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Digital twin (DT)-based predictive maintenance of a 6G communication network

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Abstract

This research leverages the potential of digital twin technology to present a novel method of predictive maintenance for 6G communication networks. With the increasing need for 6G networks to be consistently reliable and always available, this essay emphasises the need for more advanced maintenance techniques. The seamless integration of digital twin technology makes it possible to monitor, analyse, and simulate the 6G network in real time. This innovation makes it easier to use artificial intelligence to fine-tune maintenance schedules and anticipate maintenance requirements in advance. The paper fervently promotes the use of digital twin technology as a vital instrument for raising the bar for maintenance requirements in the context of 6G networks.

Keywords: Digital Twin,6G network, Predictive maintenance, Artificial intelligence, Machine learning.

1. Introduction

The increasing need for high-speed, low-latency connectivity is driving the development of 6G communication networks, which are expected to be significantly more advanced than existing 5G networks [1]. Because 6G networks must handle more devices and offer higher degrees of automation, maintenance will become more challenging. The success of applications such as autonomous cars, smart cities, and remote healthcare depends on the reliability and availability of these networks, which is why predictive maintenance solutions are essential. The use of digital twin technology for preventative maintenance is becoming more and more popular in the industry as a means of overcoming the challenges associated with maintaining 6G networks. A digital twin is a virtual replica of an actual thing, process, or system that enables simulation, real-time monitoring, and performance analysis [2]. By anticipating when maintenance is required and streamlining the maintenance schedule, the use of digital twins for predictive

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maintenance in 6G networks can help to assure the dependability and availability of these networks.

A system model for deploying digital twin technology for proactive maintenance of 6G communication networks is presented in this study. The challenges of implementing digital twins in 6G networks are discussed in the study, including the requirement for real-time data gathering and processing and the requirement for precise models that can imitate the behaviour of 6G networks. The report also focuses on the possible uses of digital twin technology in 6G networks, such as improving network efficiency and lowering downtime.

Digital twin technology has been demonstrated to be useful for predictive maintenance in a number of fields, including manufacturing transportation, and energy. However, the use of digital twin technology for preventative maintenance in 6G communication networks is still in its infancy, and more study and development in this field is required.

1.1. Objective

The lack of proper analytics to predict network catastrophes and prevent their occurrence is the motivation and inspiration for this research. In order to achieve predictive maintenance, a deep edge architecture that uses network artificial intelligence (AI) is proposed. Using network AI, distributed intelligent agents can be intelligently connected in order to proliferate large-scale deployment of AI in all network components. This research then is to explore the possible application of strategies from precision mechanics in edge computing, where preventative maintenance based on the physical understanding and real-time data exploitation for improved fault diagnosis will be designed through DT.

1.2. Context of the Problem and Research Gap

The research is driven by the absence of robust analytics for forecasting network catastrophes and implementing preemptive measures. This gap serves as the motivation and cornerstone for this study. To realize predictive maintenance, the proposal centers on a sophisticated deep edge architecture integrating network artificial intelligence (AI). This framework aims to leverage network AI to interconnect distributed intelligent agents effectively, facilitating extensive deployment of AI across all network components.

2. System Model

Consider a 6G communication service provider (CSP) that runs its network edge with network functions virtualization (NFV), where virtual machines (VMs) run on standard hardware [3]. A DT instance of the 6G gNodeB is created to enable accurate analysis and forecasting of maintenance needs as shown in Fig. 1 below. The AI agent monitors the UE-gNodeB connections for problems related to connectivity and capacity in order to prevent situations such as: (i) low-speed, (ii) call dropping, and (iii) premature service termination. These are the key performance indicators (KPIs) that are extracted as features for problem diagnosis, where problems such as: (i) gNodeB signal booster failure, (ii) operating system update issues, and (iii) data cap issues, can be results of the diagnosis. Then, the AI agent may recommend appropriate preventative actions. This is known as real-time predictive maintenance, and it increases the competitiveness and profitability of service providers by reducing system downtime. Artificial Intelligence (AI) is utilised in real-time predictive maintenance to assess the state of various network infrastructures. However, DT for predictive maintenance improves system reliability by enabling proactive fault prediction and accurate detection of equipment status. Thus, in this instance, real-time predictive maintenance refers to the system's ability to identify potential failure scenarios in the future and schedule fixes before the system malfunctions [6].

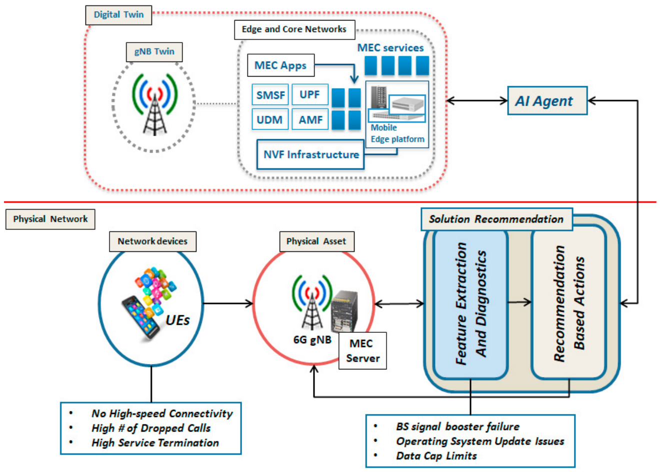

Fig. 1: Illustration of the digital twin instance of the intelligent virtual assistant for a 6G gNodeB [5]

3. Mathematical Problem Formulation

Assume the predictive model that optimizes the maintenance cycle of a gNodeB infrastructure and balances between a corrective and preventative maintenance approach. Suppose that for each KPI the problem consists of random variables

$$y(t) = \begin{cases} 0 & \text{if } t < 0 \\ 1 & \text{if } t \geq 0 \end{cases} \tag{1}$$

each representing the possibility of a failure event occurring within the time window [t, t + T], where T represents the finite horizon of prediction. Each KPI is assumed to have a feature variable X(t), which is a random variable that corresponds to the process variables up to the point t. The objective of this research project is to describe the conditional probability $p(y(t) \mid X(t))$ by the following function:
$f : u \rightarrow p \approx p(y(t) = 1 \mid X(t) = u)$.

4. Proposed system solution

In order to simulate a wireless network and estimate call drop rates using the Erds-Rényi model and a neural network, we employed the matlab programme. The Erds-Rényi model, a traditional technique for producing random graphs, is utilised to first generate the network at random. Then, each network node is given a random performance parameter, such as call drop rate, delay, or throughput.

A neural network model that consists of two layers with a logistic sigmoid activation function and is trained using the Levenberg-Marquardt algorithm is defined after the generation of the network and performance measures. The gathered data and key performance indicators (KPIs) pertaining to the drop call rate are used to train the neural network.

The performance of the trained neural network is then evaluated on a test set of data, which is also generated randomly using the Erdős-Rényi model. The test set includes the same performance metrics as the training data, and the accuracy of the neural network's predictions is calculated using mean absolute error.

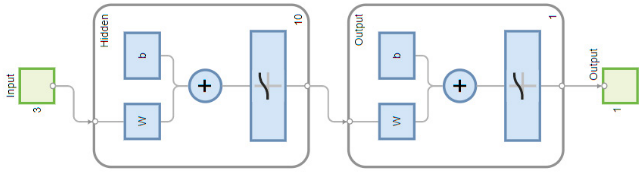

Fig. 2: : Feed Foward Neural Network

5. Results and discussions

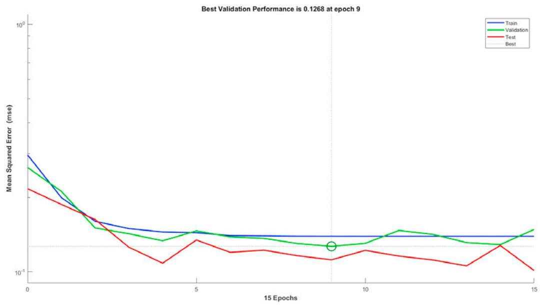

Fig. 3: :Neural network training performance

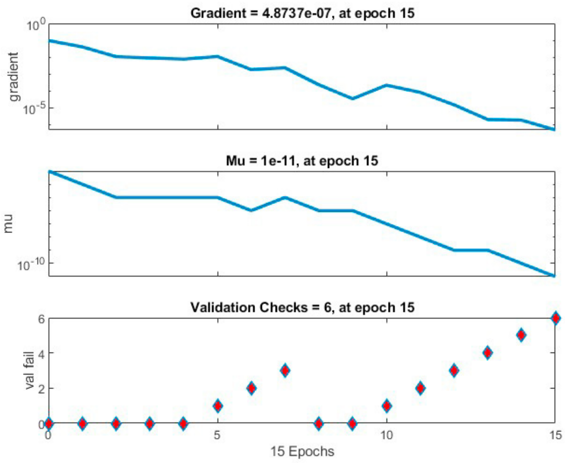

Fig. 4: : Neural network training state

The training process of a neural network involves repeatedly presenting the input data to the network and adjusting the weights and biases of the network's neurons to minimize the error between the predicted outputs and the actual outputs. This is done through an iterative optimization process called gradient descent.

Epoch refers to a single iteration of the entire dataset through the neural network during training. The number of epochs defines the number of times the entire dataset is presented to the network for training. The number of epochs is a hyperparameter that needs to be tuned to achieve the best performance of the neural network.

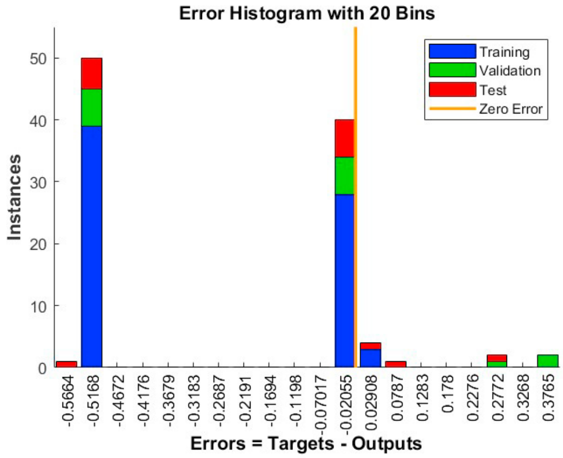

Fig. 5: : Neural network training error performance

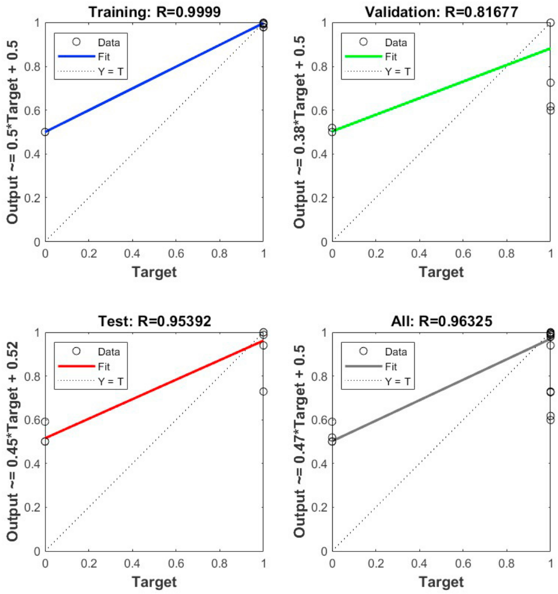

Fig. 6: :Neural network training regression

Elapsed time refers to the time taken to complete each epoch of training. This metric can be used to track the progress of training and to estimate the total time required to complete the training process.

Performance is a measure of the accuracy of the neural network's predictions. During training, the performance of the neural network is evaluated using a performance function such as mean squared error. The goal of the training process is to minimize the value of the performance function.

Gradient is the vector of partial derivatives of the performance function with respect to each of the weights and biases in the neural network. During training, the gradient is computed using backpropagation, which is a method for efficiently computing the gradient of the performance function with respect to the weights and biases.

Mu is the momentum term used in some optimization algorithms, such as the gradient descent with momentum. It is a hyperparameter that determines the amount of influence the previous updates have on the current update of the weights and biases.

Validation checks are used to monitor the performance of the neural network on a validation set during training. The validation set is a subset of the training data that is not used for training but is used to evaluate the performance of the neural network on data that it has not seen before. This helps to prevent overfitting, which is when the neural network memorizes the training data instead of learning the underlying patterns. The validation checks can be used to determine when to stop training the neural network to prevent overfitting.

6. Concluion

This research introduces a novel concept for predictive maintenance in 6G communication networks: the use of digital twin technology. The study highlights the need for more advanced maintenance approaches by highlighting the increasing need for increased dependability and continuous availability in these networks. The use of digital twin technology enables seamless artificial intelligence application for accurate maintenance scheduling and proactive anticipating of maintenance needs. It also makes real-time monitoring, analysis, and simulation of the 6G network possible. As a result, the article fervently promotes the use of digital twin technology as a vital instrument to improve maintenance standards in the context of 6G networks, guaranteeing increased operational dependability and efficiency.

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