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Application of Neural Network in Handover Predictions and Resource Allocation in Long Term Evolution

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Abstract; *This work took handover enhancement into consideration. Better handover performance is attained with the aid of two Artificial Intelligence (AI) entities. Less frequent handovers occur when the load is evenly distributed across the SeNodeBs. The suggested load balancer was built on an artificial neural network clustering model that uses a self-organizing map as a hidden layer. It was trained to predict network conditions, minimize handovers—especially for UEs at the cell edge—by carrying out only those that were absolutely necessary, and steer clear of handovers to the Macro cell for downlink directions.Hold revolving in the handover orbit, another way to keep and make use of network assets was by predicting the handovers before they arise, and allocate the desired information inside the target SeNodeB, The predictor entity within the proposed gadget architecture combined the features of Radial basis characteristic Neural community and neural community time collection tool to create and replace prediction list from the system's amassed data and learnt to predict the following SeNodeB to companion with. The prediction entity simulated the usage of MATLAB, and the effects showed that the machine was capable of supply as much as 92% accurate predictions for handovers which brought about universal throughput improvement of 75%.*

Keywords: Neural Network, Handover, Resource Allocation, Throughput

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1.0 Introduction

In wireless mobile networks, the amount of time it takes for handovers is a crucial issue that needs to be reduced, along with the frequency of incomplete or redundant handovers(Kobayashi, *et al*., 2018). This type of handover is referred to as the "ping pong effect," particularly when the user agent (UE) is traveling quickly at the cell's edge. Because of the channel interference and management signalling overhead, it lowers throughput and affects QoS (Abo-Zahhad, *et al*., 2020). This issue might be resolved by identifying the next eNodeB on the path and focusing resources there.

Knowing what might occur in the future under specific conditions and circumstances before it does is known as prediction(Bellavista, et al., 2022). Prediction is a great strategy in many areas, including disease management, telecommunications, weather and climate forecasting, and natural disaster preparedness (Wickramasuriya, *et al*., 2019).The creation of prediction models, their validation, or both are the focus of prediction studies.Every user device (UE) in a mobile communication network needs to be able to move freely, stay connected, and maintain a reasonable quality of service (QoS).Any moving UE in a wireless environment will need to have multiple points of contact with the network as a result of mobility; that is, it must execute handovers to every eNodeBthat is in its path (Kumar, *et al.*, 2019).

The deployment of diminutive cells in LTE surroundings and vital problems impacting the effectiveness concentrating on cell choice piece was studied, Authors suggested interference-based cell choice procedure as an approach to furnish greater burden stabilizing amongst the base stations (Kaaniche and Kamoun, 2020).As per the replication outcomes the offered cell choice procedure as said by intrusion levels was capable to repeat the cell-edge user SINR and to brin up the SINR of the median user by 50% in comparison with the RSRP-based cell choice (Davaslioglu & Ayanoglu, 2021).

A prediction technique committed for cutting down the handover defeat rate and ping-pong handover rate, to bypass the postpone flourishing and burdening eNodeB with too much information was proposed. Two links versions were simulated to contrast the outcomes, the offered procedure showed greater efficiency regarding handover defeat rate and ping-pong handover rate (Wang *et al.,* 2019).

The location, knowledge kind, next action type, next action timing, and forecast accuracy level are all important considerations in the prediction process. The fixed eNodeB that is connected to the user might be thought of as being located there (Stefan, *et al.*, 2022). From the perspective of the prediction unit, the precise geographic location is not really crucial for the process, even though it can be easily determined or precisely inferred (Luo, *et al.*,2020). Therefore, the UE location and its motion through the network can be considered as a sequential list of associated eNodeBs and their links, as shown in Fig.1.

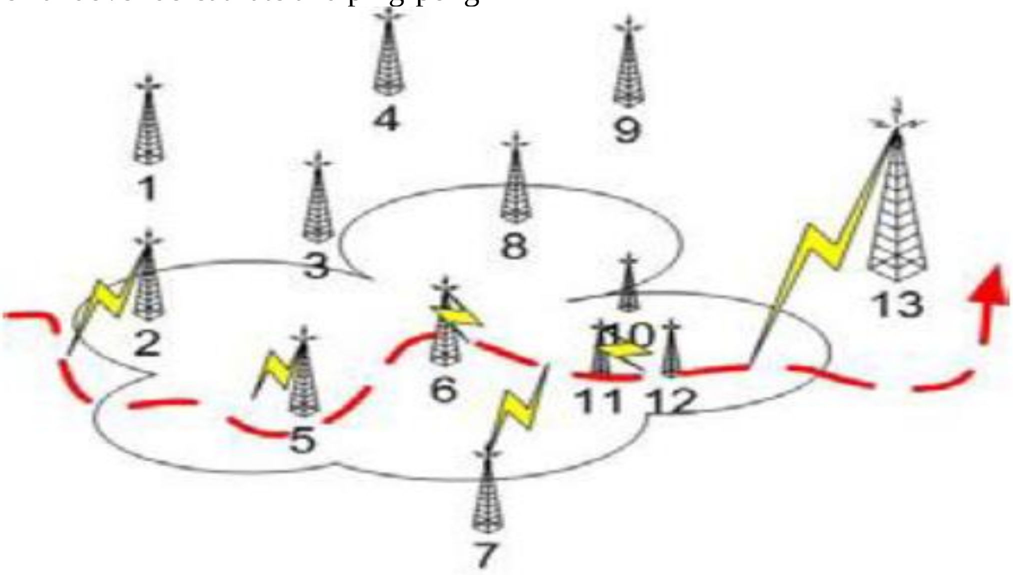

Fig.1: UE mobility path, (Capka and Boutaba, 2019)

3.0 Materials and Methods

3.1 Materials

The data rate needed by the UE to switch to perform a successful handover, to calculate a new parameter for preparing the prediction list are shown in Table 1.

This study aims to develop a neural-network-based prediction model to improve handover accuracy and optimize resource allocation in LTE networks, thereby enhancing user experience and overall system throughput.

Table 1: Simulation parameters (LTE model with predictor)

parameters	value
Deployment	13 sector MeNodeB site per micro cell area
MeNodeB Frequency	2GHz
LTE B.W/Duplex	20MHz
MeNodeB Tx Power	45dBm
UE Tx Powwer	23dBm
Traffic model	HTTP browsing with load radio
File Inter-arrival Time	Exponential
Service	As requested by UE

The prediction was done following the steps below:
1. UE scan RSSI values for source eNodeB and all neighbouring stations and report them to the predictor.
2. If RSSI of the source eNodeB is less than *StresholdAB*, then start prediction
3. Sort eNodeBs according to the RSSI values
4. Determine eNodeB bandwidth for the list
5. Obtain D rate
6. Sort eNodeBs according to Drate Values

The prediction list updated continuously to keep optimum number of handovers initiation. Fig. 2 shows the parameters collection and calculation by the network.

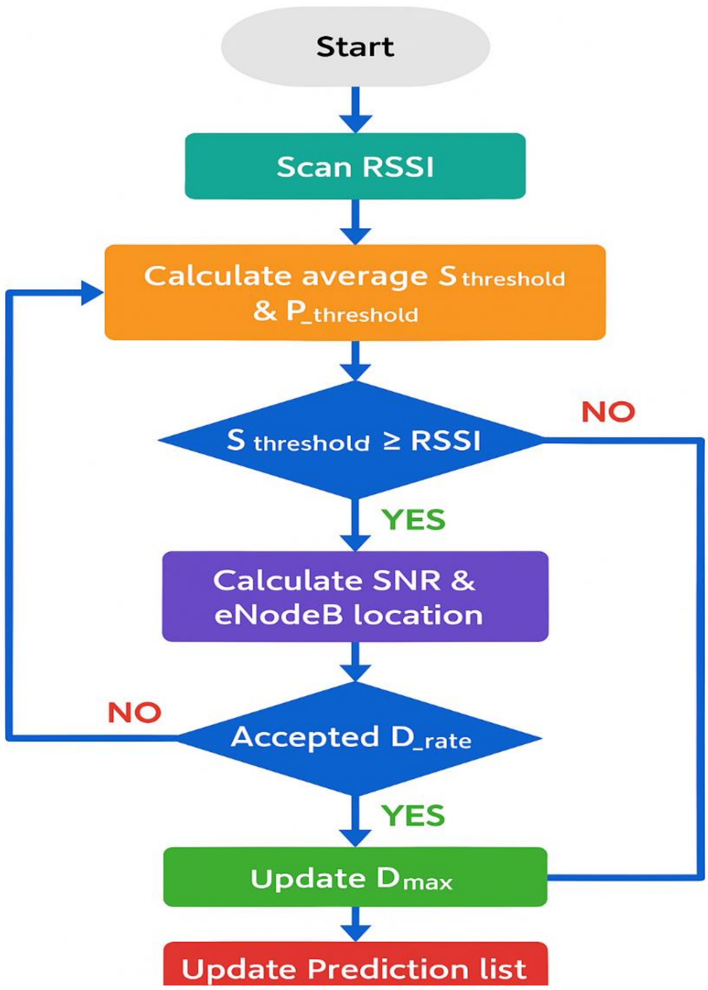

Fig. 2: Prediction parameters collection

From the definition of prediction; it might be considered as dynamic filter, that utilizes the former outcomes to foresee the future outcome. Dynamic neural networks could be utilized in nonlinear filtering and as a consequence prediction. MATLAB application furnish a ready-made software package to resolve the nonlinear time series and choosing among these tools depends on the character of the issue and the qualities of the generator itself. The ready-made software packages includeNon-Linear Autoregressive associations with Exogenous inputs (NARX), Non-Linear Autoregressive (NAR), Non-Linear input-output. The NARX prediction is as said by the time series former data and an extra time series, whereas the NAR doesn't have an input time series (only the feedback), and the Non-Linear input-output keeps the data from the former session and take advantage of it for the prediction because it has no feedback. Fig. 3 illustrates the layer architecture of the NARX generator.

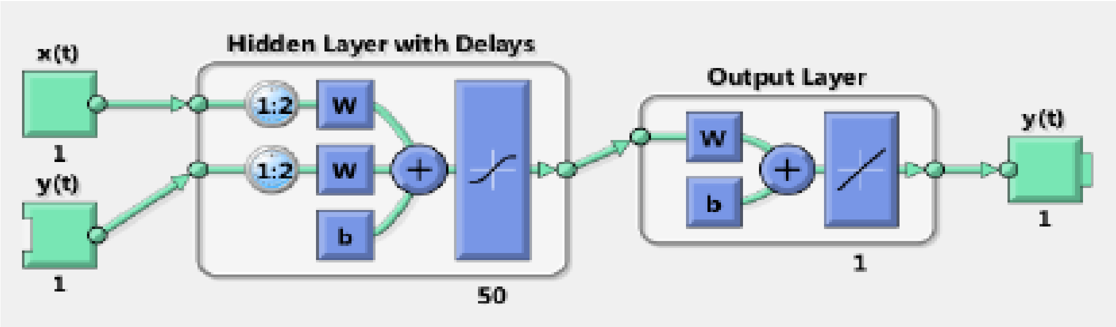

Fig. 3: Neural time series (NARX)

The contacts need to be trained to acquire knowledge of the prediction rules, and since the result sets are known, that is to say, the need for supervised acquiring and no big amounts of information is demanded. MATLAB provides 3 acquiring algorithmic program for training the neural time series: The Levenberg-Marquardt, Bayesian Regularization and Scaled conjugate gradient. Each among these algorithmic programs has distinct characteristics and need to be chosen on that basis. The Bayesian procedure has a need for more education time, but it reverts excellent generalization solutions mainly when challenging or twisted datasets have been utilized, preventing is directed by playing down the contacts weights. Conversely, the Levenberg-Marquardt is faster and extremely strong for basic issues. Whereas the Scaled conjugate gradient has a need for less retention and has been powerful when diminutive datasets have been utilized, both algorithmic programs cease the education once the generalization stops to enhance or when the intend square mistake of the validation information kicks off to boost. But sometimes, in the handover issue that stands in need of prediction-based approach, the correct region of the UE is not a crucial necessity, the predictor deals with eNodeBs list and, so the Levenberg-Marquardt procedure is utilized to train the associations.

3.2 Simulation Setup

To fully discuss and comprehend the advantages of prediction, each of the replication scenarios has 3 phases.The 1st is running the contacts before prediction, training the predictor, and running as said by prediction outcomes. The trajectory of the chosen UE was selected as shown in Fig. 4, and the cruising speed was assumed constant and selected to have an average of 5 miles/hour.

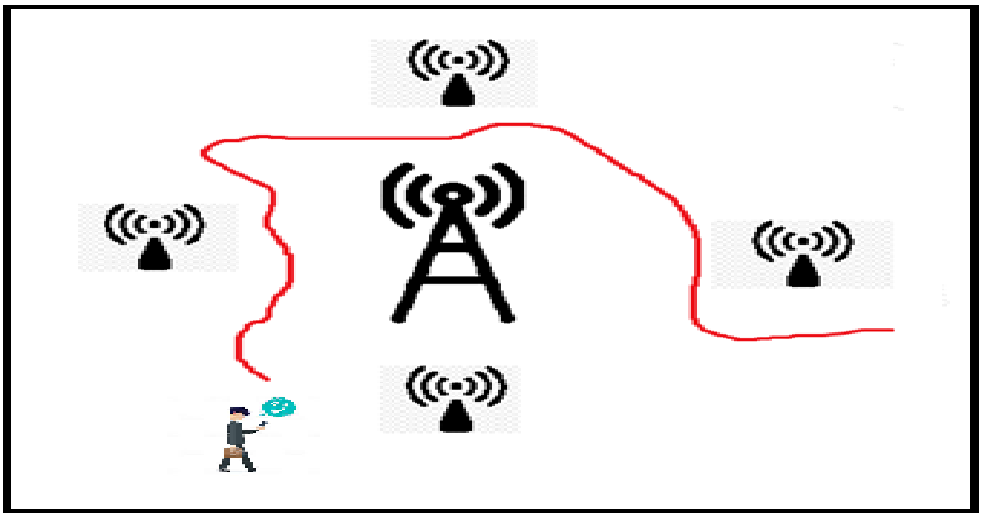

Fig. 4: Handover path for UE

4.0 Results and Discussion

Fig. 5 shows the associated eNodeB for the entire period of the simulation.

During the 2nd phase, the predictor is currently trained for handover triggering to the focus on eNodeB. The relationships between validation and testing information are segregated into time steps.These time steps are then grouped for utilizing them in training, validation and testing. The percentiles are set as: 70% for training, 15% for validation, and 15% for testing as per the replication outcomes.The relationships were 17 epochs in complete and the intended square error was at its lowest at epoch 11.

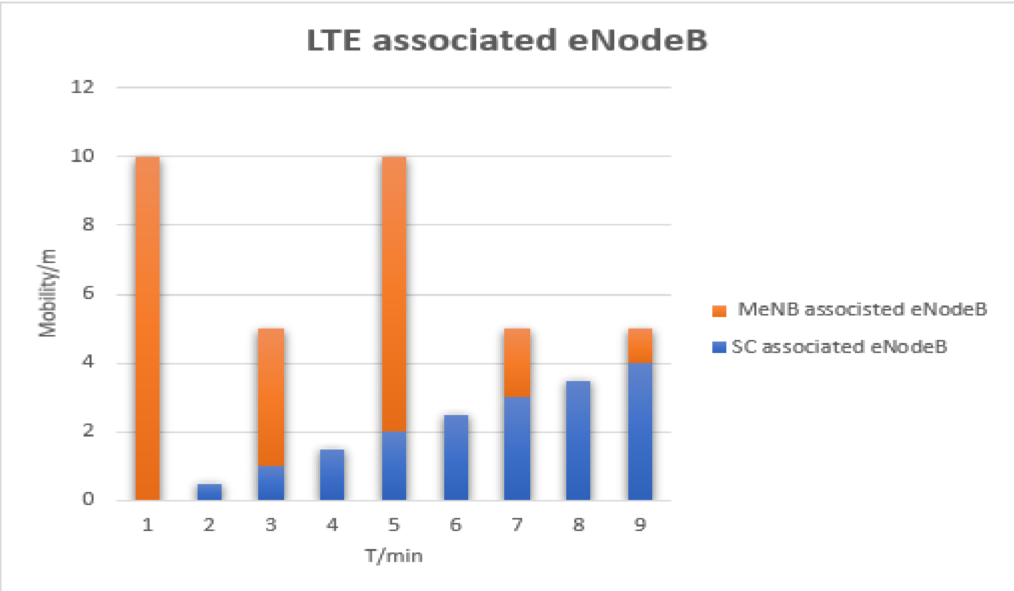

Fig. 5: Associated eNodeB sequence

The epoch is "the number of times all of the training vectors are used once to update the weights. For batch training, all of the training samples pass through the learning algorithm simultaneously in one epoch before weights are updated". The Mean Squared Error (MSE) is the average squared difference between outputs and targets. Lower values are better. Zero means no error, and Regression R values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. Fig. 6 shows the performance of the time series. Table 2 demonstrates the results obtained from the network

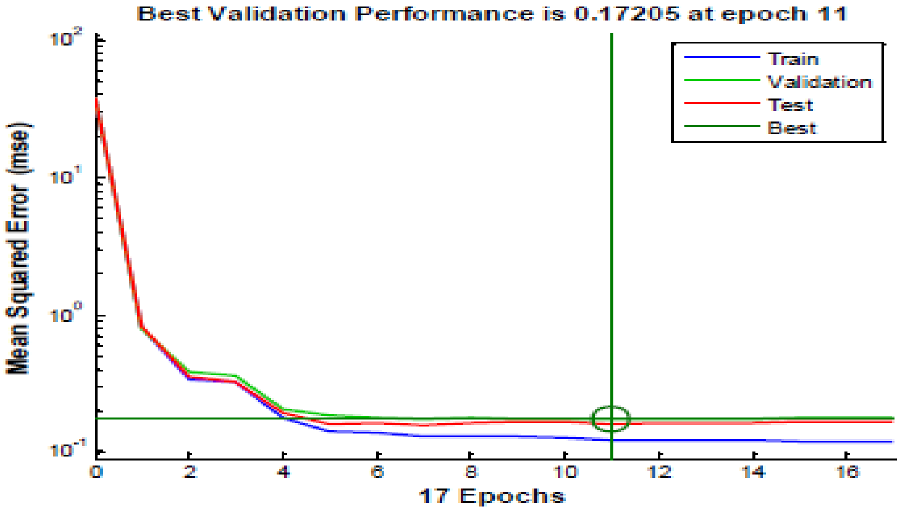

Fig. 6: Neural time series performance

Table 2: Training results

	Target values	Mean Square Error	Regression
Training	1400	1,2289e-1	9,77886e^{-1}
Validation	300	1,72054e-1	9,69093e^{-1}
Testing	300	160436e-1	9,70192e^{-1}

In the third phase, the first scenario is repeated with same trajectory and load conditions but with new information for the associated eNodeB and time. Fig. 7 shows the actual handovers results and Fig. 8 shows the predicted ones. From the graphs, it's obvious that the neural network was able to accurately predict the sequence of the handovers and the triggering time is also predicted.

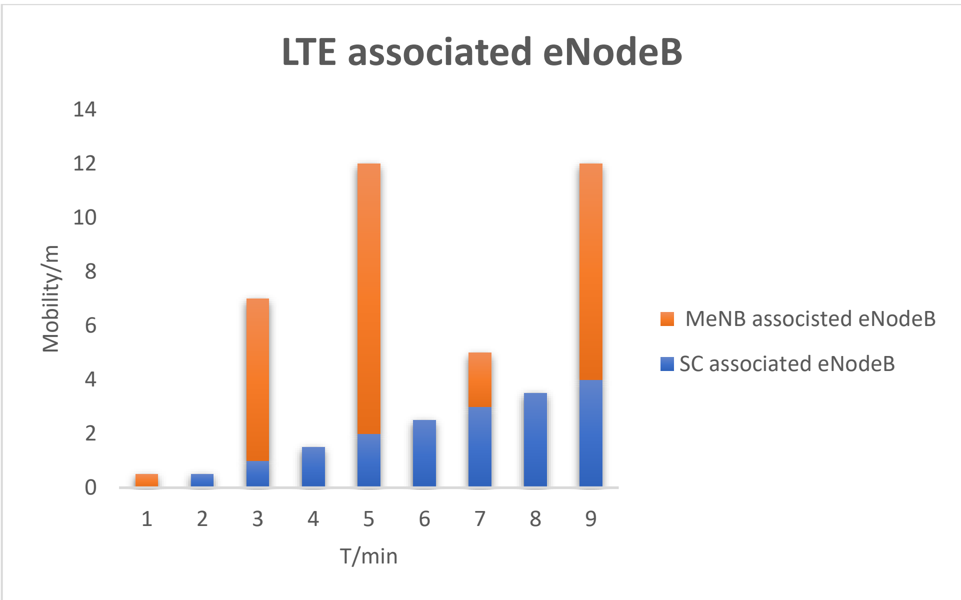

Fig. 7: Obtained associated eNodeB

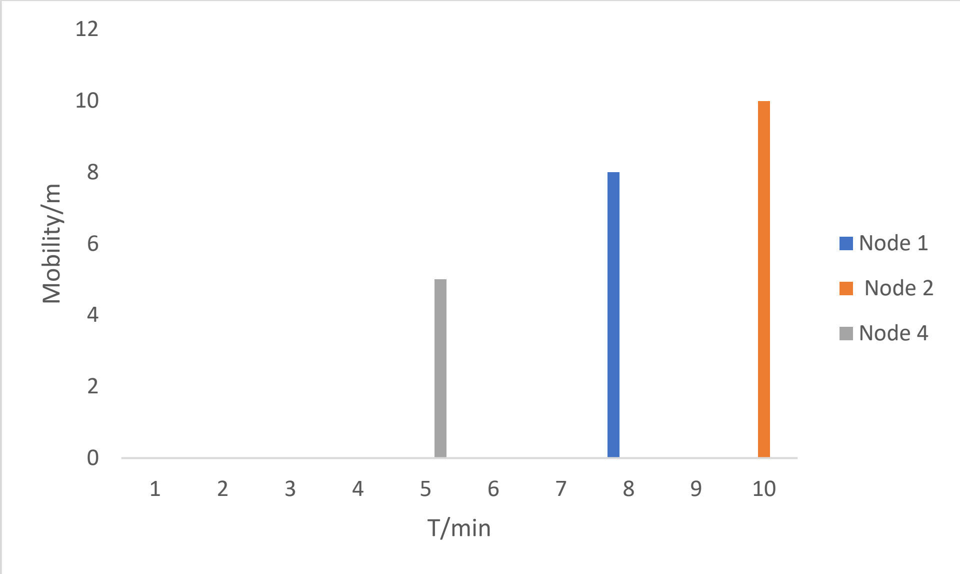

Fig. 8: Predicted associated eNodeB.

Contrasting the outcomes in Figs. 5 and 8, it could be acclaimed that the UE never started a handover towards eNodeB 3; this is because the predictor decided for the UE not to conduct a handover and connect with eNodeB 3. The prediction has been produced for the downlinkonly and the MeNodeB has not been interested in the prediction arrangement. Fig. 9 illustrates the effect of prediction arrangement upon the throughput and in what way it's impacted by the lowering the amount of handovers.From Fig. 9, it could be seen that throughput improvement of 75% was achieved when pridector operates at Full load, while at normal load, a throughput of 70% was achieved.

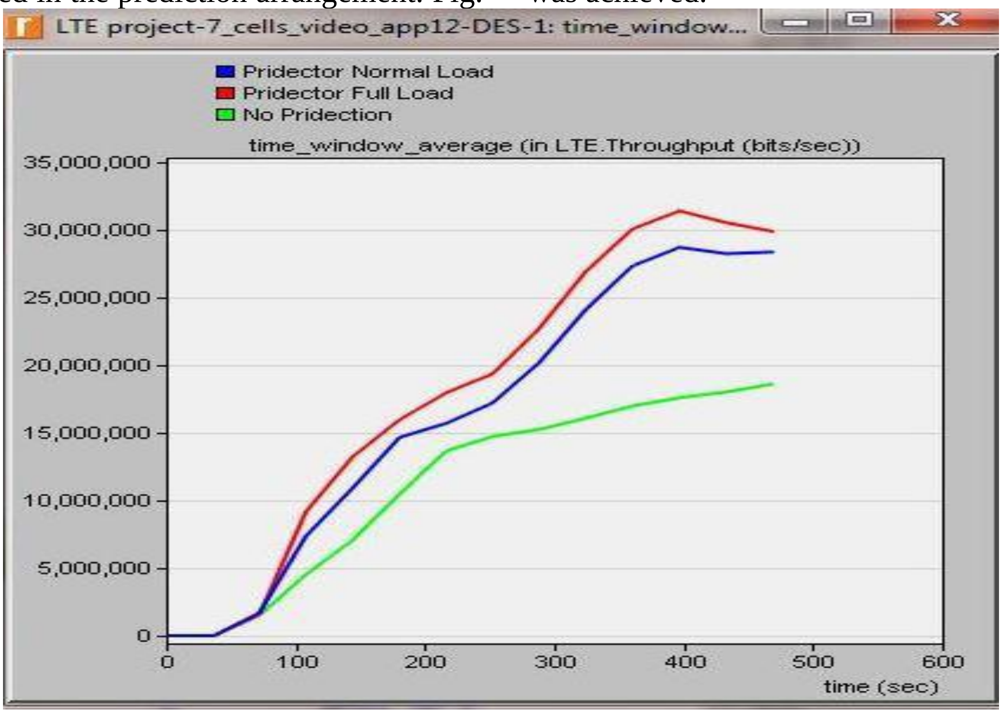

Fig. 9: Throughput evaluation.

5.0 Conclusion

Predicting the handovers before they happen, and assigning the demanded information in the focus on SeNodeB will help the contacts to utilise its resources in a greater way and do it shortly. The predictor entity in the put forward method architecture combines the characteristics of Radial Basis operate Neural contacts and neural contacts time series software to generate and modify prediction list from the system's gathered information and acquire knowledge to forecast the next SeNodeB to connect with.The prediction entity has been virtualized utilizing MATLAB, and the replication outcomes illustrate that the method was capable to bring up to 92% accurate predictions for handovers. These predictions aided augmenting the throughput of the links to its optimal worth, and it might be complied with they led to generally speaking throughput enhancement of 50% when the associations saturates.

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Consent for publication

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Availability of data
Data shall be made available on demand.

Competing interests
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