Mobility Robustness Optimization Using ANN for Call Drop Prediction

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Abstract: **Call drop in a mobile network is a much-unexpected phenomenon that is facing by every mobile consumer in today's era even society is going to adopt 5G and 6G. This issue has not been resolved till now. Many intellectuals and academicians are currently in practice to reduce call drop and they proposed many proposals but still call drop rate is 62% according to a telecom survey. This research paper is giving an approach to minimize call drop during the time of traveling. The proposed model will be helpful to predict call drop which is based on few common parameters that are catching by the nearest base station during handover. This research paper is focused on mobility robustness optimization using an artificial neural network for call drop prediction. Mobility robustness is an important feature of a self-optimizing network and it can be implemented by using deep learning artificial neural network which is well famous for automatic feature extraction, classification and prediction.**

Index Terms **- Self optimization, artificial neural network, mobility robustness optimization, call drop.**

I. INTRODUCTION

Now a day's life without a cell phone cannot be imagined. Call drop is actually an unexpected hit that can become an obstacle in your call anytime when you are having an important conversation with someone. Most of the people, whether in the village or in the city, are facing this problem. In most cities, the user has to move from one place to another for better signal quality when he wants to talk to someone on the phone. As per TRAI, now not greater than 2% call drops for telecom operators are allowed. Today some cellular subscribers are grappling with the problem of frequent voice call disconnections. The dropped call is the common term used for describing any sudden termination of a cellular call. While the subscriber base inside the country is growing very rapidly, the cell telecom infrastructure is not developing on the same ratio and continually impacting consumers by degrading the mean opinion scale and increasing the billing cycle. The rural subscribers are facing voice call drop due to loss of coverage, while in urban areas, this can be because of the growing hole between the growth in subscriber base and absence of commensurate growth in improved self-optimizing infrastructure which will be handling all the issues automatically.

A self-optimizing network is a collection of capabilities for computerized configuration, optimization, diagnostician, and recovery of cellular networks. It is considered to be a first-rate necessity in future cellular networks and operations especially because of possible savings in capital expenditure and operational expenditure by way of introducing self-optimization. As the variety of self-optimizing functions will grow with a technological boom, one of the predominant issues for operators might be to decide which features to introduce and additionally decide the best timing for activating those features to attain a nicely-behaving and fee-efficient community. This research paper focused on one of the key features of a self-optimizing network which is mobility robustness optimization using an artificial neural network to predict call drop should occur or not at a specific location. Mobility Robustness Optimization (MRO) encompasses the automated optimization of parameters affecting active mode and idle mode [3]. It automatically tuned the parameters during handover so that call does not drop.

The research adopted an artificial neural network for call drop prediction when the call has been set up. An artificial neural network is a supervised machine learning algorithm that is generally used to solve a more complex problem. Here research has found two-layer neural network is suitable to predict call drop during the above-said situation. The research paper focused on some mobility parameters which are responsible for call drop during handover such as the speed of subscriber in meter per second, signal strength in dBm, distance from a base station in meter, call setup time in seconds, call duration in seconds, longitude, latitude, and result of a call that will be in form of 0 and 1. Zero means call drop and 1 means no call drop. Dataset has been collected with the help of a network signal info app. A total of 500 samples have been collected by google survey form in 2019. Data has been collected from primary sources and it is real-time quantitative data because subscribers have given the information of their phone by google form. Dataset collected only bharti airtel and reliance jio network subscribers who are taking 4G service from these network operators.

II. LITERATURE SURVEY

Telecom regulatory authority conducts many drive tests and research surveys to find out the ratio of call drop. From July 2015 to September 2015[1], the drive test results indicate that no telecom operator has achieved the benchmark as shown in fig.1.There can be many reasons for call drop. Such as changing weather, rain, and electromagnetic effect, Non-functioning of user's mobile, more distance between mobile and base station, radio traffic, handoff, weak signal strengths, etc.

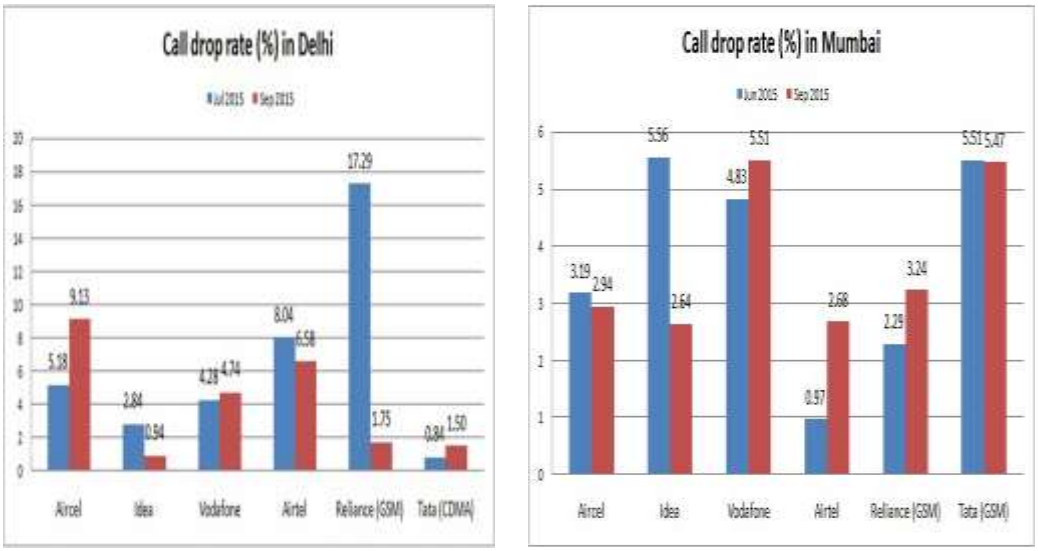

Fig.1. Call drop survey analysis

Call drop ratio

The call drop ratio is obtained by dividing the total number of dropped calls from the total setup call. The Telecom Regulatory Authority has said that the call drop ratio should be smaller than two per cent or 2 per cent [1].

Call drop ratio= (number of dropped calls/total setup calls)*100

III. METHODOLOGY

The research paper adopted the experimental methodology to find out the solution. There are few steps that have been used to develop the proposed model.

- Data gathering
- Pre-processing of dataset
- Design the model
- Training of model
- Validation of model
- Prediction of call drop

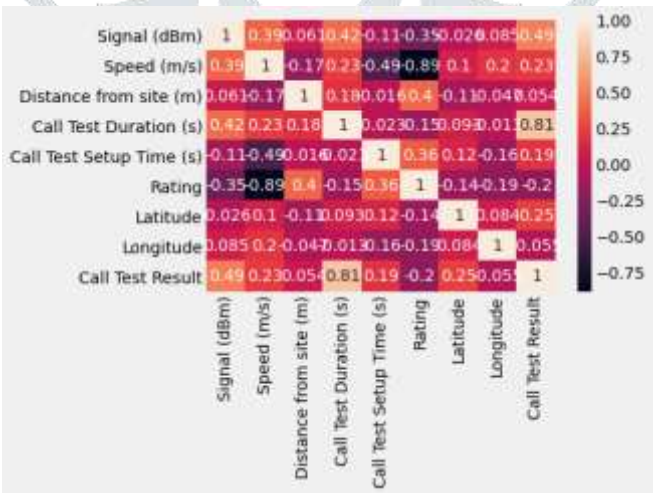

Fig.2. covariance between parameters

Data has been collected from different locations on the basis of two network operators is jio and airtel due to a lack of resources. Sampling has been done longitudinal. The research is focused on using numeric values to achieve the objective. After collecting the dataset, pre-processing of the dataset has been done. Data pre-processing takes a lot of processes such as data scaling, transforming, handling missing values, etc. After the data pre-processing dataset has been analysed and a lot of hidden facts came out. As shown in fig.2, heat map graphs show the covariance among the different irrelevant factors. In the enclosed graph negative values show no relationship between parameters while speed affects signal strengths.

IV. PROPOSED MODEL AND IMPLEMENTATION

The proposed model is a two-layer sequential neural network model which have five neurons in the input layer due to five input parameters and four neurons in the hidden layer and 1 neuron in the output layer with a sigmoid activation function. After designing the model we compiled the model with mean square loss function and adam optimizer.
The architecture of the proposed deployed model has been shown below:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 4)                 24
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 5
=================================================================
Total params: 29
Trainable params: 29
Non-trainable params: 0
_________________________________________________________________
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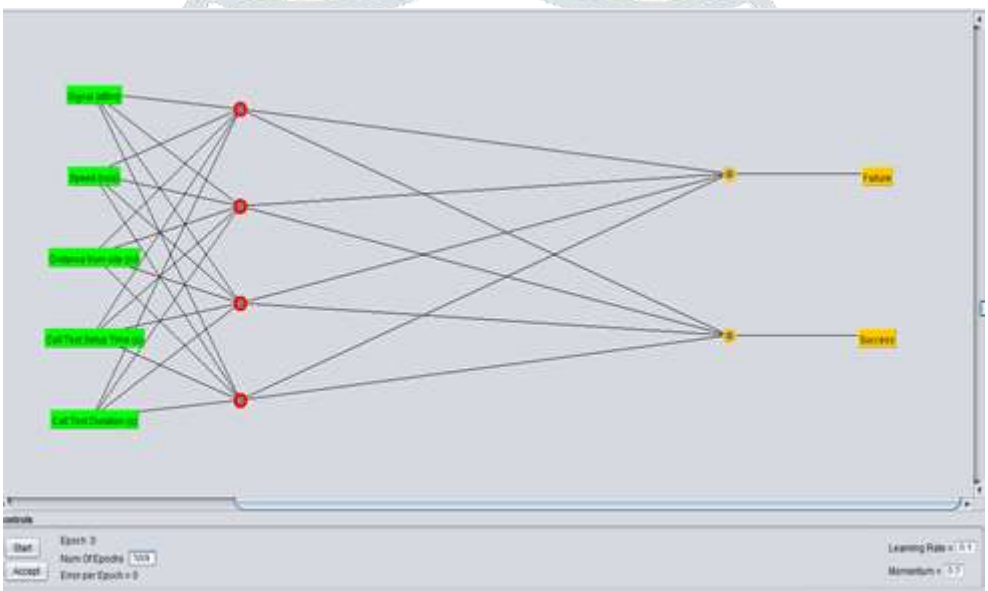

Fig.3. proposed neural network to predict call drop

After compilation training process of the model will start. It is time to fitting the data in a model with 500 epochs and 0.1 is the learning rate. The learning rate must be between 0 and 1. So that model is not under-fit or over-fit. After fitting the training data, the model is offering very good accuracy on training data and validation dataset as shown in enclosed graphs. On the training dataset, the model is providing 95% accuracy and the loss is 0.03. In another case on validation data model accuracy is 91% and loss is 0.02. Model training is based on supervised learning algorithm back propagation which is the backbone of neural networks. There are two phases of back propagation:

- *Forward phase:* where information flows in the forward direction using the below equation to find out the net input of hidden layer neuron. Finally, we got the predicted out from the output layer. We compare the predicted output from the target output. If there is a difference between both or in other words if we find the error we have to back propagate the total error in the backward direction to adjust the weights of every neuron hidden to the input layer. This process is repeating until the error will be closed to zero. For finding the error we use the mean squared error formula.

- *Backward Phase:* where error is back propagate in backward direction.

Net input yin=summation of weighted input signals+bias

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE = mean squared error

n = number of data points

Y_i = observed values

$\hat{Y}_i$ = predicted values

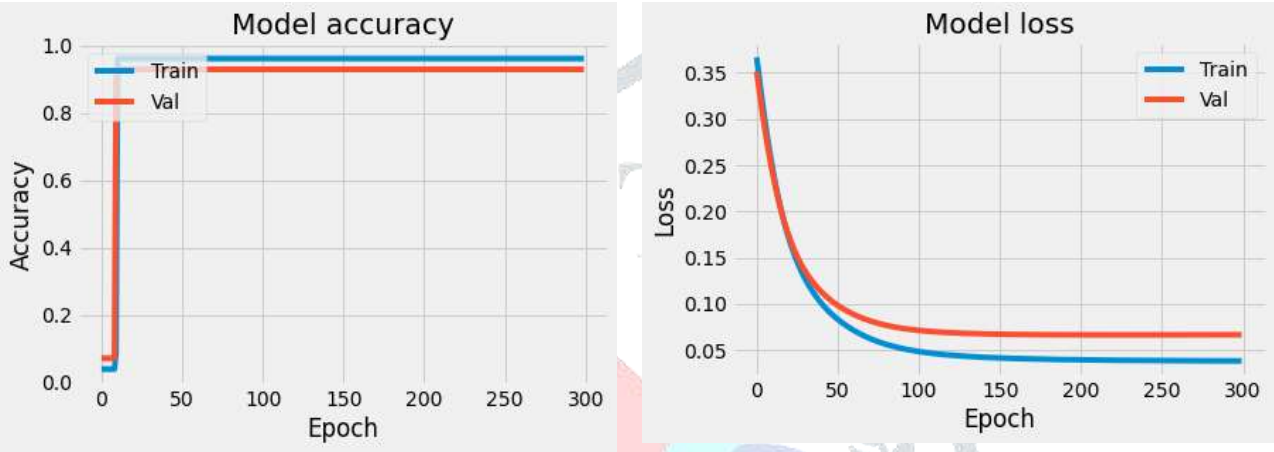

Fig.4. Model accuracy and loss on training and validation dataset

V. RESULTS AND DISCUSSION

Results are given in the form of table where predicted outcome has been compared with call test result. Zero means call drop and 1 means no call drop.

Table.1: prediction table

Signal (dBm)	Speed (m/s)	Distance from site (m)	Call Test Duration (s)	Call Test Setup Time (s)	Call Test Result	predicted
-94	0.819999993	567	90.00	4.52	1	1
-66	0.819999993	567	90.00	3.72	1	1
-87	0.819999993	1567	90.00	3.69	1	0
-116	0.619999993	1467	21.43	4.56	0	0
-87	0.819999993	567	90.00	3.5	1	1
-100	0.519999993	567	90.00	2.92	1	1
-118	0.819999993	567	60.92	3.69	0	0
-103	0.819999993	567	60.00	3.42	1	1
-106	0.819999993	1646	21.24	4.46	0	0
-97	0.919999993	567	90.00	3.57	1	1
-101	0.819999993	567	21.23	4.42	0	0
-102	0.819999993	1867	21.33	4.53	0	0
-103	0.819999993	567	90.00	3.78	1	1

VI. CONCLUSION AND FUTURE SCOPE

This model is 95% accurate on the basis of the training dataset. it can be helpful to predict the call drop during a handover situation. Call drop is an unexpected phenomenon that can be occurred due to various reasons like radiofrequency traffic, network congestion, electromagnetic effects, network signal strengths, a distance of cell site, etc. not only a single factor,

many factors impact the voice call quality. This research is based on very common and important parameters, which can be taken from a subscriber mobile through the cell site. The limitation of this research is we have used only two network operators which are reliance jio and airtel bharti due to a lack of resources.

The future of this model is very broad. It can be deployed on the base station as a mobility robustness optimization where mobility parameters will be adjusted according to requirements. The base station extracts the signal strengths, speed of subscriber, and other relevant parameters and will send the message to the subscriber if the continuing call could be disconnected. That your call could be dropped so please change your location.

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