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Prediction of Channel Stability to Optimize Signalling Overhead in 5G Networks using ML Algorithm

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Abstract - As we are leaving in 5G era which promises us to give high throughput rate, better efficiency rate, and high bandwidth etc as its feature make headlines to give advanced and enhanced services in various sector whether it could be IOT, infrastructure, agriculture, and health care [1]. Giving well-grounded communication technology possesses a fundamental challenge for 5G system in both Core network and Radio Access Network (RAN) levels [2]. To get a better credibility at RAN level, base station (EnodeB or gNodeB in 4G and 5G respectively) should allocate proper amount of resource as per UE and select appropriate Modulation and scheme (MCS) to give better user experience. The amount of Physical Resource Blocks is directly proportional to channel condition at the User Equipment (UE) end [5]. The Base Station would generally know the real time channel strength of each UE, which then later provides accordingly resource to the UE, as UE would be sending periodically CQI to Base station. However, the periodic transmission of CQI would lead to signaling overhead which hampers the performance of RAN. Henceforth its foremost thing to average it or to optimize the CQI value to give a better user experience. Therefore, will be exploring four such machine learning algorithms (ANN, reinforcement learning, KNN and SVM) to optimize the CQI and would be analyzing which Algorithm will give better performance.

Key Words: CQI, Machine Algorithm, RAN, Offloading, Handover, Base Station

1. INTRODUCTION

5G wireless networks must meet stringent requirements for latency, stability, bandwidth, and device capacity. The base stations (4G and 5G nomenclature, respectively) are in charge of guaranteeing RAN dependability by assigning enough radio resources per UE and choosing the modulation and coding scheme (MCS) to suit the needs of each evaluated application[7]. Physical Resource Blocks (pRB) are a kind of resource whose quantity and distribution are directly affected by UE-end channel conditions. The base station requires real-time data on the channel quality of each device in order to assign the required number of physical resources (NpRB)[9]. This figure is derived from the Channel Quality Indicator (CQI), which UEs send to the base station on a regular basis to assess the stability of the signal between them. However, the signalling cost imposed by the periodic transmission of CQI information may create link overload and decrease RAN performance.The quality of service (QoS) of this messaging system might be improved with some fine-tuning[11]. In this thread, we'll talk about the problem of reducing the quantity of reporting necessary. CQI values change as a result of user mobility, fading dispersion, and other causes. In this study, we investigate a pressing problem: how to determine whether or not a channel is dynamic over time. To do this, we use machine learning (ML) techniques to keep an eye on the channels for any signs of abnormal activity. Our plan is to collect information from everywhere in the system for the sake of study and comprehension. Large amounts of diverse data regarding per-UE channel quality, in addition to characteristics like user movement patterns, adverse geographical locations, etc., allow the ML system to provide a more realistic assessment of the channel's stability. However, issues of technology and privacy may make this impossible.

2. METHODOLOGY
USING MACHINE LEARNING
PREDICTION OF CHANNEL STABILITY

This part of the section is focused on cutting the signal overhead in terms of transmission of CQI data packets.

A. Overview and objectives

The UEs regularly transmit CQI to the Base station so that it can make the most informed resource allocation decisions feasible depending on the current channel quality[12]. When the channel quality is high, CQI readings tend to be stable. Since the base station's knowledge of the real radio circumstances of a given UE link is unaffected by how often UEs report their CQI, We can reduce the periodicity of CQI reports if the channel state is stable then we can retain the same CQI value ,Instead assign a new CQI value if the channel state is variable , we can get to know its varibility by taking the differnce of T time of previous channel state and present channel state ,if the differnce is huge then assign a new CQI value and that how we can optimisethe overhead of CQI and allocate the desiarable resource block to the approraite channel.

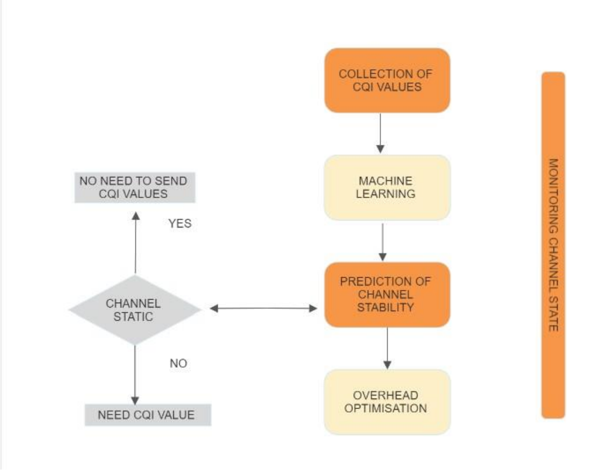

Fig 3 concept and methodology to reduce CQI monitoring overhead.

During the suggested phase of monitoring, a machine learning system makes predictions about the channel state. In this research, we compared four such ML methods and found that Neural Networks produced the best results. In the following paragraphs, we will describe the specifics of how we implement these ML methods into our networks to foretell channel mobility over a range of predetermined rates.

B. Steps to predict the channel's state.

In this project, we not only describe the methods by which we use machine learning to foretell channel behaviour, but also the criteria by which we evaluate these methods against each other. There are numerous approaches to machine learning.

The most used are:

i)Reinforcement learning- The study of decision making is known as reinforcement learning (RL). It is about learning the best behaviour in each environment to get better results. In RL, data is gathered and implements a trial-and-error approach [6].

Neural Network (NN): This approach, inspired by and fashioned by the human brain, tries to develop an artificial neural network. The steady influx of new data is the cornerstone of learning machines[15]. Each "layer" of neurons in the machine receives input from the layer underneath it, analyses it using machine perception, and then passes the results to the layer above it.

Support Vector Machine (SVM): This approach is mainly concentrated on extracting the data points and output is stated in Hyperplane, for example your 3D data is cut down to 2D further, the 2D data is made in to single line, main objective is to optimise the large amount of data and project it as in Hyperplane. It's a linear classifier.

Fig. 2 presents the different steps involved in the channel state prediction process.

1.Feature vector extraction and labelling phase:

Collecting data is the initial step in training a classifier, followed by processing that data to extract features and produce feature vectors (sometimes called characteristic vectors). The data is collected in the form of channel-specific vectors during the time period T[13]. For each channel or feature vector is then created. Parameters such as SNIR and CQI may be used to describe the channel's condition. In this project the suggested parameter taken is CQI because it provides the MAC scheduler with sufficient information about the channel state upon which to base choices about resource allocation and other parameters like the MCS. For the prediction system if the channel state is mobile or static from the given data, we first analyze the CQI data vectors and then create a feature vector from each.

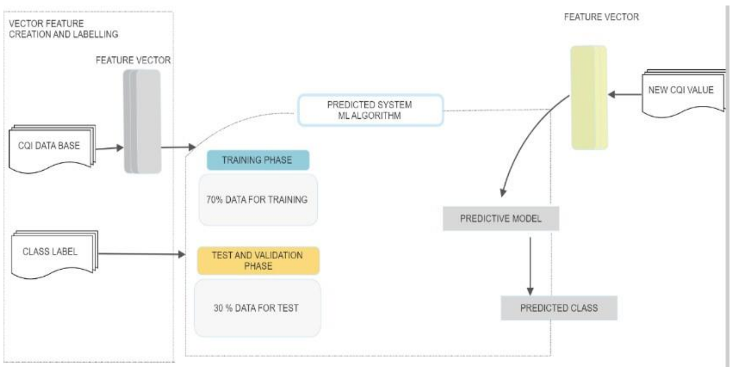

Fig 2 ML-driven channel stability prediction

The n CQI values with respect to time T period are collected [cqi1, cqi2....cqin], later given for preprocessing to get Feature vector F= [F1 F2 F3].

The Extraction are as followed:

• F1: The collected CQI values are taken and difference between the highest and lowest is shown.

$$F_1 = cqi_{max} - cqi_{min}$$

If F1 is less or zero, static channel is predicted, saying that the user equipment is also still in position and the surrounding conditions are steady.

• F2: Variance

$$F_2 = \frac{1}{n}\sum_{n=1}^{n}(cqi_i - \overline{CQI_T})$$

The variability of CQI scores in relation to the mean CQI provides insight into the extent to which individual CQI scores may lead to different results. Basically Variance give the dispertion of CQI values

• F3: The relative difference in CQI variation among samples during time period T, shown by the slope of the CQI chart.

$$F_3 = \mid CQI(t_{i+\Delta}) - CQI(t_i) \mid,$$

where CQI (ti) is the CQI collected at time ti, and CQI (ti+) is the CQI collected at time ti+, both of which fall inside the sample (here, =5). For each sample, several F3 values are calculated. Therefore, the size of F is proportional to the sum of F3. After vector F is built, it is given a label (fixed or dynamic) hence later it can be used during training.

2. Construction of a prediction system based on machine learning:

To implement the predictive system, there are two phases are as follows.

1. Training phase
2. Testing phase.

a) Training phase: In this phase 70% of feature vectors are used to train the data and classifier label it correctly. During this phase ML algorithm develops a function that map feature vector (input) to classification (output labels).

b) Testing phase: The remaining 30% of our feature vectors are used at this stage. It entails comparing the vectors' predicted labels with their observed ones. The following parameters are referred to to evaluate performance.

• Accuracy, i.e., the ratio of the number of labelled classifiers to the total number of feature vectors.

$$\text{Accuracy} = \frac{\#\ \text{correctly predicted}}{\#\ \text{feature vectors}}$$

• Precision measures the proportion of accurate predictions compared to the gross number of predictions (both true and false), while recall measures the proportion of right predictions related to the gross number of true mobile class instances. Which is also meant as sensitivity.

$$\text{F1.score} = \frac{2 * (\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})}$$

3) Application phase: In this phase we come to a conclusion and sort new data according to its time period for collecting data. Here we represent True Positive (TPR)and True Negative (TNR). Positive refers to Mobility/Dynamic whereas Negative refers to Static. TPR and TNR are both defined below.

$$TPR = \frac{\#\ \text{correctly classified as mobile}}{\#\ \text{mobile}}$$

$$TNR = \frac{\#\ \text{correctly classified as static}}{\#\ \text{static}}$$

3 Details of Result and Discussion:

Simulated 5G network in Mathlab version 2021rs, have collected data with respect 5 different frequency such as 3Mhz,5Mhz,10Mhz,15mhz and 20Mhz and collected 15,500 CQI vectors and trained and tested whether its static or dynamic depending on UE movement.

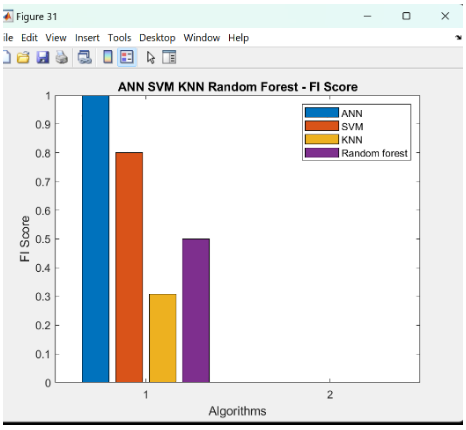

Fig 3: F1 score

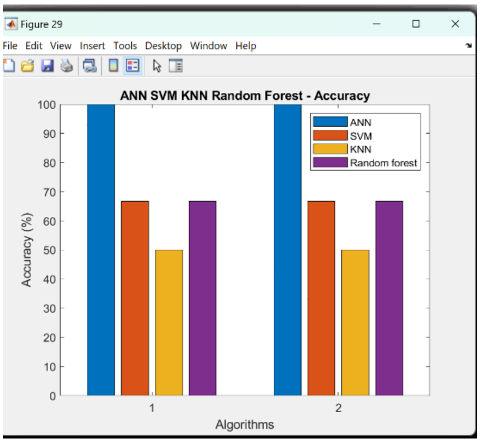

Fig 4: Accuracy

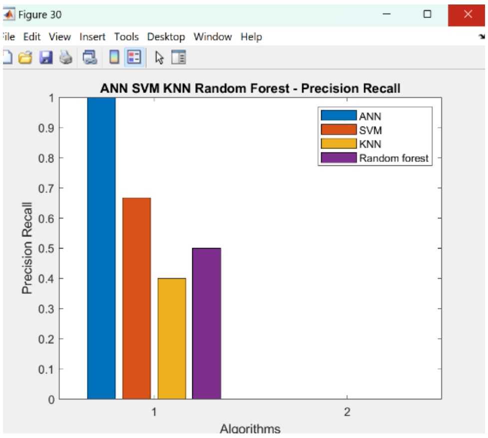

Fig 5: Precision Recall

Concluding with the peer comparison we can conclude that ANN model predicts accuracy from all the other algorithm as true positive and true false state in precise way**.**

4. CONCLUSION

LTE and new radio mobile networks has been focused on cutting down the signaling burden caused by the constant flow of reports (CQIs). My method includes reducing the amount of CQI reports sent when the latter's value does not change much over time owing to a stable channel and assigning new CQI value if its dynamic. To this purpose, I implemented machine learning-based algorithms that use solely CQI data to estimate channel stability, thereby tackling the problem of doing so. As a result, our systems adhere to all relevant standards and do not need any extraneous data, such as user locations or mobility patterns, to operate as designed. I have analyzed and compared the prediction accuracy of four different ML schemes—Support Vector Machines (SVM), Neural Networks (NN), KNN, and the Reinforcement Learning Algorithm. I also addressed the tension between data collection and prediction accuracy, and our experiments demonstrated that neural networks consistently outperformed SVM, KNN, and Reinforcement learning. To that end, I have spent much of my time on this project comparing several machine learning (ML) prediction accuracy evaluation methods.

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The heading should be treated as a 3rd level heading and should not be assigned a number.

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