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Voice Quality-Based Handover Strategies for VoLTE Networks

Amr Magdi Zakaria Hassaan[1], Karim Hammad[2], Mohamed Shehata[3,*], Mohamed S. El Mahallawy[4]

[1] Department of Electronics and Communications, Arab Academy for Science and Technology and Maritime Transport Cairo, Cairo 4471344, Egypt

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ABSTRACT

In this paper, we propose a new handover scheme for enhancing Voice over LTE (VoLTE) user experience via voice quality prediction. The proposed scheme addresses the demand to sustain smoother progression and fulfilment of the VoLTE calls service utilizing the Perceptual Objective Listening Quality Assessment (POLQA) scores prediction. A novel neural network (NN)-based prediction algorithm is presented for improving the decision-making process of the target handover (HO) scheme. Specifically, the proposed algorithm utilizes a prediction system based on a neural network that reads multiple measurements from each neighbouring cell such as Reference Signal Receive Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), Channel quality index (CQI) and Signal-to-Interference Noise Ratio (SINR). It then predicts the POLQA score of the neighbouring cells and the HO decision will be based on the highest POLQA score. The obtained results for the trained model demonstrate a 26 % improvement in terms of the VoLTE quality-of-service (QoS) compared to exiting HO mechanisms.

1. Introduction

VOLTE is an advanced technology that allows voice services to be established over a 4G LTE network [1]. From the user equipment (UE)'s perspective, the voice call quality is a fundamental factor in determining the integrity of the service based on the user's quality-of-experience (QoE). High voice quality implies more natural and uninterrupted conversations [2]. In light of the seamless mobility and connectivity requirements of the LTE network, the HO mechanism is a key factor that directly influences the VoLTE QoS and essentially the QoE.

The successful HO between different network cells or technologies is essential for ultimately achieving the ubiquitous connectivity requirement defined by advanced cellular networks [3,4].

[*] *Corresponding author*
E-mail address: mkhshehata@aast.edu

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Hence, the proposed framework in this paper strives to innovatively address the HO problem by leveraging the power of the evolving neural network architectures to attain better QoS levels compared to classical HO solutions. Unlike most existing work which adopt analytical models, the proposed NN framework uses real network measurements in the training and testing stages. The measured data were taken for VoLTE calls at different days and times. The proposed NN model adopts the Perceptual Objective Listening Quality Assessment (POLQA) [5,6] objective indicators that quantify the VoLTE perceptual quality based on the analysis of distortion, background noise and overall clarity. These dynamic indicators enhance the service provider abilities in allocating spectral and power resources for better QoS levels. This pertains to the flexibility of evolving NN models in learning the varying nature of the channel and traffic demands for making better HO decisions especially in high mobility and network overload scenarios. It is worth noting that NNs have shown a great potential in pattern recognition and decision-making and hence, can be used for optimizing HO decisions in real time [7,8].

In addition to the standard parameters of handover procedures, NN models can offer efficient adaption of HO processes by considering the actual user's QoE in advance as well. The adaptive solution has a big potential for improving the quality and reliability of VoLTE services. The proposed HO approach adopts the neural network algorithm which is capable of providing a seamless and better voice calling experience for VoLTE users. It also can improve its predictive accuracy over time as it has the ability to learn from past handovers and optimize future transitions. Therefore, the incorporation of the neural network technology into the area of handover procedures opens the new opportunity for the high quality and individualized contracting of the telecommunication services. By adopting the users' needs and accurately approximating the optimal VLAN settings, this modern approach might improve the VoLTE networks' performance and guarantee the users' continuous connection and higher satisfaction level.

1.1 Problem Statement

The VoLTE technology have revolutionized the telecommunications industry by enabling high quality/low bandwidth IP-based voice calls over 4G LTE networks. Nevertheless, similar to any cellular based technology, the performance of VoLTE heavily depends on reliable handover procedures ensuring smooth call continuity as users move from one radio cell to another. Existing VoLTE HO schemes have widely utilized the RSRP values of neighbouring cells as a collective measure for making HO decisions [9,10]. Although RSRP is an important indicator of the signal strength, it cannot be considered as a complete assessment of the voice quality. Relying on RSRP values alone for making handover (HO) decisions can be a big problem because of the small correlation between the signal strength and voice quality. This can happen that a cell with very high RSRP will not have good voice quality because of Interference or signal and network congestion, traffic load, etc. [11]. This is the reason, having handover decisions based purely on RSRP values in traditional HO scheme may bring sub-optimal HO outcome and poor call quality after all.

The discrepancy between RSRP values and voice quality in VoLTE networks is a major challenge. This challenge is further highlighted as maintaining high quality calls carries paramount importance not only for end users' satisfaction but also for the network operators' fulfilment of reliability and availability of their services. Hence, there is an urgent need to develop an innovative HO scheme which consider the assessment of voice quality (besides the RSRP) that will potentially improve the user experience in VoLTE networks. This can be addressed via the development of new algorithms that use a blend of network parameters, predictive modelling and quality assessment in order to make the optimum decision.

1.2 Related Work

There has been extensive work done on optimizing HO in cellular networks based on hybrid approaches. An Elman network-based handover algorithm [12], which has a higher efficiency and lesser impact on service linkages than the grey prediction model-based algorithm especially in high-speed rail tracks. Wang *et al.,* [13] have designed a new HO scheme for LTE networks that uses packet success rates to optimize resource utilization and QoS. The use of NNs in this scheme helps in learning the correlation between different metrics and outperforms the traditional SNR-based scheme. Hendrawan *et al.,* [9], the authors conducted a study which gauges and ranks two widely used handover algorithms of intra-LTE, A2-A4-RSRQ and A3-RSRP through simulations as well as field measurements. The objective was to find the best parameters setting for each algorithm while provisioning the handover mechanism’s role in LTE networks and the mobility as a key performance indicator. Martin [14] has focused on the complexity of hard HO in LTE and addressed the ping-pong effect during network switching and early handover for real-time services. In contrast, Harja [15] conducted a study which evaluated and optimized HO parameters in LTE networks using the RSRP and RSRQ algorithms. In addition to finding optimal parameters for each algorithm, the results showed the superiority of the RSRP algorithm over the RSRQ. Herman *et al.,* [16] presented an LTE HO algorithm based on RSRP measurements and Event A3 using the network simulator NS-3 and focused on modelling users’ mobility and the RSRP measurements to obtain accurate results. Finally, the adaptive HO algorithm reported by Xu *et al.,* [17] for LTE-Advanced networks has demonstrated an improved success rate of HO decisions that essentially reduced the frequency of ‘handover failures’ and enhanced the system throughput in contrast to traditional RSS-based algorithms.

1.3 Traditional HO Algorithms in Cellular Networks (Signal Strength-Based HO)

Before proceeding to the technical aspects of deploying NN models for optimizing VoLTE HO, it is crucial to have a brief look at the traditional HO algorithm in cellular networks. The typical HO algorithm is created to manage the transfer of a call as the UE travels from one cell to another adjacent cell without dropping the network connection. Figure 1 shows the basic HO message exchange which can either be initiated by the UE or by the network.

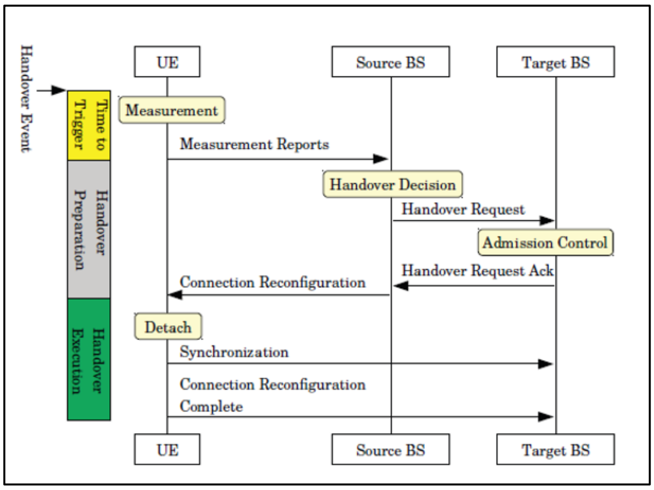

Fig. 1. The HO procedure in 3GPP

As described by Lopez-Perez *et al.,* [18], a handover consists of four main stages: measurement, processing, preparation and execution. The HO procedure is initiated with a measurement report transmitted from a UE to its serving evolved node-B (eNB). The measurement report includes the received power of the downlink reference signal (RSRP) of the serving and neighbour cells. The decision-making process in a traditional HO algorithm involves continuous monitoring of signal strength. There are several conditions to trigger the transmission of measurement reports as shown in Table 1.

Table 1
Events and triggering condition

Event	Triggering Conditions
A2	Signal strength of the serving cell < a specific threshold
A3	Signal strength of the neighbour cell > Signal strength of serving cell

One possible scenario is when the received power of a serving cell becomes worse than a threshold and the received power of a neighbour cell becomes better than a threshold. As shown in Figure 2, the reports are sent when event A3 is triggered, in which the target cell is better than the serving cell by an Offset and Handover Margin (HOM) for a certain period, Time to Trigger (TTT) as Eq. (1).

$$RSRP_T = RSRP_S + HOM \tag{1}$$

where $RSRP_T$ and $RSRP_S$ are the $RSRP$ received from the target cell and serving cell, respectively.

As a result, the UE leaves the serving cell and connects to the target cell if the target cell can afford enough resources to the UE. Nevertheless, this algorithm might not always give the best voice quality and hence, can cause call quality to deteriorate during handover events.

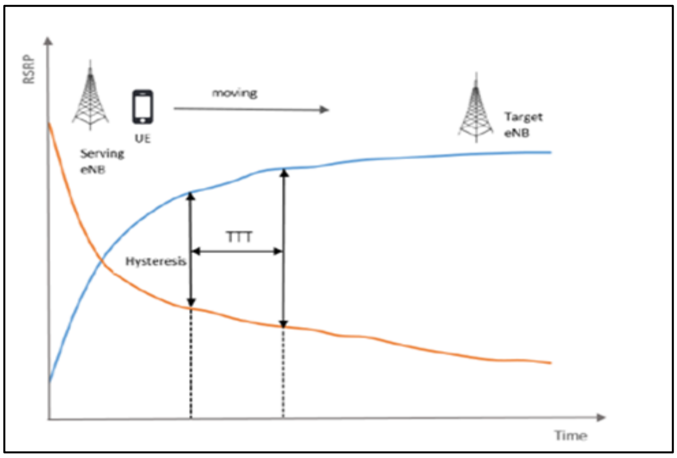

Fig. 2. A3-RSRP handover algorithm

1.4 Contributions

The current focus, in VoLTE handover techniques is mainly focusing on improving the traditional HO methods like such as utilizing the Received Signal Strength Indicator or Reference Signal Received Power of neighbouring cells. However, these methods do not directly target the aspect of end user voice quality, which's essential for user satisfaction. To overcome this issue, we propose an approach that utilizes a network model to predict POLQA score of neighbouring cells. This method enables a decision-making process, for handovers by prioritizing the selection of the cell with the highest predicted voice quality.

The primary contribution of this work lies in introducing a handover strategy that specifically aims to improve end user voice quality. By employing a network prediction of the POLQA score our approach ensures that handover decisions are based on the expected voice quality perceived by users than only relying on conventional signal strength metrics. This innovative strategy tackles the limitation of existing handover techniques, which may not always guarantee an optimal user experience in terms of voice quality.

The remaining sections are organized as follows. Section 2 presents the proposed methodology including data collection, model architecture and performance evaluation. In Section 3, Analytical and simulation results are presented. Lastly, we conclude this paper in Section 4.

2. Proposed Methodology

The traditional HO algorithm, as powerful as it is, still could not dynamically and flexibly address the changes occurring in the real time and hence, no guarantees to the user's QoE can be offered. On the other hand, neural network models are good at capturing the underlying patterns and interdependencies of the complex network data and hence are more adaptable and context-aware in making HO decisions over VoLTE networks. Therefore, NN models have better dynamic adaptation and optimization capability of user experience by drawing on the learned complexities and correlations within the network data which places them above traditional HO algorithms. This flexibility inherent in the NN models empowers these models to make more informed and suitable HO decisions of VoLTE.

The proposed NN algorithm aims at increasing the efficiency of HO decisions in VoLTE networks by including actual measurements from the field such as RSRP, RSRQ, RSSI, SINR and CQI [19,20]. The dataset we used contained these measurements for 1000 different cells from a live LTE network during five days from 10 AM to 6 PM. These measurements are the input attributes for proposed 1D convolutional NN model which is trained to forecast POLQA scores of the target cells. The following paragraphs will describe the operating steps used in the proposed algorithm, shown in Figure 3. These steps including dataset collection and clean up, dividing dataset into training sets and testing sets using k-folds technique, training data using early stopping technique, then finally evaluating the proposed NN model.

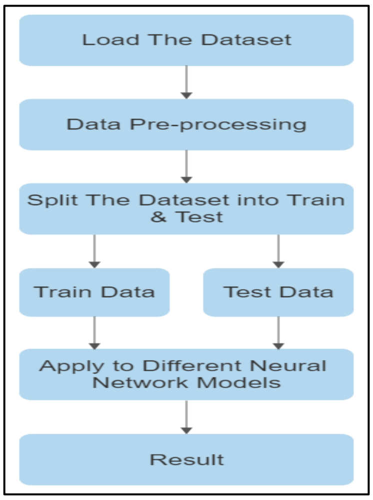

Fig. 3. Block diagram of the proposed methodology

2.1 Data Collection and Feature Extraction

Data collection forms the foundation of training NN models for VoLTE HO optimization. The success of these models relies heavily on the quality and comprehensiveness of the data used for training. The first step involves collecting relevant network data, including RSSI, CQI, RSRP, RSRQ and SINR as shown in Table 2. Through the process of data collection, 1000 cells of a live LTE network helped us have a large enough dataset to rigorously train the proposed model (as well as other models that will be investigated later in Section).

Table 2
Sample of input features

RSSI	CQI	RSRP	RSRQ	SINR
-49.39	4.83	-83.98	-14.49	2.62
-40.03	5.03	-75.33	-14.68	4.03
-41.28	6.04	-75.15	-13.19	6.07
-40.05	4.50	-79.35	-17.10	1.40
-52.69	2.46	-87.62	-14.50	2.63

A dataset cleaning was applied to remove any missing values and outliers followed by feature scaling to uniform the input features. From this data, essential features are extracted to serve as inputs for the proposed NN model. The implementation of NN model during the training phase serves to study the collected data to identify intricate patterns and interdependencies that influence the direction of HO. We formulated the objective function for these models using loss functions leveraging the Adam optimizer with different batch sizes, number of epochs, number of hidden layers and numbers of neurons per hidden layer. Moreover, one-dimensional convolution filters and pooling sizes can be used for different convolution filters and pooling sizes in the 1D convolution layer. The best performing model was saved during training to ensure that the minimum error is observed on the test data. The network model keeps iterating to decrease error results more accurate and context-oriented HO decisions in real-time situations. In addition to the iterative training process, validation methods will be used to judge the generalization and the adaptability of the NN models. As the number of nodes within a network increases, it is imperative that the model be trained and evaluated on separate datasets to ascertain a broader range of contingencies. The training phase in the two techniques most used in the evaluation of model performance and the prevention of overfitting are k-fold cross-validation and early stopping. In the process of K-fold cross-validation [21], the training dataset is divided into K subgroups in 'fold'. Each ruin act as the validation set while the whole remaining set is for training. This process is repeated K times and the fold serves as the validation set exactly once in each loop. The model iteratively uses one of k training and validation parts of the data to derive the performance metrics on the rest of the data. This provides an insight into the model's performance across all subsets of the data. On the flip side, early stopping is a method of avoiding overfitting in NN models [22]. It is done through the regular check-up of the model on the validation set during training and early stoppage of the training process when the performance is going downhill. This is done so that the system does not rely upon a memorized training dataset. Instead, it learns and adapts to the whole system which promotes generalization. Using k-fold cross-validation and early stopping, we can get a more reliable and NN model.

2.2 Proposed Neural Network Architecture

In this section, we describe the proposed NN model architecture for POLQA-based handover Scheme. The proposed model's architecture is presented in Figure 4, It is a 1D Convolutional NN model [23] that consist of:

i. An input layer
ii. 1D convolutional layer to capture spatial dependencies in the input features
iii. Subsequent hidden layers are incorporated to extract hierarchical representations
iv. An output layer for POLQA score prediction

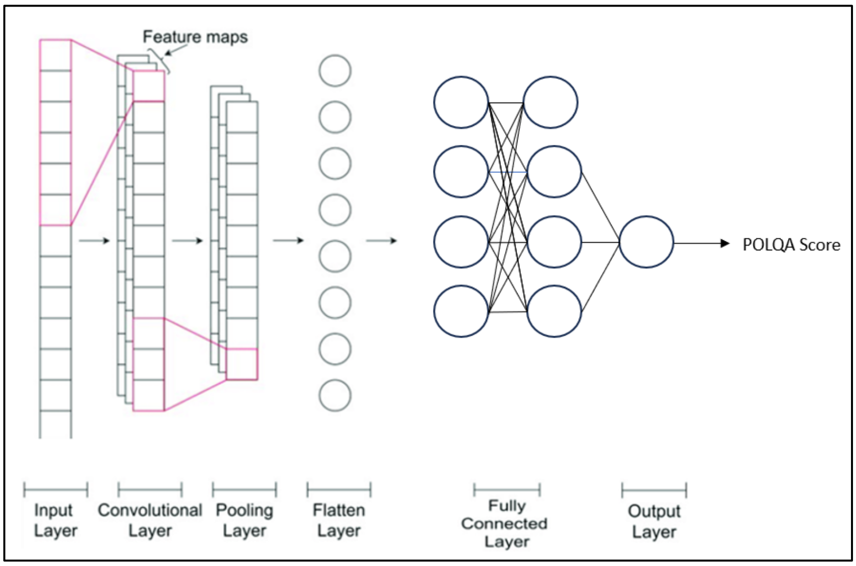

Fig. 4. 1D-convoltional neural network architecture

We conduct extensive experimentation to optimize the model's performance by varying key hyperparameters, including:

i. Filter size in the convolutional layer (16, 32, 64)
ii. Kernel size (1, 3, 6)
iii. Pooling size (2, 16)
iv. Number of hidden layers (2, 3)
v. Number of neurons per layer (4, 10)
vi. Batch size (15, 30, 100, 200)
vii. Epoch size (50, 100, 200)
viii. K-fold cross-validation (3, 5, 10)

2.3 Performance Evaluation

In order to evaluate the performance of proposed model, a comparison between the proposed 1D convolutional neural network model with linear neural network model [24] and artificial neural network model [25] has been conducted in this study. The evaluating focuses on the performance metrics such as accuracy which measures the overall correctness of the model's predictions and models architecture. The architecture includes the number of layers, types of layers (e.g., input, hidden and output layers) and the number of neurons in each layer. It is also necessary to analyse how the model processes the input data and how the layers play a role in transforming the input data into a result.

The architecture of linear NN, also known as single-layer NN, as shown in Figure 5 is consist of:

i. An input layer
ii. A single hidden layer of three neurons
iii. An output layer

A hidden layer consisting of single neuron receives the input data. Each neuron in the layer performs a weighted sum of the input and applies an activation function to generate the output. After having the output layer process, the results that were obtained from the previous layer, the final output is produced.

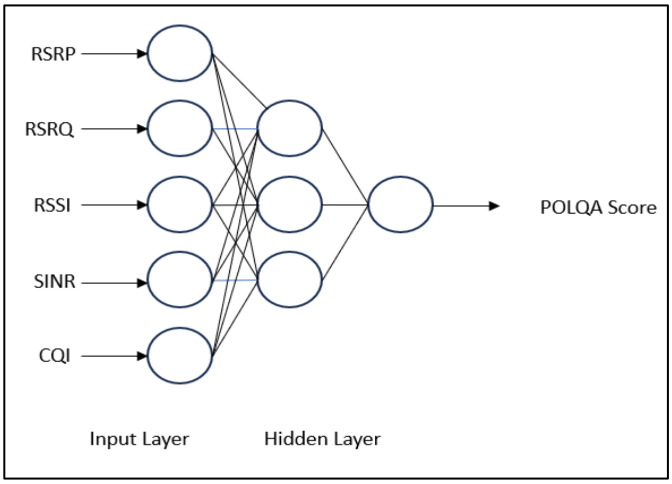

Fig. 5. Linear NN architecture

The architecture of ANN model, as shown in Figure 6 is consist of:

i. An input layer
ii. Subsequent hidden layers are incorporated to extract hierarchical representations
iii. An output layer for POLQA score prediction

We conduct extensive experimentation to optimize the model's performance by varying key hyperparameters, including:

i. Number of hidden layers (2, 3)
ii. Number of neurons per layer (4, 10)
iii. Batch size (15, 30, 100, 200)
iv. Epoch size (50, 100, 200)
v. K-fold cross-validation (3, 5, 10)

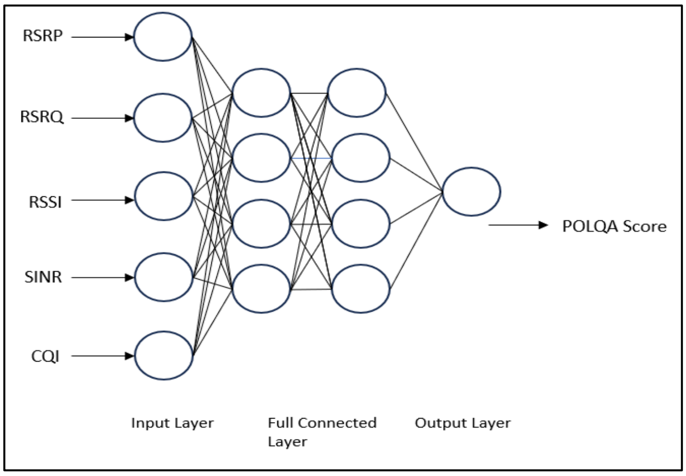

Fig. 6. Artificial neural network architecture

The performance of each model is assessed to accurately predict POLQA scores for the cells in VoLTE networks. The use of the Mean Absolute Percentage Error (MAPE) and prediction accuracy (PA) for comparing the accuracy of the models in handover is essential in the decision-making. The MAPE can provide a precise insight into the level of error present in the models' predictions [26,27]. MAPE and PA are measured using Eq. (2), Eq. (3) by calculating the average value of the absolute percentage error in the forecast POLQA score and the actual POLQA score. It gives a clear indication to the average magnitude of error in predictions made by NN models.

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|actual_t - predicted_t|}{actual_t}}{n} \times 100 \tag{2}$$

$$PA = 100 - MAPE \tag{3}$$

3. Results and Discussion

3.1 Analytical Results

Based on the MAPE results, we found that the linear NN model shows a low POLQA prediction accuracy of ~ 50%. This accuracy is due to the inherent non-linearity between POLQA scores and input features. A linear NN model may not perform well when dealing with non-linear inputs due to its limited ability in capturing complex relationships between input features and output. In the non-linear NN model, we tested different configurations (e.g., the number of hidden neurons, number of neurons per hidden layer, batch size and number of epochs). The objective is to identify optimal settings that yield superior performance and high POLQA score prediction accuracy. The ANN is known by its ability to capture and learn intricate patterns and relationships in the input data. This leads to better performance in the prediction of the POLQA scores. On the other hand, the 1D convolutional NN involves adding another layer that can separate more advanced features from the input data. Then these features can be used to comprehend more complex and abstract information rendering a good accuracy in the prediction of POLQA score.

As mentioned in Section 2, We conduct extensive experimentation to optimize the model's performance by varying key hyperparameters. In Figure 7 and Figure 8, the x-axis shows the hyperparameters combinations versus y-axis which is the model accuracy for each of these combinations. As shown in Figure 7, the ANN model with combination (5_2_(10,10)_100_30) which consists of 5 K-folds, two hidden layers with ten neurons per hidden layer while training model with number of epochs=100 and batch size= 30 leads to high prediction accuracy of 90 %.

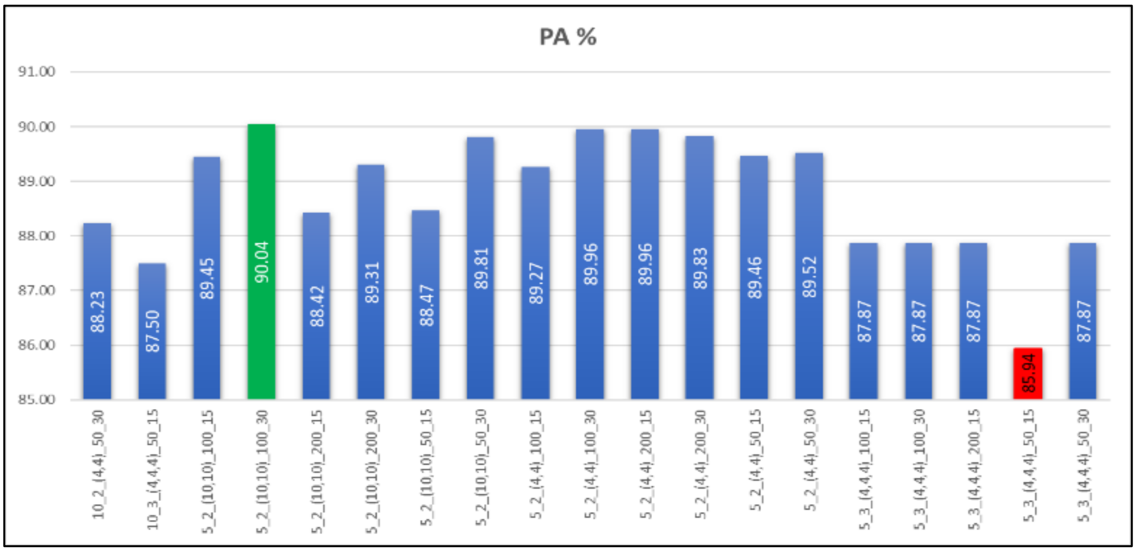

Fig. 7. Artificial neural network model output

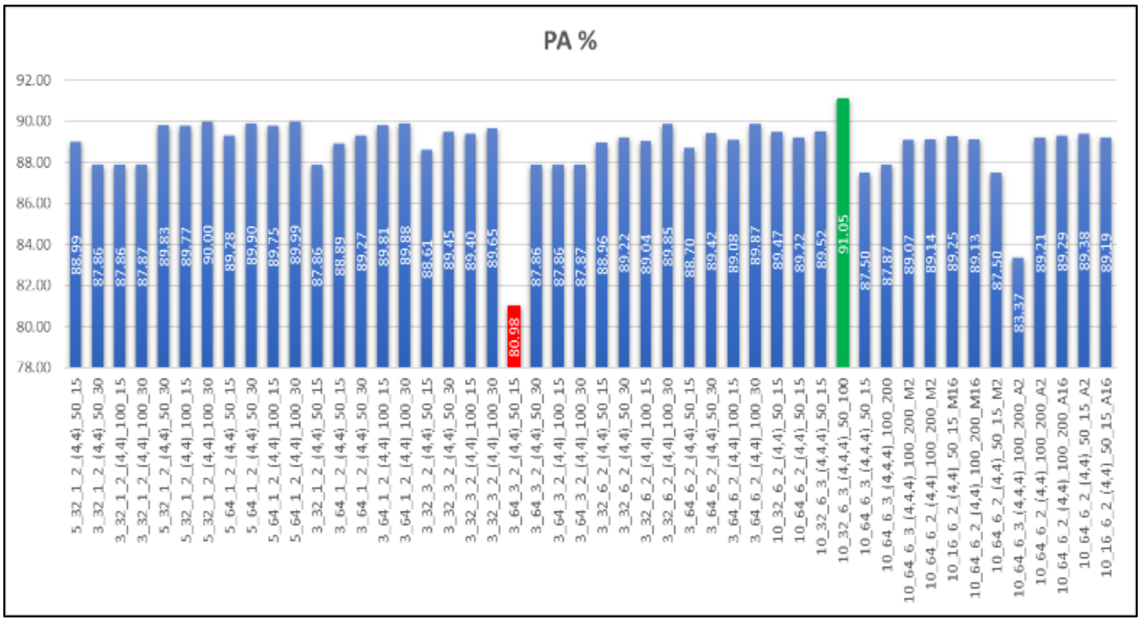

Fig. 8. 1D-convoltional neural network model output

In contrast, changing model combination to be (5_3_(4,4,4)_50_15) which means 5 K-folds, three hidden layers with four neurons per hidden layer while training model with number of epochs=50 and batch size= 15 results in a reduction in accuracy to 86% as shown in Table 3.

Table 3
Hyperparameters combinations for highest and lowest accuracies using ANN model

K	No. of Hidden layers	No. of neurons per hidden layer	No. of epochs	Batch Size	Accuracy
5	2	(10,10)	100	30	90 %
5	3	(4,4,4)	50	15	86 %

For the 1D CNN model, the combination (10_32_6_3_(4,4,4)_50_100) which consists of 10 K-folds, size of 1D convolution filter=32, kernel size=6, three hidden layers with four neurons per hidden layer while training model with number of epochs=50 and batch size= 100 leads to high prediction accuracy of 91 %. In contrast, changing model combination to be (3_64_3_2_(4,4)_50_15) which consists of 3 K-folds, size of 1D convolution filter=64, kernel size=3, two hidden layers with four neurons per hidden layer while training model with number of epochs=50 and batch size= 15 results in a reduction in accuracy to 81% as shown in Table 4.

Table 4
Hyperparameters combinations for highest and lowest accuracies using CNN model

K	1-D Conv. Filter	1-D Conv. Kernel Size	No. of Hidden layers	No. of neurons per hidden layer	No. of epochs	Batch Size	Accuracy
10	32	6	3	(4,4,4)	50	100	91%
3	64	3	2	(4,4)	50	15	81%

3.2 Simulation Results

In this study, two different HO algorithms were tested in a Python-based tool. Both of them were intended for the use within the VoLTE networks. In the first algorithm, the network uses information about the predicted POLQA score of neighbour cells to decide on a HO (i.e. neighbour cell with highest POLQA score will be chosen as the target cell). On the other side, the second algorithm represents the traditional approach for VoLTE handovers [6]. This is based on the simple fact that the mechanism selects the neighbour cell whose RSRP parameter has the highest value. The simulation involved the execution of 1000 HO iterations under same live network conditions such as interference, network load and network congestions. Each of these HO iterations corresponds to a user’s cell change which are the real handover scenarios experienced in VoLTE networks. During each of the performed iterations, both algorithms are assessed to judge their voice quality performance during handovers based on their level of effectiveness.

The results of the simulation revealed a notable improvement in the voice quality when employing the proposed VoLTE HO algorithm compared to the traditional approach as shown in Figure 9.

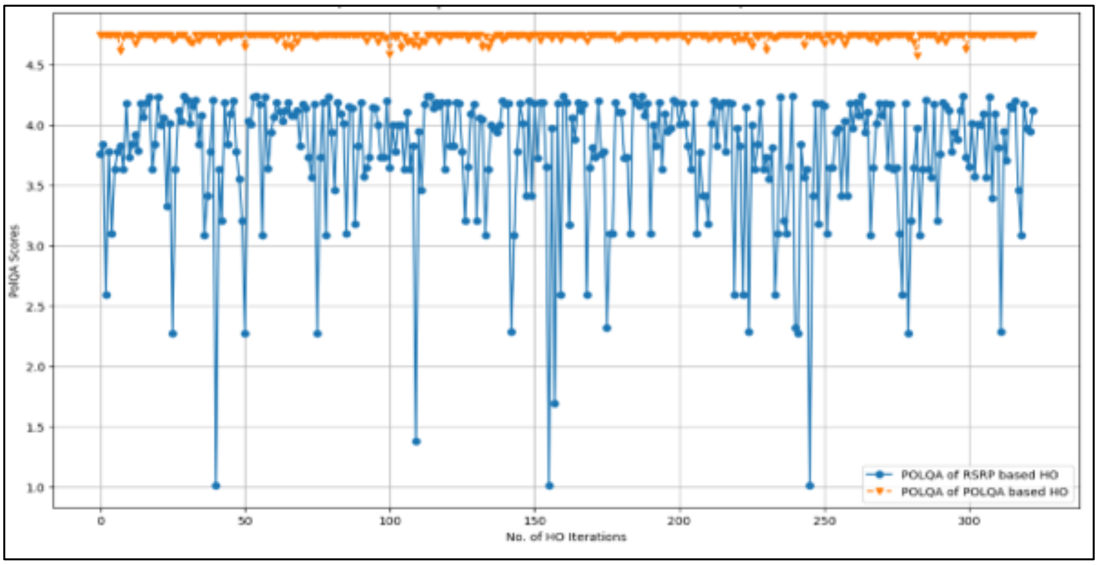

Fig. 9. POLQA score comparison between proposed POLQA-based HO scheme vs. RSRP-based HO scheme [18]

The data demonstrates that the average POLQA score across 323 out of 1000 HO iterations increased to 4.73% when utilizing the proposed algorithm. This represents a substantial enhancement of 26% over the baseline performance observed with the traditional algorithm as shown in Figure 10.

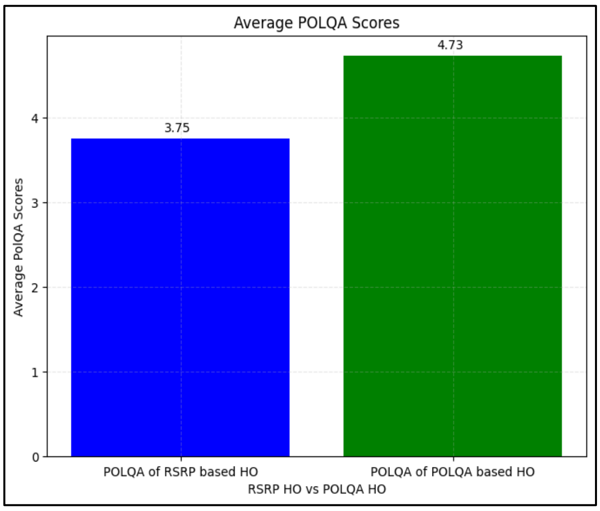

Fig. 10. Average POLQA score comparison between proposed POLQA-based HO scheme vs. RSRP-based HO scheme [18]

Furthermore, the simulation results indicate that the poor, fair and good POLQA score samples all became excellent samples as shown in Figure 11, suggesting a significant overall improvement in voice quality when using the proposed VoLTE HO algorithm.

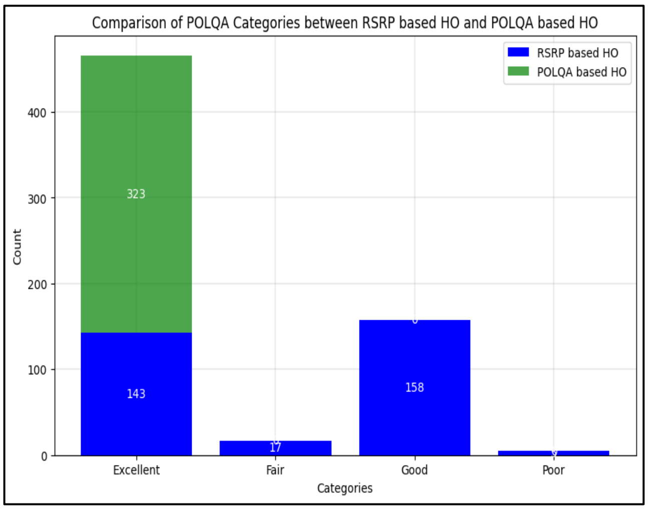

Fig. 11. POLQA score categories comparison between proposed POLQA-based HO scheme vs. RSRP-based HO scheme [18]

This significant improvement in voice quality underscores the efficiency of the proposed VoLTE handover algorithm in mitigating the shortcomings associated with traditional RSRP-based handover schemes. By incorporating predictive POLQA scores into the decision-making process, the proposed algorithm demonstrates its ability to prioritize voice quality over mere signal strength, thereby enhancing the overall user experience and satisfaction in VoLTE networks. Furthermore, these results contribute valuable insights to the ongoing efforts aimed at optimizing voice quality and network performance in next-generation cellular networks.

4. Conclusion

The innovative approach presented in this paper introduced an ambitious leap in optimizing the voice quality for customers through an advanced HO algorithm. The proposed approach has surpassed the traditional HO algorithms that only depend on the highest power level of neighbouring cells with a 26% improvement in terms of the VoLTE quality-of-service (QoS). The proposed approach adopted a predictive model that considers RSRP, RSRQ, RSSI, SINR and CQI values to predict POLQA score of neighbouring cells based on 1D convolutional NN architecture. The proposed approach emphasized the importance of the user experience when designing reliable HO mechanisms. Thus, embracing such novel solutions will have significant positive impact on the overall performance of the VoLTE network.

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