, the ray tracing method requires a large number of digital maps to simulate a wireless environment, which is difficult to conveniently apply in practical applications. To achieve a good balance between ray tracing and the Rician model, we use a geometry-based stochastic model (BGSM) to build a wireless propagation environment model. According to the influencing factors, the model parameters are divided into three parts: static wireless environment parameters, dynamic uncontrollable wireless environment parameters, and dynamic controllable wireless environment parameters.

Based on the wireless channel simulation platform QuaDRiGa [12], the channel matrices of the transmitter to the RIS, the RIS to the receiver, and transmitter-to-receiver links were obtained by representing the RIS as virtual receivers and virtual transmitters with the same coordinates and unit arrays. The intelligent wireless propagation environment was simulated and analyzed, as shown in FIGURE 2(b) from [13], and there was a significant performance difference between Rician and QuaDRiGa. Therefore, we chose QuaDRiGa instead of using Rician directly for modeling.

B. FUSION PERCEPTION OF WIRELESS COMMUNICATION ENVIRONMENT

After the data obtained from various channels are fused, detailed information on the current wireless environment can be fed back in real-time, which can provide effective data support for the comprehensive decision-making of wireless connections. We intend to enhance the semantic understanding of wireless communication environments by utilizing a multimode comparison and fusion. Fusion sensing methods include comparison-based multimodal sensing (CMMS) [14] and transformer-based multimodal sensing (TMMS) [15].

The input data contained three modes for the CMMS: RGB, Radar and LiDAR. First, three modes were connected in series to generate anchor samples. The anchor samples were then enhanced to generate the positive samples. Simultaneously, challenging negative samples were generated by disturbing anchor samples. These challenging negative samples require the learning model to check the correspondence between each element in the input samples to ensure that the weak modes and synergy between the modes are not ignored to produce a better fusion representation.

Therefore, to understand the wireless communication environment, the wireless channel $H(f) \in \mathcal{C}^{N_r \times N_t}$ between the transmitter and receiver can be modeled as.

$$\mathcal{F} : wicc(f) \rightarrow H(f, wicc(f), \; uc(f), s(f)) \qquad (1)$$

where $\mathcal{F}$ is the mapping from the dynamic controllable wireless environment parameterization $wicc(f)$ to the wireless channel matrix $H(f,\ wicc(f), uc(f),\ s(f))$ configured by WICC. $uc(f)$ and $s(f)$ are dynamic uncontrollable wireless environment parameters and static wireless environment parameters, respectively. The transmitting antenna array is composed of N_t antenna elements. The receiving antenna array equipped with N_r antenna elements. Mapping $\mathcal{F}$ is generally nonlinear. In some cases, one may consider to "blindly" learn a neural surrogate forward model, i.e., to approximate the mapping from $wicc(f)$ to $H(f,\ wicc(f), uc(f),\ s(f))$ with an artificial neural network (ANN).

For the TMMS, a deep residential network (ResNet) is employed to encode image I_t, point-cloud P_t, and radar signal R_t in the abstraction space. The transformer then learns the correction between the modalities. The fused feature maps of different modalities are propagated to the next convolutional blocks and repeated several times with transformer blocks, which produces predictions using the softmax function. The mapping between (I_t, P_t, R_t) and the channel parameters can be defined as follows.

$$\mathcal{Q} : (I_t, P_t, R_t) \rightarrow (wicc(f), uc(f), s(f)) \tag{2}$$

IV. INTELLIGENT ADAPTATION TECHNOLOGY FOR WIRELESS COMMUNICATION ENVIRONMENT

Based on the semantic understanding and adaptation mechanism of the current wireless environment, we built an open interface for the wireless transmission environment by introducing a mobile adaptive RIS, IAB nodes, and intelligent relays. Furthermore, a heterogeneous wireless communication environment is dynamically constructed by combining WICC. A mechanism for quickly handling user mobility and handovers was provided to respond to changes in the wireless environment and business requirements. Specifically, according to the sensed wireless environment information, WICC can customize the transmission of signals from the base station to single or multiple designated users to complete the wireless communication link from the base station to the adaptive wireless environment to the user by controlling IAB nodes, UAV-RIS, intelligent relays, etc. Compared to classical communication systems, this architecture can be applied to a variety of complex industrial scenarios with the significant advantages of high performance, high reliability, and low latency.

For future wireless networks, there are many variables that WICC needs to control and optimize, resulting in a large amount of training data being required to adopt the existing deep learning methods. In a highly dynamic wireless environment, it is important to achieve system optimization at a low training cost in a short time. To combat environmental changes and avoid a large number of training labels, RISs are used as reinforcement learning agents to interact with the environment based on the DRL (Deep Reinforcement Learning) algorithm. Model-based optimization is integrated into the DRL framework, which optimizes network parameters and configuration resources through empirical learning. The decision variables are divided into two parts. One part of the decision variable is obtained using the outer-loop ML method. The second part is rapidly optimized by solving the approximation problem using their physical connections when the outer-loop control variables are provided. Compared with the traditional modeless learning method, this idea has both the efficiency of model-based optimization and robustness of the modeless ML method. In addition, we plan to further reduce the workload of model training by using transfer learning and domain adaptation technologies in the future. Given the sensed dataset $\mathcal{D}_t = \{(I_t, P_t, R_t)\}$, we fit the optimal dynamic controllable wireless environment parametrization $wicc^*(f)$ by maximizing the system capacity $\max\limits_{wicc^*(f)} C\left(H(f, wicc(f),\ uc(f), s(f)), N\right)$, where N is the additive white Gaussian noise (AWGN).

V. LEARNING AND GROWTH MECHANISM OF WIRELESS COMMUNICATION ENVIRONMENT BASED ON KNOWLEDGE GRAPH

A. ADAPTIVE LEARNING AND GROWTH MECHANISM IN WIRELESS PROPAGATION ENVIRONMENT

From a machine-learning perspective, it is impractical to collect a large training dataset that covers all possible environmental dynamics (e.g., collecting wireless signals at many physical locations). Therefore, the ASRE is essentially a ubiquitous wireless environment that supports personalized adaptation based on the adaptive characteristics of the wireless environment and perceptual information (static environmental information, dynamic uncontrollable wireless environmental information, etc.), as shown in FIGURE 3.

To achieve this personalized adaptation, three core components–the propagation environment model, adaptive knowledge model, and adaptive engine–are established. Among them, the propagation environment model is a high abstraction of the sensed "dynamic" and static features (texture, depth, and other data of the scene) of the wireless environment information, which is the basis for proactive adaptation of the wireless propagation environment. The adaptive knowledge model is a collection of adaptive knowledge and its relationship and is an important foundation for realizing proactive adaptation in wireless communication environments. The adaptive engine is the intelligent core to realize proactive adaptation of the wireless communication environment, which is the bridge and link between the communication environment model and adaptive knowledge model.

The adaptive engine was then used to connect the communication environment model built with environmental awareness as the center, and the adaptive knowledge model was built with the Knowledge Graph as the core. The mechanism can select the most suitable resources, transmission path, and communication strategy in the correct manner, time, place, and scene, to provide the corresponding adaptation methods and configuration parameters according to the actual needs of dynamic changes.

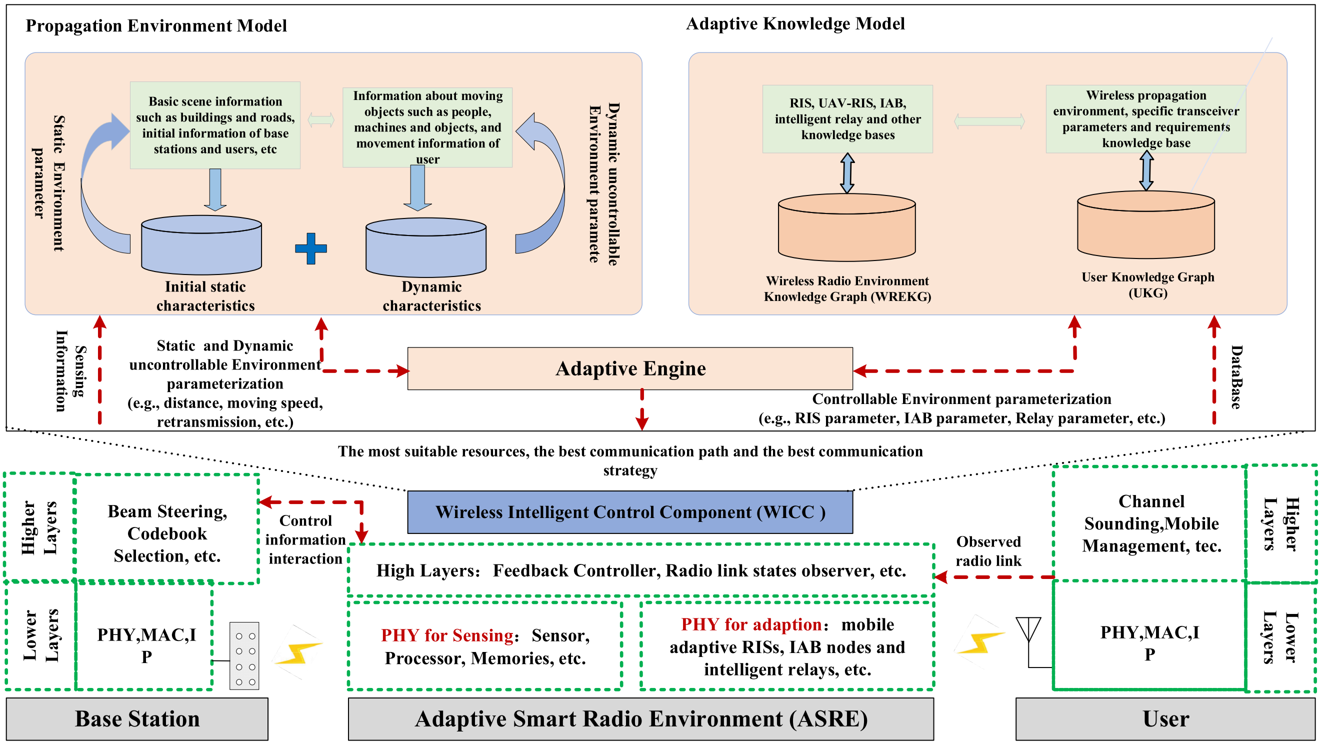


FIGURE 3. Adaptive learning method for wireless propagation environment.

B. DESIGN OF KNOWLEDGE BASE FOR TRANSFER LEARNING ACROSS DIFFERENT PHYSICAL ENVIRONMENTS

The ASRE can continuously recognize the propagation environment, obtain comprehensive wireless propagation environment information, and establish a knowledge base for transfer across different physical scenes, including the following aspects: modeling and representation of wireless environment perception information, wireless environment information storage, inference and utilization of wireless environment perception information, interaction between wireless environment perception information, and adaptive engines.

First, the entities, relationships, and attributes of the Knowledge Graph of the adaptive configuration of the environment were defined. Knowledge from the existing performance results of the environment-adaptive configuration under a variety of wireless propagation environments and business characteristics was extracted to build a Knowledge Graph of the environment-adaptive configuration. The wireless propagation environment is defined as the head entity in a Wireless Radio Environment Knowledge Graph (WREKG). The various parameter types of the wireless propagation environment are defined as the relationship set, and the specific value of the parameter is defined as the tail entity. Subsequently, a User Knowledge Graph (UKG) was built regarding specific transceiver parameters and requirements as "user" entities. Overall, the wireless communication environment, specific transceiver parameters, and requirements are defined as the header entities. Parameter type was defined as the relationship set. The specific value of parameter is defined as the tail entity.

Second, by summarizing the knowledge related to wireless communication environment adaptation, we establish a performance representation model of the environment adaptation configuration knowledge. The structured environment-adaptation configuration triplet information is mapped to low-dimensional vectors using the Trans D model. The semantic information of the environment adaptation configuration was extracted into vectors using the Word2Vec model. Numerical feature vectors were also built by defining dictionaries and parameter values. These three features are spliced to obtain the learning results of the environment-adaptive configuration knowledge representation.

Finally, for the current sensed wireless propagation environment, we recommend appropriate environmental adaptation mechanisms and parameters, including adaptive node type, number, spatial location, adaptation time, and configuration parameters, based on the determined requirements for data rate, bit error rate, and signal-to-noise ratio.

C. WIRELESS COMMUNICATION INDIVIDUAL REASONING BASED ON KNOWLEDGE GRAPH

In a complex scenario, the learning of the wireless communication environment includes the acquisition and training of original data. Training that relies solely on source-domain data renders the system cumbersome and inefficient. The method of passively adapting to changes in the wireless communication environment will no longer satisfy new requirements of wireless communication in the future. We propose a wireless environment individual-reasoning method based on a multiagent Markov decision. Its main feature and innovation lies in using the prediction function of neural networks to provide prior information for reinforcement learning, which accelerates network convergence and divides the process of business demand change into sequential and simultaneous game processes. We consider maximizing the use of wireless environmental resources to provide appropriate services for complex scenarios with the dynamic transformation of multi-agent services. By defining $\vec{H}(f, wicc(f), uc(f), s(f))$ as the inferred wireless channel environment, the mapping between $\vec{H}(f, wicc(f), uc(f), s(f))$ and proactive wireless environment adaptation can be defined as follows.

$$\mathcal{R} : \vec{H}(f, wicc(f), uc(f), s(f)) \rightarrow wicc^{*}(f) \tag{3}$$

To provide URLLC services, we use Knowledge Graph to represent, store and manage complex wireless environment adaptation knowledge, and conduct 'Proactive change' of wireless environment adaptation based on the Knowledge Graph. First, relying on historical data correlation and attribute correlation, and based on modeling the entities and their relationships, reinforcement learning based on the Markov decision process (MDP) makes the Knowledge Graph a preliminary individual reasoning ability. The importance of the environmental adaptation architecture in historical data was mined using a Bayesian neural network, and the Knowledge Graph was updated through the continuous growth of historical environmental adaptation data. Thus, entities and relationship models can be predicted and updated promptly according to the transformation of scenarios, business characteristics, and wireless environments, and the Knowledge Graph can be supplemented to enhance the generalization. Subsequently, the NashQ learning algorithm and Monte Carlo Tree Search (MCTS) method were used to solve simultaneous and sequential game problems in the wireless channel selection process (RSP) and resource allocation process (RAP), as shown in FIGURE 4. The first stage is RSP, which aims to avoid collisions and disorders as much as possible to compress the decision space. After the algorithm converges, it enters the RAP stage, which provides users with appropriate services based on limited network resources and multi-service requirements to maximize the average system throughput. In the Monte Carlo tree search, each node contains the real-time reward value used to measure the quality of resource allocation decisions, the number of visits to the node, and the Q-value of the node. An upper-bound confidence tree search (UCT) algorithm is used in the decision search to achieve $wicc^{*}(f)$. Each node must satisfy the QoS constraints of a single-user flow, whereas the root node must satisfy the maximum throughput constraints of the entire system.

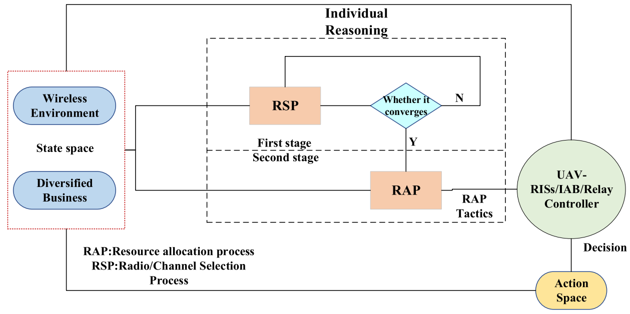


FIGURE 4. Framework of individual reasoning in industrial environment.

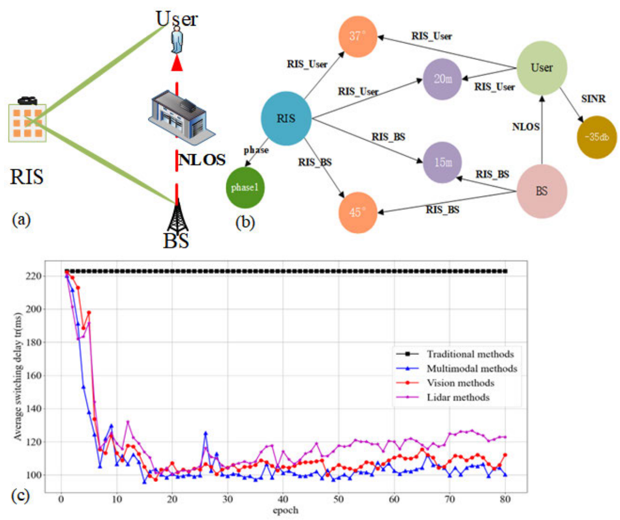


FIGURE 5. CASE of ASRE, (a) Mobile cellular network; (b) Environmental adaptive configuration knowledge graph; (c) Beam switching delay.

VI. CASE OF ASRE

In this section, we will use a beam prediction algorithm to validate the novel concept of ASRE. According to the 3GPP specification, the total system delay caused by traditional base station switching is 222.8ms, and through beam prediction, the ideal total switching delay of the system can be reduced to 11.4ms [16].

A. SETUP

We consider a mobile cellular network including one base station (BS), one moving user equipment (UE) and a fully reflective RIS, which has N elements equally spaced on a planar surface, as shown in FIGURE 5(a). The intelligent RIS controller is in charge of loading different configurations to the RIS according to the sensing information, as discussed in Section III.

B. ALGORITHMIC

First, the fusion of the above environmental information by various sensors, can boost the total sensing task with a reinforced sensing capability. Second, adaptability intelligent processing in WICC is performed using a model-enhanced data-driven approach as its fundamental tool for ASRE, as shown in FIGURE 5. Third, the entities, relationships, and attributes of the Knowledge Graph for adaptive configuration of the environment are defined. Knowledge from the existing performance results of the environment-adaptive configuration under a variety of wireless propagation environments and business characteristics was extracted to build a Knowledge Graph of the environment-adaptive configuration, as shown in FIGURE 5(b). If the beam is obtained using multimode sensing with advanced prediction and its beam prediction accuracy at a certain prediction time period is p, then the average switching delay is $p \times 11.4 + (1 - p) \times 222.8$. The reduction in the average switching delay of the link can be obtained by 41-50% as shown in FIGURE 5(c). The experimental and simulation results confirmed that the ASRE, with its proactive adaptation, enhances QoE for users who require low latency in extremely dynamic environments. Overall, the results indicate that our study can improve the operation of B5G/6G wireless networks by offering a reduced network size, thereby enabling future latency-sensitive applications. Additionally, it would be valuable to discuss other KPIs and service quality parameters when compared to the current 5G technology, which will be studied in further research.

VII. RESEARCH CHALLENGES AND OPPORTUNITIES

In this section, the future research directions and challenges related to this study are discussed.

A. ASRE COMMUNICATION THEORY AND EVALUATION

How Analysis of the relationship between the wireless propagation environment and its changes, controllable elements, optimized configuration parameters, and specific key performance indicators (KPIs), such as coverage probability, spectrum efficiency, energy efficiency, and delay, is a key problem. Therefore, an important research direction is to investigate the superposition impact of controllable and uncontrollable parameters on the wireless communication environment and its theoretical performance limit, which can establish a theoretical basis for intelligent adaptation of the ASRE.

B. ROBUSTNESS OF ASRE

An intrinsic challenge in ASRE is to address the robustness of performance changes caused by environmental and user changes. The pre-trained patterns may change if the ASRE is deployed in a new environment or used by a different user. Although ASRE can achieve optimized network deployment through environmental awareness and early inference prediction, system performance degrades with frequent retraining and updates. Therefore, how to ensure the robustness of ASRE in complex and high dynamic environments is one of the topics that needs to be studied in the future.

C. INTEGRATED SENSING AND COMMUNICATION

The fusion of communication and sensing is the consensus for future wireless networks. However, the application of ASRE to both communication and sensing has not been widely studied, and some key issues remain open, including resource allocation, mutual interference, signal processing technologies, network architectures, transmission protocols, and optimization of ASRE coefficients.

D. THE INTEGRATION OF ASRE AND B5G/6G PROTOCOL

Recent efforts have promoted ASRE to enhance reception quality in high-frequency bands via multiple mobile adaptive RISs, IAB nodes, and intelligent relays. However, the coordination of the relationship between ASRE and other potential technologies of B5G/6G, as well as its integration with B5G/6G network protocols, is a key issue.

VIII. CONCLUSION

Reconfigurable, intelligent, and adaptive environments enabled by ASRE provide a novel wireless connectivity paradigm for future B5G/6G networks, while disclosing unprecedented scientific and technological challenges. In this paper, a novel concept of adaptive SRE is proposed, which is designed to make the wireless communication environment intelligent and controllable. This is accomplished by having the design integrating three key components into the ASRE system: wireless environment recognition and prediction, wireless environment adaptation, and AI interaction. Close cooperation between these components would provide a guaranteed performance adaptively to the time-varying nature of the wireless communication environment.

Furthermore, by predicting and utilizing the potential changes in communication environments, wireless environments are expected to become both adaptive and partially intelligent. Finally, the potential challenges and promising research directions related to the proposed ASER networks are introduced.

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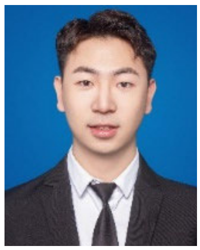

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