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Machine Learning Methods for Coverage Prediction in Interoperable Hybrid Intelligent Systems for Self-Organizing 5G Networks

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ABSTRACT
5G technology is key in enabling faster and more reliable wireless connectivity. 5G networks should be organized in the form of self-organizing networks that support the functions of self-configuration, self-optimization, self-diagnosis and self-recovery. The 5G network self-organization system is an interoperable hybrid intelligent system. The paper discusses machine learning methods that can be used in this system when implementing the task of predicting the network coverage area, which is part of the network self-optimization function. Accurate forecasts of the network coverage area contribute to the efficient allocation of resources when self-optimizing the network, ensuring high quality services while reducing their cost.
Keywords*:5G networks, network self-organization, Network self-optimization, Machine learning, Coverage forecasting, Supervised learning, Deep learning*

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I. INTRODUCTION

The rapid development and deployment of fifth-generation (5G) cellular networks lead to new challenges in the telecommunications industry. One of the new requirements for 5G networks is the implementation of the Self-Organizing Network (SON) concept in the form of a set of functions for automatic configuration (self-configuration), self-optimization, self-diagnostics and self-healing of the network with virtually no operator involvement. In essence, SON is an interoperable hybrid intelligent system, as it provides real-time data transfer between different subsystems without human intervention, and uses various methods and technologies of artificial intelligence to solve different problems. This paper discusses Machine Learning (ML) techniques that used in interoperable hybrid intelligent SON systems in implementing one of the main tasks of the network self-optimization function - network coverage prediction task.

Coverage prediction is the ability to predict how well a 5G network will cover a certain geographical area, and how well it will provide reliable services in that area. Uncovered areas (holes) in cellular network coverage can occur when network planning fails or when network parameters are incorrectly configured. Their presence can lead to dropped calls. A coverage hole is an area in which the pilot signal strength from a base station is below the threshold required for a mobile device to access the network, or the ratio of useful signal strength to the sum of noise and interference SINR (Signal to Interference + Noise Ratio) in the serving and neighboring cells is below the level required to maintain basic service. Physical obstacles such as new buildings, hills, or inappropriate antenna parameters, or simply faulty network planning usually cause coverage holes. Typical manifestations of a coverage hole are frequent handover failures that cannot be resolved by optimizing the handover parameters, or frequent call drops that cannot be recovered by re-establishing a radio connection. The ability to predict coverage is critical for effective network planning and optimization, as it helps operators identify coverage gaps, optimize network resources, and improve end-user experience [1]. Machine learning algorithms are emerging as a promising approach to solve the coverage prediction problem. These algorithms can analyze large amounts of data and identify complex patterns and dependencies affecting network coverage.

Machine Learning (ML) is the ability of systems to acquire and continuously improve their own knowledge by extracting patterns from raw data to solve real-world knowledge problems and make decisions that appear subjective and mimic human “cognitive” functions [2]. Unlike traditional programming, where the developer explicitly sets the instructions used by the system, in machine learning the model is trained based on the provided data, and the results of the training become the basis for further decisions. Machine learning is a set of techniques that make predictions based on datasets and modeling algorithms.

Machine learning algorithms can be classified into three main categories based on how they process and utilize data: learning with a teacher (supervised learning), learning without a teacher (unsupervised learning), and reinforcement learning, of which deep learning is the main variant. This categorization helps to understand how machines learn from experience and make decisions.

II. MAIN SECTION

2.1. Model training data

Training data provides the model with information about the input features and corresponding correct responses. The more diverse, qualitative, and representative the data are, the better the model will be able to train itself, recognize patterns, and make correct predictions on the new data. When using ML algorithms for coverage prediction, one of the advantages is that the model can be trained on a variety of data that can affect the prediction results. The important parameters are not only the frequency, the distance between transmitter and receiver or the height of transmit and receive antennas, but also many other parameters that can be taken into account.

The study in [3] initiated the use of a large number and variety of parameters for training. In addition to the commonly used ones, additional parameters such as: tilt angle and azimuth angle of the transmitting antenna, transmitter power, interference, building height, distance of the receiving antenna from the main lobe signal are used. The data obtained from variations and utilization of additional parameters used as training data in training the machine learning algorithm.

2.2. Supervised machine learning algorithms for coverage prediction in 5G networks

Supervised learning is an approach to machine learning based on the use of labeled datasets. Such datasets are used to create algorithms that aim to classify data or accurately predict outcomes. Using the labeled inputs and outputs, the model can match input data and outputs for accuracy and gradually learn.

Predicting the coverage of 5G mobile networks categorized as a classification type task [4]. Classification is a type of supervised machine learning in which the model tries to predict the correct label for given input data. In classification, the model is fully trained on training data and then tested on test data and used to predict new unobserved data. Classification models are able to categorize input data into multiple classes or categories based on patterns and correlations that exist in the data. The purpose of classifying different locations or regions into groups is to predict 5G coverage. The most significant characteristics affecting coverage can be found using classification models. Regression analysis based on constructing a functional relationship between one or more independent variables and one dependent variable. This helps in network optimization by allowing better knowledge of the variables that have a significant impact on the quality of coverage. Regression and classification performed using different algorithms, with classification being a regression model with a threshold: a number is classified as true if it is above the threshold and as false if it is below.

A. Logistic regression (LR)

Regression categorizes all data into two groups - correct and incorrect indicators. It gets its name because it uses a logistic function to predict the probability of an object belonging to one of the classes. The algorithm can be used to predict the relationship between two variables. Regression gives the answer of how likely it is that a particular event will occur.

In telecommunications, this algorithm is most commonly used to predict and classify telecommunication customers based on their characteristics and behavior. The use of logistic regression algorithms allows for equations and calculations of probabilities that are needed to classify customers into different groups. In addition, this algorithmic model can be used by organizations to conduct market research, understand customer needs and produce relevant products, which leads to sustainable brand and network loyalty [5]. However, the logistic regression algorithm has never been used in studies related to predicting signal strength or coverage area.

B. Random Forest (RF)

Random forest is an ensemble learning method that combines multiple decision trees to improve the accuracy and reliability of the model. The algorithm works by building multiple decision trees on random subsets of data and then combining their predictions to obtain the final forecast. Random Forest can handle both categorical and continuous variables, as well as handle missing values and outliers.

The use of Random Forest algorithm for coverage prediction in cellular communication systems has been widely used and recommended because this algorithm can produce reasonably good performance evaluation results compared to other algorithms. In the study [6] Random Forest has shown the best results compared to other machine learning algorithms. In the study [7], an ensemble learning model was developed with Random Forest algorithm as the basis. The Extremely Randomized Trees Regressor (ERTR) algorithm model is used to predict the coverage of 5G networks in dense urban areas around Victoria and Ikoyi islands in Lagos, Nigeria. Currently, the RF algorithm is the most fully investigated for coverage prediction in cellular communication systems.

C. K-Nearest Neighbors (K-NN)

The K-Nearest Neighbors (K-NN) algorithm is a classification algorithm that can be used to solve classification and regression problems. It classifies objects based on their nearest neighbors. The algorithm uses a group of named points to label another point. The data is sorted based on similarity and K-NN can be used to fill in missing values. Once the missing values are filled, the dataset is subjected to several prediction algorithms, and using different combinations can improve accuracy. This algorithm is used for classification, regression and retrieval. The method works by finding K nearest data points to a new data point and assigning the new data point to the class with the highest frequency of occurrence among the K nearest neighbors. Cross-validation or other performance measures can be used to determine the value of K.

The K-NN algorithm has been previously used for coverage prediction. In the study presented in [8], a machine learning model is developed to predict radio signal power in certain areas based on transmitter placement. The dataset consists of modeled power values for a given set of transmitter locations. Various machine learning models have been tried including generalized linear models (GLM), neural networks (NN) and k-nearest neighbors (K-NN). In the study [8], the K-NN model has the best performance with mean absolute error (MAE) and is also much faster to train than others. However, it is not specified in which type of cellular network the study was conducted. Therefore, it is possible that the prediction results using K-NN will have different values for other cellular network conditions. The K-NN algorithm can be used to predict coverage based on a number of independent characteristics such as population density, terrain, and building features.

D. Naive Bayes (NB)

Naive Bayes is a probabilistic classification algorithm that works by calculating the probability of a new data point belonging to a particular class based on the probabilities of its features for that class.

The study presented in [9] proposed an approach for customer churn prediction (CCP, customer churn prediction) using NB classifier as a base model. It assumes that features are conditionally independent of the class label, which is a simplifying assumption known as the “naive” assumption. The classifier calculates the probability of each class label given the input features and selects the class label with the highest probability as the predicted class. It uses training data to estimate the probability of each feature value for each class label, and then combines these probabilities using Bayes' theorem to calculate the posterior probability of each class label for the input feature. Previously, the Naive Bayes algorithm has never been used to predict signal strength or coverage in cellular telecommunication systems.

E. Support Vector Machine (SVM)

SVM is a kernel-based model that uses kernel functions to solve regression problems and can transform datasets into different dimensions to find the best arrangement of hyperplanes. The goal of SVM is to construct a hyperplane in N-dimensional space that unambiguously divides the data into classes. N corresponds to the number of features, and the hyperplane is a straight line that divides the objects into these classes. The distance from it to each class should be maximized as accuracy depends on it.

From the study [10], it is observed that the use of SVM algorithm has limitations including the inefficiency of the model when dealing with large datasets and the presence of noise. The SVM algorithm showed lower predictive performance compared to the others. However, the SVM algorithm never used in studies related to coverage prediction.

F. AdaBoost

AdaBoost is an ensemble learning method that combines multiple weak classifiers to create a strong classifier. The method works by iteratively training weak classifiers on the data and applying large weights to misclassified data points. The final prediction is obtained by combining the predictions of all weak classifiers and weighting them according to their accuracy.

The AdaBoost algorithm used in various applications for wireless networks, including traffic optimization and network performance prediction [11]. However, the number of studies on the use of AdaBoost for coverage prediction is still limited.

G. Bayesian network (BN)

The study presented in [12] describes the use of Bayesian network (BN) for predicting throughput in 5G wireless networks. The BN algorithm is used in this study to predict future test results by estimating parameters such as base station utilization, user location and travel speed that affect the signal-to-noise ratio (SNR) received by users and signal-to-interference-noise ratio (SINR). Computer simulation results show that the BN model can effectively determine the user throughput in low-speed traffic. In [13], the modeling of service reliability prediction of 5G wireless networks using Bayesian networks is discussed. This model used to predict the service reliability of the network and infer the latent state of the network. The use of Bayesian networks allows a compact representation of the joint probability distribution, which simplifies the modeling of network service reliability.

Bayesian networks offer several advantages over classical methods such as Markov chains, Decision trees and Petri nets, including the ability to model complex systems, make predictions and diagnoses, compute event probabilities, update calculations based on evidence, represent multimodal variables and provide a convenient graphical approach. The BN algorithm is mainly used to predict the capacity and number of users in cellular network systems. Meanwhile, there has been no research related to coverage and signal strength prediction so far.

H. Neural Networks

A neural network is a mathematical model (computational system) that consists of neurons, which are nodes organized into layers. Each layer contains several nodes, which connected to all nodes in the network by means of different links and have their own "weight" affecting the strength of the transmitted signal. This architecture allows for parallel processing of data and constant comparison with the results of processing at each stage. Neural networks are initially trained on sized data sets with obvious patterns, and then use the acquired skills for self-learning and achieving results. Neural networks are now superior to most other models, regardless of the task, as they can make millions of attempts to achieve the same results as the example provided for training. Different neural networks can be used for different tasks in telecommunications. For prediction purposes, the most suitable is the feed forward artificial neural network (ANN), which is a multilayer neural network without feedbacks and delays and is able to establish a functional relationship between the original and predicted data.

The study presented in [14] describes the possibility of using artificial neural networks to predict electromagnetic wave propagation losses and signal level deviation. The work in [15] investigates the use of ANNs to predict network traffic of a high-density three-dimensional network. The conducted neural network studies demonstrate good long-term prediction accuracy, as well as high adaptability and the ability of the algorithms to establish functional relationships under conditions of inaccuracy of the conducted measurements. Such ML method can be used to solve the problems of forecasting the coverage areas of communication networks, but there has been little research in this area.

I. XGBoost

XGBoost is an ensemble learning method that combines multiple decision trees to improve model accuracy and reliability. XGBoost is known for its scalability, speed and ability to handle large amounts of data. The XGBoost algorithm mainly used so far to develop customer churn prediction and traffic classification models [16]. The use of XGBoost algorithm is still limited, especially in coverage prediction in mobile telecommunication systems.

2.3. Deep learning algorithms for coverage prediction in 5G networks

Deep learning is a branch of machine learning that utilizes deep neural networks to understand complex and deep patterns in data. The difference between deep learning algorithms and conventional machine learning is the ability of deep learning algorithms to automatically extract more complex features without requiring manual extraction. Deep learning algorithms are better at dealing with unstructured data, and the layers in neural networks allow for a deeper understanding of patterns.

A. Multilayer Perceptron (MLP)

A multilayer perceptron (MLP) is a type of neural network architecture consisting of multiple interconnected layers. Each neuron in one layer connected to a neuron in the next layer. MLP used to solve problems such as classification, regression, and pattern recognition in complex and nonlinear data. Multilayer Perceptron (MLP) is a type of forward-looking artificial neural network that is suitable for modeling nonlinear data and is widely used in various prediction applications.

The study reported in [17] considers path loss prediction using MLP-based neural networks, which used for network planning and optimization in 5G communication systems. Path loss characterizes the decrease in the power density of any given electromagnetic wave as it propagates through space. There are various causes of path loss, ranging from the natural broadening of the radio wave, diffraction path loss caused by an obstacle, to absorption path loss, which occurs due to the presence of a medium that is opaque to electromagnetic waves.

It is important to note that even when path loss occurs, the transmitted signal can still propagate along other paths to its intended destination, a process called multipath propagation. An MLP-based path loss model created by combining measurement data and environmental characteristics. Comparative analysis of the experimental data shows that MLP neural networks can accurately predict path loss, and the inclusion of environmental features improves the model performance. To address the problem of interference noise that reduces the accuracy of MLP-based path loss models and their sensitivity to environmental changes, the authors of [17] improved the method for determining environmental features based on line-of-sight (LOs) and non-line-of-sight (NLOs) cues. As a result, the stability and generalization ability of the MLP-based model were significantly increased. However, the use of MLP algorithms is limited in studies of cellular network coverage.

B. Converged neural network (CNN)

Converged neural networks (CNNs) are a class of deep neural networks that have a specialized architecture for processing spatially structured data such as images. They are widely used in computer vision, pattern recognition, time series analysis, and other tasks where it is important to consider spatial dependencies between data. Each layer of such a network processes the data and sends the identified features to the next layer for further processing. They use filters that help to highlight important features, such as edges or shapes of objects in an image. CNNs applied in the context of predicting coverage areas of 5G networks, especially when spatial data such as maps of communication networks used as input. In addition, CNNs used to analyze satellite images or network maps to detect and be able to optimize important elements of telecommunication networks such as cell towers (base stations), network topology or user density in a specific area.

In the study presented in [18], CNN is applied as a model training algorithm to obtain power estimates with good accuracy and real-time simulation speed. The preprocessing methods for training data are improved. However, the rationale for using CNN algorithm is not explained in this study, so the advantages of using CNN in this study are not clear. The study [18] proposes a CNN-based autoencoder, CNN-AE (Convolutional Neural Network-based Auto Encoder), for predicting network throughput based on base station location and coverage probability in cellular networks. Auto Encoder is an unsupervised learning algorithm for ANNs used to train a compressed and encoded data representation, mainly for dimensionality reduction and unsupervised pre-training of direct-coupled NSs. In [18], the performance of CNN-AE is compared with analytical models based on stochastic geometry and a significant error reduction is demonstrated. In addition, this paper proposes a low complexity algorithm that utilizes the trained CNN-AE to compute the locations of new base stations to achieve certain performance goals. The improved performance of CNN-AE compared to stochastic geometry-based models suggests that deep learning-based approaches can provide more accurate estimates of network performance in real-world scenarios. The results of some studies that have been conducted and presented in other works show that the use of CNN algorithms can be one of the best options for coverage prediction, especially in systems with 5G technology.

C. Recurrent Neural Network (RNN)

A recurrent neural network (RNN) is the most sophisticated type of neural network and therefore the closest to a real human brain that processes sequential inputs. It can learn the behavior of a given training data over time to demonstrate the effect of a previous event on the next event. Compared to feed-forward neural networks, RNN is a state-tracking network. It can contain computational cycles between states and uses time as a parameter in the block-to-block transition function. Unlike MLPs and CNNs, an RNN retains information about previous characters in a sequence, which allows the context and sequence of the input data to taken into account.

There is no widely accepted approach to train RNNs, and many new methods (both supervised and unsupervised) are introduced to train RNNs. Considering RNNs in the scope of this paper, we use RNNs with long-term short-term memory LSTM (Long Short-Term Memory). One of the main advantages of LSTMs is their ability to overcome the vanishing gradient problem commonly found in conventional neural networks. This allows LSTMs to analyze information over long periods and make predictions based on long-term data and learned patterns. LSTM used to predict trends and patterns in real-time data such as network traffic, service requests or network utilization rate.

The study presented in [20] examines the prediction of throughput in LTE networks using LSTM model. The researchers collected TCP and throughput log data in LTE networks and transformed them using CUBIC and BBR trace log data. The LSTM model with attention mechanism trained based on the collected data. From the presented research results, it observed that the proposed LSTM based model achieves better throughput prediction performance.

The study [21] proposed an mLSTM model to improve mobility management in 5G networks. The number of LSTM layers and hidden units is crucial to improve mobility management in 5G networks using deep residual LSTM model. These layers act as memory units for the network to store information over time, while the hidden units perform complex computations over the input data. The results of the study showed the effectiveness of the proposed method to improve mobility management in 5G networks.

In the study [22], a prediction method for evaluating network performance based on business requirements based on VMD-LSTM time series analysis proposed. In a 5G network, by creating an appropriate VMD-LSTM model to predict the RTT (Round Trip Time) and comparing the actual RTT with the predicted one, abnormal values identified and their causes analyzed to improve the 5G network performance. The method discussed in this paper, according to the authors, used for RTT prediction and traffic control compensation during the sampling period of control systems, which reduces the impact of RTT-induced control instruction packet loss and improves the reliability of control algorithms.

Despite a large number of studies, the LSTM algorithm has not directly considered for coverage prediction, especially in 5G cellular systems.

D. Deep Neural Networks (DNN)

Deep Neural Networks, DNN is a type of neural network that consists of multiple layers with multiple layers between the input and output layers. Each neuron in one layer connects to all neurons in the next layer. One or more layers between the input and output layers called hidden layers.

Non-orthogonal multiple access (NOMA) is a promising direction for 5G that radically changes the way spectrum allocated among users. In [23], we explore the possibility of applying the DNN model to solve the user clustering (UC) problem for NOMA 5G networks. The inclusion of more hidden layers in the DNN model allowed DNN-UC to better characterize the nonlinear transformation of diversity in channel gain and power into cluster formation. After cluster formation, an efficient power allocation scheme is implemented to ensure that all users can achieve the required minimum throughput subject to the SIC constraint in each cluster. Under the best hyperparameters, the proposed DNN-UC model, according to the authors, is able to achieve near-optimal performance in terms of throughput, and is adaptive and robust in any NOMA environments without re-training the model. However, due to the deep architecture of the proposed method, which includes multiple processing layers and nonlinear transformations, the training process of DNN-UC is slower and the computational complexity for the testing phase compared to ANN-UC.

The prospect of billions of interconnected devices within the Internet of Things (IoT) paradigm has become a major driver of research and development in the ICT sector. Connected MTC (Machine Type Communications) devices include, for example, smart meters, smoke detectors and consumer electronic devices. The work [24] considers the implementation of AI techniques to estimate the current traffic load offered in an mMTC scenario consisting of a dense distribution of low power, lowcost MTC devices that sporadically transmit small packets with relaxed delay requirements. The work evaluates current access attempts based on a DNN that takes as input only information actually available at the next generation Node B (gNB, generation Node B). The DNN-based traffic load estimation method was then compared with other benchmark schemes available in the literature in terms of regression accuracy, both in a static analysis that considers an autonomous RA (Random Access) cycle and through a long-term analysis with a time-varying proposed load. This evaluation is relevant for mMTC (massive Machine Type Communications) scenarios to properly manage the access requests of a huge number of MTC devices. The use of DNN algorithms to determine the coverage area of cellular networks has not investigated.

III. RESULTS

The development of communication networks continues in the direction of using the concepts of ultra-dense networks and ultra-low latency communication networks, which determines the prospects for the creation of fifth and subsequent generations of communication networks. At the same time, the structures of such networks and the tasks of resource allocation for them are becoming so complex that the use of artificial intelligence technologies is often the only way to fulfill the requirements for quality of service and quality of perception. Machine learning algorithms have become a promising approach for solving the problem of 5G coverage prediction. These algorithms can analyze large amounts of data and identify complex patterns and dependencies affecting the coverage area of a cellular network. The coverage prediction model helps network operators to find coverage gaps, plan base station locations, evaluate quality of service, and build radio maps for spectrum sharing, interference management, localization, etc. It is evident from various studies that the coverage prediction results obtained from machine learning algorithms provide more accurate prediction results compared to the prediction results using traditional methods. However, not all the capabilities of supervised machine learning algorithms for coverage prediction of cellular communication networks have been investigated. Therefore, research on different machine learning algorithms with different examples and parameter variations is still ongoing to obtain algorithms with the best prediction results and performance evaluation metrics.

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