A Predictive 6G Network with Environment Sensing Enhancement: From Radio Wave Propagation Perspective

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Abstract: In order to support the future digital society, sixth generation (6G) network faces the challenge to work efficiently and flexibly in a wider range of scenarios. The traditional way of system design is to sequentially get the electromagnetic wave propagation model of typical scenarios firstly and then do the network design by simulation offline, which obviously leads to a 6G network lacking of adaptation to dynamic environments. Recently, with the aid of sensing enhancement, more environment information can be obtained. Based on this, from radio wave propagation perspective, we propose a predictive 6G network with environment sensing enhancement, the electromagnetic wave propagation characteristics prediction enabled network (EWaveNet), to further release the potential of 6G. To this end, a prediction plane is created to sense, predict and utilize the physical environment information in EWaveNet to realize the electromagnetic wave propagation characteristics prediction timely. A two-level closed feedback workflow is also designed to enhance the sensing and prediction ability for EWaveNet. Several promising application cases of EWaveNet are analyzed and the open issues to achieve this goal are addressed finally.

Keywords: 6G network; electromagnetic waves propagation characteristics prediction; environment information sensing enhancement

Received: Sep. 01, 2021
Revised: Dec. 20, 2021
Editor: Yongming Huang

I. INTRODUCTION

Electromagnetic wave is the basic information carrier of mobile communication systems. The pioneering works of electromagnetic wave are achieved by James Clerk Maxwell (1831-1879) [1] and Heinrich Hertz (1857-1894) [2, 3]. One of the great applications for electromagnetic wave is to carry information as an indispensable medium for each generation of wireless communication system. In the general point-to-point communication model proposed by Claude Elwood Shannon (1916-2001) [4], the electromagnetic wave propagation's effect is modeled as the channel that not only links the transmitter (Tx) and the receiver (Rx), but also determines the ultimate performance limit of wireless communications. Traditional design of mobile communication systems follows a two-step procedure. As shown on the left side of Figure 1, firstly the channel model is achieved, then extensive simulations for network are conducted. Note that the channel modeling step is offline and based on measurements of several limited scenarios. We cannot verify the fitness of channel model, unless a practical network is deployed. In step 1, static channel models are used to reveal the dynamic physical environments, which weakens the adaptability of system. The main drawback of the traditional communication systems design method is to separate the physical environments. This

strategy works well before fourth generation (4G), because there are only limited typical scenarios in the practical deployments.

Different with the previous mobile communication systems that mainly consider the performance improvement of enhanced mobile broadband (eMBB), fifth generation (5G) starts to develop the ability for ultra-reliable and low latency communication (uRLLC) and massive machine type of communication (mMTC), which extremely extends the supported service range [5]. Sixth generation (6G) inherits this talent and continues penetrating into vertical applications [5–12]. By following the proposed evolution paradigm of mobile communication systems in [6], 6G will finally enter another equilibrium state that consists of digital twin society [13]. As illustrated in Figure 2, the channel of 6G exhibits three trends in frequencies, scenarios and technologies. To support the increasingly high data rates, 6G channel will fully utilize frequencies from sub-6 GHz, millimeter-wave, terahertz band (THz) to visual light communication (VLC) for extra wide bandwidths. To support the increasingly various scenarios, 6G channel will enable ubiquitous coverage including satellite, unmanned aerial vehicle (UAV), terrestrial and marine networks, as well as new application scenarios, e.g., vehicle-to-vehicle (V2V) communication, industrial internet of things (IIoT). Thus, it is challenging for 6G network considering the dynamic characteristics under dramatically different environments, especially for the channel with expanded dimensions. By the conventional way to design 6G network, the limited channel models may lead to the networks lack of flexibility to various scenarios above, not mention to the efficiency for offline optimization.

As the artificial intelligence (AI) [14–16], big data [17] and heterogeneous computing [18] are merged into the key technologies for 6G, communication systems have gathered the fundamental abilities of sensing and prediction. On the one hand, ubiquitous connections are supported in 6G networks, the physical environment can be captured via various sensor devices, like radar, video and camera etc.. On the other hand, the AI and computing ability of 6G are powerful tools to analyze the information of physical environment. Equipped with the sensing enhancement and the electromagnetic wave prediction ability, the communication systems are able to optimize the performance by capturing real-time environmental features and predicting channel characteristics. So the environment awareness system design procedure shown on the right side of Figure 1 is a promising solution for 6G to deal with the scenario diversity challenge.

Motivated by the works that use the physical environment information to improve the system performance [19–21], in this paper, from radio wave propagation perspective, we propose a predictive 6G network with environment sensing enhancement, the electromagnetic wave propagation characteristics prediction enabled network (EWaveNet), to further release the potential of 6G. By following the essence of environment awareness system design procedure, a prediction plane that manages the physical environment information flow is designed for EWaveNet. Instead of the offline channel model construction, the physical environment's effect is directly used in the form of radio propagation characteristics or electromagnetic wave propagation characteristics. The detailed characteristics of wireless channel such as large/small-scale fading, channel state information etc., are all included in the scope of predicted radio wave propagation characteristics. The radio wave propagation characteristics measurement results are further abstracted as the environment information flow that is exchanged between the physical environments and application scenarios. Since the exchange of environment information flow is a continuous process, the physical environments could be sensed, learned or even predicted, which greatly improves the system adaptability.

The contributions of this paper are as follows. First, we propose a network architecture that could sense, predict and utilize the physical environment information. The locations, shapes, materials of objects in real physical environment are sensed and abstracted to reconstruct the virtual physical environments (VPE) to mirror the physical environment. A radio wave propagation characteristics prediction module is designed to compute and rehearse the radio wave propagation in the VPE. The wireless channel between any Tx and Rx pair could be computed and predicted in the time, frequency or space dimension. Second, a two-level closed feedback workflow is proposed to manage the physical environment information. The feedback of sensing, prediction and action module are jointly designed to enhance the fast sensing and reconstruc-

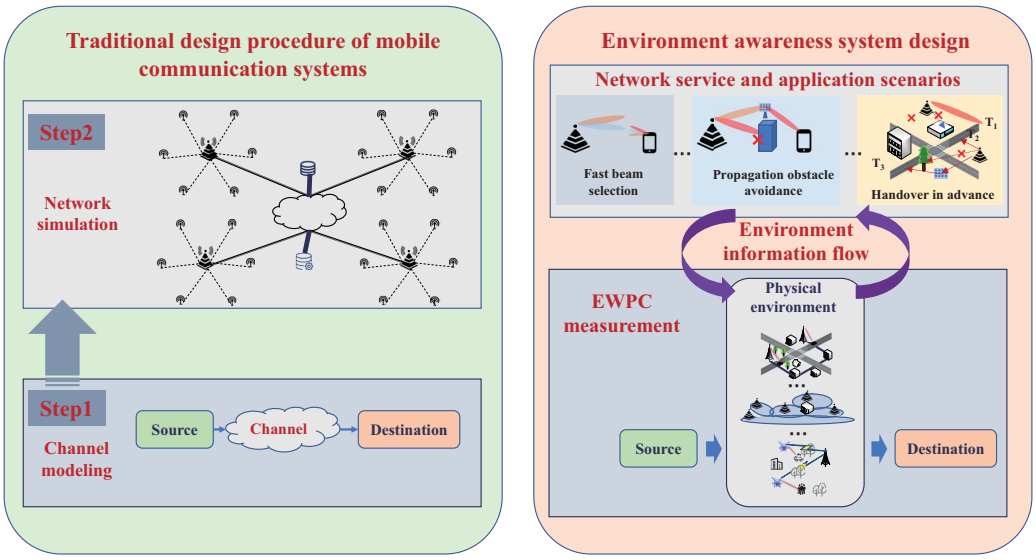

Figure 1. *Two different communication system design procedures. In the environment awareness system design case, The electromagnetic wave propagation characteristics (EWPCs) are measured to represent the dynamic physical environment.*

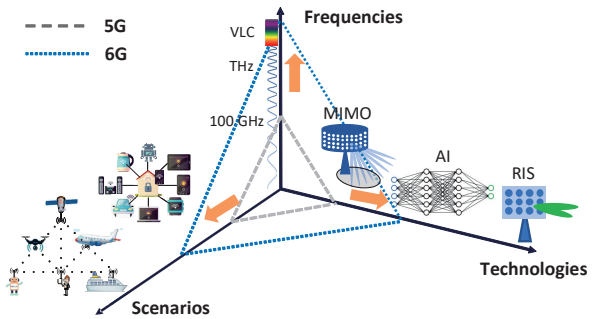

Figure 2. *The paradigm shifts of wireless channel from 5G to 6G.*

tion of the physical environment. Several application scenarios are analyzed to confirm the advantages of EWaveNet.

The rest of paper is organized as follows. The core functions, architecture and workflow of EWaveNet are described in section II. The sensing, prediction and action modules of EWaveNet are presented in section III. The challenges and open issues of EWaveNet are addressed in section IV. We draw our conclusion in section V.

II. EWAVENET

In this section, the core functions, architecture and workflow of EWaveNet are described.

2.1 Core Functions

As shown in Figure 3, the core functions of EWaveNet are sensing, prediction and action. As the information carrier, the measured electromagnetic wave propagation characteristics (EWPCs) rather than the electromagnetic wave itself are used to realize the functions of the mobile system protocols. The core functions of EWaveNet realize the connection between the physical environment and the provided services. The transmission of electromagnetic wave is highly affected by the transmission mode and the physical environment. The transmission mode contains the traditional antenna, frequency, emission power etc. and can be obtained via traditional context feedback mechanisms. The physical environment can be obtained by the physical environment sensing devices, such as the radars or cameras. To comprehensively understand the physical environment, EWaveNet supports the hybrid sense model. With the sensing-assisted devices such as the unmanned aerial vehicles (UAVs), cameras, radars and traditional electromagnetic measurements, the multi-dimension information samples (e.g., locations, shapes and materials etc.) of physical environments are collected. By conducting proper information fusion methods, the key features of physical environment are obtained and the models that depicts the physical environment are constructed. The physical environment is then reconstructed in the VPE form

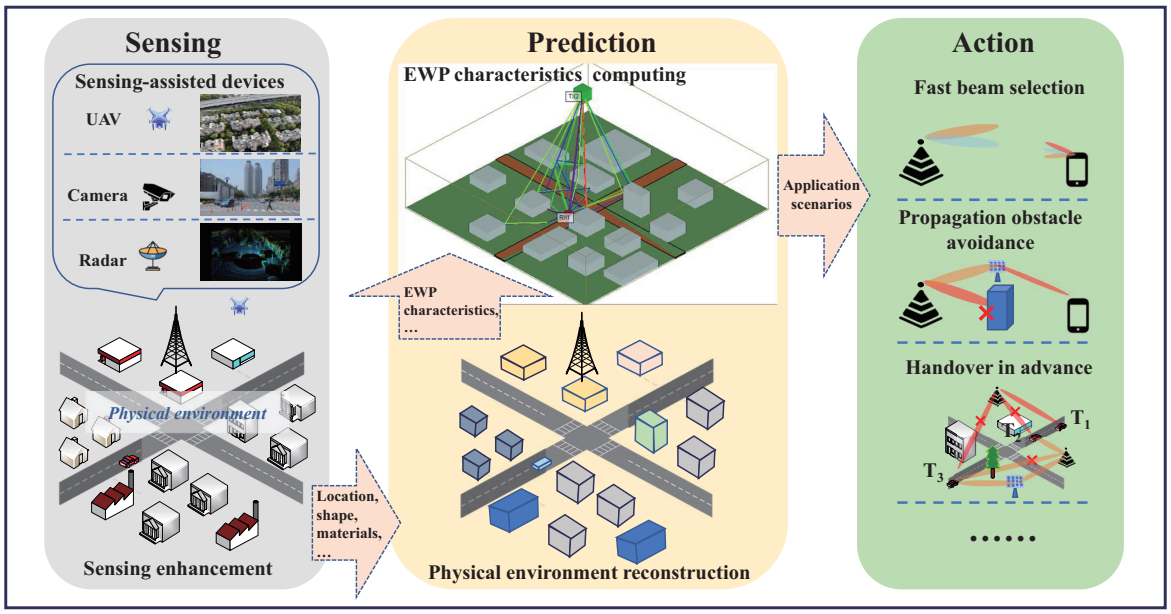

Figure 3. *The core functions of EWaveNet.*

where the characteristic of electromagnetic wave propagation (EWP) could be calculated. The shapes, locations, material features, trajectories of objects in the VPE are the precise mappings of objects in the real physical environment. The EWPC in VPE could be generated and computed in time, space and frequency domain. Given the transmission mode and VPE, we could predict the EWP in any location, at any time and on any frequency. Though we could predict the detailed EWPC, the way that the EWPCs are used varies from services to services. The action function of EWaveNet is to support various customized application scenarios. Since different applications need different EWPCs, the action function could translate the customized service requirements to the corresponding EWPCs. On the contrary, the action function can also provide the suggestions that could lead to a better system performance. The above three core functions are not independent. In fact, the three core functions work cooperatively to exploit the physical environment information.

2.2 Architecture

The architecture of EWaveNet consists the infrastructure layer, resource layer, network function layer, application layer and a prediction plane. The infrastructure layer includes the cellular and non-cellular devices in the physical environment. The resource layer represents the available resources in the system, which contains the communication, computing and storage resources. The network function layer contains the functions of the radio access network (RAN), transport network (TN) and core network (CN). The application layer provides customized services. The above four layers exist in traditional mobile systems and form the skeleton of physical environment. As shown in Figure 4, the lower layer provides the support for the higher layer. Different with the traditional mobile system architecture, EWaveNet owns a prediction plane that intersects with all the four layers. The prediction plane has a sensing module, a prediction module and an action module. The sensing module collects data from the infrastructure layer and the resource layer. With the collected data, the model & data base is constructed, which will be used for the environment construction. The sensing module could reconstruct the VPE with the model & data base. The prediction module includes an EWPC computing sub-module, an EWPC evaluation sub-module and an EWPC adjustment sub-module. The action module provides the prediction results to the network function layer and application layer for performance optimization. The requirements from network function layer and application layer are also transformed by the action model to the prediction model. With the proposed architec-

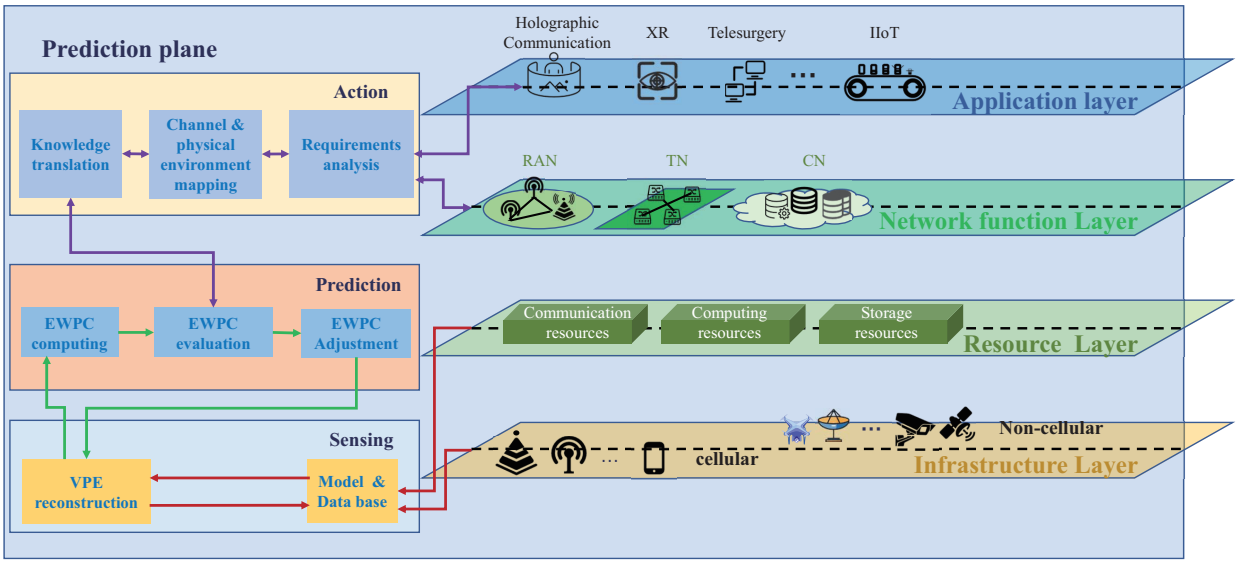

Figure 4. *The architecture of EWaveNet.*

ture, EWaveNet has the following advantages.

- **Enhanced cross-layer communication mechanism.** From Figure 4, we can see that the prediction plane connects the four layers in the vertical direction. System data from the four layers converge into the prediction plane and are used to evaluate the system performance in the form of EWPCs. Since the prediction plane could provide suggestions to the network function layer and the application layer, the prediction plane actually provides another mechanism for the cross-layer feedback.
- **Separation.** The prediction plane provides a VPE to rehearse the trend of the system performance. The VPE and the real physical environment could work in a parallel manner without interference to each other. The EWPCs could be generated or created according to the settings, which greatly reduces the complexity and cost in the real physical systems. The separation avoids the lost caused by the bad strategies.
- **Flexibility.** The prediction plane could generate, simulate and compute the EWPCs in a wide range, which provides a flexible manner to analyze the EWPCs. The prediction plane acts as an EWPC generation black box that could fully describe the EWPCs in real environment. The time, frequency and space dimensions EWPCs are all available and computable. We could create and adjust the scenarios in the prediction module to study the EWPCs in a proper dimension.

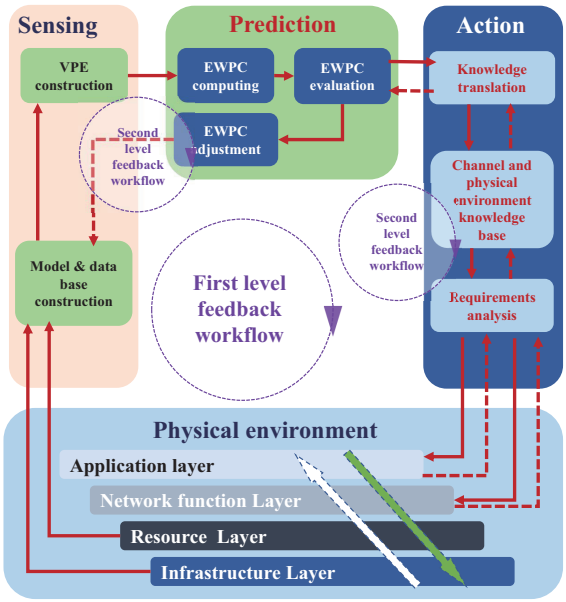

Figure 5. *The workflow of EWaveNet.*

2.3 Workflow

The EWaveNet contains four components: physical environment, sensing, prediction and action. As shown in Figure 5, traditional workflow of the four layers in the physical environment is denoted by the white arrow and the green arrow. Higher layers make

the requests (the green arrow) and the Lower layers provide the supports (the white arrow). With the other three components, a two-level closed feedback workflow structure exists in EWaveNet.

- **First level.** The first-level closed feedback workflow connects all the four components, whose trace includes the solid red arrows among the components of EWaveNet in Figure 4. The two lower layers of physical environment provide the samples or data for the sensing component. The sensing component abstracts the knowledge of physical environment by building the model & data base. Then the VPE construction sub module will reconstruct the physical environment with the knowledge, which finishes the necessary propagation environment construction. The EWP computing sub module will generate, simulate and compute the EWPCs. The obtained EWPCs with current VPE will be evaluated in the EWPC evaluation sub module. The results of the evaluation will be sent to the action module. The action module will extract and translate the evaluation results to generate the suggested predicted strategies for the application and the network function layer. The above workflow provides the path that connects the four layers of the physical environment.

- **Second level.** Compared to the first-level, the second level closed feedback workflow is much shorter and exists among the adjacent components. As shown in Figure 4, there are two feedback workflows that belong to the second level closed feedback workflow category. Each of the second-level workflows consists of both red solid lines and the red dashed lines. The first second level workflow includes lines that connects the sub modules of sensing and prediction. The feedback to the sensing component is the sensing adjustment signaling. This workflow could generate and evaluate the EWPCs in any scenario that is considered. The lines among the EWPC evaluation, action, application layer, network function layer form anther second-level closed feedback workflow. This workflow could conduct the mutual conversion between the physical environment requirements and the prediction components.

The two-level closed feedback workflow structure provides more adaptability to the physical environment dynamics. The whole system of EWaveNet could adapt to the physical environment with the first-level workflow. The information flow goes through all the four components of EWaveNet and will automatically adjust to the change of physical environment. Besides, the second-level feedback workflow provides a faster fine-tuned ability. For example, the model & data base could be refreshed by following the feedback signaling from EWPC adjustment model, where the shorter information circle leads to a faster adaptability.

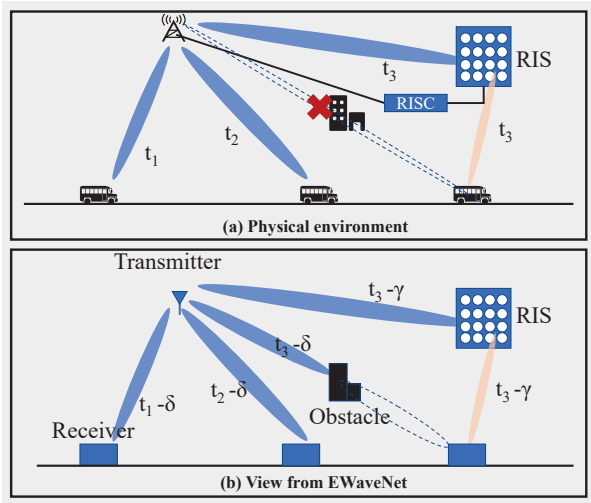

Figure 6. *The handover in advance example for EWaveNet.*

2.4 Case Study: A Handover Example

We propose a handover example in Figure 6 to show how the EWaveNet works. In the physical environment, there are five objects: a base station (BS), a car, a building, a piece of re-configurable intelligent surface (RIS) and the corresponding RIS controller (RISC). With the sensing information, EWaveNet knows these objects as the transmitter, receiver, obstacle and RIS. Note that the RISC is abstracted as the ability of the RIS from the view of EWaveNet. The time line $t_1 \rightarrow t_2 \rightarrow t_3$ is used to show the workflow of EWaveNet. At time t_1 the car is served by the BS. This state is captured by the EWaveNet at time $t_1 - \delta$, where $\delta > 0$. Since the car moves in only one direction in our example, EWaveNet predicts the physical environment communication state of time t_2 by computing the reciver's singal quality at time $t_2 - \delta$. The used beam alignment results in EWaveNet at $t_2 - \delta$ is feedback to the base staion in the physical environment, and at

time t_2 the BS could select the predicted beam to serve the car. With the obstacle information, EWaveNet predicts that there is no proper direct beam from the BS to serve the car at time $t_3 - \delta$. So by using the available RIS ability, EWaveNet provides the indirect beam solution at time $t_3 - \gamma$, where $0 \leq \gamma \leq \delta$. The indirect beam solution is also feedback to the BS to guarantee the communication service at time t_3 in the physical environment. By using the method mentioned above, the BS in the physical environment could adapt to the dynamics of the physical environment and provides continuous coverage to the moving service object.

III. KEY FUNCTION MODULES

In this section, the details of the sensing, prediction and action modules are present.

3.1 Sensing Module

The physical environment has a vital influence on wireless propagation. Wireless rays interact with scatters when the encounter happens. It can produce a further effect on the electromagnetic calculation. Therefore, environment information aided solutions of function implementation and applications always have better performance of accuracy. Not only that, adequate access to radio channel data can make further improvements in accuracy and efficiency. To this end, we propose a general framework of environment sensing which is composed of selected effective feature-based physical environment data acquisition module and channel data acquisition module as shown in Figure 7. A sensing data set consisted of original environment data, environment feature data and channel data will be generated for providing the basic data for further realization of prediction and related applications. Both the physical environment data and the channel data are needed to construct such a sensing data set.

3.1.1 Physical Environment Data Acquisition

There are several types of representation forms of physical environment images, such as image, depth image, video, satellite maps, and point cloud. The corresponding acquisition equipment is diverse. The common 2D camera can obtain RGB images, while 360 camera is used for panoramic images and depth camera is available for depth images acquisition. For large-scale area environment data acquisition, satellite maps and Geographic Information System (GIS) are capable of providing the overall situation so far as to offer the specific dimensions of buildings. Radar and depth camera like Kinect can be used as reliable devices which help get point cloud data. The UAVs can be loaded with a variety of portable acquisition devices with no location restrictions for all kinds of data collection. The acquisition equipment we mentioned above is easily accessible infrastructures with low deployment costs which can provide all-round information of the physical environment. Although wireless propagation which pays more attention to the specific and basic data such as location and dimensions of objects has different requirements of information collected from the original environment data compared with computer vision and unmanned field of research. But the basic algorithm and technologies used for data processing are identical, including object detection and recognition as well as Simultaneous Mapping and Localization (SLAM) and so on. Different from the focus on pixels and image structure in vision applications, the representation method of the wireless propagation environment relies on the object-level geometric information and the related high-dimensional information obtained based on it. In the data processing module, we integrate six functional modules for independent or cooperative feature computing. For example, object detection with 60.6 average precision on Microsoft Common Objects in Context (COCO) data set [22] can offer the quantity and class of scatters as well as the accurate shape or bounding box when combined with the results of image segmentation which can achieve 32.3fps with state of the art (SOTA) performance [23]. Furthermore, the category of the object has tight relevance with the material property. Utilizing the SLAM technique or the scanned point cloud data from LiDAR can obtain the detailed position and dimension information of scatters in the specified area when moving or stationary [24, 25]. Scatter-level detection and size measurement can be realized in real-time from video streams for effective propagation environment reconstruction [26]. We construct two modules that provide basic technology based on machine learning (ML) and deep learning (DL) to provide services for multi-technology integration. According to the mechanism of wireless propagation and the principle of electromagnetic calculation, we can conclude

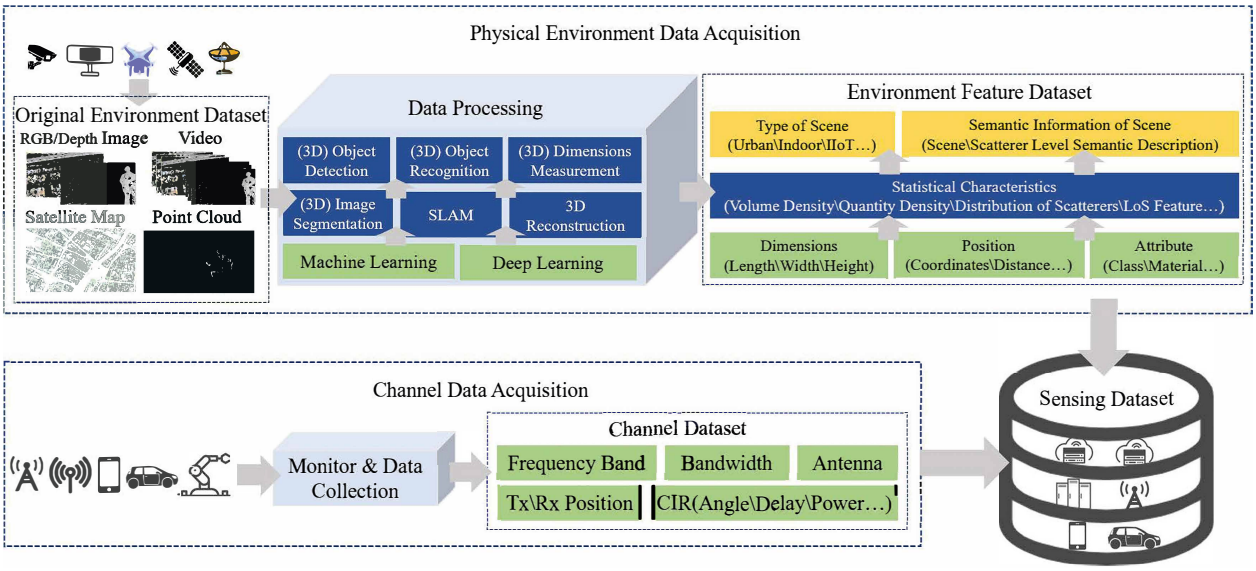

Figure 7. *The framework of sensing module.*

that information description of geometric characteristics and overall layout of the specific environment is effective environmental representation. In this paper, scatter-level features and scene-level features are designed and selected for giving a sufficient representation of the propagation environment. As shown in Figure 7, scatter-level features including dimensions, position, and attribution are basic data of each object which are relevant to the electromagnetic calculations. The category and material of scatters have a strong correlation so that category is always considered as basis conditional data which can obtain material features efficiently. In addition to obtain accurate scatter-level information from annotation and map, there are always inevitable errors in the data processing algorithms. In the circumstances, utilizing statistical characteristics to represent a specific propagation environment can also provide results with similar performance. Such as volume density, quantity density, and distribution of scatters can be described as statistical features of scatters which can be obtained from basis data of each object or data processing module directly. It's worth noting that Line-of-Sight (LOS) [27] is a vital factor for large-scale fading prediction so that should be considered as an important feature with essential information of radio rays. Furthermore, scene-level semantic data with high-dimensional information of propagation environment has the capability of highly generalized of the scene and statistical characteristics of scatters. Classify the scene using rough categories like indoor, urban, Industrial Internet of Things (IIoT), and so on. Furthermore, scatter-level and scene-level semantic descriptions can be collected according to the scenario type correlated prior information.

Figure 8. *The image of IIoT scene.*

Case study: the environment reconstruction of an IIoT scenario

Take the IIoT scene as an example, first, we can acquire several original environment images by using the most convenient camera device mobile phone with enough resolution. In a typical IIoT scene, the main scatter is the metal machine as shown in Figure 8.

Combined with industrial scene characteristics and the information obtained from the data processing

module, we can get complete basic information of this specific environment which including position, dimensions, and material of main scatters. Structure diagram of the environment with partial dimensions of main scatters and exact location of Tx and Rx illustrated in Figure 9, where the coordinates are in meters. Environment model can be reconstructed by using 3D modeling software like Google SketchUP or the commercial ray-tracing tool WirelessInsite. The corresponding reconstructed IIoT environment as shown in Figure 10 is constructed for further electromagnetic calculation and prediction which including effective area and cube-like objects with material and coordinates information.

In order to provide sufficient and exhaustive information for prediction and further applications, we propose a multi-dimensional physical environment dataset by collecting and processing data in a continuous period of time or in real-time.

3.1.2 Channel Data Acquisition

By collecting all required channel information upfront from diverse infrastructures including BSs, Wi-Fi, and terminal equipment can provide essential radio channel data and make a significant improvement of prediction performance of accuracy and reliability. Not only does the basic configuration information containing frequency band, bandwidth, antenna, and position of transmitter need to be monitored in real-time, but also require to collect the position information of terminal equipment such as phone, vehicle, and machine. More than that, channel impulse response (CIR)-based angle, delay and power parameters obtained according to the channel measurement are essential for precise channel prediction. All the channel data mentioned above constitute the channel data set. In general, we set up a sensing data set by physical environment sensing and channel data collection which is composed of the original environment data set, environment feature data set, and channel data set as shown in Figure 7. Distributed storage will be used on the participating devices and cloud storage for minimizing the transmission and time cost while centralized backup will be implemented for responding to the continuous-time data-based applications and the model updating.

Channel prediction consists of large-scale prediction and small-scale prediction related to different channel parameters. In [28], the authors use classified satellite images to calculate the point-to-point path loss while the authors in [29] estimate the path loss exponent and standard deviation of shadowing from 2D satellite images directly. For BS selection, authors in [30] utilize RGB-D camera images to estimate the mobility of pedestrians and the blockage of LOS paths prediction. In [31], distance from Tx and Rx as well as terrain clearance angle and vegetation type surrounding the RX have been utilized for point-to-point path loss prediction. Authors in [32], realize the prediction of the air-to-air channel between unmanned aerial vehicles according to the Tx/Rx altitude, distance, LOS feature, and elevation angle. There are many kinds of information included in the original environment data, thus only a few of them have relevance to the propagation mechanism directly or indirectly. Sensing module designed based on the effective features selection for exhaustive, comprehensive but not redundant data monitor and acquisition. Classification of different dimension data provides a clear and convenient data extraction mode for further prediction and other applications.

3.2 Prediction Module

In this section, we propose the workflow of electromagnetic wave propagation characteristics prediction, which mainly includes three parts: EWPC computing, EWPC evaluation, and EWPC adjustment. EWPC computing refers to selecting appropriate environmental data according to different application requirements, such as images, 3D point clouds, and video. Then, the selected data is utilized to predict the channel propagation characteristics (path loss, RMS delay spread, angular spread of departure and arrival in azimuth and elevation, shadow fading and K-Ricean factor, etc.), based on parameter extraction, deep learning, and other methods. EWP evaluation refers to measuring the predicted channel propagation characteristics accuracy according to relevant metrics. Evaluate the prediction effect of the prediction algorithm. EWP adjustment refers to adjusting the parameter of the EWP computing method to achieve better prediction results.

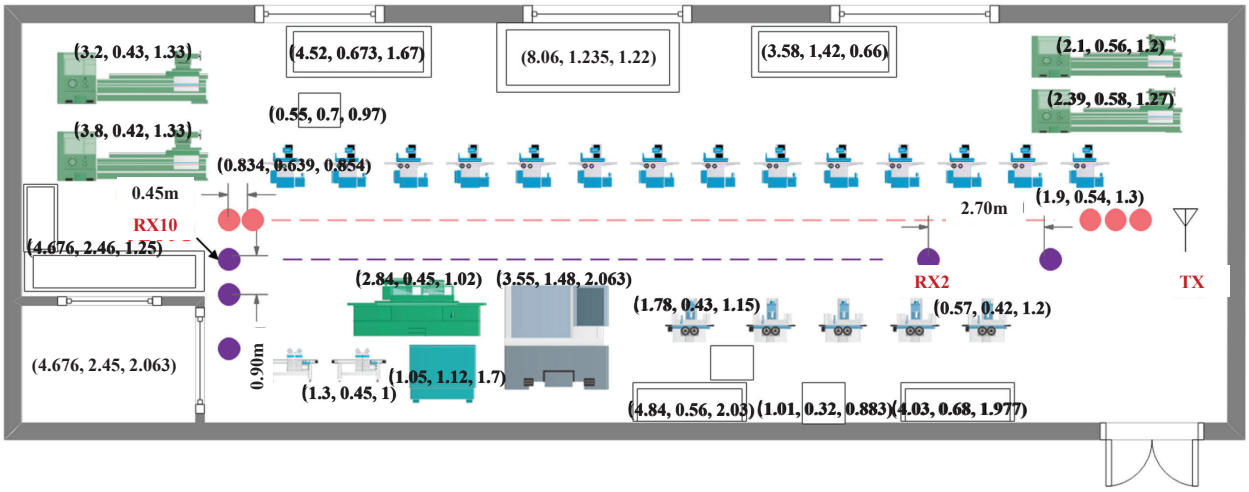

Figure 9. *The structure diagram of the environment with partial dimensions of main scatters.*

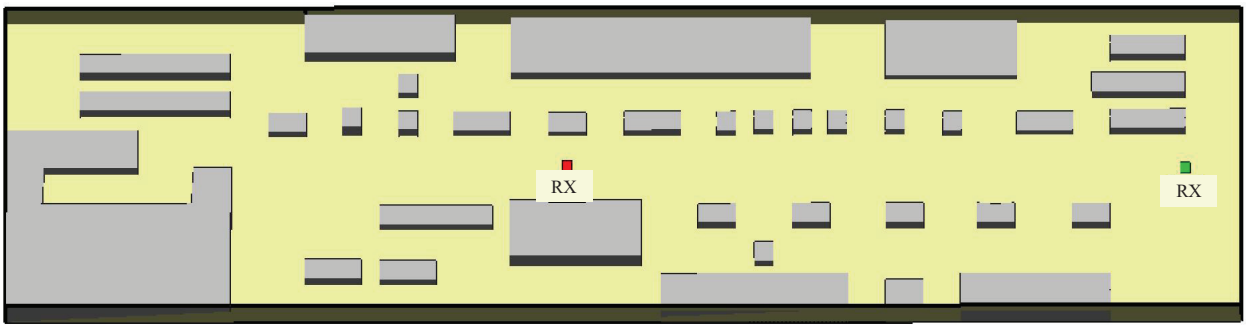

Figure 10. *The reconstructed environment.*

3.2.1 EWPC Computing

It is generally known that the wireless channels depend on the scene objects between the BS and terminal, i.e., buildings, cars, trees, etc., as the propagation paths and attenuation of transmission signals can be determined by the environmental information and the BS/terminal locations. Hence, two closely located users are bound to experience similar channel propagation effects because they share almost identical scatterers and are at a similar distance to the BS. For example, the angles of arrival (AOAs), angle of departure (AODs), and delays of multi-path components (MPCs) within each cluster smoothly evolve for small changes in user position. We refer to this similarity in propagation effects as spatial consistency property (SCP). In Figure 11, we have proved spatial consistency through channel measurement in real scenes [33]. In addition, there are also high similarities between channel multipath in different frequency bands in the same scenario. Based on Figure 12 and Figure 13, we could compare the CIR data of the 3.5 and 28 GHz frequency bands through channel measurements in real scenarios [34]. The channel correlation in the space domain and the frequency domain is due to the high similarity of the environment. Hence, it can be assumed that there exists a mapping between the environmental information and the wireless channel, i.e.,

$$\Psi(E_{ter}) = h_{ter}$$

where E_{ter} is the environmental information around the terminal, h_{ter} is the corresponding wireless channel characteristics information such as root mean square (RMS) delay spread, angular spread of departure and arrival in azimuth and elevation, shadow fading, and K-Ricean factor, etc. According to section 3.1, E_{ter} can be the environment-related image, depth image, video, satellite map, 3D point cloud and other environmental data.

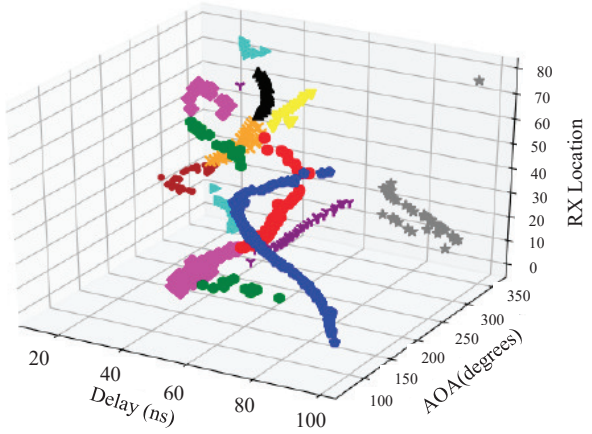

Figure 11. *The SCP of clusters in lecture room [33].*

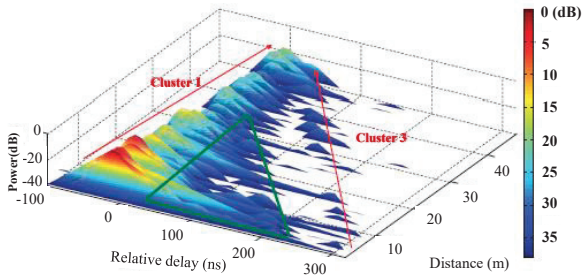

Figure 12. *The measured PDP of 3.5 GHz in corridor scenario [34].*

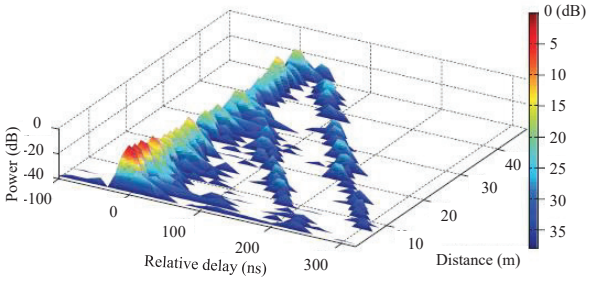

Figure 13. *The measured PDP of 28 GHz in corridor scenario [34].*

3.2.2 EWPC Evaluation and EWPC Adjustment

In the EWPC computing stage, we utilize machine learning, parameter extraction, and other methods to calculate channel propagation parameters that meet environmental information application requirements. In other words, the mapping function Ψ is implemented. However, such prediction accuracy often cannot meet the needs of 6G networks. To meet the needs of new application requirements that may appear in the future 6G network, in our EWaveNet architecture, we have added two modules, EWPC evaluation and EWPC adjustment. The purpose of EWPC evaluation is to provide real-time quantitative evaluation results based on the calculation results of EWPC computing, combined with current application requirements. For this reason, for EWPC evaluation, the most important thing is to select appropriate metrics. When the result of the EWPC evaluation is obtained, the EWPC adjustment module reversely acts on the EWP computing module based on the EWP evaluation results. For example, the EWP computing module gets the channel state information (CSI). The channel capacity C is selected as the metric of the EWPC evaluation module. The CSI obtained by the EWPC computing module is input to the EWPC evaluation module, and the EWP evaluation module outputs the calculation result of the channel capacity C. The channel capacity C obtained by the EWPC evaluation module is input into the EWPC adjustment module, and the EWPC adjustment module acts on the EWPC computing module. The EWPC computing module can adjust the algorithm category, algorithm parameters, and input environmental data type according to the instructions of the EWPC adjustment module.

Case study: Cluster-Nuclei Based Channel Model Using Environmental Mapping

Since the EWPC evaluation and adjustment module needs to be comprehensively compared under a variety of prediction algorithms, we only provide an implementation example of the EWP calculation module. In [35, 36], we proposed a cluster-nuclei-based channel model (CNCM) and validated the performance. The cluster-nuclei (CN) are mapped with the environmental objects with physical meaning. The cluster-nuclei-based method consists of four procedures, i.e., propagation environment reconstruction, CN identification, multi-path parameters generation, and channel coefficients generation. In Figure 14, we have shown the multi-path propagation characteristics calculated by the CNCM method in the 3D scene reconstructed by the sensing stage. In the propagation environment reconstruction stage, we utilized Google SketchUp to reconstruct the practical propagation environment. Three aspects of environmental information are significant in the reconstruction, i.e., the shape and position of the scatterer, the boundary of propagation environment, and surface material of environ-

mental object and boundary. In the CN identification stage, a simplified RT-based method is introduced to determine CN's spatial positions and parameters. Two main procedures obtain CN identification as following: pathway calculation and power calculation. First, geometrical optics are applied to calculate propagation pathways from Tx to Rx in the reconstructed environment. The LOS pathway is determined by free space LOS propagation between the 3D locations of Tx and Rx. The paths of CN generated by single-bounce reflection (SBR) and double-bounce reflection (DBR) are determined by Snell's law with the image-based method. Then perform power calculation to obtain the powers of CN by Friis and Fresnel equations. In the multi-path parameter generation stage, angles of the MPCs within CN are generated in a random way. The MPC delay is equal to the CN to which it belongs. Powers of the MPCs within CN are generated through the power angular spectrum (PAS). Finally, in the channel coefficients generation, the channel coefficients of the link from the u-th antenna element at Rx to the s-th antenna element at Tx are generated as the coherent sum of different CN and MPCs coupling with the RX and Tx antenna radiation patterns.

3.3 Action Module

3.3.1 Structure of the Action Module

The action module acts as an interface between the physical environment and the application/network function layer. As shown in Figure 15 the action module could collects the requirements from the application/network function layer and feedback the necessary suggestions. In fact, a channel and physical environment mapping knowledge base is constructed to support a wide range of control and service management. Any requirement is analyzed and used to act as the input of the knowledge base. The output of the knowledge base is further translated into the suggestion of various application and network function management. With the query-response structure, the action module could support a various of applications and network performance optimizations.

3.3.2 Applications and Use Cases

The required channel characteristics are often different according to different application requirements, so the required physical propagation environment knowledge is different. Therefore, predicting different channel characteristics usually requires different environmental information, different prediction methods, and different metrics. This subsection gives several different use cases in terms of real time path loss exponent, mmWave blockage, time-varying multiple input multiple output (MIMO) channel, scene-based beam selection, etc., to show the various prediction methods under different requirements.

- **Case 1 : real time path loss exponent.** In [37], the authors propose a new method for predicting the path loss exponent of outdoor millimeter-wave band channels through the deep learning method. The authors convert three-dimensional geographic information into two-dimensional images as the input of the neural network. The RGB color of each location represents the transmitter height, the ground height, the building height. In Figure 16, the examples of the image in path loss exponent prediction are shown. The authors treat path loss exponent prediction as a regression problem. The output of the convolutional neural network is the path loss exponent.

- **Case 2: mmWave blockage.** The prediction of the blockage can be realized by utilizing EWP computing [38]. The RGB image shot by BS is selected as the environmental data. The idea of using images to predict blockage state are regarded as classification problems. Based on computer vision and deep learning tools, the RGB image shot by BS is used as the neural network input. The neural network is first used to detect whether a user exists in the scene or not. If a user is detected, the link status is directly declared as unblocked. On the other hand, when the user is not detected, sub-6 GHz channels come into play to identify whether this is because it is blocked or does not exist. When those channels are not zero, this means a user exists in the scene, and it is blocked. Otherwise, a user is declared absent. It's worth noting that sub-6 GHz channel data is used as auxiliary input information in the blockage prediction. In Figure 17, we have shown the workflow of blockage prediction.

- **Case 3: time-varying MIMO channel.** In Figure 18, we have shown the application scene of

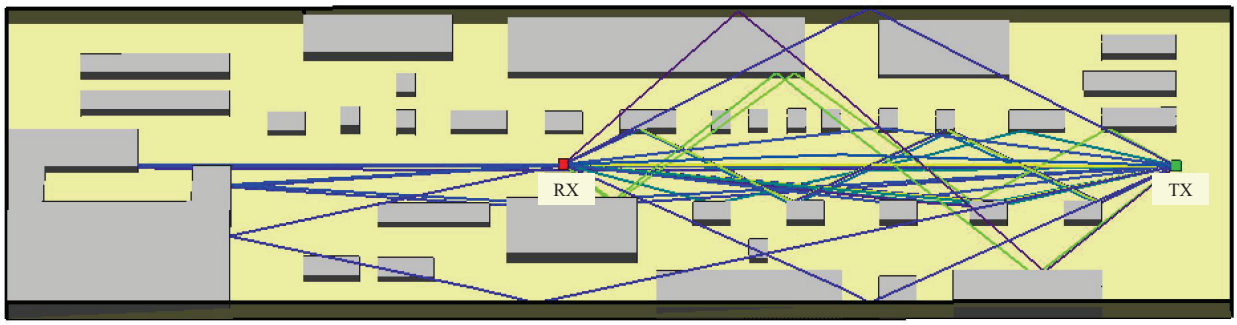

Figure 14. *Electromagnetic waves propagation characteristics prediction.*

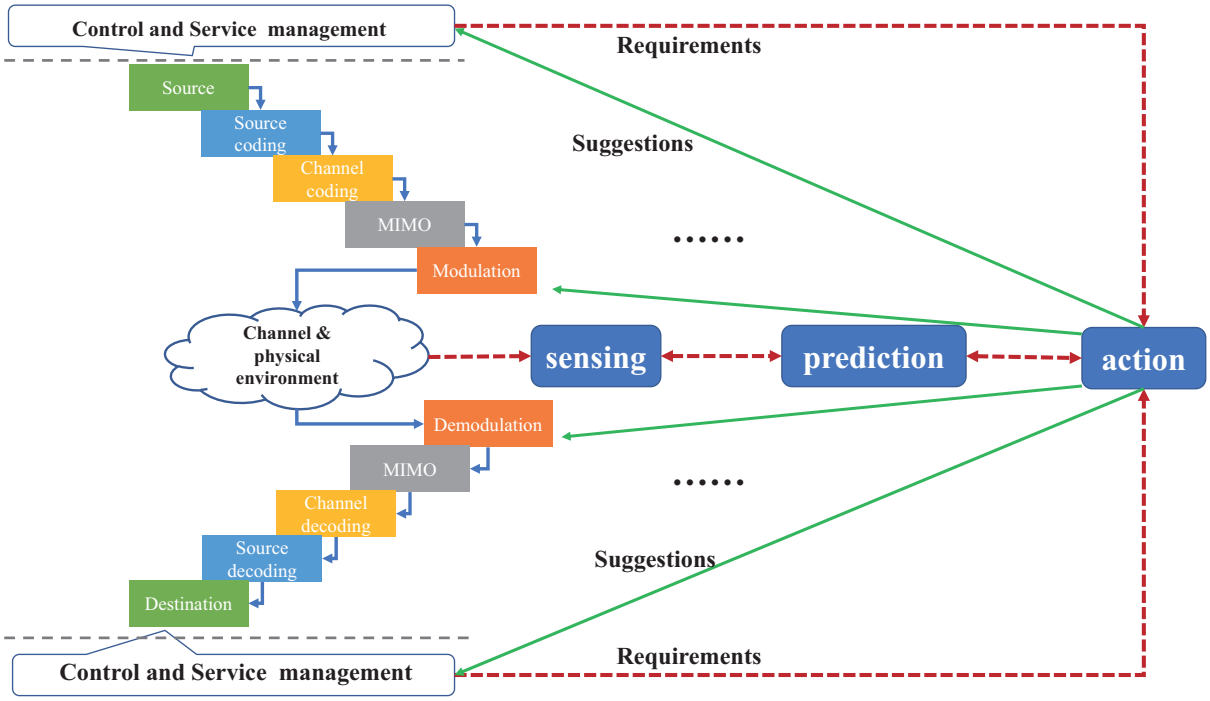

Figure 15. *The frame of the action module.*

channel state information prediction. Channel state information prediction has become a key concern in high-speed dynamic time-varying scenarios. To this end, we provide two channel state information (CSI) prediction methods in this subsection.

In [39], we proposed a time-varying MIMO channel fading prediction framework named Cluster Drifting Based Prediction (CDBP) algorithm. The principle behind the method is that the cluster-based fading channel has the spatial consistency property (SCP). The input data is previous CSI with SCP. We utilize the Bayesian Estimation Kalman Filter (BEKF) algorithm, first initialized by the VB-SAGE algorithm. Then the stages of Kalman Filter prediction and VB-SAGE-based model order update are implemented iteratively. With the BEKF algorithm, the time-varying small-scale parameters in the tracking horizon can be obtained. With the multi-bounce model, it is potential to utilize the tracking small-scale parameters to estimate the positions of first-bounce scatters (FBSs), and last-bounce scatters (LBSs). Then, based on the principle of the geometric-based channel model, the channel fading can be calculated utilizing the positions of

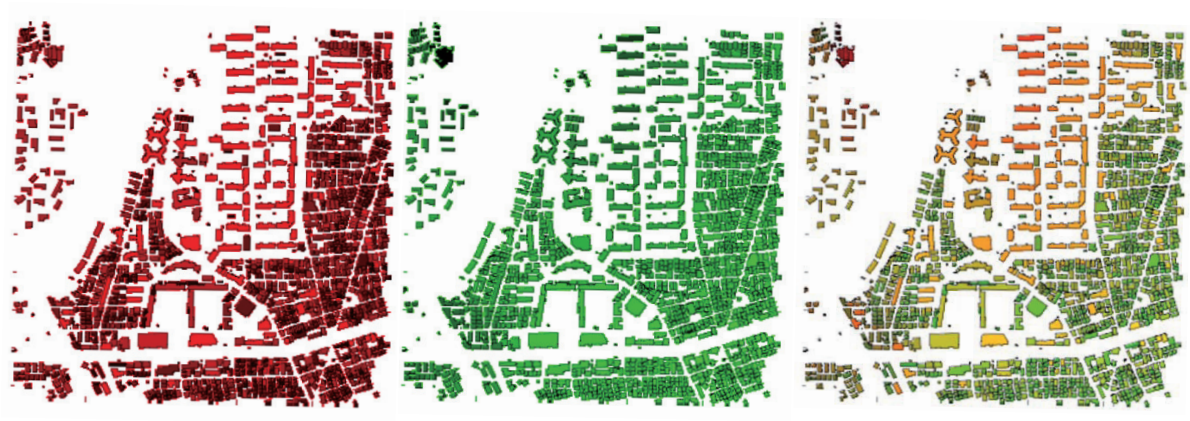

Figure 16. *Examples of image sets in path loss exponent prediction. Transmitter height, ground height, and building height are represented in each color map [37].*

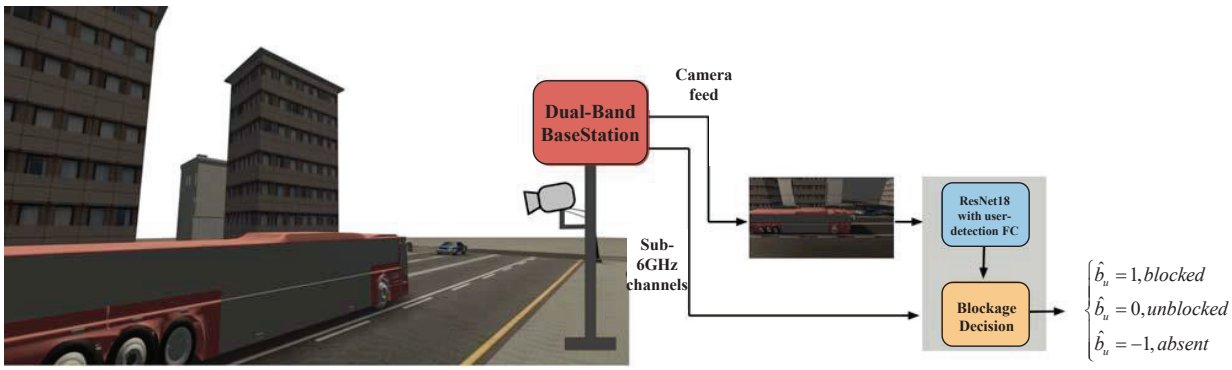

Figure 17. *The workflow of blockage prediction [38].*

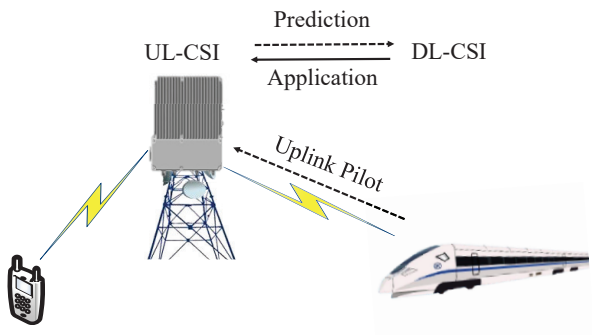

Figure 18. *The channel state information prediction scene.*

Tx, Rx, FBSs, and LBSs. The channel prediction error with the CSI obtained by uplink channel estimation and the bit-error-rate (BER) performance at Rx in the downlink system are used to evaluate the proposed scheme.

In addition, in [40], we propose a time-varying channel prediction method aided by adversarial training. The channel prediction with deep learning can consider the multiple domains and does not need channel propagation characteristics. The input data is previous uplink CSI in an orthogonal frequency division multiplexing (OFDM) system. We utilize the conditional generative adversarial network to predict the downlink CSI. The normalized mean-square error (NMSE) of downlink CSI and BER is used to evaluate the learning accuracy of the proposed method.

- **Case 4: scene-based beam selection.** In [41], the authors present a novel framework of 3D scene-based beam selection for mmWave communications that relies only on environmental data and deep learning techniques. Unlike other communication strategies, the proposed one fully utilizes the environmental information, e.g., the shape,

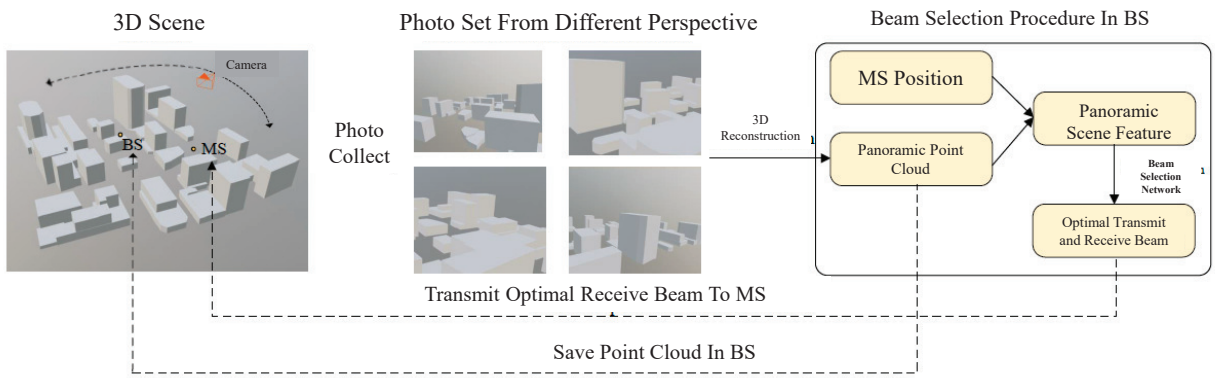

Figure 19. *The framework for 3D scene-based beam selection [41].*

position, and materials of the surrounding buildings/cars/trees obtained from 3D scene reconstruction and presents a complete picture that could determine the wireless channels. Then, the authors build a neural network with the input as the point cloud of the 3D scene and the output as the beam indices. The user's position is used as auxiliary input information in beam prediction. The proposed method can avoid the severe overhead of using expensive auxiliary devices. In Figure 19, we have shown the framework for 3D scene-based beam selection.

IV. CHALLENGES AND OPEN ISSUES

Though EWaveNet benefits from the usage of physical environment, the following challenges and open issues should be addressed to release the full potentials of system performance improvement.

- **Data collection and selection.** As for environment sensing, how to realize efficient data acquisition is one of the main challenges. In the case of limited storage resources and difficulty in online data filtering, it is become especially important to determine when to collect data and what kind of data to collect. Another important factor that affects sensing is the accuracy, real-time, and robustness of data processing. The ever-changing physical environment and increasing real-time requirements pose new challenges to the integration of multiple technologies.
- **Accuracy of VPE construction.** The accuracy requirement of VPE construction is determined by the type of EWaveNet applications, e.g., large-scale parameters and small-scale parameters, therefore construction methods are different considering construction efficiency and equipment cost. Conversely, VPE construction accuracy have direct impact on the following EWaveNet accuracy and system performance. Consequently, the VPE construction and network applications are mutual interact with each other. For integrating environmental sensing into communication systems is still is its infancy, which method to be utilized and how to evaluate the accuracy and efficiency of different VPE construction methods in terms of different types of applications is an open issue.
- **Lack of universal metrics.** In the EWPC evaluation stage, different metrics are adopted for different application requirements and channel characteristics. For the future dynamic 6G network, there is no doubt that some universal metrics are needed. Firstly, determining universal metrics can reduce computational complexity and improve prediction efficiency. Then, the determination of universal metrics is conducive to meet the needs of various composite applications. It is worth noting that the selection of universal metrics needs to consider which data is available in real-time during the prediction process, which is a hard challenge for the existing network.

V. CONCLUSION AND FUTURE WORK

This paper proposes the predictive 6G network with environment sensing enhancement, EWaveNet, to maintain the generalization ability and versatility of

6G for dramatically different environments. Different with the traditional roadmaps to 6G that separates the physical environments with the system design, EWaveNet aims at extracting the EWPCs to improve the flexibility of mobile communication networks. By sequentially conducting the sensing, prediction and action module functions, the EWPCs are abstracted, modeled, computed, learned, extracted and used. The EWaveNet obtains a faster adaptability to the various application scenarios by following the proposed two-level closed feedback workflow. In our future work, the performance of EWaveNet will be evaluted and the solutions to the challenges will be addressed.

ACKNOWLEDGEMENT

This work was supported by the National Natural Science Foundation of China (No. 92167202, 61925102, U21B2014, 62101069) and the National Key R&D Program of China (No. 2020YFB1805002).

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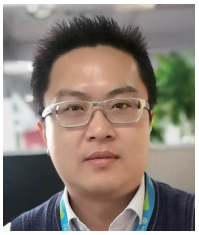

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