Predicting mobile networks' behaviors using Linear Neural Networks

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***Abstract*— Predicting cellular networks' behaviors for making network development strategies such as 3G/4G/5G technology layers, radio resource management and optimizing Capital Expenditure (CAPEX) and Operating Expenditure (OPEX) is a very important task. This paper proposes using a Linear Neural Network which has an acceptable accuracy for predicting networks' behaviors in cellular systems based on real statistical information from Operations Support Systems (OSS). Training and testing data are taken from real 4G/LTE networks for verifying and analyzing the results. Once the prediction is done then corresponding configuration tunings are carried in the network to fit service requirements and leverage network's performance.**

***Keywords*— predicting, behavior, Machine Learning, mobile network, data.**

I. Introduction

Nowadays, in the period of digital transformation and industrial revolution 4.0, Artificial Intelligence (AI) plays an important role in all areas of our daily life. With the great development of AI in recent years, AI technologies are expected to be combined into future wireless communication systems and solve the massive traffic and accessing with ultra-reliable and low latency constraints [1]. Breakthroughs in AI and Machine Learning (ML), including deep neural networks and probability models, are creating paths for computing technology to perform tasks that once seemed out of reach [2].

The mobile communication system is one of the most complex inventions in history yet has had a deep and impactful effect on the daily lives of users around our planet. Vendors and operators are continuously planning new features to enhance the performance and capacity of the global network, including the tools and services necessary for operators to manage and optimize their technical facilities [2].

Recent achievements of AI in general and ML in particular emerge as a typical example of the industrial revolution 4.0 ('Smart' technologies, big data, cloud computing and networked machines) with some of the numerous AI/ML applications such as Google's and Tesla's self-driving cars, Facebook's facial recognition system, Apple's Siri virtual assistant, image to text conversion system Google Vision API, Amazon's product suggestion system, etc. Embedding AI/ML in mobile communications promises to bring positive breakthroughs. Today's mobile network system creates a tremendous amount of big data, which can help to significantly leverage the design and management of networks and communication components when combined with advanced ML methods [3].

Data analytics and exploration of mobile networks are the process of collecting, organizing, and analyzing large data sets to extract patterns and make decisions. There are four types of analytics that can be applied for wireless pipe design, operation, and optimization [2]:

- Diagnostic Analytics
- Descriptive Analytics
- Prescriptive Analytics
- Predictive Analytics

In this paper, we focus on predictive analytics which is the process of using data analytics to make predictions about unknown future outcomes based on data. Predictive analytics employs many techniques from statistics, data mining, modelling, ML and AI to assess current and historical facts to predict future events.

This paper is concerned with supervised learning algorithm which is a type of AI algorithm in which the mapping function between the input and output can be inferred by the labeled training data. We use Linear Neural Networks integrated Linear Regression algorithm to predict networks' behaviors with limited datasets extracted from NetAct OSS systems [4].

II. Dataset of mobile networks' behaviors

A. Dataset of Mobile Networks Behaviors

Over time, mobile communications have made great leaps to connect people and communities by various multiple access technologies from analog telecommunications standards (1G) to complex digital telecommunications standards (5G, 6G). Approximately, every 10 years a new generation of mobile technologies is introduced [5] that brings improvements in experience, performance, efficiency and capability. The telecom industries have commercially witnessed the mobile communication evolution from 1G to 5G so far.

Regardless of the mobile technology, the overall architecture has the common ground of radio access network, core network and transmission network as illustrated in Fig. 1. These mobile networks are all connected to the operator's OSS to operate, exploit and manage. Network behaviors including customer's behaviors, network incidents, critical alarms, etc. are collected and stored on servers to optimize and improve network quality.

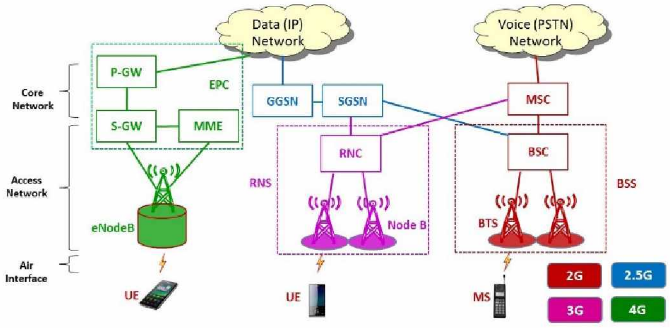

Fig.1. 2G to 4G simplified architecture [6]

The OSS's servers record and store data included Key Performance Indicators (KPIs) which consist of a set of common performance counters for accessibility, retainability, and mobility KPIs is generated by network elements like eNodeBs (eNBs) and mobility management entity (MME) [7] and network behaviors and measurements also.

The 4G/LTE network behaviors such as Random Access Channel (RACH) attempts, Radio Resource Control (RRC) attempts, E-UTRAN RACH Setup Attempts, etc. are recorded by millions of counters. This paper investigates the prediction of these behaviors based on dataset collected from some of these counters.

III. THE LINEAR NEURAL NETWORK MODEL

A. Linear Model with Linear Regression

Linear Regression is a ML algorithm based on supervised learning which is employed for finding linear relationship between a scalar response and one or more explanatory variables. It is a basic and widely used type of predictive analytics. Linear regression performs the task to model a linear relationship between dependent variable value y and a given independent variable x [8].

We use n to denote the number of examples in our dataset and index the samples by i, representing each input data point as $x^{(i)} = [x_1^{(i)}, x_2^{(i)}]$ and the corresponding label as $y^{(i)}$ [9].

When our input consists of d features, prediction results are expressed as Γ:

$$\Gamma = \theta_1 x_1 + \ldots + \theta_d x_d + b \qquad (1)$$

Collecting all features into a vector x and all weights into a vector w, our model compactly using a dot product can be written as:

$$\Gamma = \theta^T x + b \qquad (2)$$

The vector x corresponds to a single data point. Finding it convenient to refer our entire dataset via the design matrix X. For a collection of data points X, the prediction Γ is as:

$$\Gamma = Xw + b \qquad (3)$$

Given a training dataset X and corresponding known targets y, the purpose of linear regression is to find the weight vector θ and bias term b that given some a new data point x_i, sampled from the same distribution as the training data will predict the target y_i with the lowest error. When our prediction for some example i is $\Gamma^{(i)}$ and the corresponding true label is $y^{(i)}$ the squared error is given by:

$$l^{(i)}(\theta, b) = \frac{1}{2}\left[\Gamma^{(i)} - y^{(i)}\right]^2 \qquad (4)$$

Large differences between estimates $\Gamma^{(i)}$ and observations lead to even larger contributions to the loss, due to the quadratic dependence. For measuring the accuracy of a model on the whole dataset, we average the loss on the training set.

$$L(\theta, b) = \frac{1}{n}\sum_{i=1}^{n} l^{(i)}(\theta, b) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{2}\left[\theta^T x^{(i)} + b - y^{(i)}\right]^2 \qquad (5)$$

We would like to find parameters (θ^*, b^*) that minimize the total loss across all training samples:

$$\theta^*, b^* = \underset{\theta, b}{argmin}\, L(\theta, b) \qquad (6)$$

The prediction problem is to minimize $\|y - X\theta\|$ which is tightly convex, therefore, there is one critical point on the loss surface and it corresponds to the absolute minimum. Taking the derivative of the loss with respect to θ and setting it equal to zero yields the analytic solution:

$$\theta^* = \left(X^T X\right)^{-1} X^T y \qquad (7)$$

B. Gradient Descent Algorithm

In this paper, the learning model is optimized by gradient descent algorithm which reduces the error by updating the parameters in the direction that incrementally lowers the loss function [9]. Sampling a minibatch Ω consisting of a fixed number of training data at random. Then, computing the gradient of the average loss on the minibatch and finally multiplying the gradient by a predetermined step size $\lambda > 0$ and subtracting the result term from the current parameters values. The update process can be written as:

$$(\theta, b) \leftarrow (\theta, b) - \frac{\lambda}{|\Omega|}\sum_{i \in \Omega} \partial_{(\theta, b)} l^{(i)}(\theta, b) \qquad (8)$$

The expression (8) can be represented explicitly as:

$$\theta \leftarrow \theta - \frac{\lambda}{|\Omega|}\sum_{i \in \Omega} x^{(i)}\left[\theta^T x^{(i)} + b - y^{(i)}\right] \qquad (9)$$

$$b \leftarrow b - \frac{\lambda}{|\Omega|}\sum_{i \in \Omega} x^{(i)}\left[\theta^T x^{(i)} + b - y^{(i)}\right] \qquad (10)$$

C. Neural Network Diagram

The linear model built in this paper can be illustrated as Fig. 2

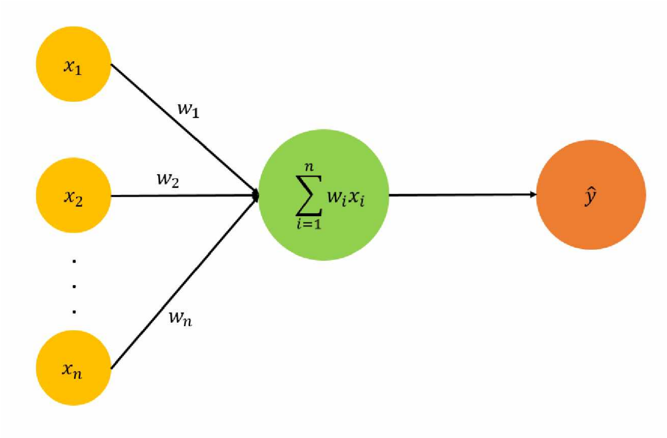

Fig. 2. Linear regression is a single-layer neural network

The diagram depicts the connectivity pattern and linear models can be considered as neural networks consisting of just a single artificial neuron. According to Fig. 2, every input is connected to every output so that we can regard this transformation as a fully-connected layer [2].

IV. Numerical Results

A. Model Implementation

The data used to train and validate the proposed Linear Neural Networks is collected from the OSS. There are millions of counters on the multi-layer technology mobile network, so the data collected and stored in the OSS is relatively limited in size due to the limitation of servers' storage capacity. Data is integer values of three KPIs including E-UTRAN RACH Setup Attempts, RRC Setup Attempts and E-UTRAN Data Radio Bearer Attempts over time. It was collected during two weeks with 15-minute granularity of 2 different eNodeBs located in 2 different cities which are Hue and Danang City in Vietnam to have objective and independent evaluation results, respectively. The whole dataset is divided into two sub-datasets at ratio 80% and 20% for training data and testing data, respectively.

The implementation of the network's behaviors prediction model is done in Python programming language with Keras and Tensorflow libraries.

We choose the Mean Square Error as the metric to measure the accuracy of prediction algorithm, which is expressed as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \Gamma_i\right)^2 \qquad (11)$$

B. Result Analysis

In this section, we present the visual results of fit-levels of prediction as graphs from Fig. 3 to Fig. 11 and multi-step prediction of three 4G/LTE KPIs reflected networks' behavior which is performed for four later time instants. In addition, the accuracy of each prediction per eNodeB is calculated and shown in Table 2.

- The eNB 1 located in Hue city

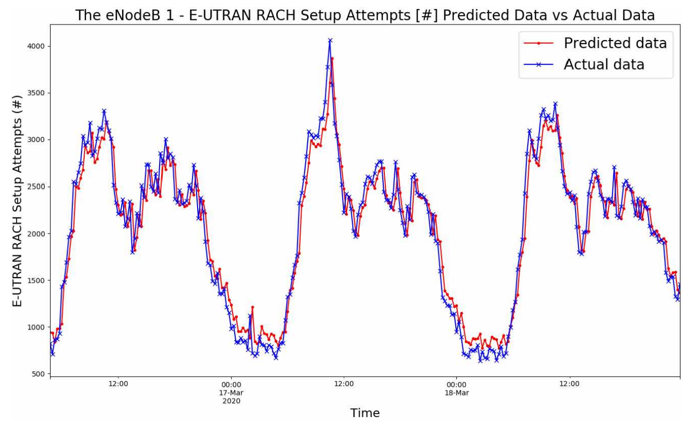

Fig. 3: E-UTRAN RACH Setup Attempts - predicted data versus actual data of the eNB 1

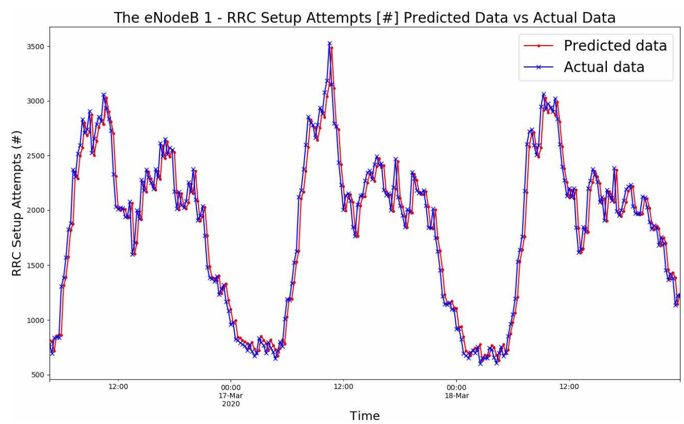

Fig. 4. RRC Setup Attempts - predicted data versus actual data of the eNB 1

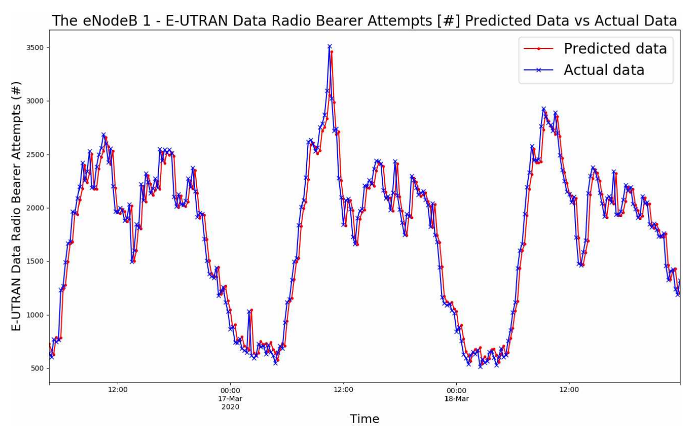

Fig. 5. E-UTRAN Data Radio Bearer Attempts - predicted data versus actual data of the eNB 1

- The eNB 2 located in Danang city

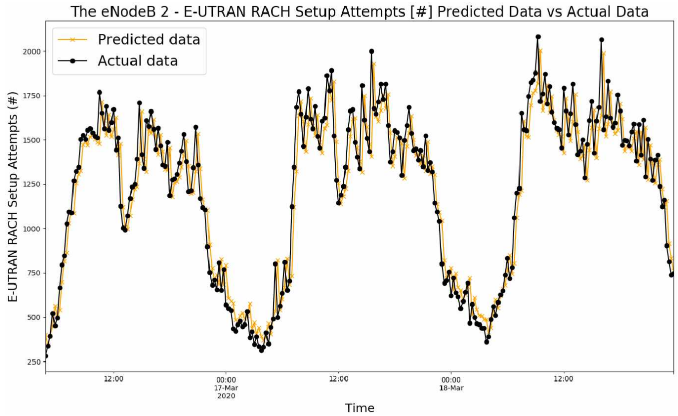

Fig. 6. E-UTRAN RACH Setup Attempts - predicted data versus actual data of the eNB 2

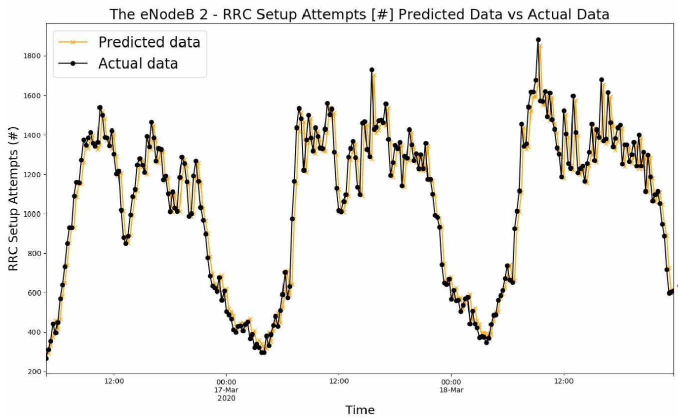

Fig. 7. RRC Setup Attempts - predicted data versus actual data of the eNB 2

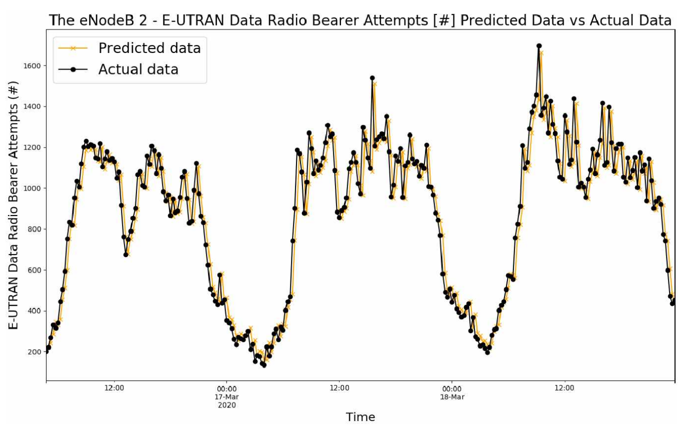

Fig. 8. E-UTRAN Data Radio Bearer Attempts - predicted data versus actual data of the eNB 2

MSEs is the average of the square of errors. It is always non-negative and errors in this case means the difference between true values and predicted ones. The smaller the number is the smaller the error is. The model is perfect if and only if the MSE's value equals zero. The accuracy of each prediction of each behavior is inferred from all calculated results of MSEs and synthesized as the table Table 1 below:

TABLE 1: ACCURACY OF EACH PREDICTION

eNodeB	Accuracy of prediction (%)		
	E-UTRAN RACH Setup Attempts	**RRC Setup Attempts**	**E-UTRAN Data Radio Bearer Attempts**
1 (Hue)	92.12	94.62	94.06
2 (Danang)	88.53	91.33	91.07

According to Table 1, the accuracy values vary from 88% up to ~94%. Due to the limitation of dataset stored on OSS used to train the model, we can extend the dataset by data aggregation techniques in order to improve the accuracy of prediction.

Fig. 9 to Fig. 11 illustrates prediction results as graphs of four future data points of the eNB 1 located in Hue City.

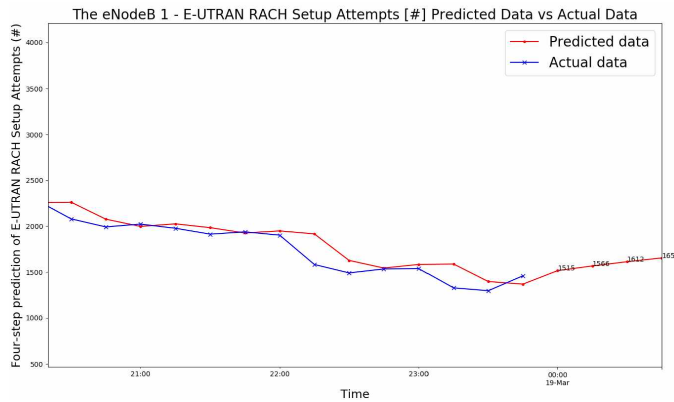

Fig. 9. Four future data points of E-UTRAN RACH Setup Attempts of eNB 1

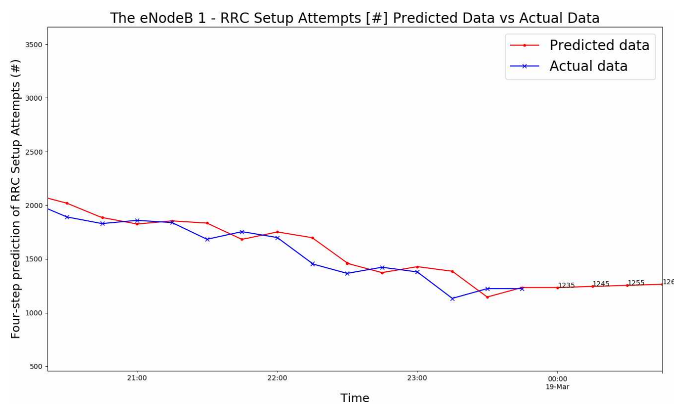

Fig. 10. Four future data points of RRC Setup Attempts of eNB 1

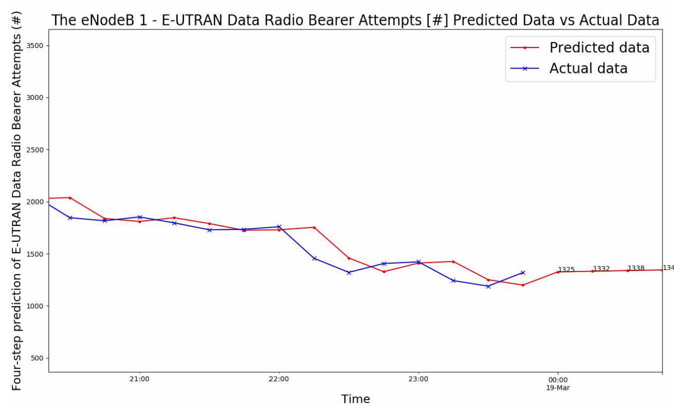

Fig. 11. Four future data points of E-UTRAN Data Radio Bearer Attempts of eNB 1

Fig. 12 to Fig. 14 illustrates prediction results as graphs of four future data points of the eNB 2 located in Danang City.

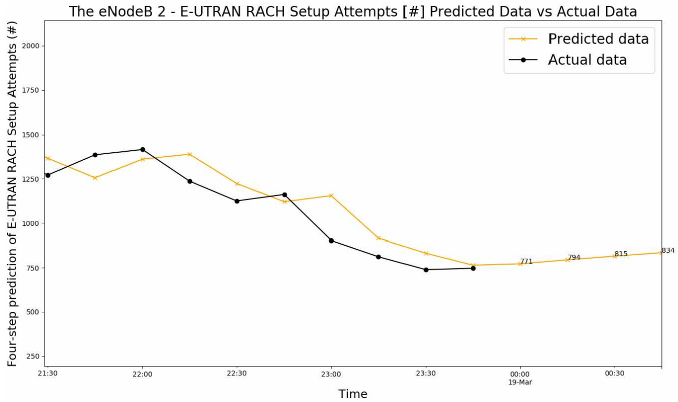

Fig. 12. Four future data points of E-UTRAN RACH Setup Attempts of eNB 2

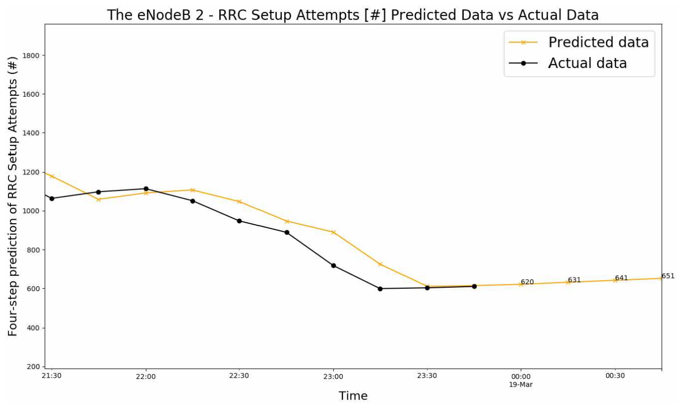

Fig. 13. Four future data points of RRC Setup Attempts of eNB 2

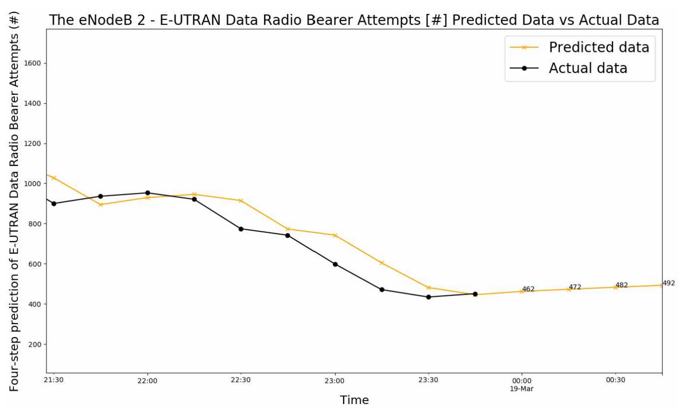

Fig. 14. Four future data points of E-UTRAN Data Radio Bearer Attempts of eNB 2

The Table 2 summarizes prediction results of four future data points of three KPIs which belong to the eNB1 and eNB2. These KPIs represent three main phases for establishing a data connection between the UE and the mobile network through eNBs.

TABLE 2: SUMMARY OF 4 FUTURE DATA POINTS OF THE ENB 1 AND ENB 2

Prediction data point	Prediction values [#]					
	E-UTRAN RACH Setup Attempts		RRC Setup Attempts		E-UTRAN Data Radio Bearer Attempts	
	eNB 1	eNB 2	eNB 1	eNB 2	eNB 1	eNB 2
1	1515	771	1235	620	1325	462
2	1566	794	1245	631	1332	472
3	1612	815	1255	641	1338	482
4	1653	834	1265	651	1344	492

According to prediction values in table 2 with accuracy varying from 88% to ~94%, the radio resource allocation strategies can be derived and prepared to optimize network's qualities. Based on the model of Linear Neural Networks we can apply it into the other prediction of counters reflecting other behaviors related to different technology such as 2G, 3G and 5G to have prediction data for rolling out reasonable solutions.

With the forecasted information in advance, operators can monitor their mobile networks proactively and plan user experienced-driven networks [2]. Moreover, self-learning and adaptive networks are being researching and built to improve the quality of mobile networks [2] so as to meet subscribers' satisfaction in the near future.

V. Conclusion

This paper proposes using Linear Neural Networks as single-layer neural networks for predicting networks' behaviors in cellular systems based real statistical information from networks' counters in OSS. The accuracy of the model is up to 94% so that it is suitable for predicting bulk of counters reflecting networks' behaviors with the limited dataset size. With future prediction data of networks, operators can optimize resources and deploy technical solutions in order to improve the quality of services and quality of experience.

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