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Original Article

Enhancement of Signal to Interference plus Noise Ratio Prediction (SINR) in 5G Networks using a Machine Learning Approach

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Abstract - *Due to the increasing number of connected users and devices, 5G networks require higher data rates for various applications. However, its applications or services and other next-generation wireless networks still need resources such as large bandwidth, less latency, and reduced interferences to improve their efficiency. The efficient management of resources is one of the main challenges in the network itself. Monitoring an important parameter like the Signal-to Interference plus Noise-Ratio helps to minimize the wastage of radio resources due to poor channel conditions. It is worthwhile to take advantage of machine learning for predicting channel conditions. Therefore, knowing the channel conditions helps efficiently utilize the network's resources. There are existing papers in the literature dealing with the same prediction of Signal-to-Interference plus Noise Ration, but the presented results of their models are insufficient enough for a real-world scenario of a 5G network. The proposed method is based on supervised learning using logistic regression. Batch Gradient Descent has been applied as an optimization algorithm for better results. The application of this algorithm helped to obtain minimum loss and great accuracy. The research objective is to obtain higher accuracy and minimize the loss function of the prediction model compared to the most recently reported works in the literature. The predicted Signal-to-Interference-plus-Noise-Ratio is a discrete value for each established connection between the mobile station and the base station. After a simulation of 1000 epochs, results obtained showed an accuracy of 0.90 and an error of 0.1, indicating some significant improvement over other works reported in the literature*.

Keywords - *5G, Artificial Intelligence, Logistic Regression, Machine learning, Signal to Interference plus Noise Ratio.*

1. Introduction

The fifth generation (5G) of mobile networks is built for multi-services and multi-tenancy support. Also, it greatly impacts industries and the general society [1]. This new type of mobile network offers three categories of services: enhanced Mobile Broadband (eMBB), Ultra-Reliable and Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC). The first category of services is eMBB, which is made for applications that need more data rates anytime and anywhere. It allows more data rates for multimedia content access or services. Also, it improves connectivity, performance, and user experiences. The second type of service is URLLC. Here, this type is made for applications that require less latency, reliability, and availability. Those kinds of applications can be wireless control in industrial manufacturing, remote medical interventions, smart grid operations, and remote vehicle guidance [20]. The last one is mMTC [3], which includes services with many connected devices at low cost and low power consumption. It offers logistic applications and smart metering [1].

Mobile networks have greatly enhanced social interaction and improved the quality of life. This ease has also brought a lot of questions or challenges to mobile network operators and researchers, such as efficient spectrum management.

The signal quality between the users and the network (base station) is measured by the signal-to-interference plus Noise Ratio (SINR). The spectrum in 5G and other networks is allocated based on the channel conditions, which depend on the SINR value [4]. R. Ullah et al. in [4] proposed a machine learning model based on an Artificial Neural Network (ANN) to solve this network radio resource wastage issue. Their work was to predict the channel conditions (SINR) based on the location of the Cyber-Physical System (CPS), which is the geographical coordinate. Then, the location of the CPS is sent to the base station as a signal containing the Position Reference Signal (PRS) and the Observed Time Difference of Arrival (OTDoA).

In this paper, a novel approach for predicting channel conditions has been proposed. The approach is built based on supervised learning using logistic regression. The objective is to optimize the prediction of SINR with higher accuracy and less error. To achieve that objective, Batch Gradient Descent has been applied. This technique permitted the minimization of the loss function for the model. This approach has achieved an accuracy of 0.90 and an error of 0.1 for predicting the Signal-to-Interference plus Noise Ratio (SINR). After comparisons, the novel approach is more accurate and significantly improved over other proposed methods reported in the literature below. The paper starts with a brief presentation of previous works in the SINR or SNR prediction domain. Then a clear description of the method used is provided. Lastly, the results and discussion are presented. At the end of the paper, a conclusion is made.

2. Literature Review

Ways to save the spectrum in mobile wireless networks are new research directions. For the 5G networks, the New Radio channel (NR) has been standardized in the 3GPP release 15[5]. Also, the data for the 5G is up to 10 Gbps and operates in millimeter band frequency from 30 GHz up to 300 GHz [6]. The reference signals consume up to 25% of the spectrum in the mobile network system. New approaches present machine learning as a suitable candidate to deal successfully with resource utilization in 5G [4].

K. Saija et al., in [24], proposed machine learning approaches to mitigate the long delay of the channel state information (CSI) feedback. This approach was based on batch, online, and deep learning. There is a communication between the BS and the MS, during which the BS sends a CSI-RS signal in the downlink to the Mobile Station (MS), and the MS sends back to the BS the CSI-RS (CSI Reference-Signal) in the uplink as a response. The Signal Noise Ratio (SNR) and the time were used to target the Channel Quality Indicator (CQI) to improve the SNR prediction using machine learning.

In [8], F. D. Calabrese et al. considered two different approaches to machine learning. The first is Reinforcement Learning (RL), and the second is Artificial Neural Networks (ANN). The problem was focused on radio resource management using a machine learning model. The authors proposed an architecture to train the model in 5G networks. The main parameters for the prediction were the power control, the cell, and the bandwidth.

M. Chen et al. in [9] focused on the issues of spectrum management and multiple access systems. An Artificial Neural Network approach has been adopted to solve resource management problems. In this model, the inputs were the network conditions and the model frequency as a target. The model was able to switch between different bands of frequency. This switching feature permits a selection of a frequency used according to an available Line Of Sight (LOS) in the chosen environment.

In [10], D. Kumar et al. were interested in web internet services. They proposed a machine learning model for HTTP service, which is the upper layer of the OSI model. The aim was to get fast and smooth data transmission over the network. The approach here was an unsupervised learning method. The work reported a 7% improvement in the peak of SNR, and up to 25% improvement in video performance was realized.

P. Casas in [11] proposed a method based on Ensemble Learning (EL), chosen among seven different algorithms. The other six algorithms were decision trees, Naïve Bayes, machine learning (Multi Layers Perceptron), SVM (Support vector machine), RF (Random Forest), and K Nearest Neighbors. The purpose was to solve smartphone traffic problems over the mobile network. Indeed, smartphones generated abnormal large data traffic using different applications. The Quality of Experience (QoE) prediction was based on the use of those applications. As a result, 99% of the Ensemble Learning model was achieved.

In [12], N. Strodthoff et al. investigated E-HARQ, which means Early Hybrid Automatic Repeat reQuest. The authors proposed a machine-learning method for predicting the decoding system at the end of the transmission process. A supervised auto-encoders algorithm was used. The system was evaluated based on the prospect of conformity with the URLLC requirements, including a small block error rate of less than 10 to 5.

J. Suomalainen et al. in [13] present some faults related to machine learning techniques in mobile wireless communications. Indeed, using machine learning approaches in 5G networks to solve problems will open serious and several cyber security attacks. The process of machine learning is collecting data from the environment. So, the data represent potential sources of vulnerabilities like denial of service, phishing, and leakage of privacy or confidentiality.

In [14], F. Mismar et al. worked on optimizing the SINR in the downlink. In their paper, the main concern was the multi-access OFDM in a cellular network from the multi-antenna used by the base station to the unique antenna for the user equipment. The design of the system was made on two bands of frequency. The sub-6 GHz was used for the voice and the millimeter-wave for data testing.

K Yang et al. in [15] used the deep learning method to estimate the Signal Noise Ratio (SNR). That technique mainly focuses on the advantages of deep learning or the inconvenience caused by the classical estimation method. The technique used is the Non-Data-Aid (NDA). The proposed model allowed the estimation of the SNR in the baseband as the SNR of an IF signal.

In [16], E. Balevi interconnects the fog and heterogeneous cellular networks. The method used was an unsupervised algorithm where the objective was to reduce latency and improve the QoS. Enough latency has been reduced to reach the 5G latency requirement, which is 1 millisecond.

In [17], F. Mismar et al. worked on the SINR in 5G networks. The aim was to enhance communication performance by maximizing the SINR. Using deep learning, they used a joint design of beamforming, power control, and interference coordination as a non-convex optimization method.

R. Falkenberg et al. in [18] proposed a novel machine-learning approach for predicting the uplink transmission power used for data transmissions in 5G networks. The model was based on the available passive network quality indicators and application-level information.

In [4], R. Ullah et al. proposed a machine learning technique to estimate or predict the channel condition (SINR). The method was based on the Artificial Neural Network scheme (Non-Linear Auto regressive External/Exogenous: NARX). Most of the radio resources of the 5G network have been improved (the bandwidth, the throughput, and less consumption of energy). Around 4.1 milliwatts of energy were saved, the bandwidth was increased by 4%, and the throughput by 2%. The performance of the machine learning model is given respectively by the accuracy of 0.87 and the Mean Squared Error (MSE) value of 12.88.

3. Materials and Methods

3.1. Materials

The software Matlab coupled to Vienna 5G System Level (SL) Simulator has been used to simulate the 5G network. The data have been generated from the Vienna simulator. In this case, the generated data are imported into Jupyter, a web-based interactive computing platform for python coding. A laptop model HP Omen 15, corei7, NVidia GeForce RTX, 16 GB RAM, and 12 cores were employed in the simulation.

3.2. Methods

3.2.1. Conventional Method

Conventionally, the base stations perform SINR estimation in mobile systems. In the classical model, the Cyber-Physical System sends the Sounding Reference Signal (estimation of the channel) and the Positioning Reference Signal (its position) to the base station.

The BS estimates the SINR based on the received SRS value. This process consumes a lot of the bandwidth resources over the network. Almost 25% of the bandwidth is used [4]. After estimating the SINR value, the radio resources are assigned (scheduling process) according to the value of the SINR obtained for each user in the downlink. The classical system is depicted in figure 1.

3.2.2. Proposed Method

The new aspect of this proposed method is the machine learning application. In the machine learning approach, it is possible to deal successfully with the problem of the classical method. In the classical method, significant radio resources are spent on estimating the channel conditions in mobile networks. For instance, the reference signals consume up to 25% of the spectrum in predicting the SINR [4]. For this work, an intelligent system has been elaborated to replace the classical method to save the spectrum.

The proposed model is based on the work done by Ullah et al. [4] but with notable differences. For example, with the use of logistic regression instead of non-linear auto-autoregression. In addition, the number of base stations has been increased from 1 to 15. Using 15 node B for the simulation is a more realistic simulation involving interference intra-BS and inter-BS.

The proposed method follows these steps: 5G network scenario simulation, problem modeling, data extraction or acquisition, data preprocessing, model training, and model testing.

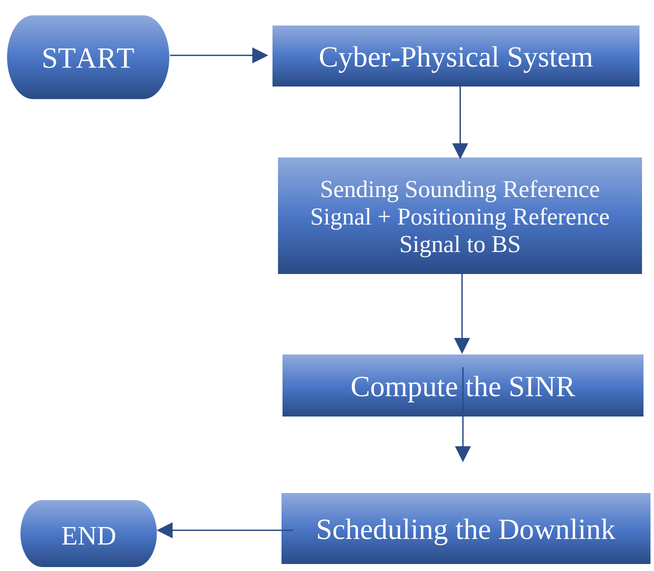

Fig. 1 Flow chart of the classical system [4]

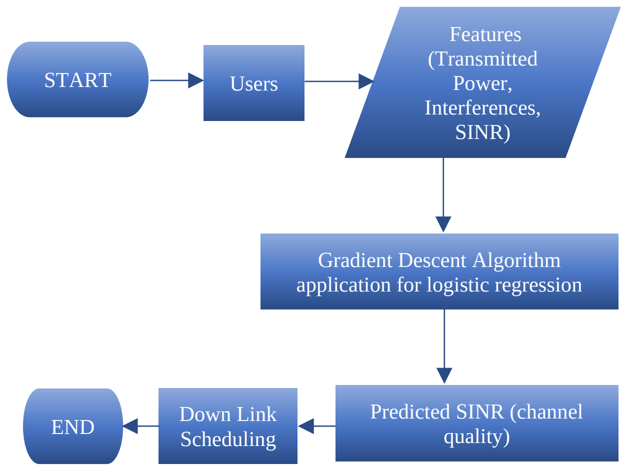

Fig. 2 Flow chart of the proposed method-based machine

Fig. 2 shows the proposed method based on a machine-learning model. From the flow chart in figure 2, the process is as follows. After the network simulation, the features obtained from the users are the transmitted powers, the interferences, and the SINR between each base station and the user. Then those features are extracted and arranged in the preprocessing phase. After preprocessing the data, the features are given as inputs to the machine learning algorithm or model. So, the model predicts the channel quality: SINR. Finally, the radio resources are allocated according to the predicted channel quality.

3.2.3. Scenario Definition

The first step was simulating a 5G network using Vienna Simulator coupled with Matlab.

Compared to the others in the literature, this scenario is more realistic. The most recent paper in [4], using the same simulator and dealing with the same topic, defined the network simulation with only one base station. More than one base station was used to properly evaluate interferences and noise between the users and the Base Stations and between the base stations. The parameters (For eMBB applications) of the system are presented in table 1. Those parameters are chosen based on ITU's requirements for 5G network simulation [4].

4. Simulation Configurations

For each link between the user and the BS, the SINR is computed using the following equations:

$$\text{SINR}=\frac{Transmitted\_Power}{Noise\ spectral\ Density + Interferences} \quad (1)$$

$$SINR_i = \frac{P_i}{NO_i + I_i} \quad (2)$$

$$SINR_i = \frac{P_i}{\sum_1^k NO_l + \sum_1^N I_j} \quad (3)$$

Where,

P_i: is the transmitted power from the BS to the related user number i.
NO_i: Noise spectral density for ith established communication
I_i: All interferences due to the ith established communication and neighboring
N: Number of interferences sources
K: Number of noise sources
$SINR_i$: It determines the SINR value for each established link.

Where, the noise:

$$No = -174 + 10\log_{10}(B) \quad (4)$$

And where B is the bandwidth in Hertz (Hz). The interference value used in the Vienna Simulator is obtained by combining three parameters: path loss (L), shadow fading, and channel modeling [4]. In the software Vienna 5G, the path-loss model L for the free space is defined by the equation.

$$L = 128.1 + 37.6\log_{10} d \quad (5)$$

Here, d is the distance between the transmitter and the receiver in km. The constant parameters 128.1 and 37.6 are dependent on the antenna gain.

The channel modeling depends on the antenna technology (MIMO or SISO), and shadowing refers to obstacles along the transmission path.

Table 1. Configuration parameters

Parameters	Values
Number of vehicles	500
Number of Pedestrians	500
Indoor users	500
Mobility	Vehicular & Pedestrian
Type of BS	Macro, Femto, Pico
Number of BS	15
Antenna Heights	10 meters
Transmitted power	0.1W Femto, 2W for micro, 40 W for macro
Channel condition	NLOS & LOS
Path loss model	Urban Macro 3D, Free space
User max speed	30 km/h
Inter BS distance	500 meters
Number of rings	3
Channel model	Pedestrian, Vehicular
Frequency	100 GHz
User distribution	Random
BS distribution	Poisson Point Process
5G application	Dense Urban for eMMB

This model uses 15 BS for the defined Region Of Interest (ROI). Random distribution is used to place the users over the ROI. Using 15 BS for the simulation is a more realistic simulation involving interference intra-BS and inter-BS.

4.1. Problem Modeling

The problem can be modeled into a classification problem. Table 2 shows a classification made according to the SINR values. A binary classification made from table 2 is given in table 3.

Table 2. SINR classification

SINR Value	Signal strength	Comments
>20 dB	Excellent	Very strong signal
13Db – 20dB	Good	Strong signal
0 dB- 12.99 dB	Fair to poor	Smallest enough
< 0 dB	No signal	Very bad connection

The system works in the perspective of allocating the resources or not, depending on the channel quality (SINR) in a given direction. If the channel quality is bad, then there is no need to send the radio resources to waste them. Once the channel is good, the system can send the radio resource in the given direction. So, the decision to make is binary and suitable for the problem. Also, the conversion from table 2 to table 3 has been done for optimization purposes. Table 2 shows the suitable algorithm for this kind of problem is multiclass regression. It could have been possible to do so, but for optimization purposes, conversion from the multiclass problem to a binary problem has been made. The conversion permitted to saving of computational resources and time. Simulation estimates the computational time for this problem in the multiclass regression approach at 6s (double the binary approach time, which is 3s).

Table 3. SINR Classification

SINR Values	Signal strength	Binary decision
For values greater or equal to 13 dB	Good enough for transmission	1
For values smaller than 13 dB	Bad signal	0

4.2. Data Acquisition

The data are generated using the scenario already chosen in Matlab coupled with Vienna Simulator. The features are the transmitted power, the interferences, and the SINR values for each established link user-BS. The transmitted power and interferences are the inputs. The SINR is the label. The dataset generated for the coordinates is a 2x1500 matrix, and the one for the SINR is a 1x1500 matrix.

4.3. Data Preprocessing

To automate this process, a Matlab code has been created. The SINR is extracted from the variable result.SINR_DL, the transmitted power, and the interferences values from the variable result.networkResults.user list. Excel files are used to extract the data (function of copy and paste). A Visual Basic for Applications (VBA) code is also used to process the data.

4.3. Data Labeling

The data are labeled in table 4

Table 4. Labeled data

Data	Signal Strength
Transmitted power	Ptx
Interferences	I
SINR	SINR_values

The transmitted power is labeled Ptx. The interferences noted as I and the SINR labeled as SINR values.

4.5. Training and Testing

The model's training is based on the data initially labeled in the training set. The model is trained to predict the SINR quality based on those inputs. The method used is logistic regression.

The training is done using stochastic gradient descent and cross-entropy loss. For the test, with an example x, we compute p (y\x) and get a higher probability for the label y=1 or y=0.

The chosen training set and testing set are each 50 percent of the total dataset. The training is 750 data as well as the testing set.

4.6. Logistic Regression

It helps to solve classification problems. It uses probability to classify an element belonging to a particular class. According to the probability associated with the element, the class is determined. Logistic regression is a function that associates an element from R (a set of real numbers) to the interval [0, 1]. The logistic regression is modeled mathematically by the logistic function, which is:

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{6}$$

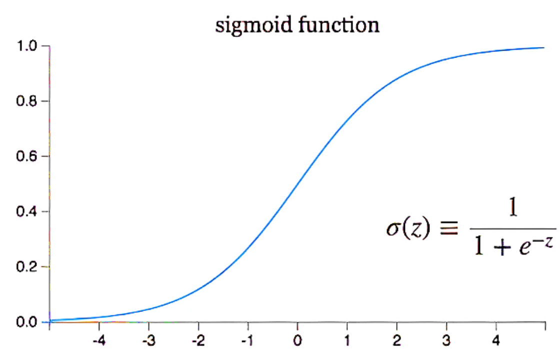

Fig. 3 Sigmoid function

This function is called the sigmoid function, and its graphical representation is shown in figure 3.

Here the z-variable is defined as:

$$z = b + w_1x_1 + w_2x_2 + \cdots + w_nx_n = b + \sum_{k=1}^{n} w_ix_i \quad (7)$$

The idea is to predict the class of the dependent variable z using independent variables $x_1, x_2 \ldots x_n$

Where b is the bias, w is the weight, and x is the input. The weight is a real number and represents the importance of each feature in the classification decision. For this work, the interference will get a higher weight. It means interference is the most important for this model. The transmitted power is a constant value depending on the type of base station; the noise in Vienna 5G defined is also a constant.

The following initial parameters have been defined for the model, w_1=1.5; $w_2 = 2.5$ and b=0. These parameters are randomly chosen and updated at each epoch to get the optimal accuracy and error function values.

The weight w_1 is attributed to the transmitted power and w_2 to the interference. The parameter w_2 is bigger than w_1 1 because interference is the most important parameter in estimating the Signal Interference plus Noise Ratio.

The learning rate is a hyperparameter; it controls the changing rate for the parameters. If the learning rate is too small, the model will take time to get to the minimum cost or give better results. But if the learning rate is too high, the learning will take too large steps and go beyond the minimum cost for the model. The good learning rate values range from 0.1 to 0.3[21]. For this model, 0.1 has been used as the learning rate.

Combining equation (6) with equation (7) gives:

$$\sigma(z) = \frac{1}{1+ e^{-(b+\sum_1^n w_iX_i)}} \quad (8)$$

n: number of inputs variables.

The decision process is made according to a decision boundary. The decision boundary is:

$$\text{Decision (x)} = \begin{cases} 1, \text{ if } p(y=1|x) > 0.5 \\ 0, \text{ otherwise} \end{cases}$$

The probability p(y=1|x) is a computed probability, for instance, x.

4.7. The stochastic Gradient Descent Algorithm

Gradient Descent aims to find the optimal weights and biases that minimize the loss function. In the logistic regression case, the loss function is characterized by a parameter noted θ (θ= w, b) [21]. The Gradient Descent Algorithm is a method to find the minimum loss function by analyzing in which direction the function's shape is raising the most steeply and going forward in the opposite direction. The loss function is convex, with just one minimum and no local minima getting stuck. So, the Gradient Descent guarantees finding the minimum for the loss function.

The following paragraph is an illustration. A random initialization for the weights w for the first step and the loss function is L in figure 4. There is a need for an algorithm to identify whether, at the next iteration, a movement to the left or the right can help reach the minimum: This is the role of the Gradient Descent Algorithm.

The value of the slope gives the direction in which the movement is done $\frac{d}{dw}L(f(x; w), y)$ weighted by the learning rate α. Alpha is called the learning rate.

For updating the weights of the parameters, the following formulas have been used:

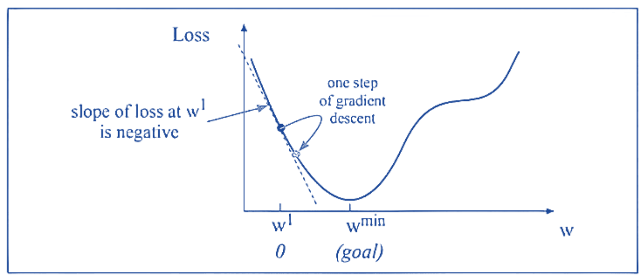

Fig. 4 The stochastic gradient descent

$$w^{t+1} = w^t - \alpha \frac{d}{dw} L(f(x; w), y) \quad (9)$$

Generalization of the previous formula permitted this next equation and updated the bias.

$$\theta^{t+1} = \theta^t - \alpha \nabla L(f(x; \theta), y) \quad (10)$$

$\frac{d}{dw}L(f(x; w), y)$ is the partial derivative of the loss function following w.

$\nabla L(f(x; \theta), y)$ is the gradient of the loss function.

$$\text{Where, } \nabla L(f(x; \theta), y) = \begin{bmatrix} \frac{\partial}{\partial w_1} L(f(x; \theta), y) \\ \frac{\partial}{\partial w_2} L(f(x; \theta), y) \\ \vdots \\ \frac{\partial}{\partial w_n} L(f(x; \theta), y) \\ \frac{\partial}{\partial b} L(f(x; \theta), y) \end{bmatrix} \quad (11)$$

The Stochastic Gradient Descent Algorithm is shown below:

Function STOCHASTIC GRADIENT DESCENT (L (), x, y) returns θ

where: L is the loss function

f is a function parameterized by θ

x is the set of training inputs $x^{(1)}$, $x^{(2)}$, ..., $x^{(m)}$

#y is the set of the training outputs (labels) $y^{(1)}$, $y^{(2)}$, ..., $y^{(m)}$

#m is the size of the sample

$\theta \leftarrow 0$

Repeat til done # see caption

For each training tuple $(x^{(1)}, y^{(1)})$ (in random order)

1. Optimal (for reporting): # How this tuple is done

Compute $\hat{y}^{(i)} = f(x^{(i)};\ \theta)$ # What is the estimated output $\hat{y}$?

Compute the loss $L(\hat{y}^{(i)};\ y^{(i)})$ #How far off is $\hat{y}^{(i)}$ from the true output $y^{(i)}$?

2. g $\leftarrow \nabla_{\theta} L\big(f(x^{(i)};\ \theta), y^{(i)}\big)$ #How should θ be moved to maximize the loss
3. $\theta \leftarrow \theta$ - αg #Go the other way instead

Return θ

At 1000 epochs, the values of weights and bias of the model optimization are: $w_1 = .5$; $w_2 = 1.0$ and b=0.05. Those values are optimal for a minimum loss function and the best accuracy.

5. Results and discussion

After the 5G network simulation, the following figures are obtained (Figures 5, 6, 7, 8, and 9). The first one (figure 5) presents the geographical positions of the users.

5.1. Geographical Positions

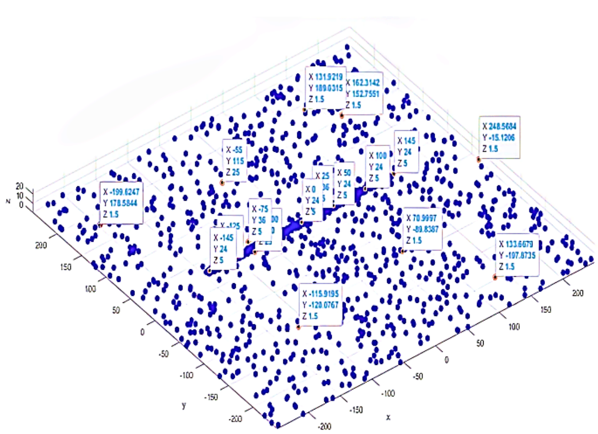

Fig. 5 Geographical coordinates of users

A footprint of the Region Of Interest (ROI) is obtained through simulation using Vienna 5G. The users are placed according to the random distribution process defined in Vienna simulator. Defining the users according to a random process is one of the most suitable configurations which describes reality. Here, depicted in figure 5 shows their positions.

In figure 5, diverse users are shown. The vehicles are aligned and form a straight line on the map. The indoor and pedestrian users are distributed separately, forming a footprint over the whole chart. The position of each mobile user is represented by coordinates x,y, and z.

5.2. Users' Movement

Here figure 6 shows the movement of the users distributed randomly along the defined area (Region Of Interest). According to the previously defined parameters, the types of users are pedestrians, vehicular, and indoors. The pedestrians are all along the street and are colored by the green spots. Their average speed is around 5km/h. The cars are also along the street, representing a red spot following each other.

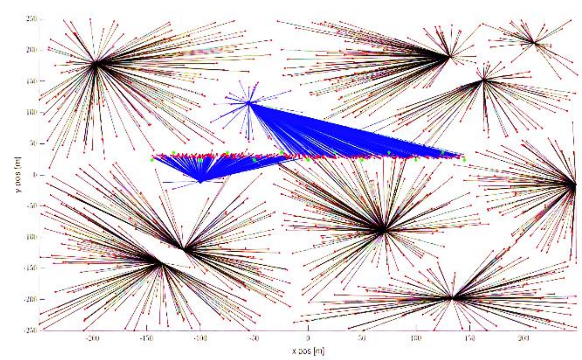

Fig. 6 Users' movement

The speed of the cars is an average of 30 km/h. The other users (also in a black spot but not along the street) are the indoor users who are supposed to be stationary. Each spot is associated with its coordinates X and Y. The coordinates are the geographical positions of each mobile user. The spots represent the users.

5.3. SINR

After running the simulation, one of the most important features of the machine learning model is obtained, the SINR. The SINR, the label for the machine learning model, is obtained for each link between the mobile stations and the base stations. The results are presented in the dataset and used for prediction.

5.4. The System Performance

The system performance evaluation depends on parameters which are the accuracy R and the error function (loss function).

The accuracy of the model is computed as follows:

$$R = \frac{sum(Correct_{Predictions})}{Total\ Predictions} \quad (12)$$

The correct prediction happens when the predicted and expected values have the same value. After computation, the model gave an accuracy of *R= 0.90*. The accuracy obtained is shown in figure 8, displayed against the number of epochs. The figure shows that at 1000 epochs, the model reaches saturation at 90% accuracy, or the function used here is the cost function generally used for logistic regression. The formula is defined as follows [21]

$$L_{CE}(\hat{y}, y) = -[y \log_{10}(\hat{y}) + (1-y)\log_{10}(1-\hat{y})] \quad (13)$$

$$\hat{y} = sigmoid((\sum_1^n w_i x_i) + b) \quad (14)$$

x_i is a predictor or input at each instance of i.
n is the number of inputs
y is the label
$\hat{y}$ is the predicted value.

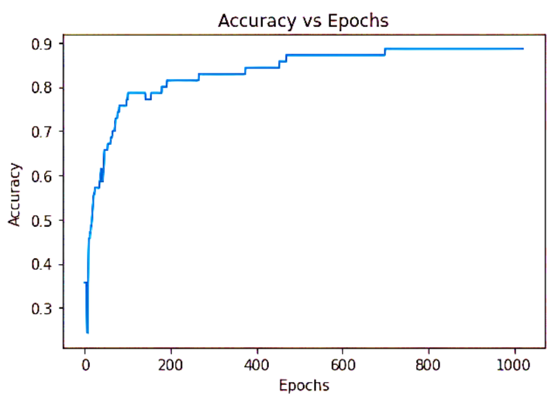

Fig. 7 Epochs vs Accuracy

The graph shows the error obtained against the number of epochs. At 1000 epochs, the error is minimized to 0.1.

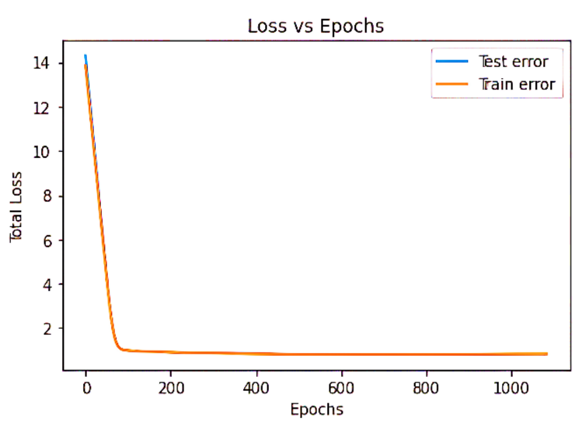

Fig. 8 Epochs versus Loss

5.5. Discussion

The main purpose of this work is to improve an existing system-based machine learning. It means another method based on machine learning has been proposed to improve the predictions which were done before. The comparison is based on the previous methods already applied for the same purpose. Here, Table 5 compares the proposed model's performance to the other models in the literature.

The following accuracies were obtained using the same data and performing the tests with different models. A defined tool for machine learning or deep learning in Matlab has been used for SVM, NARX, and Non-linear Input-Output.

The logistic regression model shows the best performance in terms of accuracy, which is 90%.

Table 5. Models' Comparison

Models	**Accuracy**	**Error**
Logistic regression	0.90	0.10
SVM	0.70	0.30
NARX	0.56	0.44
Non-linear Input-Output	0.50	0.50

Also, the error function gives an error of 0.1, which is the lowest in this table. The logistic regression approach showed the best accuracy and error minimization results.

Defining suitable parameters and finding the best model helped have a better result. Indeed, the modeling of this issue for predicting the SINR is well done.

Also, the data are cleaned up without any distortion. The gradient descent algorithm is suitable for modelizing this type of issue. It reduces the loss as much as possible, which is one of the main projects.

6. Conclusion

An SINR-Based channel quality prediction method has been proposed in this paper. The method used is the gradient Descent Algorithm for logistic regression application. It gives more information on when the channel is appropriate for transmitting the signal or not. The resources are sent in a given relation depending on the channel quality available. The proposed method showed better accuracy and less error than the previous works. Moreover, the simulation part is more realistic because it is based not only on one base station but on multiple base stations, which define a larger region of interferences.

In future work, a new model could be proposed to have perfect system accuracy, and methods such as deep learning should be investigated. Nowadays, more scientists are focused on deep learning as a machine learning tool for better results, as deep reinforcement learning uses many hidden layers to outperform other models. Furthermore, a more realistic scenario could be used. For example, researchers could define more than 15 BS and optimize the network traffic generated during the simulation.

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