Telecom Voice Traffic Prediction for GSM using Feed Forward Neural Network

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Abstract:

The prediction of the voice traffic and their accurate model is a challenge for telecom provider. It is important for the quality & service analysis of mobile network. The study in this paper concern predicting the voice traffic (Erlang) of mobile network at busy hour(5 to 7 pm) of a day which is nonlinear & dynamic. This voice traffic also depends on many other non-linear &dynamic parameter which best predict for voice traffic. The data is collected from quality & service report (QOS) of telecom service provider. Correlation analysis is used to select proper input variables from QOS report. Feed forward back propagation algorithm is proposed to make traffic prediction at busy hours on daily basis.

Keywords: Voice Traffic Prediction, traffic data, ANN

1. Introduction

For a successful completion of voice traffic at busy hour is most important task for any telecom service provider. Resource availability is prime concern for predicting voice traffic. Analysis of resource data for making prediction is key task and Artificial Neural Network (ANN) is best suited based on generalization and approximation. Many other prediction techniques are used today such as Genetic algorithm, Artificial Neural Networks, Fuzzy Logic and Statistical analysis.

To provide maximum utilization of voice traffic, we observe QOS report at constant interval. This QOS report has many resource parameters as number of traffic channel(TCH), number of stand-alone dedicated channel(SDCCH),number of SDCCH seizure attempt,SDCCH success calls, SDCCH block calls, SDCCH drop calls, total calls ,TCH assign, TCH success calls, TCH availability rate,TCH drop, Incoming hand-off(HO) success rate, Outgoing hand-off(HO) success rate, Half rate(HR) traffic and Mean holding time.

In above resource parameter, telecom provider check SDCCH drop and TCH drop to see air interface and hardware health at constant interval especially on busy hours. Temperature is also a prime concern which builds our recourses healthy. Another atmosphere parameter as storm , rain and snowing makes insulation in air interface, so it influences much on traffic.SMS ,which is governed through different logical channel, do not affect voice traffic of base terminal station(BTS).Traffic of BTS is mostly affected by GPRS packet.

In this paper, my work is mainly focused on voice traffic prediction with above mentioned QOS parameter using neural network on daily basis. Here neural network models are proposed to voice traffic prediction at busy hour (5 to 7 pm) of a day. We work on data from the real word for quality test and verify that our models are effective.

The paper is presented as follows. In section 2, we show a brief description on voice traffic and all resource parameter which predict the traffic as well as hardware and air interface health status. In section 3,a brief detailing on Back-Propagation algorithm. Section 4 shows designing of multilayer neuron model & their parameter. In section 5, we show performance test result of our models by applying resource parameter to predict the traffic. In section 6, conclusion of paper in the end.

2. Voice Traffic & Resource Parameter

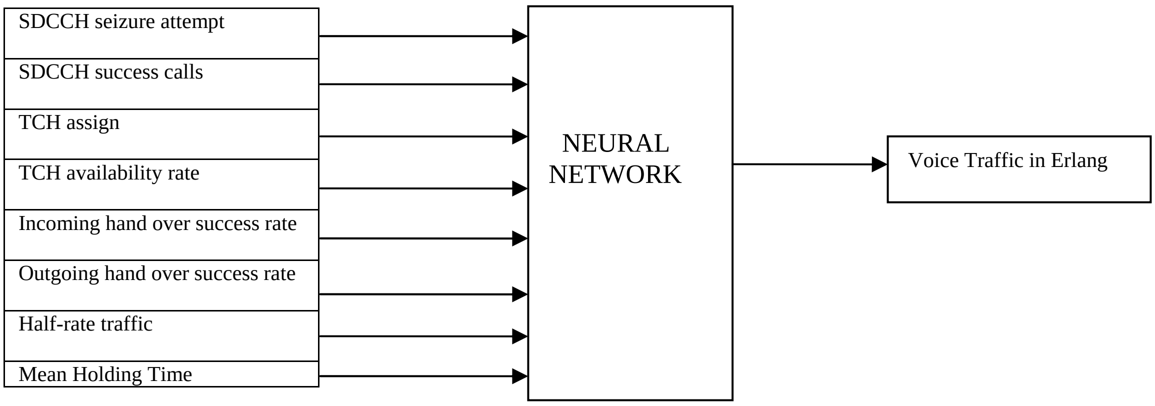
Telecom voice traffic is product of number of running calls on switch with its mean holding time. It's unit in per hour is Erlang.

$$\text{Voice traffic [I]} = \sum_{i=1}^{M_c} g_i = \frac{M_c \bar{g}}{T} = m_c\,\bar{g}$$

Where I is traffic intensity, T is duration of monitoring period in hours. $g_i$is holding time of the i^{th} individual call, M_c is total running call in monitoring period,$\bar{g}$ is average call holding time &m_c is call per unit time. Voice traffic in a day is not constant. It is non uniform & dynamic. At a particular hour, it is at its maxima. This particular period is called busy hour. Our best efforts are to manage & control traffic at busy hour.

Voice traffic at particular BTS (base terminal station) is determined by average load on all sector. A BTS is mainly divided into three sectors. These sectors are duplexer antenna for using uplink & downlink communication. Orientation of these sectors is determined by numbers of population which gives offered load of voice traffic. The direction of particular sector shows a high density population in that side. Voice traffic mainly includes four type of traffic 1. Half Rate 2.Full Rate 3.Adaptive Multi Rate (AMR) full rate, 4. AMR half rate. These all traffic is configured on switch at which calls runs. Switch is hardware parts which have constant number of time slots. At each time slot one calls runs. Many configurations are possible on each time slot. Two main configuration of each slot has to provide SDCCH & TCH channel in each BTS according to offered load. SDCCH (stand alone control channel) is a type of control channel & TCH (Traffic Control Channel) is channel which support voice in GSM. After completion of availability of SDCCH, TCH channel are kept available. Max 2% & 5% drop are permitted respectively for SDCCH & TCH.

On switch, number of TCH is constant. Our voice traffic prediction is a non linear & dynamic which depends on many other dynamic resources as SDCCH Seizure Attempts, SDCCH Success Calls, TCH Assign, TCH Success Calls, TCH Availability Rate, Incoming Hand Over Success Rate, Outgoing Hand Over Success Rate, Half Rate Traffic, Mean Holding Time. Above parameter has been selected for input variable in neural network after correlation analysis with voice traffic. Correlation analysis of resource parameter with traffic is present in result part



3. Back-Propagation Algorithm Technique

Back-propagation algorithm is a supervised learning algorithm. It is created by generalizing the Windrow- Hoff learning rule to feed forward multilayer network. Input vector & their corresponding target vector are used to train the network until it reaches to desired performance function. In this algorithm, weight & biases of neural network are moved along the negative of the gradient of the performance function (surface of mean square error). There are other variations on this basic algorithm as conjugate gradient, Resilient Back propagation, Line Search Routines, Newton Methods etc. The simplest implementation of back-propagation learning updates the network's weight & biases in the direction in which performance function decreases most rapidly, in the negative of the gradient. One iteration of this algorithm can be written as $X_{K+1}= X_k - \alpha_K g_K$, where X_k is a vector of current weights & biases, g_K is current gradients &α_K is the learning rate. There are two way to implement this gradient descent, 1) Incremental mode 2) Batch mode. In incremental mode, gradient is calculated & weights are updated after each input is applied to the network. In batch mode, all the inputs are applied to the network before the weights are updated. In our work, batch training has been used.

4. Designing of Multilayer Neuron Model &their Parameter

Designing of neural network model start with following steps-

1) Partitioning of data
   a) Training Data
   b) Testing Data
2) Preprocessing of data
   a) Normalization of data ranging from -1 to 1.
   b) Set data with zero mean & unity standard deviation
   c) Principal component analysis
3) Form the neural network & training of data
   a) Selection of number of layer
   b) Selection of number of neuron in each layer
   c) Selection of fastest training function

d) Selection of Transfer Function

4) Simulate the network response to new inputs with saving last weights and biases of network

5) Post processing of data

In our model tan-sigmoid transfer function has been used in every layer which gives best generalization of data normalize between -1 & 1. Selection of layer depends on complexity of model. The complexity is measured from performance of training which shows deviation of predicted data from actual data. Mainly two types of layer is conventionally used (1) Output Layer (2) Hidden Layer. In our model , only one parameter 'traffic' has to be measured so one neuron is present in output layer. Selection of layer and number of neuron in each hidden layer depends on increment and decrement of performance. Performance value with each layer has been kept in result part2. Selection of training function has two trade-off (1) Faster computation (2) Memory availability. In our model, we have selected training function behalf of faster computation and has been assumed sufficient memory availability. Levenberg- Marquardt(L-M) training function has been used due to faster computation than other training function available as Resilient Backpropagation, Conjugate Gradient Algorithms, Line Search Routines, Quasi-Newton Algorithms. In L-M algorithm, weight and biases are updated as $X_{K+1}= X_K - (J^T J + \mu I)^{-1} J^T e$, where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases,μ is momentum and e is a vector of network errors.

Tic-toc function has been used available in Matlab to measure time taken using L-M and other training function to justify that L-M is faster for our model. This time calculation has been kept in result part.3.Settings of epochs, goal, initial value of momentum (mμ), increment (mμ_inc)/decrement(mμ_dec) constant value multiplied with mμ,when step would increase the performance function or performance function is reduced by a step and maximum value of mμ are other sub-parameter available in LM algorithm whose trade- off is important while training the traffic predicting input data.

5. Performing Tests & Results

In our experiment, we have taken data from real world. We have estimated the traffic at busy hours on a day. Taking the former 7 days of data series of busy hours as the inputs of NN, the desired output series is the predicted day's busy hour of a day. 2/3'rd of data has been used for training purpose & rest is used for testing of the network. All results are organized as different part, (1) Correlation analysis, (2) Performance analysis with increasing layers and neurons. (3) Faster training result(4) Prediction plot

1. Correlation Analysis

	Traffic (Erlang)	SDCCH Seizure Attempt	SDCCH Success Calls	TCH Assign	TCH Success Calls	TCH Availability Rate	Incoming HO Success Rate	Outgoing HO Success Rate	Half Rate Traffic	Mean Holding Time
Traffic(Erlang)	1									
SDCCH eizure Attempt	1	1								
SDCCH success Calls	.9643	.9987	1							
TCH Assign	.9802	.9080	.9092	1						
TCH Success Calls	.9574	.8638	.8752	.9386	1					
TCH Availability Rate	.9156	.8945	.8984	.8816	.9176	1				
Incoming HO Success Rate	.9666	.9213	.9300	.9324	.9582	.9677	1			
Outgoing HO Success Rate	.9104	.8306	.8396	.8950	.9139	.9724	.9240	1		
Half Rate Traffic	.9821	.9445	.9433	.9832	.9073	.8430	.9057	.8849	1	
Mean Holding Time	.9363	.9478	.9481	.9055	.8680	.9642	.9314	.9205	.8966	1

2. Performance Analysis with Increasing Layers and Neurons

We have started our training with one hidden layer and output layer. Hidden layer ranging from 2 to 9 has been used to check with our training. With 4 number of neuron in hidden layer gives less mean square (MSE) value. In our analysis, max error and min error has shown for deviation of predicted value with actual value. Here we can see that at lower MSE value, we get lesser deviation of predicted value with actual data. We start with two hidden layer of network with 4 numbers of neurons in second hidden layer and their respected saved weights and biases value. Ranging from 4 to 15 neurons in first hidden layer has been again used for training to network for getting lesser MSE value. At 10 numbers of neurons in first hidden layer again shows with lesser MSE. We have finalized our model at (10, 4, 1) neurons in second, first and output layer.

No. of layer	No of neurons in layer(Hidden layer, Hidden layer, output layer)	Epochs	MSE(Performance)	Max error	Min error
2	(-,2,1)	75	9.75355e-10	3.856e-4	1.282e-6
2	(-,3,1)	100	1.81591e-11	6.406e-4	7.482e-7
2	**(-,4,1)**	**20**	**1.33253e-13**	**1.2510e-5**	**9.3482e-7**
2	(-,5,1)	24	7.40023e-11	4.4350e-4	2.62e-7
2	(-,6,1)	25	6.65473e-11	4.6372e-4	2.472e-11
2	(-,7,1)	22	5.24721e-11	2.7820e-004	2.5209e-007
2	(-,8,1)	24	9.91544e-11	4.5724e-004	3.2455e-007
2	(-,9,1)	26	4.67943e-11	2.8747e-004	2.7311e-007
3	(1,4,1)	39	8.08790e-007	7.4103e-003	2.3417e-006
3	(2,4,1)	40	4.10339e-007	4.2335e-004	2.7500e-006
3	(3,4,1)	40	4.11350e-008	4.8907e-003	1.7750e-006
3	(4,4,1)	37	2.09776e-007	4.7625e-003	1.9803e-006
3	(5,4,1)	38	4-05271e-008	7.6403e-003	1.6302e-006
4	(6,4,1)	37	5.00738e-008	3.0965e-003	1.7503e-006
3	(7,4,1)	34	2.55489e-008	3.0960e-003	1.3203e-006
3	(8,4,1)	34	2.22697e-008	4.0082e-003	1.6012e-006
3	(9,4,1)	33	7.99644e-009	6.4006e-003	1.4719e-006
3	**(10,4,1)**	**30**	**9.78488e-011**	**4.8692e-004**	**1.6198e-007**
3	(11,4,1)	37	2.16542e-008	4.6423e-004	2.3102e-007
3	(12,4,1)	40	2.33404e-008	9.7908-003	1.7153e-006
3	(13,4,1)	33	5.33324e-009	1.9986-003	1.8641e-006
3	(14,4,1)	33	5.87240e-009	3.2238e-003	7.6445e-007
3	(15,4,1)	35	2.88457e-007	1.8795e-003	3.2195e-007

3. Faster Training Results

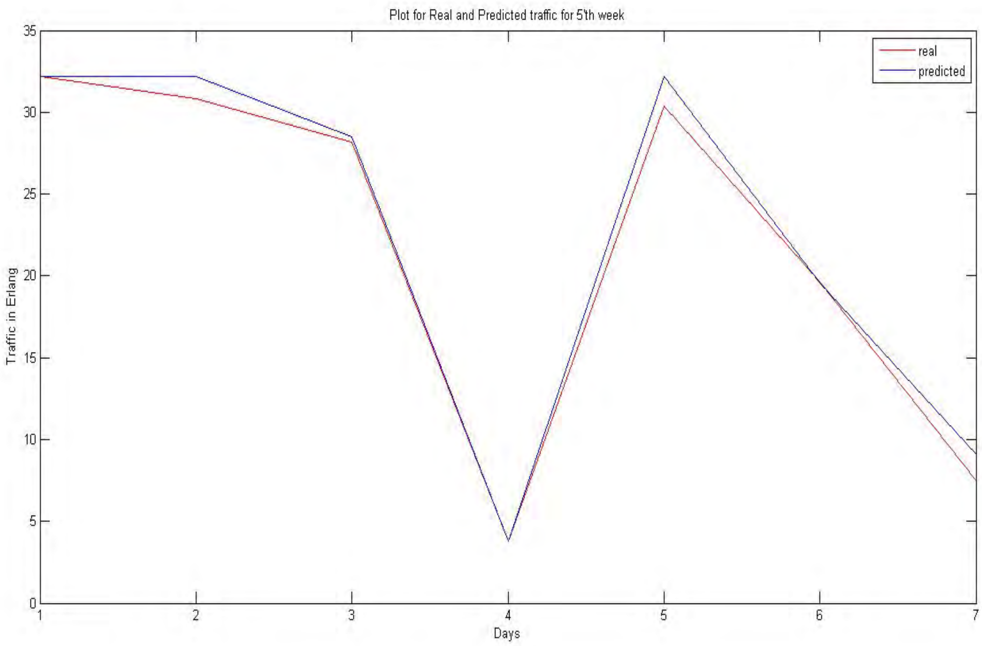
Selection of faster training function is other concern for getting our model to work at good run complexity. Many training algorithm has been used to check our model. Levenberg-Marquand (L-M) algorithm has been finalized for our model to achieve better run.

Training Algorithm	Average Run Time using tic-toc function(in second)			
	For 5'th week simulation	For 6'th week simulation	For 7'th week simulation	For 8'th week simulation
Levenberg-Marquardt(L-M)	**.3647**	**.3688**	**0.4449**	**.3018**
Resilient Backpropagation	1.0675	1.0687	1.0881	1.0372
Conjugate Gradient Algorithms	1.0359	1.0665	1.0540	1.0665
Line Search Routines	1.0058	1.0055	1.0052	1.0047
Quasi-Newton Algorithms	1.0092	1.0096	1.0090	1.0096

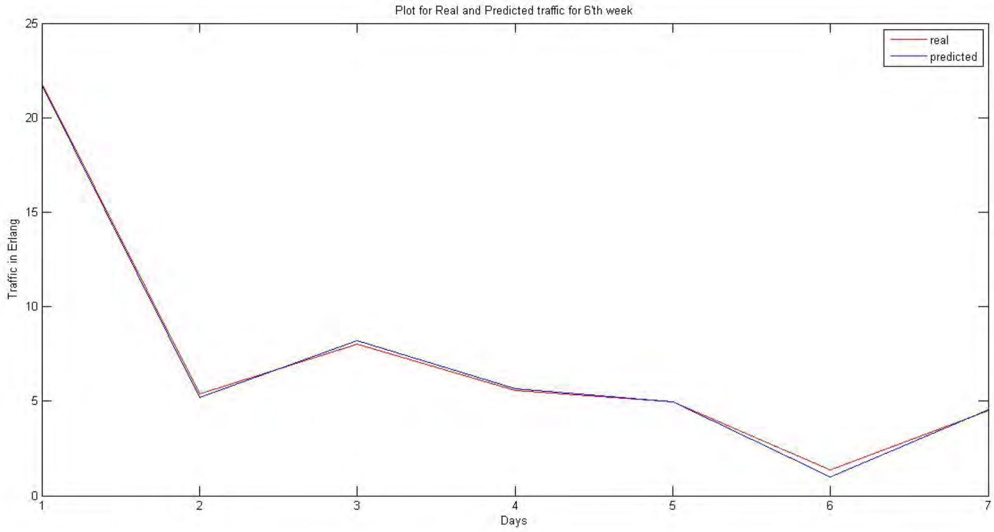
Prediction plots

With (10,4,1) neurons and Levenberg-Marquard training algorithm , we have simulated our 5'th , 6'th ,7,th and 8,th weeks test data and their respective plot has been shown in fig(a), (b) , (c) and (d). These plots are in Real and Predicted traffic data in Erlang on daily basis.

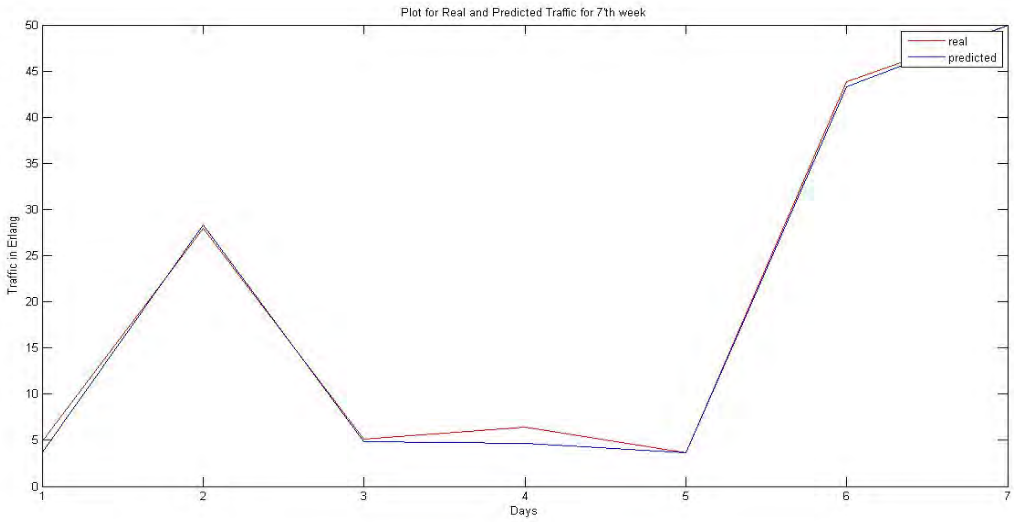
For 5'th week simulation



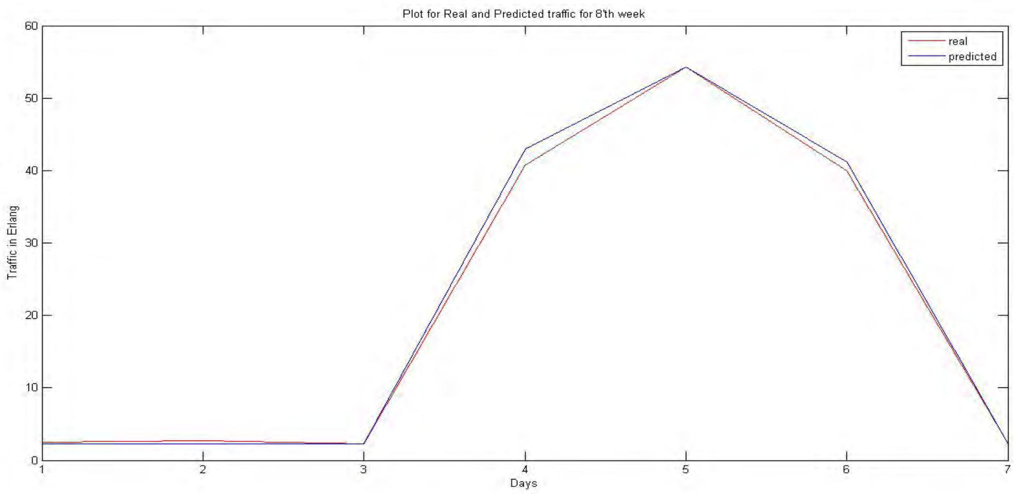
For 6'th week simulation



For 7'th week simulation



For 8'th week simulation



6. Conclusion

In this paper, our concentration is to find best correlated resource parameter for traffic prediction over GSM, search for faster training algorithm and to achieve good performance result for our model. Finding of mean and standard deviation with normalization of data has given result at lower epochs. Our effort of building model is to focus on speed not on memory consideration for saving first derivative of Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases. On the other hand in future we can also implement this technique for CDMA model.

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