Neuro-Symbolic Explainable Artificial Intelligence Twin for Zero-Touch IoE in Wireless Network

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Abstract—Explainable artificial intelligence (XAI) systems will be a fundamental enabler of zero-touch network and service management (ZSM) for sixth-generation (6G) wireless networks. Thus, a reliable XAI twin system becomes essential to discretizing the physical behavior of the Internet of Everything (IoE) and identifying the reasons behind that behavior for enabling ZSM. To address the challenges of extensible, modular, and stateless management functions in ZSM, a novel neuro-symbolic XAI twin framework is proposed that enables trustworthy ZSM for a wireless IoE. The proposed neuro-symbolic XAI twin framework consists of two learning systems: 1) implicit learner that acts as an unconscious learner in physical space and 2) explicit learner that can exploit symbolic reasoning based on implicit learner decisions and prior evidence. The physical space of the XAI twin executes a neural-network-driven multivariate regression to capture the time-dependent wireless IoE environment while determining unconscious decisions of IoE service aggregation, such as uplink, downlink, and service provisioning. Subsequently, the virtual space of the XAI twin constructs a directed acyclic graph (DAG)-based Bayesian network that can infer a symbolic reasoning score over unconscious decisions through a first-order probabilistic language model. Furthermore, a Bayesian multivariate bandit-based learning problem is proposed for reducing the gap between the expected explained score and the current obtained score of the proposed neuro-symbolic XAI twin. Experimental results show that the proposed neuro-symbolic XAI twin can achieve around 96.26% accuracy while guaranteeing from 18% to 44% more trust score in terms of reasoning and closed-loop automation.

Index Terms—Declarative semantics, explainable artificial intelligence (XAI), Internet of Everything (IoE), neuro-symbolic XAI, trustworthy artificial intelligence (AI), zero-touch network and service management (ZSM).

I. INTRODUCTION

EXPLAINABLE artificial intelligence (XAI) functions must be integrated into next-generation wireless networks such as 6G so as to enable an inherent analytical ability for characterizing the behavior of the Internet of Everything (IoE), inferring causes from the generated network data, and delivering correct processes to the right users\cite{1}, \cite{2}, \cite{3}, \cite{4}. In this work, zero-touch refers to a unique intelligent system for the wireless network that can autonomously capture the current networking environment and execute self-ruling communications and computational service decisions by interpreting the cause and effect of such decisions.

A. Motivation

Existing approaches for ZSM \cite{13}, \cite{14}, \cite{15}, \cite{16}, \cite{17} are based on data-driven learning schemes. Those are focused on hierarchical federated learning for network resource slicing \cite{13}, deep reinforcement learning (DRL) for computational resources management of flying ad-hoc networks \cite{14}, a statistical federated learning framework for network slicing \cite{15}, an
unsupervised clustering for wireless network resource management and slicing \[16\], and model-free DRL for virtual network function deployment \[17\]. These research works \[13\], \[14\], \[15\], \[16\], \[17\] are not sufficient for enabling ZSM for wireless IoE because of various reasons.

First, these prior approaches \[13\], \[14\], \[15\], \[16\], \[17\] are focused on a particular network and computational resource management function without consideration of service-domain data collection, domain analytics based on collected data, and intelligence orchestration based on service-domain analytics for wireless IoE. Second, the efforts in the prior art do not meet several fundamental principles of ZSM that are suggested by the European Telecommunications Standards Institute (ETSI) \[8\], such as scalability, modularity, and stateless management functions on service provisioning. Third, the artificial intelligence (AI)-based techniques in prior works do not comply with reliability and trustworthiness since they are unable to characterize the causes of strengths and weaknesses of their resource management decisions due to a lack of interpretability. Therefore, to establish a ZSM for wireless IoE, there is a need for an intelligent system that can capture the current networking environment for decision making while also being capable of reasoning causes, analyzing effects \[7\], and executing autonomous decisions with a higher reliability.

Thus, designing a neuro-symbolic AI \[7\], \[18\], \[19\] becomes suitable because neuro-symbolic AI (NeSy AI) aims to fuse deep learning methods with conventional rules-based AI techniques to solve the challenges of reasoning the cause and effect for the AI model outcome.

B. Goal and Challenges

The main goal of this work is to develop an XAI twin system for a network service provider that assures the reasoning and trustworthiness of zero-touch IoE service management. To guarantee the reasoning and trustworthy operation of zero-touch IoE, an AI system must maintain the observing capabilities of physical behavior through a neural-network-driven model and preserve interpretability by a rule-based symbolic reasoning scheme. In other words, we will focus on a mechanism that can capture and observe the time-dependent physical behavior of wireless IoE from the current networking dynamics, service users’ requirements, and contextual metrics. Then, the XAI system will be capable of correcting erroneous decisions on service user association, uplink, downlink data rates control, and service provisioning based on its reasoning. In order to do this, we must address several challenges. First, characterizing correlation among the networking dynamics \[9\], \[10\], \[11\], \[12\], such as reference-signal-received power (RSRP), user uplink and downlink data rates, communication and computational capacity, user speed, signal-to-interference-plus-noise ratio (SINR), and reference-signal-received quality (RSRQ) is a key challenge due to distinct communication and computational requirements of each IoE service. Second, determining the most contributing coefficient of network parameters for zero-touch IoE service aggregation decisions is another challenge since service data, user mobility, service processes, and the capacity of physical devices are not fixed and are random over time. Last but not least, in the traditional AI mechanisms, it is hard to balance the accuracy and interoperability tradeoff of zero-touch IoE service management for deciding service user association, uplink, downlink data rates control, and service provisioning.

C. Summary of Contributions

The main contribution of this article is, therefore, a novel neuro-symbolic XAI twin framework for zero-touch IoE network and service management. The proposed approach creates an AI system that can reason the root causes of each IoE service requirement and execution decision, analyze the effects of reasoning, achieve a certain level of channel quality index (CQI), and provide autonomous IoE service association and data rates control to IoE service. Our main contributions include the following.

1) We introduce a novel XAI-twin framework for ZSM in wireless networks that can characterize both the reasoning and effects for achieving higher accuracy, data efficiency, transparency, and trustworthy IoE service execution decisions. In particular, we develop a neuro-symbolic XAI twin framework that consists of two learning systems: a) implicit learner that acts as an unconscious decision maker in physical space via a neural-network-driven model and b) explicit learner that exploits symbolic reasoning based on implicit learner decisions and prior knowledge.

2) We formulate a decision problem, where the main objective is to minimize the residual between an expected explained score and the current obtained score on the corresponding decisions in virtual space by coordinating with each physical space. The formulated problem is reduced to a Bayesian multiarm bandit \[20\], in which, each physical space (i.e., gNB) of the XAI twin is considered as a bandit’s arm.

3) We devise an implicit learner for capturing the current IoE environmental dynamics of each physical space, we propose a multivariate regression approach by developing a neural-network-driven model to determine unconscious decisions for IoE service association, uplink, and downlink data rates control since these outcomes rely entirely on time-variant network parameters. The unconscious decision cannot do introspection due to its trained memory.

4) Then, we design an explicit learner, by constructing a directed acyclic graph (DAG)-based Bayesian network (BN) on each network parameter and contextual feature that can infer a symbolic reasoning score of physical space decisions through a first-order probabilistic language model. In particular, the symbolic reasoning score is determined by the marginalized joint probability distribution (JPD) of all network parameters and contextual metrics.

5) Through experiments using a state-of-the-art 5G data set (B_2020.02.13_13.03.24) \[21\], we show that our neuro-symbolic XAI twin framework can outperform the other benchmarking approaches in terms of accuracy,
explainable score, and closed-loop IoE service execution. In particular, the developed neuro-symbolic XAI twin framework affords around 96.26% accuracy for both uplink and downlink rates allocation while yielding 44% and 18% more reasoning score than that of the Gradient-based bandit and Epsilon-greedy-based schemes for closed-loop IoE service execution. Additionally, the proposed approach can provide higher CQI to IoE services while 72% of IoE service can achieve a CQI over 10.

In the proposed neuro-symbolic XAI twin framework, the physical space of the XAI twin can capture the dynamic environment of network parameters and contextual metrics of each IoE element to devise an unconscious decision on communication and computation resources. Meanwhile, each of the decisions is observed evidently by a virtual space to secure a closed-loop IoE service execution with reliability. Furthermore, the explicit learner finds reasoning of the network dynamics and contextual metrics and executes a Bayesian multiarm bandit system for accomplishing the corrected IoE service execution decisions based on the reasoning and explanation.

The concept of DAG in explicit learners for mapping networking requirements and contextual metrics under a BBN assures the extensibility of ZSM. In particular, a DAG has the capability to determine each decision separately and can flexibly add new contextual metric nodes to the BBN. Furthermore, distinct networking environment sensing and decision-making capabilities of implicit learners at each gNB ensure a modular aspect of ZSM in the proposed neuro-symbolic XAI twin framework.

The remainder of this article is organized as follows. In Section II, we present a brief literature review based on the prior research. We present the proposed system model of a neuro-symbolic XAI twin for ZSM in Section III and important notations are summarized in Table I. In Section IV, we formalize the learning problem of XAI twin. Then, our neuro-symbolic XAI twin framework is designed in Section V. Experimental results are analyzed in Section VI, and conclusions are drawn in Section VII.

II. PRIOR WORKS

In this section, we provide a brief discussion on the background of zero-touch IoE in the wireless network, some of the interesting prior works, and their shortcomings that are addressed in the proposed neuro-symbolic XAI twin framework for the zero-touch IoE network and service management.

A. Background on Zero-Touch IoE in Wireless Network

ZSM envisioned end-to-end closed-loop automation as the next-generation networking system [8], [22], [23]. In particular, operational process and task execution must be performed through 100% automation. The concept of IoE service brings a new dimension of challenges in ZSM since IoE is not only relay on physical things (i.e., devices) but it also has intelligent connection among four fundamental elements, such as people, processes, data, and physical things [9], [10], [11], [12], [27]. Thus, in the next-generation wireless network [1], [2], [8], [22], [23], the fundamental requirement is to support distinct IoE applications and services by employing closed-loop intelligent automation of network orchestration and control.

Work [7] proposed and investigated one of the first NeSy AI framework for quantifying reasoning in wireless communication. In particular, this work leveraged the concept of generative flow networks (GFlowNets) to learn encoding and decoding for semantic communication in wireless network. Unlike work [7], our work focuses on developing an XAI twin system for the network service provider that assures the reasoning and trustworthiness of zero-touch IoE service management. The proposed neuro-symbolic XAI twin framework, in particular, comprises two distinct learning systems: 1) implicit learner that leverages a neural network-driven model to behave as an unconscious learning entity in physical space and 2) explicit learner that makes use of symbolic reasoning based on learner decisions that are implicit and past knowledge via BBN. To execute the updated IoE service execution decisions based on reasoning, an explicit learner finds the reasoning of the network dynamics and contextual metrics and implements a Bayesian multiarm bandit system.

B. Role of AI Toward ZSM

Recently, researchers investigated the role of AI for ZSM in beyond 5G wireless networks in [13], [14], [15], [16], [17], [24], [25], and [26]. Chergui et al. [13] proposed a distributed management and orchestration framework using a hierarchical AI-driven closed-loop control system for addressing the challenge of network slicing in large-scale networks. However, this prior work does not capture the network dynamics, such as IoE service data heterogeneity, CQI, and service user mobility. The work in [14] developed a DRL-based zero-touch adaptation approach for computing task offloading in a drone system. However, this approach is not scalable because this only works for the predefined fixed number of drone deployments.

Chergui et al. [15] proposed a statistical federated learning approach for closed-loop network resource slicing automation on different technological domains. However, the technical approach was limited mostly to qualitative discussions. The work in [16] used a k-means clustering approach integrated with domain expert feedback to perform network management. However, this work does not take into account network service association and data rates control. Rezazadeh et al. [17] investigated a continuous model-free DRL approach for minimizing the system’s energy consumption and virtual network function deployment cost. This approach is not appropriate when extreme reasoning becomes more important for enabling a reliable automated network and service management and meeting the key performance indicator (KPI) of ZSM.

Baccour et al. [24] envisioned pervasive AI (PAI)-based solution for ZSM to enable self-configuration, self-monitoring, and self-healing 6G services. Baccour et al. [24] provided a proof-of-concept of PAI for ZSM without a concrete solution.
In [25], a security orchestration framework for ZSM was studied by developing a federated-learning-based intrusion detection scheme. However, the authors have not discussed how to anticipate the security threats of upcoming 6G ML-empowered functions and services through the proposed security orchestration framework. The work in [26] proposed minimization of drive test (MDT) reports identification framework for investigating adversarial attacks on the self-organizing network (SON) functions in ZSM. This work discussed the conceptual view of the MDT reports identification framework, but does not provide concrete technical insight on how the proposed framework works on adversarial attacks protection in ZSM.

In summary, the works [13], [14], [15], [16], [17], [24], [25], [26] have attempted to define a couple of principles toward ZSM, such as closed-loop automation and scalability; however, they did not consider extensibility, modularity, and stateless management functions [8] through reasoning.

C. IoE Service Management

Recently, some of the challenges related to IoE network and service management over wireless networks were studied in [9], [10], [11], [12], [27], and [28]. The work in [9] proposed an XAI-enabled IoE service delivery framework by designing a multivariant regression problem. The proposed framework can enable both intelligence and interpretation during the IoE service delivery decisions. Pant et al. [10] investigated the problem of malicious and benign nodes detection for an IoE network by proposing a machine learning architecture. Manogaran et al. [11] proposed a mutable service distribution model based on deep recurrent learning to enable unified IoE service response by preventing service overlapping. Adhikari et al. [12] used DRL to design a cyber twin-enabled edge framework for finding a strategy based on dynamic IoE service requirements.

Zheng et al. [28] investigated the energy efficiency problem of low-power Industrial IoE (IIoE) devices by considering the Age of Information (AoI). In particular, the authors designed a dual-layer deep Q-network for IIoE devices scheduling and transmit power control. A hypothetical road map on IoE and their advancement were discussed in work [27]. The authors found that the integration of adaptive connectivity and ubiquity becomes a key enabler for interfacing between the universe and unprecedented IoE applications.

However, these works [9], [10], [11], [12], [27], [28] do not investigate the root causes and effects on wireless IoE service association and data rates assignment, nor do they meet self-adaptive service requirements.

D. Digital Twin and Learning

The use of learning in digital twins (DTs) was studied in [29], [30], [31], and [32]. In [29], a cyber twin-assisted asynchronous federated learning (AFL) scheme was proposed for communication and computation resource allocation in an edge computing network, where the role of a cyber twin is to coordinate between each client learning model and cloud server for aggregation during the training process. The work in [30] developed a new reinforcement learning approach for a personalized vehicular service provision scheme in 6G vehicle-to-everything (6G-V2X). The work in [31] investigated a DT framework by proposing a federated Markov chain Monte Carlo model to solve the challenge of distributed data privacy for federated analytics. Hashash et al. [32] developed a continual learning approach to enable the operation of DTs in nonstationary environments.

While the studies in [29], [30], [31], and [32] have incorporated the concept of DT for solving interesting research challenges from an edge learning perspective in stationary and non-stationary settings, they have not investigated the role of DT in analyzing the interoperability of the AI models’ decisions for a wireless network. Therefore, this work develops a novel neuro-symbolic XAI twin for wireless IoE. The physical space of the XAI twin executes a neural network-driven multivariate regression to capture the time-dependent wireless IoE environment, and the virtual space of the XAI twin constructs a DAG-based BN to infer a symbolic reasoning score over physical space decisions. The system model of XAI twin for wireless network is presented in the following section.

III. SYSTEM MODEL OF XAI TWIN FOR WIRELESS NETWORK

A. System Overview

We consider a wireless network having a set $G$ of $G$ gNBs are physically deployed to serve network users in a certain geographical area. Each gNB $g \in G$ is equipped with a computational server to enable a set $I$ of IoE services. Each gNB $g \in G$ is connected to a core network (i.e., 5G core) through wired connectivity. In order to enable connected intelligence in this system, we consider a neuro-symbolic XAI twin of the entire network as seen in Fig. 1. In Fig. 1, each gNB consists of its own physical space that can sense Speed, RSRP, SINR, RSRQ, and CQI while executing the AI process to determine uplink and downlink resource allocation.

![Fig. 1. System model of neuro-symbolic XAI twin for ZSM.](image-url)
Each physical gNB can send physical space outcomes to a 5G core that is marked as 2 in Fig. 1. The virtual space of the proposed neuro-symbolic XAI twin physically executes at the 5G core. In Fig. 1, steps 3–5 represent the working sequence of virtual space at the 5G core for autonomous reasoning and error-correction decision making of ZSM functions.

In particular, each gNB $g \in \mathcal{G}$ is considered as a physical space of XAI twin that can capture current time-dependent network parameters of network entities and execute a neural-network driven multivariate regression for solving networking problems, such as IoE service association, uplink, and downlink data rates control. The virtual side of the XAI twin in the 5G core can perform reasoning and error-correction on physical space decisions based on prior knowledge by enabling symbolic reasoning.

The network’s dynamics depend on both states of wireless node (i.e., gNB) and service user equipment. In particular, network parameters, such as user mobility (i.e., speed) $s$, RSRP $p$, RSRQ $q$, SINR $\delta$, and CQI $c$ are prominent contextual features for deciding on the downlink data rate, uplink data rate, and service user association to the gNB. Each IoE service $i \in \mathcal{I}$ at gNB $g \in \mathcal{G}$ can serve a set $\mathcal{J}_i$ of $j_i$ user. Therefore, the network and service dynamics of each user $j_i \in \mathcal{J}_i$ will have distinct requirements, such as downlink data transfer rate $d_{ij}^{\text{req}}$, uplink data transfer rate $u_{ij}^{\text{req}}$, communication and computational delay $\delta_{ij}^{\text{phy}}$, and a tuple $X := (s_{ij}^{\text{phy}}, p_{ij}, q_{ij}, \delta_{ij}^{\text{phy}}, c_{ij}^{\text{phy}})$ of $N$ contextual features in the physical space. Here, $s_{ij}^{\text{phy}}$, $p_{ij}$, $q_{ij}$, $\delta_{ij}^{\text{phy}}$, and $c_{ij}^{\text{phy}}$ represent speed, RSRP, RSRQ, SINR, and CQI, respectively, of an IoE service user $j_i \in \mathcal{J}_i$. Each IoE service user $j_i \in \mathcal{J}_i$ sends $d_{ij}^{\text{req}}$ [Mb] data to gNB $g \in \mathcal{G}$ via uplink communication while the computational unit of gNB $g \in \mathcal{G}$ processes that request based on service $i \in \mathcal{I}$. Subsequently, user $j_i \in \mathcal{J}_i$ receives $u_{ij}^{\text{req}}$ [Mb] through the downlink communication from gNB $g \in \mathcal{G}$. In the above scenario, the challenge is to allocate the downlink data transfer rate $d_{ij}^{\text{req}}$ and uplink data transfer rate $u_{ij}^{\text{req}}$ to the user $j_i \in \mathcal{J}_i$ when maintaining a certain level of CQI $c_{ij}^{\text{phy}}$ under the service completion delay requirement $\delta_{ij}^{\text{req}}$ due to service heterogeneity. Additionally, user mobility (i.e., speed) $s_{ij}^{\text{phy}}$ also affects the CQI since the service user association will be shifted from one gNB $g \in \mathcal{G}$ to another gNB $g + 1 \in \mathcal{G}$ due to its location changes.

### B. Network and Service Dynamics in Physical Space of XAI Twin

Each gNB $g \in \mathcal{G}$ is considered as a physical space of the XAI twin. Here, our goal is to capture the contextual features of the network and service dynamics for allocating uplink $d_{ij}^{\text{req}}$ and downlink $d_{ij}^{\text{exe}}$ data rates while maintaining a certain level of CQI. Therefore, we consider a tuple $X := (s_{ij}^{\text{phy}}, p_{ij}, q_{ij}, \delta_{ij}^{\text{phy}}, c_{ij}^{\text{phy}})$ of $N$ contextual features that are already known in physical space, where the procedure for calculating the contextual features $X$ follows the 3GPP standard [33], [34]. Then, we can formalize a multivariate regression [35], [36], [37] for capturing the coefficients of $N$ contextual features and, thus, we can get a $J \times 2$ response matrix $Y$ for allocating uplink $u_{ij}^{\text{exe}}$ and downlink $d_{ij}^{\text{exe}}$ data rates to the IoE service users. The system of equations of a multivariate regression [35], [36], [37] in the physical space of XAI twin can be defined as follows:

$$Y = X\xi + \epsilon$$  (1)

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**Table I**

| Notation | Description |
|----------|-------------|
| $\mathcal{G}$ | Set of next generation NodeBs (gNBs) |
| $\mathcal{I}$ | Set of IoE services |
| $\mathcal{J}_i$ | Set of users for IoE service $i \in \mathcal{I}$ |
| $d_{ij}^{\text{req}}$ [Mbps] | Required downlink data transfer rate of user $j_i \in \mathcal{J}_i$ |
| $u_{ij}^{\text{req}}$ [Mbps] | Required uplink data transfer rate of user $j_i \in \mathcal{J}_i$ |
| $\tau_{ij}$ | Communication and computational tolerable delay of user $j_i \in \mathcal{J}_i$ |
| $X$ | A tuple for contextual features on physical space of user $j_i \in \mathcal{J}_i$ |
| $s_{ij}^{\text{req}}$ [km/h] | User mobility speed of user $j_i \in \mathcal{J}_i$ |
| $p_{ij}$ [dBm] | Reference signal received power of user $j_i \in \mathcal{J}_i$ |
| $q_{ij}$ [dB] | Reference signal received quality of user $j_i \in \mathcal{J}_i$ |
| $\delta_{ij}^{\text{req}}$ [dB] | Signal-to-interference-plus-noise ratio of user $j_i \in \mathcal{J}_i$ |
| $c_{ij}^{\text{req}}$ | Channel quality indicator |
| $u_{ij}^{\text{req}}$ [Mb] | Amount of uploaded data for user $j_i \in \mathcal{J}_i$ |
| $d_{ij}^{\text{req}}$ [Mb] | Amount of downloaded data for user $j_i \in \mathcal{J}_i$ |
| $d_{ij}^{\text{exe}}$ [Mb] | Allocated downlink data rate for user $j_i \in \mathcal{J}_i$ |
| $\delta_{ij}^{\text{exe}}$ [Mb] | Allocated uplink data rate for user $j_i \in \mathcal{J}_i$ |
| $X$ | Context matrix with a dimension of $J \times (N + 1)$ at the physical space of XAI twin |
| $\xi$ | Parameters matrix with a dimension of $(N + 1) \times 2$ at the physical space of XAI twin |
| $\epsilon$ | $J \times 2$ matrix with zero mean and covariance $\Xi$ at the physical space of XAI twin |
| $\tau_{ij}$ | Uplink data transfer duration for user $j_i \in \mathcal{J}_i$ of IoE service $i$ |
| $\tau_{ij}^{\text{req}}$ | Queuing waiting duration of user $j_i \in \mathcal{J}_i$ for IoE service execution $i$ |
| $\tau_{ij}^{\text{exe}}$ | Execution duration for user $j_i \in \mathcal{J}_i$ of IoE service $i$ |
| $\tau_{ij}^{\text{down}}$ | Downlink data transfer duration for user $j_i \in \mathcal{J}_i$ of IoE service $i$ |
| $\tau_{ij}^{\text{exe}}$ | The overall delay of IoE service $i$ fulfillment for user $j_i \in \mathcal{J}_i$ |
| $\gamma_i$ | Computational capacity for IoE service $i$ at gNB $g \in \mathcal{G}$ |
| $\lambda_i$ | Arrival rate of IoE service request $i$ at gNB $g \in \mathcal{G}$ |
| $\mu_i$ | Computational rate for IoE service $i$ at gNB $g \in \mathcal{G}$ |
| $\alpha_i$ | Server utilization rate for IoE service $i$ at gNB $g \in \mathcal{G}$ |
| $W$ | A tuple of random variables for $M$ network dynamics and contextual parameters |
| $E$ | Evidence of all observed network dynamics and contextual metric parameters at virtual space of XAI twin |
| $Z$ | Unobserved evidence of network dynamics and contextual metric parameters at virtual space of XAI twin |
| $\phi$ | Knowledge base (KB) at virtual space of XAI twin |
| $\varphi_{\text{exe}}$ [MHz] | Bandwidth for uplink communication |
| $\varphi_{\text{down}}$ [MHz] | Bandwidth for downlink communication |
| $\eta$ | Minimum level of channel quality indicator |
| $\alpha_{\text{max}}$ | Maximum computational capacity for executing IoE service $i$ at $g \in \mathcal{G}$ |
| $\alpha_{\text{j}}$ | gNB selection decision indicator |

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where \( X \) is a \( J \times (N + 1) \) matrix of the contextual features \( X \), \( \xi \) is a parameters matrix with a dimension of \((N + 1) \times 2\), and \( \epsilon \) is a \( J \times 2 \) matrix with zero mean and covariance \( \Omega \). By solving the system of in (1), we can allocate uplink \( a_{ij}^{ex} \) and downlink \( d_{ij}^{exe} \) data rates for each IoE service user \( j \in J \) [see the expansion of (1) in the Appendix (18)].

We define \( T_j^{req} \) as an end-to-end (E2E) tolerable delay requirement for IoE service user \( j \in J \). Thus, to assure E2E maximum-tolerable delay of each IoE service execution, it is essential to characterize four types of delays, such as uplink data transfer duration \( T_{ij}^{up} \), waiting time duration \( T_{ij}^{queue} \) for computation, computational duration \( T_{ij}^{exe} \), and downlink data transfer duration \( T_{ij}^{down} \). For an uplink data rate \( a_{ij}^{exe} \), each IoE service user sends an amount of data \( a_{ij}^{req} \) to gNB \( g \in G \) and the uplink data transfer duration is \( T_{ij}^{up} = (a_{ij}^{req} / u_{ij}^{exe}) \). The arrival of each amount of data \( a_{ij}^{req} \) at gNB \( g \in G \) follows a Poisson process with a probability \( \lambda \). Therefore, the mean uplink duration will be \( E[T_{ij}^{up}] = \sum_{j \in J_i} T_{ij}^{up} P(t_{ij}^{up}) \) at gNB \( g \in G \).

We consider that each IoE service \( i \in I \) is computed at a dedicated computational host at gNB \( g \in G \) with a computational capacity \( \gamma_i \). Each IoE user task \( j \in J \) arrives at gNB \( g \in G \) by following a Poisson process [38] with an arrival rate of \( \lambda_i \). Then, we can find the service computational rate \( \mu_i = (\lambda_i a_{ij}^{req} / \gamma_i) \), and the service time \( T_{ij}^{service} = (1/\mu_i) \) of IoE user \( j \in J \) will follow a general holding time distribution. For an arrival rate of \( \lambda_i \) and service computational rate \( \mu_i \), the server utilization rate becomes \( \omega_i = \sum_{j \in J_i} (\lambda_i / \mu_i) \). In this computational delay model, we consider an M/G/1 queuing system [38], [39] which is suitable here since the arrival of IoE task follows a Poisson process and service time of the computational host at gNB \( g \in G \) belongs to a general distribution. By applying the Pollaczek–Khinchin formula [40], [41], the expectation of waiting time of IoE service can be calculated as \( E[T_{ij}^{queue}] = (\lambda_i E[T_{ij}^{service}] / 2(1 - \omega_i)) \) and, thus, computational delay at gNB \( g \in G \) becomes \( E[T_{ij}^{exe}] = E[T_{ij}^{queue}] + (\lambda_i E[T_{ij}^{service}] / 2(1 - \omega_i)) \). For squared coefficient of variation \( C^2 = (\lambda_i E[T_{ij}^{queue}] / E[T_{ij}^{queue}]) \), the total delay for computation is calculated as \( E[T_{ij}^{exe}] = (1 + (1 + C^2/2)(\omega_i/1 - \omega_i)) E[T_{ij}^{service}] \). Here, to fulfill each IoE service execution, the considered system requires to send \( b_{ij}^{req} \) amount of data to the IoE service user \( j \in J \). For a downlink data rate \( d_{ij}^{exe} \), the duration of transferring \( d_{ij}^{req} \) can be calculated as \( T_{ij}^{down} = (b_{ij}^{req} / d_{ij}^{exe}) \). Then, the mean downlink time will be \( E[T_{ij}^{down}] = \sum_{j \in J_i} T_{ij}^{down} P(t_{ij}^{down}) \), where \( P(t_{ij}^{down}) \) is a probability of departure duration \( t_{ij}^{down} \) and that follows a Poisson distribution. Thus, an average E2E duration for executing each IoE service by gNB \( g \in G \) is determined as follows:

\[
\begin{align*}
E[T_{ij}^{exe}] &= E[T_{ij}^{up}] + (1 + \frac{1 + C^2}{2} \frac{\omega_i}{1 - \omega_i}) E[T_{ij}^{queue}] + E[T_{ij}^{down}] \\
(2)
\end{align*}
\]

where \( E[T_{ij}^{queue}] \) must be smaller than or equal to the communication and computational delay requirement \( T_{ij}^{req} \), \( E[T_{ij}^{queue}] \leq T_{ij}^{req} \). An user \( j \in J_i \) of IoE service \( i \in I \) does not know which gNB \( g \in G \) becomes suitable for desired service execution while nearby gNB can receive service request simultaneously. Additionally, the physical space environment of each at each \( g \in G \) is independent and distinct. Therefore, to allocate uplink \( u_{ij}^{exe} \) and downlink \( d_{ij}^{exe} \) data rates along with appropriate gNB \( g \in G \), it is imperative to characterize the causes and effects of the current network and service dynamics. For assuring sufficient uplink and downlink data rates to IoE service, the reasoning for the effects of user mobility, RSRP, SINR, and RSRQ on CQI become essential. Therefore, the reasoning of the IoE service execution decisions can be determined by utilizing the concept of NeSy AI. The detailed description of the reasoning mechanisms are formalized in the next section.

C. Reasoning in Virtual Space of XAI Twin

The role of the virtual space within the XAI twin is to reason the root causes and accomplish an updated allocation decision for the considered IoE service execution. We consider a BN [42] with first-order probabilistic languages [43] to capture a logical reasoning by encoding influences among the contextual metrics and network dynamics. Thus, in the virtual space, a DAG [42] is considered for characterizing quantitative probability densities of network dynamics and contextual parameters, such as user mobility, RSRP, SINR, RSRQ, and CQI.

We define \( M \) network dynamics and contextual parameters as a tuple of random variables \( W = (W_1, W_2, \ldots, W_M) \) and each random variable \( W_m \) is indexed by \( m \), where \( m \in \{1, \ldots, M\} \). Each random variable \( W_m \) follows bimodal distribution due to the distinct requirements and physical condition of IoE services. The random variables \( W \) are physically known metrics and they are observed by physical space. Thus, the tuple of random variables \( W \) includes user speed \( v_{ij}^{phy} \), RSRP \( p_{ij}^{phy} \), RSRQ \( q_{ij}^{phy} \), SINR \( \delta_{ij}^{phy} \), CQI \( c_{ij}^{phy} \), uplink data rate \( u_{ij}^{exe} \), downlink data rate \( d_{ij}^{exe} \), and user association of gNB \( a_{ij}^{g} \) for all users in the considered network. To build a BN, we consider a directed DAG \( D \) that is encompassed with \( M \) nodes, where each node \( W_m \) denotes a random variable of each network dynamics and contextual parameter. Therefore, each directional edge will head from a cause contextual metric node (i.e., random variable) to an effect contextual metric node. Thus, the parents \( Pa(W_m) \) of each parameter node \( W_m \) will be all nodes that are pointing toward node \( W_m \). The factorization of a JPD of the network dynamics and contextual parameters is as follows [42]:

\[
P(W_1, W_2, \ldots, W_M) = P(W_1)P(W_2|W_1, W_3) P(W_3|W_1, W_2) \ldots P(W_M|W_1, W_{M-1}).
(3)
\]

The JPD of the network dynamics and contextual parameters \( (3) \) contains both descendants and nondescendants. However, our goal is to characterize the JPD with respect to descendants of each parameters. Therefore, by removing nondescendants of \( W_m \), we can rewrite \( (3) \) as

\[
P(W_1, W_2, \ldots, W_M) = P(W_1|Pa(W_n)) \ldots P(W_M|Pa(W_M)).
(4)
\]

Formula (4) represents a generic model of JPD for the considered network dynamics and contextual parameters in the
virtual space of the XAI twin. Therefore, the network structure completely follows a DAG since (4) is a factorization of the JPD of all network dynamics and contextual metrics parameters $W = (W_1, W_2, \ldots, W_M)$. In particular, for random variables $W = (W_1, W_2, \ldots, W_M)$, the JPD can be written as follows:

$$P(W_1, W_2, \ldots, W_M) = \prod_{m=1}^{M} P(W_m|Pa(W_m))$$

(5)

where $Pa(W_m)$ represents a set of parents for each parameter node $W_m$.

In this model, we consider both conditional probability queries (CPQs) and maximum a posterior probability (MAP) queries for inference since CPQ can handle many interconnected variables from distribution while MAP can estimate the mode of a posterior distribution. We define $E$ as the vector of evidence values of all observed network dynamics and contextual metric parameters, where each evidence $e \in E$ can query on parameter $W_m$. As a result, the unobserved (i.e., non-evidence) network dynamics and contextual metric parameters $\forall z \in Z$ can be calculated by utilizing the known evidences $E$. Therefore, we can find the reason of unobserved network dynamics and contextual metric variables $\forall z \in Z$, as follows [44]:

$$P(W_m|e) = \frac{P(W_m, e)}{P(e)} \propto \sum_{z \in Z} P(W_m, e, z).$$

(6)

In other words, we marginalize the JPD over the unobserved network dynamics and contextual metric variables $Z \in W \setminus E$ for inference. Then, we determine most probable explanation $\Lambda$ for $Z$ of all network dynamics and contextual metric variables $W$ except observed $E$ as follows [44]:

$$P(\Lambda) = \arg\max_{\forall z \in Z} P_{e-E}(z|e)$$

(7)

where (7) can determine a statistical explanation for the root cause of candidate uplink $u^{exe}_ij$ and downlink $d^{exe}_ij$ data rates for each IoE service uses. Additionally, the virtual space of the XAI twin generates the corresponding candidate gNBs $\forall a^{ij}_i \in a$ toward IoE service association. Thus, we can construct a knowledge base (KB) $\theta$ using the proposed BBN-based explainer for the virtual space of the XAI twin, where for given $W$, KB of each user represents by $\theta^{ij}_r$, and $\Psi^{ij}_r \in \theta$. Now, based on the reasoning of such network dynamics and contextual metrics, we need to cope with the stochastic nature of such environment for allocating uplink and downlink data rates along with gNB association. In the next section, thus, we formalize a decision problem for the virtual space of the XAI twin that can guarantee a ZSM and also provide an explained decision for the network service provider.

IV. LEARNING PROBLEM FORMULATION FOR XAI TWIN

Given the marginal JPD of network dynamics and contextual metric variables $Z \in W \setminus E$ in (7), we can determine a score for each physical space (i.e., gNB) decision $u^{exe}_ij, d^{exe}_ij$ as follows:

$$\Upsilon(W|a^{ij}_i) = P(\Lambda(u^{exe}_ij, d^{exe}_ij))$$

(8)

where $a^{ij}_i$ represents a candidate gNB association decision in virtual space of XAI twin and $a$ is a vector of all gNB association decisions. We consider a finite time domain $T$ consisting of $T$ slots with each being indexed by $t$. During $t$, the number of requested IoE service users becomes $|J_t||Z|$. Therefore, the expectation of the reasoning score can be determined as follows:

$$E_p(\Lambda((u^{exe}_ij, d^{exe}_ij))|\Gamma(a)) = \sum_{j \in J_t} \sum_{i \in Z} \left( \Upsilon(W|a^{ij}_i) - \Upsilon(a^{ij}_i) \right)$$

(9)

where $\Gamma(a^{ij}_i)$ is a current score for the candidate gNB $a^{ij}_i \in a$ while $\Upsilon(W|a^{ij}_i)$ is the reasoning score based on evidence in (8).

Thus, the updated score of each candidate gNB $a^{ij}_i$ is calculated as follows:

$$\Theta(a^{ij}_i) = \Theta(a^{ij}_i) + \frac{\Upsilon(W|a^{ij}_i) - \Theta(a^{ij}_i)}{\theta|a^{ij}_i}$$

(10)

where $\theta$ represents a KB that is generated from the evidence $E$ in the virtual space of the XAI twin. As a result, we can now devise a learning problem of the XAI twin for reasoning causes, analyzing effects, and executing zero touch network and service management, as follows:

$$\min_{u.d.a} \frac{1}{T} \sum_{t \in T} \left( E[\Gamma(a)]|J_t||Z| - \sum_{j \in J_t} \sum_{i \in Z} \Theta(a^{ij}_i) \right)$$

(11)

s.t. $\sum_{z \in Z} P(W_m, e, z) \leq \Theta(a^{ij}_i)$, $m \in (1, \ldots, M)$

(11a)

$$a^{ij}_i^{req} \leq a^{ij}_i^{req} \leq \Xi^{up}_{ij}$$

(11b)

$$\beta^{ij}_i^{req} \leq \beta^{ij}_i^{req} \leq \Xi^{down}_{ij}$$

(11c)

$$\chi^{up} \log_2 \left( 1 + d^{phy}_{ij} \right) \geq a^{ij}_i^{req}$$

(11d)

$$\chi^{down} \log_2 \left( 1 + d^{phy}_{ij} \right) \geq a^{ij}_i^{req}$$

(11e)

$$\alpha^{ij}_i \left( \nu_1 \log_2 \left( 1 + d^{phy}_{ij} \right) + \nu_2 \right) \geq \eta$$

(11f)

$$\alpha^{ij}_i \left( \nu_1 \log_2 \left( 1 + d^{phy}_{ij} \right) + \nu_2 \right) \geq \eta$$

(11g)

$$\alpha^{ij}_i \leq \omega^{max}$$

(11h)

$$\alpha^{ij}_i \in [0, 1] \ \forall i \in I \ \forall j \in J_t$$

(11i)

where the learning objective is to minimize the residual between the expected explained score (9) and current obtained score (10) on the decision variables of allocated uplink data rate $\forall u^{exe}_{ij} \in u$, downlink data rate $\forall d^{exe}_{ij} \in d$, and gNB association $\forall a^{ij}_i \in a$. Constraint (11a) obtains the marginal JPD from the unobserved networks dynamics and contextual features for discretizing probable reasoning on obtained explainable score (10). Constraints (11b) and (11c) guarantee that the uplink $u^{exe}_{ij}$ and downlink $d^{exe}_{ij}$ data rates will be assigned to IoE user $j \in J_t$ at gNB $g \in G$ for a sufficient amount of time such that the amount of uplink $u^{req}_{ij}$ and downlink $d^{req}_{ij}$ data can be successfully transmitted through the wireless network. In the physical space of XAI twin, for fixed uplink $\chi^{up}$ and downlink $\chi^{down}$ bandwidths, (11d) and (11e) guarantee that the allocated
uplink $u_{ij}^{exe}$ and downlink $d_{ij}^{exe}$ data rates must be bounded with the systems’ capacities. Constraint (11f) ensures a minimum level of CQI $\eta$ for the successful IoE service fulfillment, where $v_1 = 0.5223$ and $v_2 = 4.6176$ are known coefficients [45] for CQI measure on SINR $\delta_{ij}^{phy}$. Constraint (11g) meets the requirement of maximum-tolerable delay $\tau_{ij}^{req}$ for each IoE service user $j \in J_i$ by characterizing uplink data transfer duration $T_{ij}^{up}$, waiting time duration $T_{ij}^{queue}$, execution duration $T_{ij}^{exe}$, and downlink data transfer duration $T_{ij}^{down}$ as $E[\tau_{ij}^{tot}]$ [in (2)] to assign the suitable gNB $a_{ij}^g \in a$. The server utilization rate $\omega_{ij}$ at the assigned gNB $a_{ij}^g \in a$ for IoE service $i \in I$ must be smaller or equal to its maximum computational capacity $\omega_{ij}^{max}$, which is captured by (11h). Finally, (11i) guarantees that each IoE service user $j \in J_i$ is assigned exactly one gNB $a_{ij}^g \in a$, $g \in G$ for accomplishing the corresponding service.

In (11), the gNB $a_{ij}^g \in a$ selection depends on the explainable score at the virtual space where the corresponding uplink $u_{ij}^{exe}$ and downlink $d_{ij}^{exe}$ data rates allocation completely depend on the network dynamics and contextual metrics of each IoE service request in physical space. Problem (11) leads to a dynamic programming problem [20] in a stochastic networking environment due to contextual metrics in physical space of each IoE service request is random over time. To solve (11), first we estimate uplink $u_{ij}^{exe}$ and downlink $d_{ij}^{exe}$ data rates in physical space via a neural-network-driven multivariate regression model. The procedure of finding the uplink $u_{ij}^{exe}$ and downlink $d_{ij}^{exe}$ data rates from a predetermined neural-networks model based on current network dynamics and contextual metrics is called the unconscious decisions into physical space of XAI twin. The unconscious decisions are not aware of the evidence. Then, forming a DAG-based BN [44] becomes more proper to infer the cause and effects of such decisions through a first-order probabilistic language model [42], [43] due to the reasoning score of each gNB $a_{ij} \in a$ selection trusted on the marginalized JPD of all $M$ networks dynamic and contextual metrics. Finally, the learning problem (11) can be reduced to a Bayesian multiarm bandits [20] as a base problem, where each physical space (i.e., gNB) of the XAI twin can perform the role of a bandit arm. More precisely, we train the virtual space of the XAI twin to reduce the residual between the expected explained score and current incurred score to assign a gNB $a_{ij} \in a$, given that the unconscious decisions of uplink $u_{ij}^{exe}$ and downlink $d_{ij}^{exe}$ data rates for the physical space of XAI twin. A detailed solution procedure for the proposed XAI twin for zero-touch IoE is described in the following section.

V. NEURO-SYMBOLIC XAI TWIN FRAMEWORK DESIGN FOR WIRELESS NETWORK

The neuro-symbolic XAI twin plays a key role in reasoning the perfect decision of each IoE service execution. In particular, the neuro-symbolic XAI twin has a neural-network-driven multivariate regression model for data rate estimation and the DAG-based BN with a Bayesian multiarm bandit for symbolic reasoning and IoE service control. On the one hand, the physical space of the XAI-twin at each gNB $g \in G$ performs the role of an implicit learner that can automatically capture the current dynamics of the physical environment and make an unconscious decision. On the other hand, the virtual space at the 5G core executes exploitation by symbolic reasoning of the physical space decisions and prior knowledge for error correction by an explicit learner. A holistic view of the proposed neuro-symbolic XAI twin framework is shown in Fig. 2.

A. Implicit Learner of XAI Twin

A tuple $X := (s_{ij}^{phy}, p_{ij}^{phy}, q_{ij}^{phy}, \delta_{ij}^{phy}, \epsilon_{ij}^{phy})$ of contextual metrics at a physical space (i.e., gNB) will play the key role for allocating uplink $u_{ij}^{exe}$ and downlink $d_{ij}^{exe}$ data transfer rates to each IoE user. Here, it is necessary to meet the IoE service requirements, such as amount of upload $u_{ij}^{exe}$ and download $d_{ij}^{exe}$ data rates to each IoE user. To solve this problem, we design a least square estimator $\hat{\xi} \in \Omega_1$ in (11) and (11d), download $\beta_{ij}^{req}$ data [in (11c) and (11e)], maintaining CQI [in (11f)], end to end communication and computational delay $\tau_{ij}^{req}$ [in (11g)], and utilization of computational capacity $\omega_{ij}$ in (11b) become crucial on contextual metrics $X$ at the physical space. On top of the proposed implicit learner, we can flexibly deploy numerous regression algorithms [46], [47], such as long short-term memory (LSTM), deep neural network-based regression, extraTrees, random forest, adaboost, and logistic regression based on the service provider requirements. However, the challenge is to determine a maximum likelihood estimation of $\hat{\xi}$ in (1). Thus, we design a least square estimator $\hat{\xi} \in \Omega_1$ [35], [36], [37] of (1) as follows:

$$\hat{\xi} = (X^T X)^{-1} X^T Y$$

(12)

where $u_{ij}^{exe}, d_{ij}^{exe} \in Y$ and $X \in X$. Therefore, $(Y - X\hat{\xi})^T(Y - X\hat{\xi})$ is a learning objective of (12). Equation (12) becomes a least square minimization problem for an estimator $\hat{\xi}$. However, the dynamics of each IoE user $j \in J_i$ is heterogeneous in nature based on observed contextual metrics $X$. As a result, the estimator $\hat{\xi}$ belongs to an biased decision. Thus, to eliminate the bias of the estimator $\hat{\xi}$, utilization of a covariance matrix $\Omega$ of $\epsilon$ [in (1)] is more suitable. Therefore, an unbiased estimator
Algorithm 1 Implicit Learner at Each gNB \( g \in \tilde{G} \)

**Input:** \( \forall X := (s^\text{phy}, p^\text{phy}, q^\text{phy}, \delta^\text{phy}, c^\text{phy}, u^\text{exe}, d^\text{exe}, a^\text{g}, \omega^\text{req}, \delta^\text{req}, \tau^\text{req}) \in X \forall (u^\text{req}, c^\text{req}) \in Y \forall (\alpha^\text{ij}, \beta^\text{ij}, \gamma^\text{ij}) \in \tilde{J}_i \tilde{I} \)

**Output:** \( \forall (u^\text{exe}, a^\text{exe}) \in \tilde{Y}, \forall I \in \tilde{I}, W \)

Initialization: \( W, \omega^\max, \eta, \chi^\text{up}, \chi^\text{down}, \Omega, \lambda, \nu, v \), regression parameters based on specific regression algorithms

1: while \( (\forall X \in X) \) do
2: \( \hat{\xi} \) using unbiased least square minimization objective \( \Omega(Y - \hat{X})^T(Y - \hat{X}) \) in (13)
3: Model fit: \( \hat{\xi} : Y \xrightarrow{\hat{\xi}} X \) using (14), \( \forall (u^\text{exe}, a^\text{exe}) \in \tilde{Y} \)
4: Evaluate: \( \hat{\epsilon} = Y - \hat{Y} \)
5: if \( (\hat{\epsilon} \leq \nu) \) then
6: Break
7: end if
8: end while
9: while \( \forall I \in \tilde{I} \) do
10: for \( \forall j \in \tilde{J}_i \) do
11: Mean uplink duration \( \mathbb{E}[t^\text{up}] = \sum_{\forall i,j\in\tilde{J}_i} P(t^\text{up})_i^j \)
12: Service computational rate \( \mu_i \):
13: Estimate server utilization rate \( \alpha_i \):
14: Mean waiting duration \( \mathbb{E}[t^\text{queue}] = \frac{1}{2(1 - \alpha_i)} \mathbb{E}[T_{i\text{service}}] \)
15: Mean computational and waiting duration:
16: Mean downlink duration \( \mathbb{E}[t^\text{down}] = \sum_{\forall i,j\in\tilde{J}_i} P(t^\text{down})_i^j \)
17: Calculate mean of total delay \( \mathbb{E}[t^\text{tot}] = \mathbb{E}[t^\text{up}] + \mathbb{E}[t^\text{queue}] + \mathbb{E}[t^\text{exe}] + \mathbb{E}[t^\text{down}] \)
18: if (Satisfy constraints (11b), (11c), (11d), (11e), (11f), (11g), and (11h)) then
19: Assign: \( a^\text{g} = 1 \)
20: else
21: Assign: \( a^\text{g} = 0 \)
22: end if
23: Concatenation: \( W = X + u^\text{exe}, a^\text{exe}, a^\text{g} \)
24: end for
25: end while
26: return \( \forall \forall J, I \in \tilde{J}_i \tilde{I} \)

\( \hat{\Omega} \) can be defined as follows:

\[
\hat{\Omega} = \Omega (Y - \hat{X})^T(Y - \hat{X})
\]  
(13)

where \( \Omega = (1/([I] - N - 1)) \) represents a covariance matrix with a zero mean. Then, the implicit learner of XAI twin fits the for the unconscious decision as follows:

\[
\hat{Y} = X \hat{\xi}
\]  
(14)

where estimation error become \( \hat{\epsilon} = Y - \hat{Y} \). We illustrate the working procedure of the proposed implicit learner in Algorithm 1.

Each gNB \( g \in \tilde{G} \) is responsible to execute the proposed implicit learner Algorithm 1. The role of Algorithm 1 is to make an unconscious decisions \( u^\text{exe}, d^\text{exe}, a^\text{g} \) based on current contextual metrics \( X = (s^\text{phy}, p^\text{phy}, q^\text{phy}, \delta^\text{phy}, c^\text{phy}, u^\text{exe}, d^\text{exe}, a^\text{g}) \) and each IoE service requirements \( \alpha^\text{ij}, \beta^\text{ij}, \gamma^\text{ij} \) at each gNB \( g \in \tilde{G} \). Lines 1–8 in Algorithm 1 are responsible to execute a multivariate regression [35], [36], [37] scheme, where numerous regression process [46], [47] can be flexibly deployed based on the service provider demands. Thus, we estimate \( \hat{\xi} \) using the proposed unbiased least square minimization objective (14) at line 2 in Algorithm 1. Lines 3 and 4 fit the estimator \( \hat{\xi} \) to predict \( (u^\text{exe}, a^\text{exe}) \in \tilde{Y} \) and evaluate the prediction error \( \nu \). A termination decision of the regression process is made in line 5 of Algorithm 1 based on the required tolerable prediction error \( \nu \). The convergence of regression process depends on the value of parameter \( \nu \leq v [35], [36], [37] \) and number of iterations relies on parameter settings of specific regression algorithms [46], [47], such as LSTM, deep neural-network-based regression, extra Trees, random forest, adaboost, and logistic regression [46], [47].

An expectation of the total IoE service fulfillment delay \( \mathbb{E}[t^\text{tot}] \) is estimated in Algorithm 1 at line 16. This delay is then combined with uplink delay \( \mathbb{E}[t^\text{up}] \), waiting time delay \( \mathbb{E}[t^\text{queue}] \), computational delay \( \mathbb{E}[t^\text{exe}] \), and downlink delay \( \mathbb{E}[t^\text{down}] \) that are calculated in lines 11 and 14–16 of Algorithm 1, respectively. Line 18 in Algorithm 1 is responsible to evaluate (11b)–(11h) based on the implicit decisions of \( u^\text{exe}, d^\text{exe} \) at gNB \( g \in \tilde{G} \). An decision indicator \( a^\text{g} \) is marked in lines 19 or 21 based on the constraints satisfaction of line 18 in Algorithm 1. Finally, network dynamics and contextual metrics are preserved in line 23 (in Algorithm 1) for reasoning and error correction by utilizing these findings in the virtual space of the XAI twin.

The output of Algorithm 1 includes unconscious decisions \( u^\text{exe}, d^\text{exe}, \) and \( a^\text{g} \) based on current contextual metrics \( X := (s^\text{phy}, p^\text{phy}, q^\text{phy}, \delta^\text{phy}, c^\text{phy}, u^\text{exe}, d^\text{exe}, a^\text{g}) \) for all IoE service \( \forall g, i \in \tilde{I} \) at gNB \( g \in \tilde{G} \). Thus, Algorithm 1 at physical space determines \( W = X + u^\text{exe}, d^\text{exe}, a^\text{g} \) that will use for symbolic reasoning by a building Bayesian DAG. The complexity of the proposed implicit learner Algorithm 1 belongs to \( O(\{|X| + |I||J_i|)\) where \( |X|, |I|, \) and \( |J_i| \) are size of contextual metrics, number of IoE service by the service provider, and number of user for each IoE service \( j \in J_i \), respectively. However, the complexity of the multivariate regression \( O(|X|) \) [35], [36], [37] can vary depending on the algorithmic procedures of several schemes and network configuration [46], [47]. In the following section, we present an explicit learner of the XAI twin for reasoning and error correction on implicit learners’ decisions for assuring ZSM.

B. Explicit Learner of XAI Twin

The role of an explicit learner in our XAI twin is to find the root causes behind the physical space decisions for each gNB \( g \in \tilde{G} \) and perform autonomous error correction based on the reasoning. However, the interpretation of reasoning and error correction become challenging since the network dynamics and contextual metrics are nondeterministic for all physical space \( \forall g \in \tilde{G} \) due to each IoE service includes indispensable characteristics, such as user, data, processes, and things [10], [11], [12]. Thus, to design an explicit learner, a
symbolic reasoning approach [4], [18] can be more appropriate for achieving higher accuracy, data efficiency, transparent, and trustworthy decisions toward the ZSM [8], [15], [33]. We design the explicit learner of the XAI twin by incorporating a first-order probabilistic language model [42], [43] for reasoning the network dynamics and contextual metrics, and we devise a Bayesian multi-armed bandit system [20] for making autonomous corrected decisions based on the reasoning.

We consider a DAG [42] as seen in Fig. 3, where a set of rules is defined by the service provider for each network dynamic and contextual metric $W_m$ (i.e., node in DAG) to meet the IoE service requirements. For instance, we consider $S$, $P$, $Q$, $R$, $C$, $U$, $D$, and $G$ as the sets of rules for observing user speed $s^\text{phy}_{ij}$, RSRP $p^\text{phy}_{ij}$, RSRQ $q^\text{phy}_{ij}$, SINR $\phi_{ij}^\text{phy}$, CQI $c_{ij}^\text{exe}$, uplink data rate $u_{ij}^\text{exe}$, downlink data rate $d_{ij}^\text{exe}$, and user association of gNB $a_{ij}^e$, respectively. Thus, we can characterize unobserved network dynamics and contextual metric variables $\forall z \in Z$ for (6), where $Z \in W \setminus E$. A Bayesian-based [44] first-order probabilistic language model [42], [43] allows us to estimate a tuple of random variables $W = (W_1, W_2, \ldots, W_M)$ for reasoning network dynamics and contextual parameters as follows:

$$\sum_{z \in Z} P(W_m, e, z) \quad \forall m \in M$$

where (15) determines a marginalized JPD over the unobserved network dynamics and contextual metrics using (7) while from (15a) to (15h) represent the nodes of the considered DAG. Equations (15a)–(15h) can determine the marginal JPD of $M$ network dynamics and contextual parameters $W = (W_1, W_2, \ldots, W_M)$ for reasoning. The left side of the constraint (11a) can be captured by (15a)–(15h) while (10) can determine the right side of (11a). To learn the objective of (11), we can redefine it as a function of expected score (9) given that the observed evidence of the physical space decisions on uplink $u_{ij}^\text{exe}$ and downlink $d_{ij}^\text{exe}$ data rates for each IoE service user $j \in J_i$. Therefore, for a gNB selection decision variable $a_{ij}^e \in a$, the residual of reasoning for the explicit learner is defined as follows:

$$\Phi(\Gamma(\mathbf{a})|Z) = \min_{\forall a_{ij}^e} \mathbb{E}_{Z \sim P(\Lambda)} \left[ \mathbb{E}[\Gamma(\mathbf{a})]|J_i||Z] - \sum_{j \in J_i} \sum_{i \in I} \Theta(a_{ij}^e) \right].$$

Each physical space of the XAI twin is considered as a bandit and we can select a gNB $a_{ij}^e \in a$ for fulfilling each IoE service. Thus, the exploration can be determined by the well-known upper confidence bound (UCB) bandit scheme since it can handle the fact of uncertainty for the reasoning [20] and the exploration mechanism for explicit learner is given as follows:

$$a_{ij}^e = \underset{a_{ij}^e \in a}{\text{argmax}} \left( \Theta(a_{ij}^e) + \phi \sqrt{\frac{\log(j)}{\theta}} \right)$$

where $\phi$ is the exploration coefficient, $j$ is the index of current IoE user, and $\theta$ represents the KB of all user $\forall a_{ij}^e \in \theta$. We summarize the working procedure of the proposed explicit learner in Algorithm 2.

The role of Algorithm 2 is to determine a conscious decision for assuring ZSM with reliability. The input of Algorithm 2 is an output of Algorithm 1 which includes the network dynamics and contextual metrics $W$ based on implicit decision by Algorithm 1. In Algorithm 2, lines 1–11, we determine the probable explanation score based on evidence and symbolic reasoning. In particular, line 5 determines the probable explanation while line 6 validates the symbolic reasoning using (15a)–(15h) in Algorithm 2. We learn the system from lines 12 to 19 in Algorithm 2. In Algorithm 2, lines 14–17 are responsible for devising each explainable score, mean score, gNB selection, and updated explainable score, respectively, for each IoE service fulfillment decision. Finally, residual score is evaluated in line 19 of Algorithm 2 for determining $z \in Z$ $\forall u_{ij}^\text{exe} \in u$ $\forall d_{ij}^\text{exe} \in d$ $\forall a_{ij}^e \in a$ to assure a ZSM in wireless

![Figure 3](https://example.com/figure3.png)

Fig. 3. Logical reasoning by encoding influences among the network dynamics and contextual metrics using a DAG for the explicit learner.
Algorithm 2 Explicit Learner at Virtual Space of XAI Twin

Input: \((s_{ij}, p_{ij}, q_{ij}, \delta_{ij}, \theta_{ij}, u_{ij}, d_{ij}^e, d_{ij}^s) \in W \forall \mathcal{J}_i, \mathcal{J}_j\)

Output: \(z \in Z \forall u_{ij} \in u \forall d_{ij} \in d \forall a \in a\)

1: for \(\forall g \in G\) do
2: Collect all: \(\forall W \in W, t \in T\)
3: for \(\forall m \in W \in W\) do
4: Estimate: \(P(W_m|e)\) using (6)
5: Probable explanation: \(P(\Lambda)\) using (7)
6: if (15a)-(15h) then
7: Calculate: \(\sum_{z \in Z} P(W_m, e, z)\)
8: end if
9: end for
10: Append: \(\forall \theta_{ij, e} \in \theta\)
11: end for
12: for \(\forall t \in T\) do
13: for Until \(|G|/|\mathcal{I}|/|\mathcal{J}|\) do
14: Estimate each score: \(P(\Lambda(u_{ij}^e, d_{ij}^e))\) using (8)
15: Mean score: \(\mathbb{E}[\Gamma(a)]\) using (9),
16: Find gNB: \(a_{ij} = \alpha \max(\Theta(a_{ij}) + \phi \sqrt{\log(j)})\)
17: Update current score: \(\Theta(a_{ij})\) using (10)
18: end for
19: Evaluate residual score: \(\Phi(\mathbb{E}[\Gamma(a)|Z])\) using (16)
20: end for
21: return \(z \in Z \forall u_{ij} \in u \forall d_{ij}^e \in d \forall a_{ij}^s \in a\)

C. Reasoning Capabilities of Explicit Learner in XAI Twin Framework

In (16), left part represents expectation of reasoning score and that come from the KB of BBN through (9) while the right part is the estimation based on the current networking demand. The estimation part of (16) completely relies on distribution of \(Y(W|a_{ij})\) in (10). Thus, reasoning of (16) relies on the directed DAG D that consists of network dynamics and contextual parameter \(M\) nodes. Each directional node \(W_m\) acts as a random variable while the parents \(Pa(W_m)\) of each node \(W_m\) become all nodes that are pointing toward the considered node \(W_m\). Thus, each node \(W_m\) in DAG encodes direct influence relation among them that can conclude on the following proposition [42].

Proposition 1 (Declarative Semantics): There exists an edge from \(Pa(W_m)\) to \(W_m\) if and only if there is \(\exists W_m \in \{S, P, Q, R, C, U, D, \mathcal{G}\}\).

Proof: Considering \(\mathcal{S}, \mathcal{P}, \mathcal{Q}, \mathcal{R}, \mathcal{C}, \mathcal{U}, \mathcal{D}, \mathcal{G}\) and \(\mathcal{G}\) represent declarative semantics of speed \(s_{ij}^e\), RSRP \(p_{ij}^e\), RSRQ \(q_{ij}^e\), SINR \(s_{ij}^\text{phy}\), CQI \(q_{ij}^\text{phy}\), uplink data rate \(d_{ij}^e\), downlink data rate \(d_{ij}^s\), and user association of gNB \(d_{ij}^a\), respectively. Thus, \(\mathcal{S}, \mathcal{P}, \mathcal{Q}, \mathcal{R}, \mathcal{C}, \mathcal{U}, \mathcal{D}, \mathcal{G}\) are the sets of rules that can observe network dynamics and contextual parameters of the network. The worst case execution complexity of Algorithm 2 leads to \(O((|I||J|)log(|I||J|) + M^2)\), where \(|I|, |J|, \) and \(M\) are the number of IoT services, number of IoT service sessions, and number of DAG nodes.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

For our experiments, we consider a state-of-the-art 5G data set (B_2020.02.13_13.03.24) [21] and important parameters are shown in Table II. Since this experiment uses the 5G data set, thus, all of the assumptions of this experimental analysis for the network settings follow the data acquisition settings of the base this article [21]. We have implemented both Algorithms 1 and 2 in Python [46], [48], [49] over a desktop environment with a core i7 processor and 64 GB random access memory. In fact, in case of real deployment, the implicit learner 1 and explicit learner 2 will be deployed in each gNB (i.e., physical space) and EPC core (i.e., virtual space), respectively. We benchmark the proposed neuro-symbolic XAI twin by comparing it with a theoretical analogy similar to the considered data set’s (B_2020.02.13_13.03.24) [21] ground

| Description | Values |
|-------------|--------|
| Set of gNB S | \{1, \ldots, 5\} [21] |
| No. of IoT sessions | 2206 [21] |
| Set of speed range S | \{[> = 80, 60 - 80, 30 - 60, <= 30] [km/h] [21] |
| Set of RSRP range P | \{[> = -80, -80 - (-90), -90 - (-100), <= -100] [db] [21] |
| Set of RSRQ range Q | \{[> = -10, (-10) - (-15), <= -15] [db] [21] |
| Set of SINR range \(\mathcal{R}\) | \{[> = 20, 13 - 20, 0 - 43, <= 0] | [db] [21] |
| Set of CQI range \(\mathcal{C}\) | \{[> = 7, 10 - 7, <= 7] [21] |
| Set of uplink data rate range U | \{[> = 100000, 50000 - 100000, <= 50000] [Kbps] [21] |
| Set of downlink data rate range D | \{[> = 800, 100 - 800, <= 100] [Kbps] [21] |
| Downloaded size | 20 MHz [34] |
| No. of sub-carriers | 12 [34] |
| Carrier frequency of each resource block | 180 KHz [34] |
| RBS at per channel bandwidth | 100 [34] |
| Phy. space pertraining epochs | 5000 |
| Phy. space optimizer | ADAM |
| Phy. space LSTM units | 128 |
| Phy. space activation | ReLU |
| No. of random variables in virtual space | 7 |
| No. of iteration in virtual space | 200 |
| Exploration coefficient \(\phi\) | 1 |
| Virtual space KB sessions | 662 |
| XAI twin testing sessions | 100, 205 |
truth and several XAI-supported ensemble-based regression schemes [46], such as Random Forest, Extra Trees, AdaBoost, and Linear Regression. Note that, in comparison result, LSTM refers to a centralized deployment [47], where the LSTM model is trained with accumulated networking data of considered all gNBs. On the other hand, Table II describes the parameters of the proposed LSTM for implicit learners. In particular, the proposed implicit learner’s LSTM can learn distinct gNB environments individually in each physical space. Furthermore, we have compared the proposed neuro-symbolic XAI twin with the LSTM and deep neural networks-based regression model in terms of accuracy for IoE service execution. We validate the trustworthiness score of the proposed neuro-symbolic XAI twin by comparing it with Gradient-based bandit and Epsilon-greedy [20] mechanisms.

A. Performance and Reliability of the Proposed Neuro-Symbolic XAI Twin

We first investigate the correctness of the proposed neuro-symbolic XAI twin. We know that, each IoE service requirements are distinct over time. In Figs. 4 and 5, we show the allocated downlink and uplink data rates to the 100 IoE sessions. In particular, we compare the accuracy of the both downlink and uplink data rates allocation of the proposed neuro-symbolic XAI twin with Random Forest, Extra Trees, AdaBoost, and Linear Regression, DNN, and LSTM. Fig. 4 shows that the maximum downlink error resulting from the proposed method is 0.18 Mb/s while Random Forest, Extra Trees, AdaBoost, and Linear Regression, DNN, and LSTM are 8.05, 9.97, 11.91, 11.63, 28.16, and 15.14 Mb/s, respectively. Clearly the proposed neuro-symbolic XAI twin outperforms others baselines in terms of downlink data rate allocation which is near to the theoretical throughput. Furthermore, in case of the uplink data rate allocation to IoE service execution, the maximum error rate by the Random Forest, Extra Trees, AdaBoost, and Linear Regression, DNN, and LSTM yield 0.09, 0.08, 0.07, 0.10, 0.08, and 0.1 Mb/s, respectively, where as the proposed neuro-symbolic XAI twin can make a maximum 0.07-Mb/s error during uplink bandwidth allocation to the IoE services as shown in Fig. 5.

Then, we illustrate a performance gap analysis of the proposed neuro-symbolic XAI twin with other baselines in Fig. 6. In this work, we have designed a multivariate regression for the physical space of the proposed neuro-symbolic XAI twin, thus, we can take both the downlink and uplink data rate decisions at the same iteration of Algorithm 1 at each gNB. As a result, we can minimize the average tradeoff between downlink and uplink bandwidth allocation decisions over other baselines. We analyze such a performance gap in Fig. 6, in which, the proposed multivariate regression of the neuro-symbolic XAI twin can achieve better performance than others due to interaction between network dynamics and contextual features during the learning. The average performance gap between the proposed method and the ground truth (theoretical) is 3.74%, which is negligible since the environment is nonstationary. In Fig. 6, we observe that Adaboost and LSTM achieve a very high gap because of the lack of adapting capability with high variance and a small amount of data. The performance of Adaboost [50] completely relies on high-quality data while outliers of the data set affect model accuracy. In this work, we have used a 5G data set (B_2020.02.13_13.03.24) [21] that contains high variance among the network dynamics and contextual metrics. Therefore, Adaboost is unable to handle such variations among features which result in high performance gaps in the experiment. Similarly, compared LSTM was unable to quantify high variation and a small amount of data during training due to exploding, and vanishing gradient challenges [9], [47].

Now, we analyze the gNB association of IoE services and their achieved throughput of the proposed neuro-symbolic
Fig. 7. Comparison of the gNB association and throughput among the proposed neuro-symbolic XAI twin and other baselines for 205 IoE sessions. (a) IoE service association analysis for each gNB. (b) Downlink throughput analysis for each gNB. (c) Uplink throughput analysis for each gNB.

XAI twin with other baselines, such as Gradient bandit, and Epsilon-greedy in Fig. 7. Fig. 7(a)–(c) shows the IoE service associations, achieved downlink, and uplink throughput for 205 IoE session execution. From these figures, we can clearly see that IoE session association of the proposed neuro-symbolic XAI twin is well balanced since this scheme can infer the symbolic reasoning among the network dynamics based on marginal probability distribution of evidences by a DAG of BBN.

Thus, Fig. 8 indicates the power of symbolic reasoning on gNB association and bandwidth allocation on IoE service user mobility and achieved CQI. In Fig. 8(a), most of the users' speed belongs to 30–60 km/h which infers that at the end of a certain duration, the IoE uses moves from gNB 1 to gNB 5; thus, the analogies that are shown in Fig. 7 becomes well justified. The proposed neuro-symbolic XAI twin can also maintain a higher CQI during IoE service execution as shown in Fig. 8(b). We show a relationship between the achieved downlink data rate, uplink data rate, and CQI of the proposed neuro-symbolic XAI twin in Fig. 9. In particular, 72% of IoE service can maintain the highest level of CQI while 28% of IoE achieve CQI in the mid range 7–10. In summary, the proposed approach is clearly more reliable and effective than the other baselines.

Empirical cumulative distribution function (ECDF) analysis of achievable data rate for both downlink [in Fig. 10(a)] and uplink [in Fig. 10(b)] with optimal (same as the used data set) and greedy approach is shown in Fig. 10. The proposed XAI twin gains around 9% more data rate than that of the greedy method while about 3.7% performance gap with optimal result.
B. Explainability and Trustworthiness of the Proposed Neuro-Symbolic XAI Twin

Fig. 11 shows the statistical explanation based on the maximum marginal JPD of evidence for each random variable of DAG on IoE service properties such as gNB, speed, downlink, uplink, and CQI. Fig. 11 clearly shows the most prominent explainable evidence by achieving higher probability distribution. Furthermore, we observed a strong correlation over this evidence, as shown in Fig. 12. The proposed symbolic reasoning approach found that each gNB association decision has at least 83%, 83%, 90%, and 58% positive correlation over IoE service user’s mobility, downlink, uplink, and CQI, respectively. Furthermore, mobility and uplink data rates have a significant impact on downlink data rate decisions. Particularly, 100% and 98% dependencies with mobility and uplink data rate on downlink data rate, respectively.

Fig. 12 shows that the CQI of IoE services completely relies on the user’s mobility, downlink, and uplink data rate with a correlation of 75%, 79%, and 82%, respectively. To this end, the proposed neuro-symbolic XAI twin not only has a strong
symbolic reasoning ability but also can capture the fundamental principle of IoE, such as users’ behavior, data, processes, and physical things.

Next, we concentrate on the analogy of the trustworthiness of the proposed neuro-symbolic XAI twin in Fig. 13 since one of the main goals of this work is to provide a trustworthy solution for assuring ZSM. In particular, in Fig. 13, we illustrate a comparison based on the achieved normalized trust score for the learning objective (16) among the proposed scheme and other baselines such Gradient-based bandits and Epsilon-greedy [20]. Fig. 13 shows that we can trust the proposed neuro-symbolic XAI twin around 44% and 18% more than that of the Gradient-based bandits and Epsilon-greedy, respectively, in order to ZSM of IoE. Finally, Fig. 14 demonstrated the marginal trust distribution among the gNBs of 100 IoE service fulfillment by the proposed neuro-symbolic XAI twin.

We illustrate a use case outcome of the proposed XAI twin framework in Fig. 15 to show how this work can meet the requirements of extensible, modular, and stateless management functions in ZSM.

VII. CONCLUSION

In this article, we have proposed a new neuro-symbolic XAI twin framework to enable trustworthy and zero-touch IoE service management in wireless networks. To guarantee evidence-based reasoning on network parameters and contextual metrics, we devise a multivariate regression for capturing an unconscious decision while posing with declarative semantics through a DAG-based BN. We have formulated Bayesian multiarm bandit learning problem to train our proposed neuro-symbolic XAI twin framework, where the learning objective is to minimize the gap between the expected and current explainable scores. We have implemented our neuro-symbolic XAI twin framework by developing duel-learning systems that include an implicit learner to take an unconscious decision in the physical space of the XAI twin by solving a multivariate regression problem and an explicit learner that exploits symbolic reasoning on implicit learner decisions and evidence via prior knowledge. The experimental result shows that the proposed solution significantly outperforms the baselines Gradient-based bandits, Epsilon-greedy, regression models, such as ensemble, LSTM, and DNN in terms of accuracy, explainable score, and closed-loop IoE service execution.

APPENDIX

We can describe (1) as follows:

\[
\begin{align*}
    &\begin{bmatrix}
        \phi_{\text{exec}}^{1ex} & \phi_{\text{exec}}^{2ex} \\
        \phi_{\text{exec}}^{11} & \phi_{\text{exec}}^{12} \\
        \ldots & \ldots \\
        \phi_{\text{exec}}^{1J} & \phi_{\text{exec}}^{2J}
    \end{bmatrix}
    \begin{bmatrix}
        X \\
        Y
    \end{bmatrix} \\
    &=
    \begin{bmatrix}
        1 & \phi_{\text{phy}}^{11} & \phi_{\text{phy}}^{12} & \ldots & \phi_{\text{phy}}^{1J} \\
        1 & \phi_{\text{phy}}^{21} & \phi_{\text{phy}}^{22} & \ldots & \phi_{\text{phy}}^{2J} \\
        \vdots & \vdots & \vdots & \ddots & \vdots \\
        1 & \phi_{\text{phy}}^{11} & \phi_{\text{phy}}^{12} & \ldots & \phi_{\text{phy}}^{1J}
    \end{bmatrix}
    \begin{bmatrix}
        \phi_{\text{exec}}^{1ex} \\
        \phi_{\text{exec}}^{2ex} \\
        \ldots \\
        \phi_{\text{exec}}^{1J} \\
        \phi_{\text{exec}}^{2J}
    \end{bmatrix}
\end{align*}
\]
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