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Fault Detection Framework with Digital Twin Based on Artificial Intelligence Models for Wireless Networks

Sercan Yalçın[1], Hüseyin Vural[2]
[1,2]*Department of Computer Engineering/ University of Adiyaman, Türkiye*
[1]svancin@adiyaman.edu.tr, [2]hvural@adiyaman.edu.tr

ABSTRACT : *This paper presents a fault detection scheme for an artificial intelligence (AI) based-digital twin (DT) architecture integrated Long Range (LoRa) onto the wireless 5G networks. The proposed scheme combines the capabilities of AI and DT technology to detect anomalies in the network. By deploying LoRa-based sensors strategically, real-time spectrum-related data such as signal strength, interference levels, and occupancy can be collected. The DT leverages AI techniques, including machine learning (ML) and data analytics, to analyze the spectrum data and extract valuable insights. These insights enable the identification of interference sources, prediction of spectrum usage patterns, and minimization of the faults. Performance evaluations are conducted to assess the accuracy and effectiveness of the proposed scheme in improving detection mechanisms and networks performance. The results demonstrate the potential of the AI-based DT approach in enhancing the efficiency and reliability of wireless 5G networks with LoRa.*

KEYWORDS - *Artificial Intelligence, Digital Twin, Low Power Networks, Wireless 5G Network.*

I. INTRODUCTION

A digital twin (DT) is a virtual representation or a digital replica of a physical object, process, or system. It is created by capturing and integrating real-time data from sensors, Internet of Things (IoTs) devices, and other sources, along with relevant contextual information [1]. DTs enable real-time monitoring, analysis, and simulation of the physical counterpart, providing valuable insights, predictive capabilities, and decision support. Future generation wireless networks, such as 5G and beyond, are envisioned to support unprecedented levels of connectivity, data rates, and diverse applications [2]. To realize the full potential of these networks, intelligent management and optimization approaches are required. In this context, the concept of DT has emerged as a promising technology that combines virtual representations and artificial intelligence (AI) techniques to enhance the intelligence and efficiency of wireless networks. A DT for intelligence-based future generation wireless networks leverages real-time data collection from network devices, sensors, and management systems to create a virtual replica of the network [3, 4]. This virtual representation is integrated with AI algorithms, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), to enable advanced analytics, predictive modeling, and optimization. By analyzing network data and patterns, the DT provides insights into network performance, predicts potential issues, and facilitates proactive decision-making. The DT enhances network planning and optimization by simulating different scenarios and evaluating the impact of network parameters. It enables predictive maintenance by detecting anomalies, predicting equipment failures, and optimizing maintenance schedules. Spectrum management benefits from DTs by dynamically allocating and optimizing frequency bands based on spectrum availability and demand [5-7]. Furthermore, DTs contribute to IoT network management, network security, traffic prediction, and virtual testing and validation. The integration of DT technology with intelligence-based future generation wireless networks opens up new possibilities for optimizing network performance, ensuring reliable connectivity, and adapting to dynamic network conditions. It empowers network operators and administrators with valuable insights, automated decision support, and efficient resource allocation. However, challenges such as data privacy, scalability, and real-time synchronization between the physical network and the DT need to be addressed to fully realize the potential of this technology. Finally, the DT concept combined with AI techniques holds great promise for intelligence-based future generation wireless networks [8,9]. By creating a virtual replica of the network and leveraging AI algorithms, DTs enable intelligent network management, optimization, and decision-making. They contribute to improved network performance, enhanced user experience, and efficient utilization of network resources in the evolving landscape of wireless communication [10].

In recent studies, several areas and applications of DTs have emerged in the context of wireless networks [11, 12]. DTs are utilized for network planning and optimization tasks, such as determining optimal base station locations, antenna configurations, and network capacity planning. By simulating different scenarios and analyzing the impact of network parameters, DTs assist in optimizing coverage, capacity, and quality of service for wireless networks. DTs are employed for predictive maintenance of wireless network infrastructure. By analyzing data from network devices, sensors, and historical maintenance records, DTs can detect anomalies, predict equipment failures, and recommend proactive maintenance actions. This helps in reducing downtime, optimizing maintenance schedules, and improving network reliability. DTs play a role in optimizing spectrum utilization and management [13]. They can analyze spectrum availability, interference patterns, and traffic demand to dynamically allocate and optimize frequency bands. DTs help in mitigating interference issues, improving network performance, and maximizing spectrum efficiency. DTs are applied in managing and optimizing the IoT networks. By creating DTs of IoT devices and their connectivity, it becomes possible to monitor device behavior, analyze data patterns, and optimize network performance. DTs assist in managing device configurations, handling scalability challenges, and ensuring reliable connectivity for IoT applications [14]. DTs contribute to enhancing network security in wireless networks. By creating digital replicas of network infrastructure and applying AI algorithms, DTs can monitor network traffic, detect anomalies, and identify potential security threats. DTs aid in real-time threat detection, incident response, and network security management [15].

In summary, while several studies have explored DT frameworks, AI techniques, and wireless network optimization, limited research has specifically addressed the integration of DT, AI, LoRa protocol, and spectrum sensing management in the context of wireless 5G networks. Errors related to LoRa node identification, transmission, and reception are decreased via effective spectrum management. The proposed DT framework presented in this study bridges this gap, providing a foundation for leveraging AI-driven DTs to minimize the faults.

In the proposed study related to the fault detection in DT wireless 5G network based on LoRa, several key activities and contributions have been made. These include:

- Design and Development of the DT Architecture: The study involves designing and developing a comprehensive DT architecture specifically tailored for wireless 5G networks with LoRa spectrum sensing management. The architecture encompasses components such as data collection, pre-processing, storage, AI and analytics, visualization, and control/optimization, as discussed earlier.
- Integration of LoRa Spectrum Sensing: The study focuses on integrating LoRa spectrum sensing capabilities within the DT framework. This involved deploying LoRa-based sensors strategically to monitor and gather spectrum-related data, including signal strength, interference levels, and occupancy in different frequency bands. The collected data is fed into the DT for analysis and decision-making.
- AI-Driven Spectrum Analysis: The proposed study leverages AI techniques within the DT to analyze the spectrum data collected through LoRa sensors. ML algorithms and data analytics methods were employed to detect patterns, identify interference sources, predict spectrum usage, and optimize spectrum allocation and management in the 5G network.
- Optimization and Decision-Making: Based on the insights derived from the AI-driven spectrum analysis, the DT facilitated optimization and decision-making processes. It provides recommendations for spectrum allocation, dynamic channel selection, interference mitigation strategies, and resource optimization in real-time or near real-time. This enabled efficient utilization of the available spectrum resources in the wireless 5G network.
- Performance Evaluation and Validation: The study involves conducting performance evaluations and validation of the proposed DT wireless 5G network. This included assessing the accuracy and fault detection, evaluating the performance of AI algorithms for measuring the impact of the proposed strategies on network performance and resource utilization.

Overall, the study aimed to demonstrate the feasibility and theoretical infrastructure of utilizing a DT architecture combined with LoRa spectrum sensing for intelligent management of wireless 5G networks. The integration of AI-driven analytics and optimization techniques within the DT framework enables proactive decision-making, efficient spectrum management, and improved performance in 5G networks with LoRa spectrum sensing. The rest of the paper is organized as follows. Section 2 presents the related work, and Section 3 presents materials and methods with wireless 5G network and LoRa standard. Then, the proposed DT framework is described. Section 4 puts forward the experimental analysis and evaluates the performance results. Section 5 discusses the the presented study and gives the future aspects of the DT area. Finally, Section 6 presents the conclusion remarks.

II. RELATED WORKS

According to Rasheed et al. (2019), DTs are adaptive models of complex systems [16]. DTs are becoming a more realistic possibility thanks to recent advancements in computing pipelines, multiphysics solvers, AI, big data cybernetics, data processing, and management tools. In a variety of applications, DTs are currently a significant rising trend. Also known as synchronized virtual prototypes, device shadows, mirroring systems, avatars, and computing gigantic models. In order to encourage the modularization of interdisciplinary systems and overcome basic hurdles, DTs play a transformative role not just in how we design and manage cyber-physical intelligent systems. Alexopoulo et al. (2020) emphasized that by creating a suitable training data set and automatically labeling it using a simulation tool chain, the DT's model can be leveraged to speed up the ML training phase while minimizing human involvement [17]. These artificial datasets can be expanded and cross-validated utilizing a large amount of real-world data with little to no use. In order to actualize the multidisciplinary integration of information and communication technology (ICT) in crisis informatics and disaster response, Fan et al. (2021) researched and offered a vision of a catastrophe city DTs idea [18]. To improve situation assessment, decision-making, and coordination among various stakeholders and hence increase insight into the dynamics of complex disaster response and humanitarian assistance, AI algorithms and approaches must be incorporated. Yurkevich et al. (2021) proposed a neural model created for digital air traffic control [19]. The components of this technique are connected to wireless 4G and 5G networks, and it embraces the idea of a physical self-organizing social network of a distributed organization and technical system. This method has the advantage of a sophisticated integration with hybrid AI and a very promising analysis and management principle. Li et al. (2021) went into great length on the traits, the most cutting-edge makeup, and the corresponding constraints of the future DTs in the aerospace industry [20]. They presented the aero DTs in three dimensions. The community conducting research and development on aviation DTs may benefit from these, which include interaction, standardization, and cognitive. They assisted in quadrupling the effectiveness of current and upcoming aeronautical systems and related procedures. Bécue et al. (2020) proposed novel cognitive modeling and cooperative simulation environment [21]. To assess the human behavior models and security testing skills in aerospace, they introduced holistic DTs and AI technologies. Finally, they showed how to use holistic DTs and AI technologies to deliver new services for optimizing and recovering future factories. Grigoropoulos, et al. (2020) provided an analog environment and support for DTs for a platform that makes it easier to manage and run drone-based applications on a standard drone architecture [22]. The platform and the functions of the apps running on it can first be thoroughly tested in the simulation environment before being deployed to the real world. When apps are deployed, the DT is used to identify gaps and expected behaviors between them. When the simulation test is run or no errors have been detected, this information can be used as an error indicator. Xiong, et al. (2020) investigated a DT-driven aviation engine predictive maintenance framework and found an implicit DT Implicit DTs (IDT) model to enhance the effectiveness of engine predictive maintenance [23]. The validity of the model is assessed by comparing virtual and real data assets. By combining the data-driven DL method with the Long Short-Term Memory (LSTM) model and using an illustration of an aviation engine, the approach's utility is shown. Angin et al. (2020) suggested AgriLoRa, a low-cost farmland DT system, for intelligent agriculture [24]. In order to identify plant illnesses, weed clusters, and nutritional deficits in plants, AgriLoRa uses a wireless sensor network (WSN) installed in agricultural areas in conjunction with cloud servers that run computer vision algorithms. In a study [25], Dangana et al. (2022) investigated the behavior of Narrow Band (NB)-IoT wireless communication in an indoor industrial setting. A situation in the industrial sector was modelled and simulated using Wireless Insite software. Their study looked at how this situation or environment affects the physical layer of the NB-IoT's communication characteristics. In this context, signal-to-noise ratios (SNRs) in the environment, throughput levels among terminals as well as between terminals and transceiver towers, the power received at signal destination locations, and distances between terminals and transceivers are taken into account. Gao et al. (2023) studied the time delay of bridge DT services in relation to communication and computation complexity, exposing the different influence of their order [26]. They proposed an AIoT-informed DT communication architecture. To reduce communication complexity in the framework, the information hierarchy and two-way communication can be used. A Petri net is used to illustrate how the proposed framework's data flow and robustness. Additionally, the framework is cross-platform integrated into a generic DT and tested with various situations. The findings show that, in comparison to other bridge DTs now in use, the proposed framework has high efficiency, low latency, and superior fault tolerance, which can improve the effectiveness and safety of bridge O&M, particularly in situations where communication is limited.

III. MATERIALS AND METHODS

3.1. Wireless 5G Networks and LoRa Standard

Wireless 5G network refers to the fifth generation of wireless network technology, which is designed to provide faster data transmission, lower latency, higher capacity, and more reliable connectivity compared to previous generations. It is an advanced wireless network technology that aims to meet the increasing demands of modern applications, such as IoTs, virtual reality (VR), augmented reality (AR), and high-definition video streaming [27, 28].

The wireless 5G network consists of 5G base stations that transmit and receive data to and from user devices. These base stations are equipped with advanced antenna technologies to provide high-speed wireless connectivity. The user devices, such as smartphones or IoT devices, communicate with the base stations wirelessly, allowing users to access various applications and services with improved performance [29]. The wireless 5G network utilizes higher frequency bands, advanced modulation techniques, and beamforming to enable faster data transmission rates and lower latency. It also employs advanced network management techniques, such as network slicing, to allocate network resources efficiently and provide customized services to different types of applications and users. Overall, the wireless 5G network offers enhanced connectivity and enables a wide range of innovative applications and services that require high-speed, low-latency, and reliable wireless communication [30].

LoRa, short for Long Range, is a low-power, wide-area networking (LPWAN) technology designed for long-range wireless communication. It operates in unlicensed frequency bands, typically using sub-GHz frequencies, and is known for its ability to provide long-range connectivity while consuming minimal power [31].

In the proposed DT wireless 5G network spectrum sensing scheme, LoRa is utilized for specific reasons:

- Long Range Sensing: LoRa's long-range capabilities make it suitable for spectrum sensing in wireless networks, including 5G. By deploying LoRa-based devices as sensors, the DT can gather spectrum-related data across a wide area, providing comprehensive information for spectrum management and optimization.
- Low Power Consumption: The low-power nature of LoRa devices allows for prolonged sensing operations without draining excessive energy. This is essential for continuous spectrum monitoring and ensures the sustainability of the proposed DT scheme.
- Chirp Spread Spectrum (CSS): LoRa utilizes CSS modulation, which spreads the signal over a wide frequency range. This modulation technique allows LoRa devices to achieve long-range communication and high resistance to noise and interference.
- Adaptive Data Rate (ADR): LoRa-based LPWANs employ data rate techniques to optimize the data rate and power consumption based on the signal strength and distance between devices. This operation dynamically adjusts the communication parameters to maintain an optimal balance between range, data rate, and energy efficiency.

- Robustness and Penetration: LoRa exhibits excellent robustness against interference and can penetrate through obstacles such as walls and buildings, ensuring reliable connectivity even in challenging environments.
- Wide Coverage: LoRa's ability to cover large areas facilitates spectrum sensing in a distributed manner. By deploying LoRa-based sensors strategically, the DT can monitor the spectrum usage across a wide range, capturing variations and patterns in different locations.

By integrating LoRa-based LPWANs into the DT architecture for wireless 5G network spectrum sensing, the scheme can leverage LoRa's long-range communication, low power consumption, and wide coverage to collect spectrum data efficiently and accurately [32, 33]. This data can then be utilized for spectrum management, optimization, and decision-making within the DT system, ultimately enhancing the performance and efficiency of wireless 5G networks. LoRa operates in the unlicensed spectrum and provides long-range communication with low power consumption. On the other hand, 5G is a cellular network technology that operates in licensed spectrum bands, offering high-speed connectivity and supporting various use cases beyond IoT. As such, there isn't a direct combination of 5G and LoRa in terms of protocol integration. However, it is possible to consider scenarios where a hybrid network architecture combines the capabilities of both technologies to address diverse connectivity requirements. In such cases, 5G can be used for high-speed data transmission and LoRa can be utilized for low-power, long-range IoT communication. The 5G base station provides high-speed connectivity to 5G user devices, enabling applications that require fast data transmission, such as video streaming or real-time communication. The 5G network operates in licensed spectrum bands and supports advanced features like network slicing and low latency. On the other hand, the LoRa gateway connects to LoRa devices, which are typically low-power IoT sensors or devices [34]. It is suitable for IoT applications that require long battery life and connectivity in remote areas. In a hybrid scenario, the 5G and LoRa networks can be interconnected to provide seamless connectivity for different use cases. In the proposed framework, the 5G network was used for high-speed data transfer and control of IoT devices, while LoRa was utilized for low-power, wide-area networks applications that require long-range connectivity.

3.2. Proposed Framework

In this section, the DT architecture for 5G wireless network management with LoRa communication protocol, is explained along with the relationships between its components:

a) Data Collection Layer: The Data Collection Layer is responsible for gathering real-time data from various sources within the 5G network, including base stations, user devices, sensors, and LoRa gateways. This data includes network performance metrics, signal strength, device statuses, environmental conditions, and LoRa-specific parameters such as SNR and packet error rate (PER).

b) Data Ingestion and Pre-processing: The collected data from the Data Collection Layer is ingested into the DT platform and undergoes pre-processing. This stage involves data cleaning, normalization, filtering, and transformation to ensure the quality and consistency of the data. For LoRa-specific data, additional pre-processing steps may include decoding LoRaWAN messages and extracting relevant information.

c) Data Storage and Management: The pre-processed data is stored in a suitable database or data management system. This allows for efficient storage, retrieval, and query operations on both historical and real-time network data. The stored data includes 5G network parameters, LoRa-specific metrics, device information, and environmental data.

d) Integration of 5G Network Data: The DT incorporates data from the 5G network, including information from 5G base stations, user devices, and network management systems. This data provides insights into network performance, user experience, and resource utilization within the 5G network.

e) Integration of LoRa Network Data: The DT integrates data from the LoRa network, which includes information from LoRa gateways, LoRa devices, and IoT sensors. This data enables monitoring of IoT device connectivity, sensor data collection, and overall performance of the LoRa network.

f) AI and Analytics Layer: The AI and Analytics Layer consists of various AI techniques such as ML, DL, and statistical analysis algorithms. These algorithms analyze the collected data to extract insights, detect patterns, and predict network behavior. The AI models are trained using historical data to provide accurate predictions and optimizations for 5G network management with LoRa.

In the AI and Analytics layer of the wireless network's DT, a Convolutional Neural Network (CNN) can play a significant role in analyzing and processing the collected data. CNN is a DL algorithm specifically designed for making it well-suited for various applications in the wireless network domain. Here is further information in the AI and Analytics layer of the DT:

- Anomaly Detection: CNNs were used to detect anomalies or unusual patterns in network data in this study. By training on normal network behavior, CNNs can learn to identify deviations from the expected patterns, such as network intrusions, security breaches, or performance anomalies. This aids in early detection and mitigation of potential network issues. A mathematical model was designed for fault detection using AI-based wireless network (see Section 3.2.2).
- Network Modeling and Simulation: The Network Modeling and Simulation component creates a virtual replica or model of the 5G wireless network with integrated LoRa communication. This model captures the network topology, connectivity, device configurations, and the impact of LoRa parameters. Simulation techniques were employed to simulate different scenarios and evaluate the performance of the network under various conditions.
- Control and Optimization: The Control and Optimization component takes inputs from the AI models, simulation results, and user interactions to drive intelligent decision-making and optimization actions. It enables automated or semi-automated control and optimization of network parameters, device configurations, LoRa gateway placement, and LoRa channel allocation to improve the overall performance, capacity, and reliability of the 5G network with LoRa.

Overall, the CNN-based AI and Analytics layer empowers the DT to extract valuable insights, make informed decisions, and optimize network operations in wireless networks. By leveraging the capabilities of DL, CNNs enable intelligent analysis of complex data, leading to improved network performance, enhanced security, and better user experience. Fig. 1 represented the proposed framework.

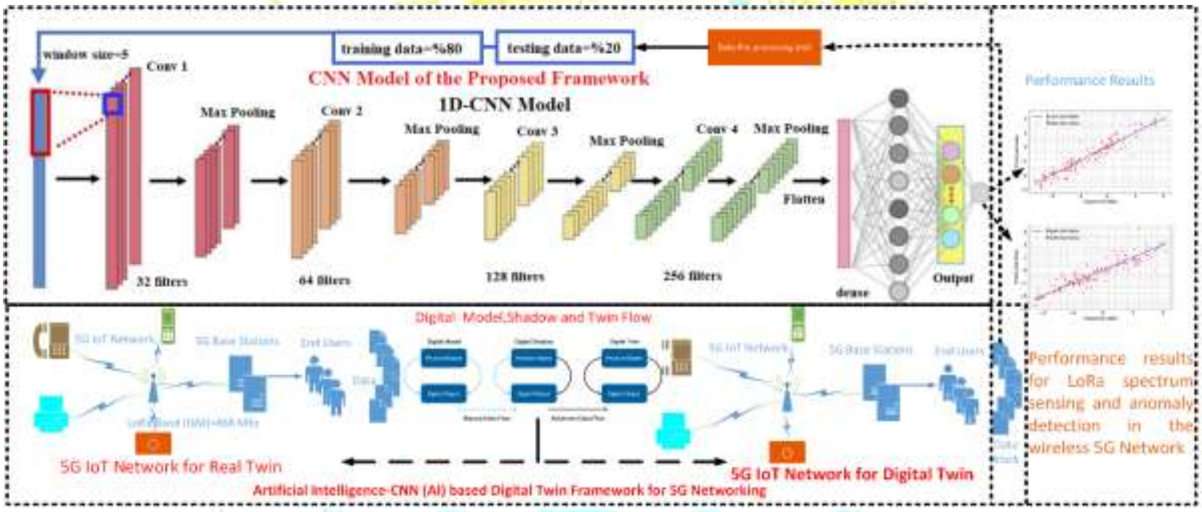

Fig.1. The proposed framework: AI-CNN based DT framework for wireless 5G networks

In the proposed model, 4 convolution and max pooling layers are used based on the 1D-CNN structure. These layers are combined in the dense layer after the flatten layer and transferred to the output layer. Filters of 32, 64, 128 and 256 are considered, respectively. An AI-based (CNN) system of 5G and LoRa network has been established. As seen in Fig. 1, the digital mirror block consists of model, shadow and flow mirroring. The physical (real) and digital (virtual) data in the 5G network obtained using the DT are compared and forwarding to the CNN layer for training. 80% of the total data is set for training and the rest for testing. In the output layer, the expected and predicted values of the data are analyzed. The relationships between these components involve the flow of data and information. The Data Collection Layer feeds real-time data to the Data Ingestion and Pre-processing stage, which then delivers the pre-processed data to the Data Storage and Management component. The AI and Analytics Layer utilizes the stored data for analysis and generates insights, which are then visualized and presented through the Visualization and User Interface component. The Control and Optimization component takes inputs from AI models, simulation results, and user interactions to drive network optimization actions, thus completing the feedback loop. In this way, the proposed DT architecture for 5G wireless network management with LoRa communication protocol enables efficient monitoring, analysis, and optimization of network performance, device configurations, and LoRa-specific parameters. It leverages AI techniques, simulation capabilities, and user-friendly interfaces to enhance decision-making and improve the overall management of 5G networks incorporating LoRa technology. By integrating the 5G and LoRa networks within the DT framework, network operators can have a holistic view of their wireless infrastructure. They can optimize resource allocation, identify potential issues, and make data-driven decisions for network management and optimization in a hybrid environment.

The mathematical model of a DT for wireless 5G network involves various components and their relationships. Here is the proposed mathematical representation of the DT model:

a) Network Topology: Consider $G(V,E)$ as the network topology, where V is the set of network nodes (LoRa devices) and E is the set of links connecting these nodes. Each node $v \in V$ is associated with its coordinates (x_v, y_v) in the network.
b) Signal Propagation Model: The signal propagation model determines the path loss and interference between nodes. Define $P_l(v_i, v_j)$ as the path loss between nodes v_i and v_j, which depends on factors such as distance, antenna characteristics, and environmental conditions. The interference level between nodes v_i and v_j is denoted as $I(v_i, v_j)$.
c) Spectrum Sensing: Spectrum sensing measures the occupancy and availability of the spectrum bands. Consider $O(v_i, b)$ as the occupancy status of spectrum band b at node v_i, where $O(v_i, b) = 1$ indicates the band is occupied, and $O(v_i, b) = 0$ represents an available band.
d) Resource Allocation: Resource allocation involves assigning spectrum bands, transmit power, and other network resources to optimize network performance. Represent $R(v_i, b)$ as the allocated resources for node v_i on spectrum band b. This includes the allocated transmit power, bandwidth, modulation scheme, and coding rate.
e) Performance Metrics: Various performance metrics can be considered, such as throughput, latency, energy efficiency, and coverage. Let $P(v_i)$ denote the achieved throughput at node v_i, and $T(v_i)$ represent the latency experienced by node v_i.
f) Optimization Objective: The objective of the DT model is to optimize network performance based on specific criteria. Let $f(O,R)$ be the objective function representing the optimization goal, which can be formulated as a minimization or maximization problem.
g) Constraints: There may be various constraints in the DT model, such as maximum transmit power limits, interference thresholds, and quality of service requirements. These constraints can be represented as mathematical inequalities or equations.

The proposed mathematical model of the DT for a LoRa wireless 5G network incorporates these components and their relationships to simulate, analyze, and optimize network operations. It provides a mathematical framework to study the interactions between different network elements, predict network behavior, and optimize resource allocation to achieve desired network performance. The specific formulation of the mathematical model may vary depending on the objectives, constraints, and performance metrics considered in a particular DT implementation.

The proposed mathematical modeling of a DT for fault detection in a wireless network typically involves capturing the relationship between the sensor measurements and the occurrence of faults or anomalies. The proposed mathematical model for fault detection in a wireless network, is presented as:

a) LoRa sensor node measurements: The sensor measurements are considered as $v_1, v_2, \ldots v_{N_s}$ where N_s represents the number of LoRa nodes in the network. These measurements are related to the physical volt amounts ranging from -3 to 3 of the LoRa sensor nodes, which are considered homogeneous and of the same type in the network. In fact, although there are many different types of nodes in IoT 5G networks and the physical variable environment data these nodes detect, the battery voltage values of low power consuming nodes are taken as the basis in this study. The obtained data in the network is passed through a pre-processing operation such as filtering before being trained.
b) Fault Detection Model: The specific form of the proposed fault detection model depends on the three-step approach.
   - Training and Validation: The fault detection model requires training and validation using historical sensor data. This involves collecting a dataset that includes both normal operating conditions and known fault instances. The dataset is used to train the model to distinguish between normal and faulty situations. The model is then validated on unseen data to assess its performance.
   - Decision Threshold: In threshold-based approaches, a decision threshold is defined to determine when a fault is detected. The threshold λ was set to the system for wireless network application.
   - Alarm Generation: When a fault is detected, an alarm can be generated to notify the network administrator or appropriate personnel. The alarm can be in the form of a notification, message, or any other mechanism that indicates the presence of a fault.

The fault detection model captures the relationship between the sensor measurements and the fault detection variable. This can be done by comparing the measured values with expected or predicted values. The goal is to detect faults or anomalies in the sensor measurements. This has been performed by the proposed algorithm.

The absence or presence of an end user in the network sensing area is determined by the two hypotheses H_0 and H_1. Eq (1) gives the signal D_i that the LoRa node i recevied signal by the DT user.

$$D_i = \begin{cases} n_i & H_0 \\ c_i\, R_i + n_i & H_1 \end{cases} \tag{1}$$

where D_i is the signal that the digital end user i perceives, R_i is the transmitted signal by a real end user i, c_i is the channel amplitude gain, and n_i is the additive white gaussian noise (AWGN). According to the H_0 hypothesis, there is no end user and the received signal sample D_i is made up entirely of noise. Contrarily, the noise and the signal broadcast after the c_i channel are likewise present in the signal received according to the H_1 hypothesis. Examining the signal acquired during the fault detection technique is necessary to select between binary hypotheses [34,35]. The presence of digital end user and its signal can only be determined by measuring the power considered in the frequency band and comparing it to a number of thresholds. The test static T_s for signal/data detection of the LoRa node, which ascertains whether the end user is active or not, is defined in Eq. (2).

$$T_s = \frac{1}{N_s} \sum_{i=1}^{N_s} |f_v(v_1, v_2, \ldots\ v_i)\ |^2 \tag{2}$$

where f_v is defined for the fault detection variable in terms of $v_1, v_2, \ldots\ v_i$ measurements, N_s is the number of LoRa node signal samples. The tests are expressed as in Eqs. (3) and (4) with the test static T_s for both of the hypotheses H_0 and H_1, respectively [31,36].

$$T_s|H_0 \sim G(w_a^2, \frac{w_a^4}{N_s}) \tag{3}$$

$$T_s|H_1 \sim G(w_t^2 + w_a^2, \frac{(w_t^2 + w_a^2)^2}{N_s}) \tag{4}$$

where G is gaussian distribution, w_t^2 and w_a^2 denote to the variances of the forwarded data signal and AWGN, respectively. If $(T_s > \lambda|H_1)$ and $(T_s > \lambda|H_0)$, Eqs. (5) and (6) are satisfied, and the probability of detection P_d and the false alarm (fault signal) P_a are presented by Eqs. (5) and (6).

$$P_d = Q(\frac{\lambda - w_a^2(1+\Upsilon)}{\frac{w_a^2(1+\Upsilon_s)}{\sqrt{N_s}}}) \tag{5}$$

$$P_a = Q(\frac{\lambda - w_a^2}{\frac{w_a^2}{\sqrt{N_s}}}) \tag{6}$$

where Υ represents the SNR of the end user's signal measured, $Q()$ defines the gaussian function, and λ is the threshold value. Finaly, fault detection function f_d is presented in Eq.(7).

$$f_d = P_d \sim P_a \tag{7}$$

where f_d is defined for the fault detection, which indicates the presence (f_d= 1) or absence (f_d = 0) of a fault, as given in Eq.(8). Here, $\sim$ is the operator that creates the output of the decision (classifier) between P_d and P_a, performed by the proposed CNN model.

$$fault = \begin{cases} 0, & if\ f_d = 0 \\ 1, & if\ f_d = 1 \end{cases} \tag{8}$$

By incorporating this mathematical model into the DT framework, the DT continuously monitors the sensor measurements, apply the fault detection model, and generate alerts when anomalies or faults are detected.

This enables proactive fault management and improves the overall reliability and performance of the DT based wireless network.

Using the RMSE, MAPE, MAE, and coefficient of determination (R^2) metrics [31,36], the proposed approach has been assessed and verified in this study.

Root mean square error, sometimes referred to as the quadratic mean of expected and actual value discrepancies, is abbreviated as RMSE. The RMSE calculates the model's average residual magnitude, or the difference between predicted and actual values. Better performance is indicated by a lower RMSE since it shows less prediction errors and a closer match between the predicted and actual values. The RMSE is calculated using Eq. (9). The RMSE number decreases in direct proportion to the degree of data prediction accuracy. Therefore, if high performance of the suggested models is needed, the RMSE values must be decreased.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(x_t^p - x_t^e)^2}{T}} \tag{9}$$

where T is the number of samples, x_p and x_t^e are the predicted and expected value at sample t, respectively.

Mean Absolute Error (MAE) measures the average absolute difference between the predicted and actual values. Like RMSE, a lower MAE indicates better performance, as it represents smaller prediction errors and closer agreement between the predicted and actual values. MAE avoids the problem of estimating mistakes damping one another in both the positive and negative directions. In Eq (10), the MAE computation is given.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|x_t^p - x_t^e\right| \tag{10}$$

Mean Absolute Percentage Error (MAPE) measures the average percentage difference between the predicted and actual values, expressed as a percentage. A lower MAPE indicates better performance, as it represents smaller percentage errors and closer agreement between the predicted and actual values. A formula for calculating the MAPE is provided by Eq. (11).

$$MAPE = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{x_t^p - x_t^e}{x_t^e}\right| \tag{11}$$

R^2 is called as coefficient of determination. The R^2 measures the proportion of the variance in the dependent variable that is explained by the independent variables in the regression model. R^2 ranges between 0 and 1, with a higher value indicating better performance. A higher R^2 suggests that a larger proportion of the variance in the dependent variable can be predicted by the independent variables in the model. The R^2 is calculated as given by Eq. (12).

$$R^2 = 1 - \frac{\sum_{t=1}^{T}(x_t^e - x_t^p)^2}{\sum_{t=1}^{T}\left(x_t^e - \frac{\sum_{t=1}^{T}x_t^e}{T}\right)^2} \tag{12}$$

IV. EXPERIMENTAL ANALYSIS

The application and outcomes of the experiment are presented in this section, and fault detection for 5G network in the designed DT framework. The computer language Matlab has been utilized to carry out the investigation. In the study, different numbers of LoRa nodes used for DT and real environment have been considered. According to the proposed AI-CNN based DT framework for wireless 5G networks, the different number of N_s nodes ranging from 100 to 400 are deployed to different locations in the network, and they notice the DT channel in the wireless network. In this application, a very low noise SDR and a 915 MHz monopole antenna are used. It contains the SDR receiver's background noise that was utilized to record the signal. This eliminates the disparity that was caused by rectifying the AWGN on the obtained I/Q samples. Table 1 shows the LoRa parameters used in a Matlab application as in [31] and [36].

Table 1. The Simulation Parameters of the LoRa Standard

Parameters	**Value**
Frequency band	915 Mhz
Transmission power	6 dBi

Reception sensitivity	-146 dBm
SDR sample rate	20 Mhz
Number of nodes (N_s)	100 to 400
LoRa node measured noise number	6 dB
SDR average noise	-121 dBm
LoRa node average noise	-117 dBm
Distance	>15 km

In this study, the correlation between estimated voltage data values (ranges from -3 to 3) of the LoRa nodes are compared based on different models and the observed data with a perfect reliable line. In this way, a useful approach is performed to assess the fault detection performance and reliability of the models. The predicted and observed data in scattered points for different AI methods such as SVM [37], ANN [38], LSTM [39], and proposed method are presented. In terms of the performance metrics RMSE, MAPE, MAE, and R^2, the AI methods are compared with each other.

a) SVM (Support Vector Machines) [37]: SVM is a popular supervised learning algorithm used for both classification and regression tasks. It constructs a hyperplane or set of hyperplanes in a high-dimensional space to separate different classes or predict continuous values. SVM aims to maximize the margin between the decision boundary and the training data points. It can handle linear and non-linear data through the use of different kernel functions such as linear, polynomial, radial basis function (RBF), and sigmoid.
b) ANN (Artificial Neural Network) [38]: ANN is a class of ML models inspired by the structure and function of biological neural networks. It consists of interconnected artificial neurons or nodes organized in layers. ANN models can be feedforward, recurrent, or a combination of both. They learn from data through a process called backpropagation, where the model adjusts the weights and biases between nodes to minimize the difference between predicted and actual outputs. ANN can handle a wide range of tasks, including classification, regression, and pattern recognition.
c) LSTM (Long Short-Term Memory) [39]: LSTM is a type of recurrent neural network (RNN) designed to overcome the vanishing gradient problem and capture long-term dependencies in sequential data. It introduces memory cells and specialized gates that allow information to be stored, updated, and retrieved over long sequences. LSTM is particularly effective in tasks that require modeling sequential patterns, such as natural language processing, speech recognition, and time series analysis.
   To carried out performance analysis, the following issues are addressed.

- Data Preparation: First the observed data values are obtained for a specific region and time period. The estimated data values are collected from different models for the same region and time period, it is ensured that the observed and estimated data values are appropriately matched in terms of temporal resolution and spatial coverage.
- Calculation the Correlation Coefficients: Then, the correlation coefficient is calculated between the observed data values and the estimated data values from each model. The correlation coefficient measures the linear relationship between two variables and ranges from -1 to 1. A positive correlation indicates a direct relationship, while a negative correlation indicates an inverse relationship. The closer the correlation coefficient is to 1 (or -1), the stronger the linear relationship. This step is repeated for each model to obtain correlation coefficients for each model-observed data pair.
- Generation of Scatter Plots: Scatter plots are created for each model, with the x-axis representing the observed data values and the y-axis representing the estimated data values from that particular model. Here, a diagonal line is included with a slope of 1 (Y=X) on the scatter plots, which represents the perfect reliable relationship between the observed and estimated data values.

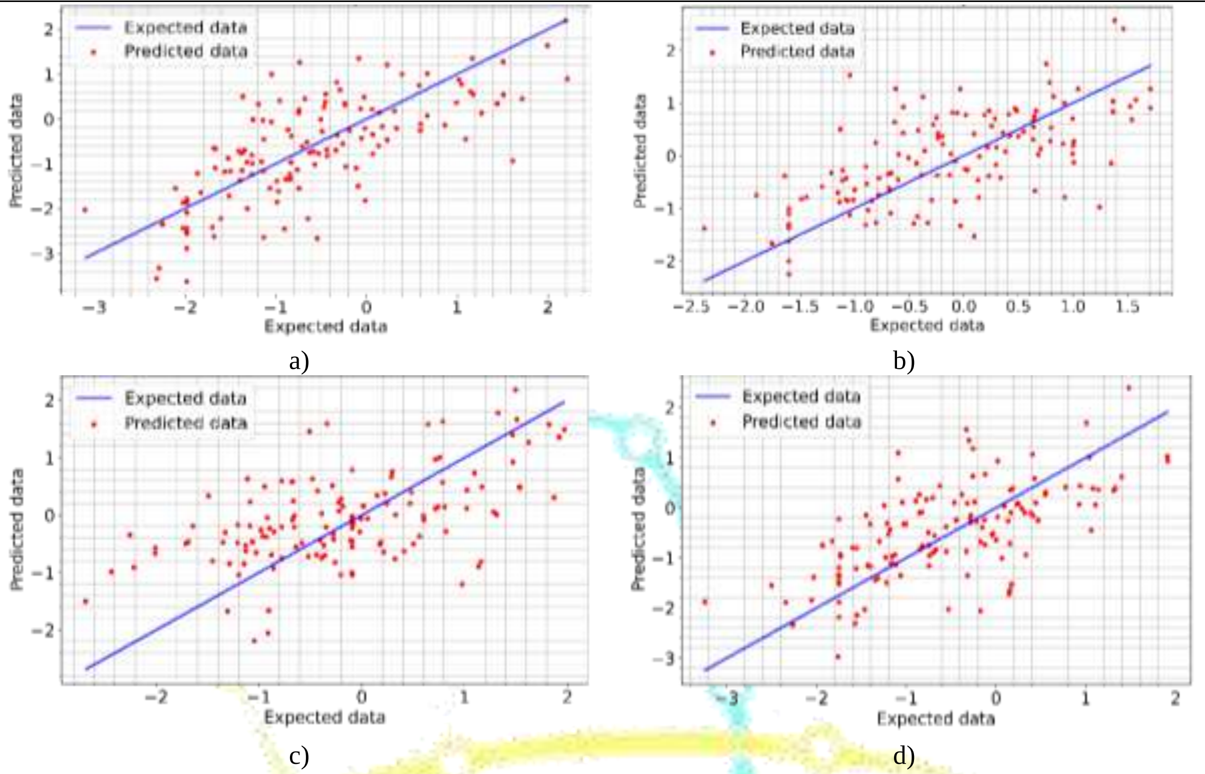

Fig. 2. Predicted and expected data results for SVM with: (a) 400 nodes, (b) 300 nodes, (c) 200 nodes, and (d) 100 nodes

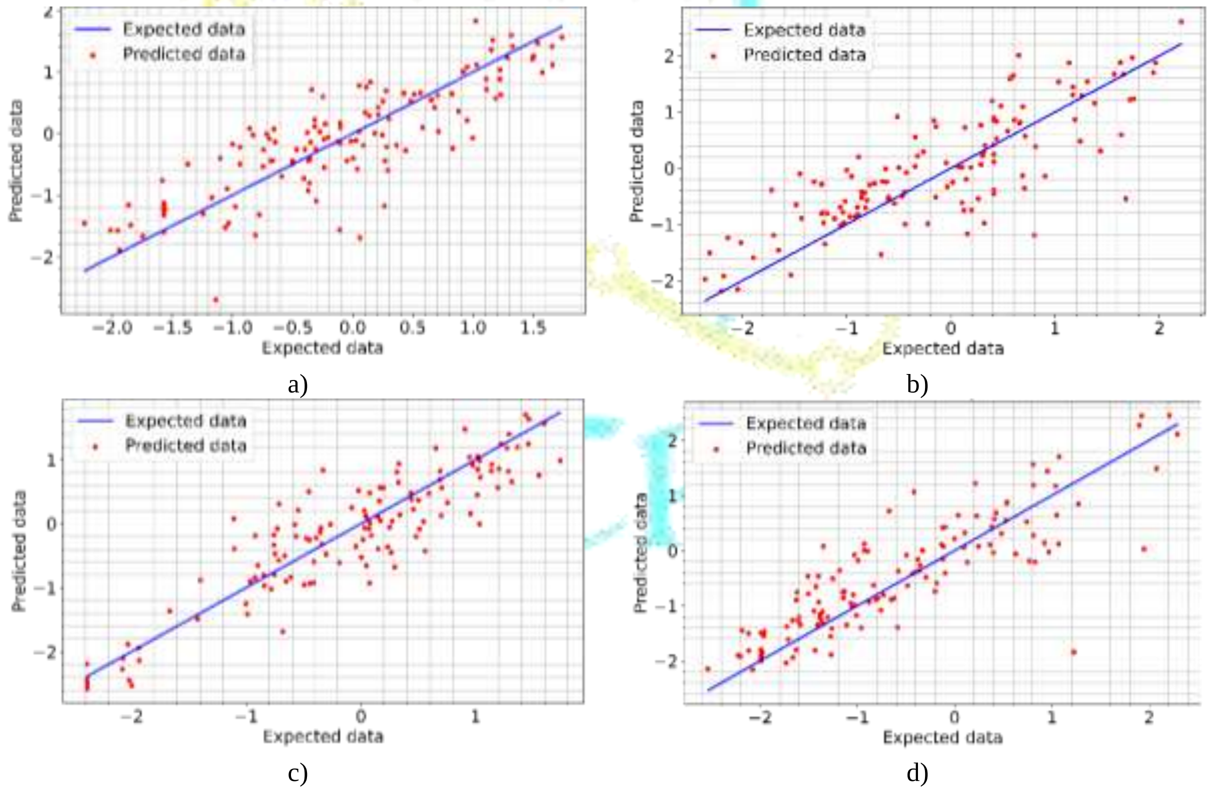

Fig. 3. Predicted and expected data results for ANN with: (a) 400 nodes, (b) 300 nodes, (c) 200 nodes, and (d) 100 nodes

By following these steps, it is compared the estimated data values from different models with the observed data and assess their correlation and agreement. Figs. 2 to 5 show the predicted and observed data in scattered points for SVM, ANN, LSTM, and proposed method, respectively. It has been understood from the results that the best performances are obtained for all LoRa nodes.

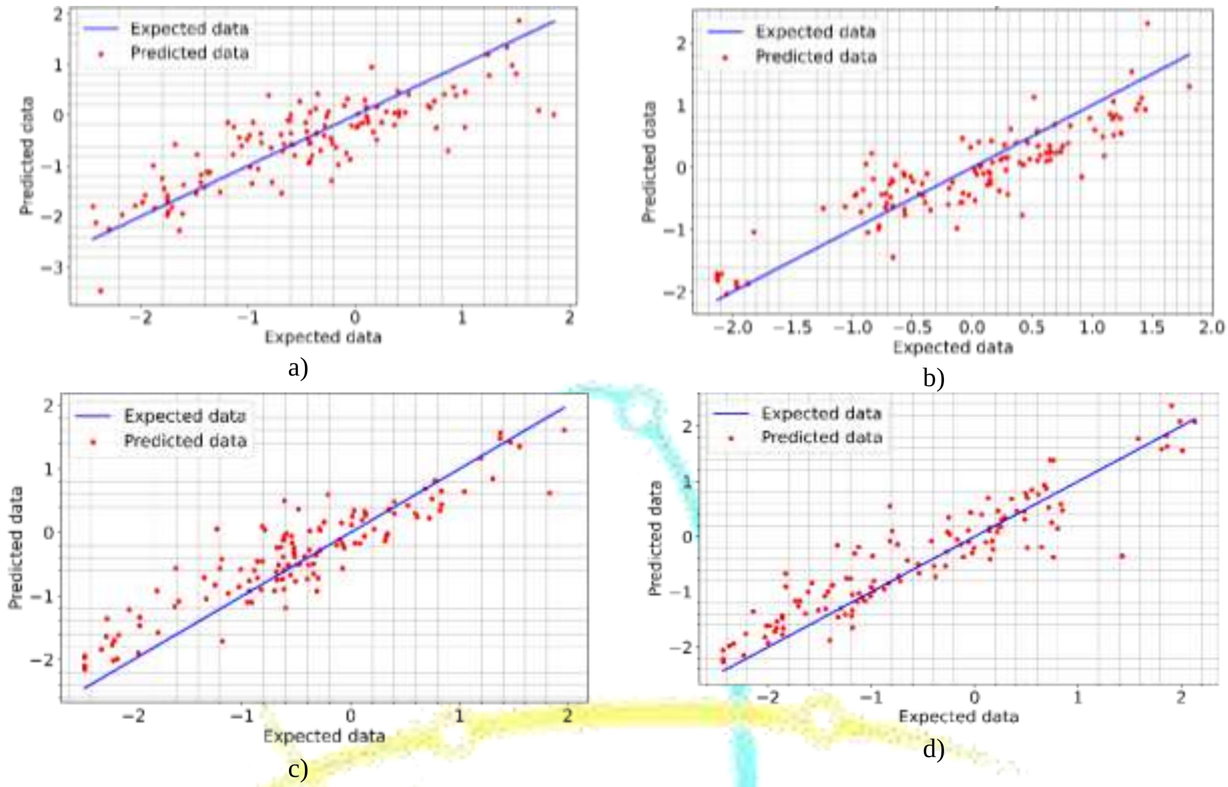

Fig. 4. Predicted and expected data results for LSTM with: (a) 400 nodes, (b) 300 nodes, (c) 200 nodes, and (d) 100 nodes

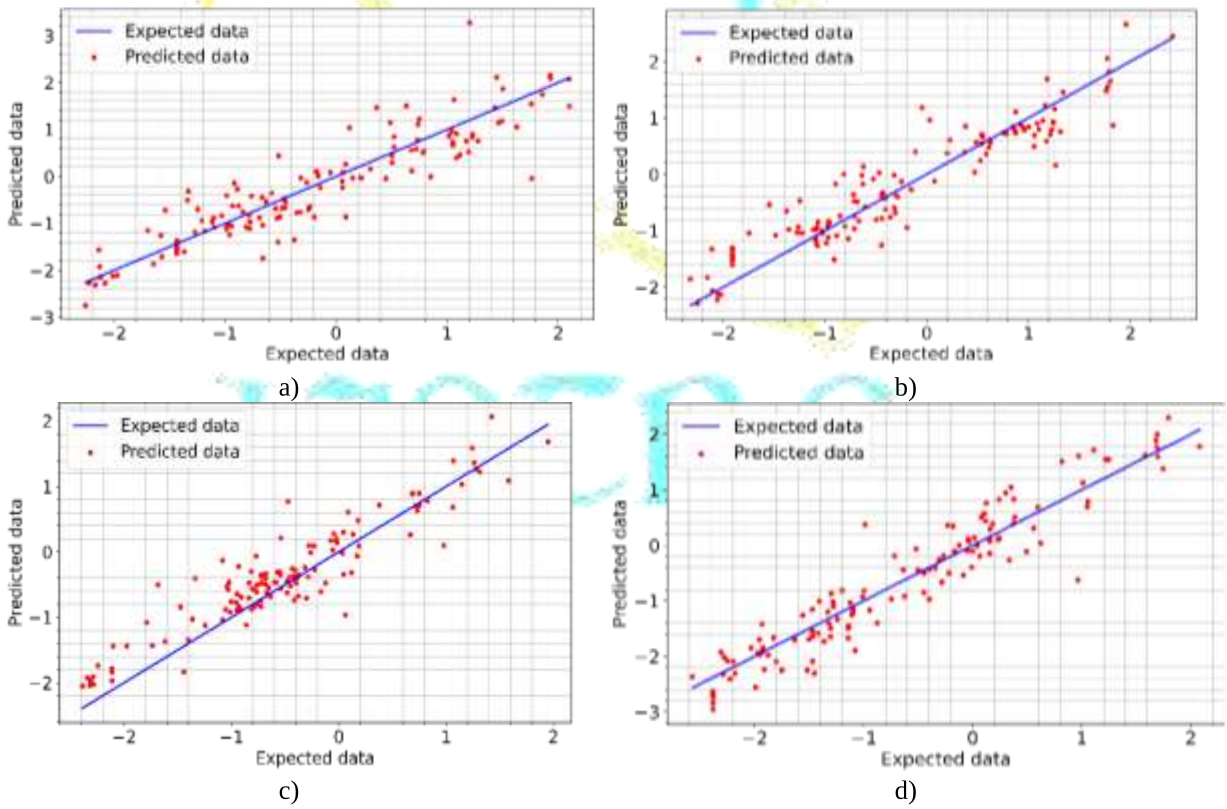

Fig. 5. Predicted and expected data results for proposed method with: (a) 400 nodes, (b) 300 nodes, (c) 200 nodes, and (d) 100 nodes

The performances of the SVM, ANN, LSTM, and the proposed method are compared in terms of RMSE, MAE, R^2, and MAPE for different numbers of nodes:

For SVM; the SVM algorithm's RMSE values increase as the number of nodes increases, ranging from 21.41 to 31.48. The highest RMSE is obtained with 400 nodes. The SVM algorithm's MAE values also increase with the number of nodes, ranging from 19.72 to 27.91. The highest MAE is obtained with 400 nodes. Similarly, the SVM algorithm's MAPE values increase from 17.33% to 24.37% as the number of nodes increases. The highest MAPE is observed with 400 nodes. The R^2 values decrease with the number of nodes, ranging from 0.8172 to 0.7276. The lowest R^2 is obtained with 400 nodes.

For ANN; the ANN algorithm's RMSE values also increase as the number of nodes increases, ranging from 20.18 to 28.56. The highest RMSE is obtained with 400 nodes. The ANN algorithm's MAE values increase with the number of nodes, ranging from 18.35 to 25.41. The highest MAE is obtained with 400 nodes. The ANN algorithm's MAPE values range from 15.98% to 21.63%, increasing with the number of nodes. The highest MAPE is observed with 400 nodes. The R^2 values decrease with the number of nodes, ranging from 0.8384 to 0.7714. The lowest R^2 is obtained with 400 nodes.

For LSTM; the LSTM algorithm's RMSE values increase as the number of nodes increases, ranging from 18.25 to 25.88. The highest RMSE is obtained with 400 nodes. The LSTM algorithm's MAE values increase with the number of nodes, ranging from 16.54 to 23.72. The highest MAE is obtained with 400 nodes. The LSTM algorithm's MAPE values range from 13.18% to 19.40%, increasing with the number of nodes. The highest MAPE is observed with 400 nodes. The R^2 values decrease with the number of nodes, ranging from 0.8646 to 0.8013. The lowest R^2 is obtained with 400 nodes.

For proposed method; the proposed method consistently achieves the lowest RMSE values across all numbers of nodes, ranging from 15.67 to 21.76. The lowest RMSE is obtained with 100 nodes. The proposed method also consistently achieves the lowest MAE values, ranging from 13.38 to 20.55. The lowest MAE is obtained with 100 nodes. The proposed method's MAPE values range from 10.29% to 17.29%, consistently being the lowest among all algorithms and numbers of nodes. The lowest MAPE is observed with 100 nodes. The R^2 values consistently remain higher for the proposed method, ranging from 0.8849 to 0.8114. The highest R^2 is obtained with 100 nodes.

Based on these results, the proposed method consistently outperforms SVM, ANN, and LSTM across all metrics (RMSE, MAE, MAPE, and R^2) and for all numbers of nodes. It achieves lower error values (RMSE, MAE, MAPE) and higher R^2 values, indicating better predictive performance and a better fit to the data. The reasons for the superior performance of the proposed method can be attributed to several factors. The proposed CNNs are specifically designed for voltage sequence data analysis. They excel at capturing spatial and temporal patterns, making them well-suited for time series forecasting tasks. The proposed method might have better feature extraction capabilities, allowing it to capture and represent more relevant information from the input data. This ability enables the model to make more accurate predictions. The CNN architecture used in the proposed method is better optimized for the specific characteristics of the dataset, resulting in improved performance compared to SVM, ANN, and LSTM. The training process and optimization techniques used in the proposed method is more effective in finding optimal model parameters and reducing prediction errors.

Table 2 reports the detailed performance results of SVM, ANN, LSTM, and the proposed method based on the provided data.

In this study, it has been also evaluated the false alarm rate (FAR) versus signal-to-noise ratio (SNR) in the context of a proposed scheme. These two concepts need to be explained briefly so that it is possible to make a correct and healthy performance analysis.

- False Alarm Rate (FAR): The FAR refers to the probability of incorrectly detecting a signal or event when there is no actual signal present. In other words, it measures how often the system mistakenly identifies noise or interference as a valid signal.
- Signal-to-Noise Ratio (SNR): SNR is a measure of the strength or quality of the signal compared to the background noise. It quantifies the ratio of the power of the signal to the power of the noise. Higher SNR values indicate a stronger, more distinguishable signal relative to the noise.

From Fig. 6, it has been inferenced that the relationship between FAR and SNR is typically an inverse one. As the SNR increases, the quality of the signal improves, making it easier to distinguish the signal from the background noise. Although the highest FAR is when the SNR is -15, the lowest FAR value is observed when the SNR increases towards -5. Consequently, the FAR tends to decrease as the SNR increases. Also, the expected and observed FAR values are very similar. To put it another way, the data acquired via the DT is extremely close to the real data and the margin of error is at the minimum level. Moreover, it is understood that the data estimated by the DT has a high accuracy rate.

Table 2. The performance comparison of the methods

Methods	Error Metrics	Number of LoRa nodes in the network			
		100	200	300	400
SVM [37]	RMSE	21.41	23.96	27.61	31.48
	MAE	19.72	20.34	24.49	27.91
	MAPE	17.33	18.61	21.58	24.37
	R^2	0.8172	0.7943	0.7539	0.7276
ANN [38]	RMSE	20.18	21.64	24.96	28.56
	MAE	18.35	20.99	22.84	25.41
	MAPE	15.98	17.94	18.25	21.63
	R^2	0.8384	0.8247	0.8018	0.7714
LSTM [39]	RMSE	18.25	20.49	22.19	25.88
	MAE	16.54	18.62	20.55	23.72
	MAPE	13.18	15.63	16.78	19.40
	R^2	0.8646	0.8466	0.8260	0.8013
Proposed method	RMSE	15.67	17.83	19.68	21.76
	MAE	13.38	16.35	18.46	20.55
	MAPE	10.29	13.67	15.37	17.29
	R^2	0.8849	0.8594	0.8337	0.8114

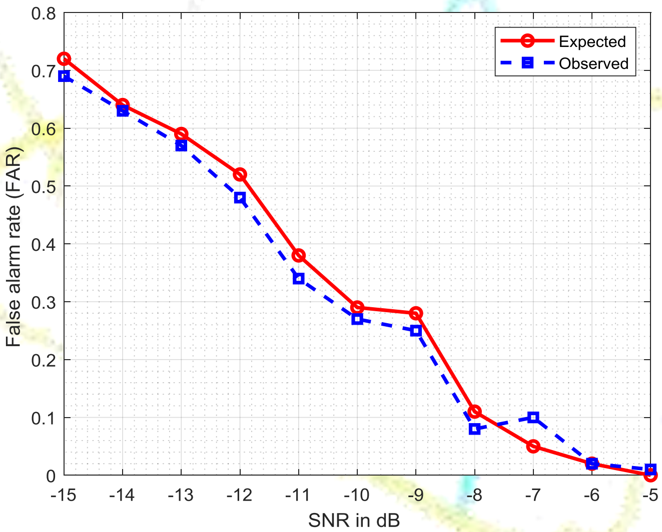

Fig. 6. False alarm rate (FAR) versus SNR with the proposed method

V. CONCLUSION

In this paper, a DT framework based on AI for wireless 5G networks with LoRa protocol which presents a promising approach is proposed to detect the faults in the network. By integrating AI techniques within the DT architecture, the framework enables efficient data collection, analysis, and decision-making processes. The use of LoRa protocol for spectrum sensing adds an additional layer of flexibility and scalability to the framework. Through the deployment of LoRa-based sensors, real-time spectrum-related data can be gathered, facilitating accurate fault detection. The AI algorithms applied within the DT framework allow for the identification of interference sources, prediction of spectrum usage patterns, and the strategies, which reduce faults or sensor disorders in the wireless network. This results in improved network performance, and better fault detection in wireless 5G networks. The proposed DT framework offers a foundation for future research and development in the field, opening doors for practical implementation and real-world deployments of AI-driven DT solutions for wireless 5G networks.

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