International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 06 | June - 2022 Impact Factor: 7.185 ISSN: 2582-3930

A Machine Learning Approach to Predict Channel Stability Using Channel Quality Index

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Abstract - Channel quality feedback is crucial for the operation of 4G and 5G radio networks, as it allows to control User Equipment (UE) connectivity, transmission scheduling, and the modulation and rate of the data transmitted over the wireless link. However, when such feedback is frequent and the number of UEs in a cell is large, the channel may be overloaded by signalling messages, resulting in lower throughput and data loss. Optimizing this signaling process thus represents a key challenge. In this paper, a focus on Channel Quality Indicator (CQI) reports that are periodically sent from a UE to the base station, and propose mechanisms to optimize the reporting process with the aim of reducing signaling overhead and avoiding the associated channel overloads, particularly when channel conditions are stable. To this end, we apply machine learning mechanisms to predict channel stability, which can be used to decide if the CQI of a UE is necessary to be reported, and in turn to control the reporting frequency. For this purpose,four machine learning models,namely Support Vector Machines (SVM),K-Nearest Neighbour (KNN),Random Forest and Neural Networks (ANN). Simulation results shows that both provide a high prediction accuracy, with ANN consistently outperforming, especially as CQI reporting frequency reduces.

***Keywords*:** ANN,KNN,SVM,Random Forest,CQI,5G,UE

1.Introduction

5G mobile networks [1] are designed to provide new and enhanced services that make life easier in several areas introduced in the Internet of Things (IoT), such as smart cities, health care, agriculture, transportation, and manufacturing. To accommodate these services, 5G has to meet critical requirements in terms of low latency, high reliability, high bandwidth, and the support for massive numbers of connected devices.

Providing a reliable communication technology represents a key challenge for 5G systems in both Core Network [2] and Radio Access Network (RAN) levels. In order to achieve reliability at the RAN level, a base station (eNodeB or gNodeB, in 4G and 5G terminology, respectively) should allocate a sufficient amount of radio resources per UE, and appropriately select the modulation and coding scheme (MCS) in order to meet the requirements of each considered application. The amount and configuration of these resources, i.e., physical Resource Blocks (pRB), are directly related with the channel conditions at the UE end. For this reason, the base station should ideally know in real time the quality of the channel of each device,which allows it to properly schedule the necessary number of physical resources (NpRB) for transmission [3].

In 4G and 5G networks, this number depends on the Channel Quality Indicator (CQI) value, which is periodically reported by UEs to the base station, and conveys their current communication channel quality [4]. Nevertheless, the periodic transmission of CQI information incurs signaling overhead; this may overload links and negatively impact RAN performance. Therefore, it is important to optimize this signaling process, in order to beable to improve on Quality of Service (QoS).

The architecture requires accurate channel quality information per UE at the gNodeB and at the slice orchestrator level, in order to be able to estimate and dynamically adjust the radio resource allocation to satisfy the heterogeneous requirements of coexisting network slices. This information is reported by UEs via standard procedures, and propagates to the slice orchestrator via a southbound protocol by base stations. The challenge that we face and the particular motivation for this paper is to reduce this reporting overhead.

The key element responsible for fluctuations in CQI values are the changes in the radio environment which may be due to user mobility, multi-path effects, and other phenomena. We introduce the term channel mobility to denote time-varying changes in the radio environment of a UE: On the one hand, the channel is considered static if its conditions are mostly stable, when typically the UE is static or low-mobility for a period of time. Thus, the reported CQI values remain constant or show minimal variation, which does not impact radio resource allocation. On the other hand, the channel is considered mobile when it varies significantly due to factors such as UE mobility and other effects. In this case, the CQI values exhibit significant fluctuations. Consequently, it is crucial that the base station is informed about the changed channel quality information, in order to determine the appropriate amount of resources to be allocated, and update the NpRB values for the different UEs.

2. Literature Review

Techniques of this kind are based on compression models. Indeed, the idea to reduce the signaling overhead consists in sending a compressed CQI value of a series of pRBs, instead of sending a CQI value for each one. In this context, three categories were proposed as follows [7]: i) Broadband compression, where a single CQI value transmitted refers to all pRBs of the bandwidth, ii) sub-band compression, where the bandwidth is divided into multiple sub-bands with the same size, and the UE selects only one CQI value to be transmitted to the base station, and iii) full band compression, where the base station estimates the total bandwidth quality, using mathematical transformations such as the discrete cosine transform and the Haar wavelet transform.

In this paper[5],analysis of two different MU-MIMO CQI prediction schemes for LTE systems with different releases and different precoding schemes, focussing on the link level system performance in terms of throughput and channel condition and the tradeoff between the performance gain and the feedback overhead w.r.t. MU-MIMO CQI prediction were investigated.The results have shown that the CQI prediction accuracy deteriorates in low spatially correlated channels due to less freedom for UE pairing. However, this limitation can be compensated through the rank adaption since more feedback information is provided by the UE.

Sivridis and He [8] presented a non-predictive signaling reduction scheme, where users with high signal-to-interferenceplus- noise ratio (SINR) transmit only broadband information, while users with low SINR are allowed to return on-demand instant CQI information at high rates. Therefore, a technique was proposed to determine the threshold that separates users required to use full-band feedback from users required to use compression in the wide-band frequency domain.

The work of Kang and Kim [9] is based on the sub-band compression method, allowing to analyze and select the best M-feedback for orthogonal frequency division multiple access (OFDMA) systems. In addition, a combined optimization was applied to minimize feedback overhead costs based on the number of reported resource blocks per user and the signal to quantization noise ratio bits.

Abdulhasan et al. [10] presented a compression scheme for CQIs in a 3GPP-LTE and LTE-A system, where CQI values are communicated to eNodeBs based on a defined threshold. A trade-off was presented to select the appropriate threshold, since a high threshold is recommended for high speed conditions, whereas a low threshold is recommended to ensure reliable transmission mainly in an overloaded network.

M. Q. Abdulhasan et al. [6] proposed a CQI prediction scheme using Feed Forward-Neural Network (FF-NN) algorithm for MU-MIMO-LTE Advanced systems. Initially, a channel model for MU-MIMO-LTE advanced network is carried out. Through this model, CQI is predicted and the obtained values are compressed using a feedback compression technique. Finally, the proposed technique makes use of FF-NN algorithm to train and achieve enhanced CQI values. An enhanced and accurate CQI values are acquired. Results show that the system SE of single user (SU)-MIMO proportionally increases with the SNR values at the cost of BER.Further, it achieves a best tradeoff between the SE and the BER. We intend to examine the dynamic switch between SU-MIMO and MU-MIMO in our future work. This new technique can use a weighting factor to prioritize the SE or BER according to the speed and traffic load condition of the users.

This paper[17], studies on a number of CQI correction techniques that can minimize the impact of imperfect CQI report on the QoS of Real-Time (RT) applications in the downlink Long Term EvolutionAdvanced (LTE-A). Simulation results demonstrate that the Modified Average Smoothing CQI Correction (MASCC) technique has the best performance at 30 kmph user speed (i.e. 7.4% improvement compared to the ideal case) whereas its performance is comparable to the ideal case at 60 kmph user speed. Based on the results obtained, it can be concluded that the MASCC algorithm is superior to other CQI correction techniques where it is capable to minimize the impact of the outdated CQI report compared to the ideal case (IC technique).But New CQI correction techniques needs to be investigated inorder to tackle other types of imperfect channel conditions.

3. Methodology

CQI messages are sent periodically from UEs to the e/gNodeB, in order to provide it information about the channel quality allowing it to appropriately allocate resources. When channel quality is relatively stable, the CQI values do not vary a lot. Therefore, an increased CQI reporting frequency does not contribute to the view the base station has on the actual radio conditions of a UE link, and does not affect the quality of the radio resource allocation. Thus by taking the advantage of channel stability to avoid transmitting unnecessary CQI reports and aleviate the associated overhead.

Our approach consists in monitoring the channel state for a period T. If channel mobility is identified by the predictor, a new CQI value is required to adjust resource allocation. Otherwise, there is no need to receive new CQI values; the e/gNodeB allocates radio resources considering the last received CQI value as accurate and stable, and the CQI reporting frequency can be reduced. The different steps of this concept are illustrated in Fig. 1.

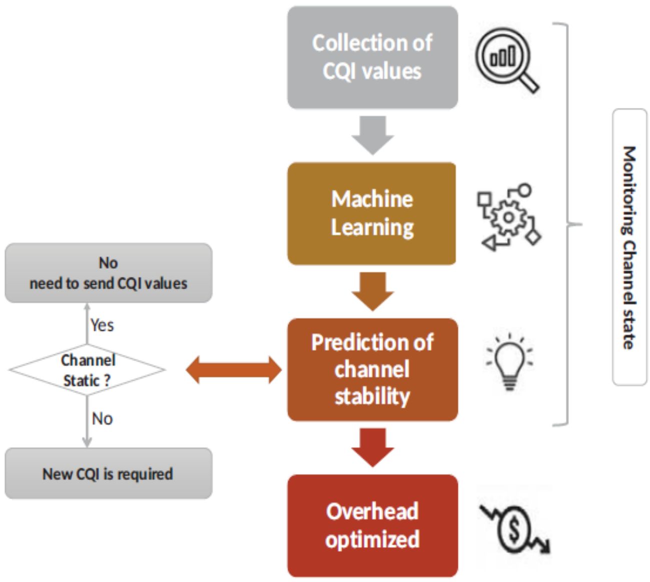

Fig 1.Methodology to reduce CQI monitoring overhead.

The proposed monitoring phase is based on a machine learning algorithms, which helps predict the channel state. In this paper, some ML algorithms were tested, then ANN and Random Forest has been selected as they offer better accuracy.The Block diagram given below in Fig 2.

describing how these ML schemes are applied in our network settings in order to predict channel mobility based on different frequencies of collected data.

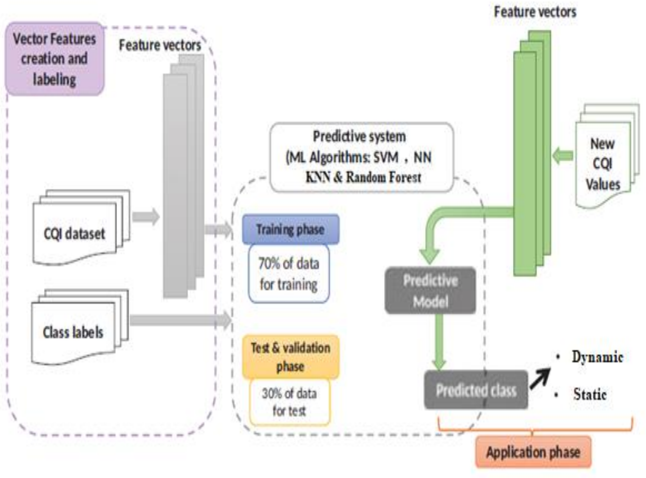

Fig 2. Block Diagram

3.1 Feature vector creation and labeling phase

This phase involves the collection of data and their processing in order to extract specific features and create feature vectors (also called characteristic vectors) that will be used for training a classifier. Raw data are collected in the form of vectors for different channels during a period T. A feature vector is then created for each data vector (i.e, for each channel).

In fact, different types of data representing the channel state may be used, such as SNIR, CQI, and others [17]. The CQI parameter is selected for the proposed predictive system, as this parameter provides sufficient information on the channel state and is used by the MAC scheduler to allocate resources and decide on parameters such as the MCS. From each CQI data vector, feature vector is extracted after a preprocessing step,in order to have the relevant data for the predictive system to identify the channel state (mobile or static).

Preprocessing is carried out on the data vector $CQI_T = [cqi_1, cqi_2 .... cqi_n]$ of n CQI values collected during a period T in order to extract the characteristic vector $F = [F_1\ F_2\ F_3]$.

The extracted features are the following.

i) F_1: The difference between the maximum and minimum values of collected CQIs in the data vector CQIT .

$$F_1 = cqi_{max} - cqi_{min} \qquad (1)$$

The channel may be static if F_1 is small or zero, which might mean that the UE is static and the environment is stable (there are no significant effects that cause a drastic change in the CQI value). This feature can provide an idea of the channel state, but it is not sufficient to make a decision.

ii) F_2: Variance.

$$F_2 = \frac{1}{n}\sum_{n=1}^{n}(cqi_i - \overline{CQI_T}) \qquad (2)$$

This feature measures the dispersion of CQI values relatively to the average $(\overline{CQIT})$, which characterizes the level at which the CQI can have a value more or less far from its expectation.

iii) F_3: The vertical change of the CQI curve slope, representing the CQI change in different samples in period T.

$$F_3 = | CQI(t_{i+\Delta}) - CQI(t_i) |, \qquad (3)$$

where $CQI(t_i)$ and $CQI(t_{i+\Delta})$ are the CQIs collected at t_i and $t_{i+\Delta}$ respectively, where these two times are inside the sample (Δ=5 in our case). Multiple F3 values are extracted for each sample. Thus, the size of F depends on the number of F3.
After the creation of vector F, a known label (static or dynamic) is assigned to it, in order to be used for the training phase.

3.2 Machine Learning predictive system

To create the predictive system, a machine learning algorithm operates in two phases as follows.

i) Training phase: 70% of the feature vectors with their labels (representing the real classes) are used to train the classifier. During this training phase, the ML algorithm creates a function that maps inputs (feature vectors) to outputs (labels), used then to classify new vectors. In this stage, the SVM algorithm learns a linear function, while the NN algorithm also supports non linear functions.

ii) Test and validation phase: This phase uses the rest of the feature vectors (30%). It consists in checking the predicted classes of these vectors against their assigned labels. The validation of the predictive system is based on a confusion matrix [18], which consists of the number correctly and incorrectly classified samples per class.

Performance is evaluated in terms of Accuracy.It is the ratio of the number of correctly predicted vectors to the total number of vectors.

$$\text{Accuracy} = \frac{\#\text{ correctly predicted}}{\#\text{ feature vectors}} \qquad (4)$$

3.3 Application Phase

This step consists in classifying a new CQI data set over different frequencies of collecting data (i.e., sample size variation). To evaluate this phase, the True Positive Rate (TPR) and the True Negative Rate (TNR) metrics, where the positive class refers to the Dynamic class and the negative one refers to the Static class. TPR and TNR are defined as follows:

$$TPR = \frac{\#\text{ correctly classified as } \textbf{Dynamic}}{\#\ \textbf{Dynamic}} \qquad (6)$$

$$TNR = \frac{\#\text{ correctly classified as } \textbf{Static}}{\#\ \textbf{Static}} \qquad (7)$$

4.Results And Discussions

The project is implemented using MATLAB Software.A GUI interface is designed as shown in the Fig.3 given below.

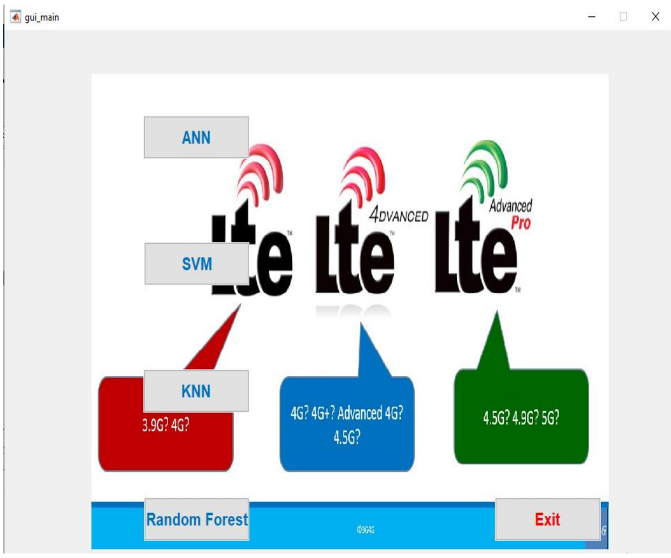

Fig 3. GUI Interface for CQI Classification

4.1 ANN Algorithm

On operating the ANN in the GUI Window,ANN Model was created with 13 Values as Input,there are two hidden layers,with 5 neurons in the first hidden layer and 3 neurons in the second hidden layer and one output layer. All the four frequencies, 3Mhz,5Mhz,10Mhz and 15Mhz and its channels were trained in the network created. Fig 4. shows the Training and Testing phase carried out using ANN.

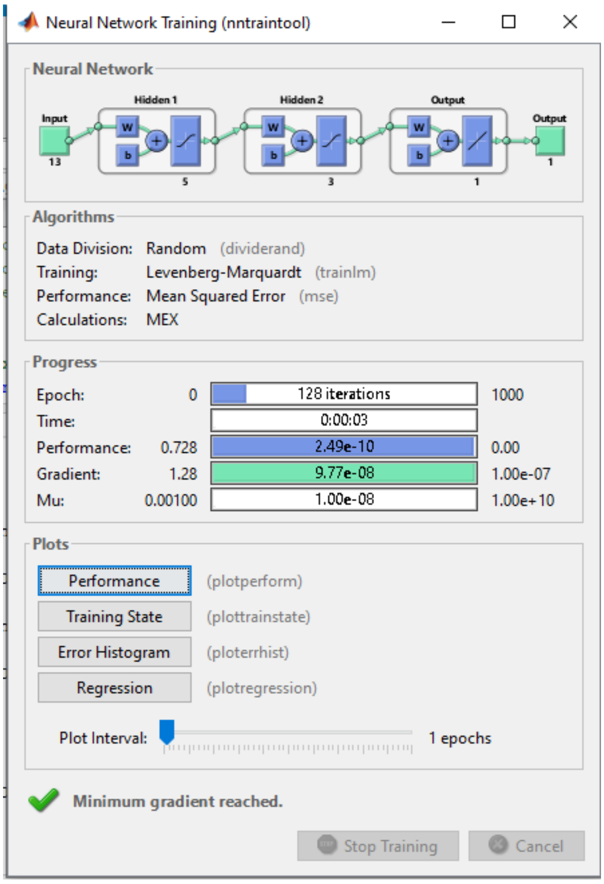

Fig 4. ANN Training

The algorithm was tested with a sample taken from 5Mhz Frequency of Channel No.6 and the obtained results of classification as Dynamic is displayed as shown in the Fig 5. below.

Fig 5. ANN Classification

4.2 SVM Algorithm

Matlab has a great function called fitcecoc which fits multi class models for SVM . We train a support vector machine (SVM) classifier using the CQI values extracted. All the four frequencies, 3Mhz,5Mhz,10Mhz and 15Mhz and its channels trained using SVM Classifier.The algorithm was tested with a sample taken from 5Mhz Frequency of Channel No.6 and the obtained results of classification as Dynamic is displayed as shown in the Fig 6. below.

Fig 6. SVM Classification

4.3 KNN Algorithm

KNN is a nearest-neighbor classification model in which you can alter both the distance metric and the number of nearest neighbors. The extracted features of CQI values are used to train using a k-nearest neighbor classifier, where k, the number of nearest neighbors in the predictors.The algorithm was then tested with a sample taken from 5Mhz Frequency of Channel No.6 and the obtained results of classification as Dynamic is displayed as shown in the Fig.7 below.

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Volume: 06 Issue: 06 | June - 2022 Impact Factor: 7.185 ISSN: 2582-3930

Fig 7. KNN Classification

4.4 Random Forest Algorithm

In Matlab,TreeBagger relies on the ClassificationTree and RegressionTree functionality for growing individual trees. In particular, ClassificationTree and RegressionTree accepts the number of features selected at random for each decision split as an optional input argument. That is, TreeBagger implements the random forest algorithm. For each observation that is in bag for all trees, the predicted class is the weighted, most popular class over all training responses. The algorithm was then tested with a sample taken from 5Mhz Frequency of Channel No.6 and the obtained results of classification as Dynamic is displayed as shown in the Fig.8 below.

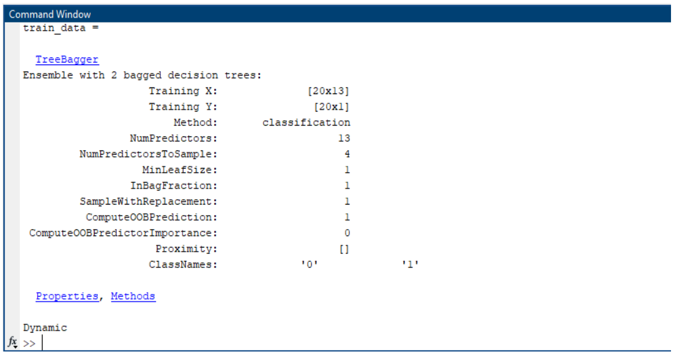

Fig 8. Random Forest Classification

4.5 Comparison of Algorithms

Table I presents the results of the validation phase in terms of accuracy for the four Machine Learning Algorithms.

	ANN	SVM	KNN	RF
Accuracy	100%	66.66%	50%	100%
Sensitivity	100%	60%	62.5%	87.5%
Specificity	100%	60%	61%	75%
Precision	99%	60%	97%	98.9%

Table I. Validation Results of the ML Algorithms.

As shown in this table, all the four algorithms are able to learn and predict the channel state with high performance. It can be noticed that the ANN and Random Forest scheme outperforms the other algorithms in terms of accuracy by approximately 50%.This can be explained by the fact that other algorithms is based on the margin maximization of the linear hyperplane separator between the two classes (static and dynamic).That is why it is not able to well classify vectors close to this separation. On the other hand, ANN is based on a non-linear function to separate between classes allowing it to better handle such cases. The obtained results of accuracy for the different algorithms are illustrated in Fig.9.

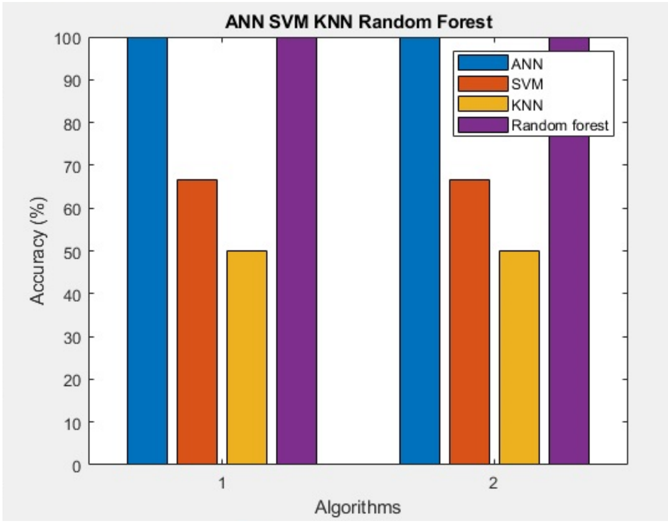

Fig 9. Accuracy of ML Algorithms

4.6 Advantages

- Reduces the signaling overhead
- Avoids the associated channel overloads
- Increases Channel Stability
- Optimizes the reporting CQI information
- Detects whether the channel is static or dynamic over time
- Avoid the collection of many data metrics and focuses only on the CQI parameter
- Increases the accuracy of identifying the channel mobility
- Improves network performance and spectral efficiency

5. Conclusions

There was a focus on the way to reduce the signaling overhead caused by the periodic transmission of channel quality feedback in the form of CQI reports in 4G and 5G mobile networks. Our approach consists in avoiding to transmit unnecessary CQI messages by taking into account the stability of channel conditions, i.e., reducing the amount of CQI reports when the value of the latter does not change significantly over time, as a result of a stable channel. To this end, we addressed the challenge of predicting the channel's stability, proposing machine learning-based mechanisms that only require CQI information as input. Our mechanisms thus operate in a standards-compliant way and require no cross-layer or other external information, such as user locations or mobility patterns. We compared four ML schemes for this purpose, namely Support Vector Machines (SVM) and Neural Networks (NN), evaluating and analyzing their prediction accuracy. We further addressed the tradeoff between prediction accuracy and data collection frequency, and experimentally showed ANN to consistently outperform than the other algorithms.

6. Future Scope

In this paper, we mainly focused on evaluating the prediction accuracy of the candidate ML schemes. The next step is to launch a deeper study on the impact of our proposed methodology and mechanisms, integrating them in the 5G network slice management architecture that we have proposed in our prior work. Our immediate goal is to evaluate the signaling cost improvements that can be achieved, and the impact of our proposed mechanisms on the allocated resources and the attained performance in terms of latency and throughput for heterogeneous 5G network slices.

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