

Mobile Soft Switch Traffic Prediction using Polynomial Neural Networks

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Abstract—This work investigates busy hour (BH) traffic demand pattern of mobile soft switch (MSS) over a period of two years and propose the application of Group Method of Data Handling (GMDH) polynomial neural network for seven-days to three-month ahead BH traffic forecasting for effective optimization of network resources. Busy hour call attempt (BHCA) utilization and A-interface utilization key performance indicators (KPI) are used as inputs into GMDH prediction model and BH traffic as model target. The performance of the model was evaluated based on three statistical performance indices: mean absolute percentage error (MAPE), root mean square percentage error (RMSPE) and goodness of fit (R^2) values. Experimental results show that R^2 value as high as 96% was achieved with the proposed model for both short-term and mid-term forecasting. The GMDH model proves an effective tool for accurate prediction of traffic demand and hence, proper optimization of GSM/GPRS MSS network resources.

Index Terms—Busy Hour Traffic; Busy Hour Call Attempt Utilization; A-Interface Utilization and Mobile Soft Switch.

I. INTRODUCTION

The astronomical increase in subscribers of GSM/GPRS network in Nigeria is responsible for huge rise in demand for the network services and the network providers are faced with the challenge of how to continually plan and optimize the network resources in order to meet up with the ever increasing demands and guaranteed Quality of Service (QoS). To ensure good planning and management of network resources, accurate prediction of busy hour traffic demand is necessary. The prediction is intended to facilitate capacity expansion and how much traffic could be carried in short and mid terms by the mobile soft switches (MSSs) in order to properly dimension the GSM/GPRS resources.

Prediction of network traffic is of significant interest in many domains and it has been suggested by [1] that real network traffic is fractal in nature. To capture this fractal behaviour, this work explores the use of polynomial neural network approach for seven days to three months ahead forecasting of four mobile soft switches (MSSs) busy hour traffic demand. Traffic in cellular network exhibit complex user phenomenon which is a complex relationship between user traffic and various key performance indicators (KPI) that are used to measure QoS [2]. Since comprehensive theoretical perception does not exist in terms of the relationships and interactions between these KPIs, using smart neural network like Group Method of Data Handling

(GMDH) for modeling these relationships is a useful approach.

Traffic prediction in this work is divided into two categories: short-term (7 days to 30 days) traffic forecasting which deals with daily and weekly forecasts for efficient operation and management of existing network resources while mid-term (2 months to 3 months) traffic forecasting is required for resource planning and system capacity expansion [3].

In this research, the Group Method of Data Handling (GMDH) polynomial neural network is used to forecast the BH traffic of four MSSs (MSS01, MSS02, MSS03 and MSS04) for proper network optimization. GMDH algorithm is useful for establishing pattern of relationship between input and output variables in high degree complex systems like traffic demand pattern. The GMDH model automatically selects only influential input parameters (KPIs) and expresses the input-output relationship in polynomial form.

II. POLYNOMIAL NEURAL NETWORKS

Various polynomial techniques for modeling user traffic as a nonlinear function approximation have been reported in the literature [4]. Polynomial classifiers are non-linear system identification techniques that provide an effective way to describe complex non-linear input/output relationships. They have been used for nonlinear systems regression and it has been shown that they are superior to other classical modeling techniques such as neural networks [5].

Due to numerical instabilities that arise as a result of prohibitive computational and storage requirements when modeling high order polynomials, the technique of Group Method of Data Handling (GMDH) was introduced. It is ideal for complex and unstructured systems where the relationship between high order input - output is of paramount interest. The algorithm allows computer to construct a self-organizing model by identifying non-linear relationships between inputs and outputs data through external criterion [6].

Neural networks developed using the GMDH algorithm are called GMDH-type neural networks and can be classified within the group of polynomial neural networks (PNN). Each node of the polynomial exhibits a high degree of flexibility and realizes a polynomial mapping between the input and the output [7]. A GMDH model with multiple inputs and one output is a subset of components of the base function as expressed (1).

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$$y = a_0 + \sum_{i=1}^N a_i x_i \quad (1)$$

where x_i are elementary functions dependent on different sets of inputs, a_0 and a_i are coefficients and N is the number of the base function components. All neurons in GMDH shell have two inputs and one output as shown in Fig. 1.

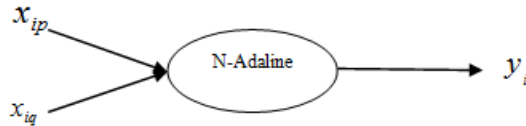


Fig. 1. A Single GMDH Neuron Model

Each GMDH neuron is an N-Adaline which is an adaptive linear element with a nonlinear pre-processor. It has five weights and one bias that provide processing operation between the input and output data.

GMDH algorithms consider various component subsets of the base function called *partial models* to find the best solution. Coefficients of these models are estimated by the least squares method. The algorithms gradually increase the number of partial model components and find a model structure with optimal complexity indicated by the minimum value of an *external criterion*. This process is called self-organization and the most popular base function used in GMDH is the Kolmogorov-Gabor polynomial and it is expressed as shown in (2).

$$y_i = f(x_{ip}, x_{iq}) = a_0 + a_1 x_{ip} + a_2 x_{iq} + a_3 x_{ip} x_{iq} + a_4 x_{ip}^2 + a_5 x_{iq}^2 \quad (2)$$

The function f is equipped with six x factor estimating $\{(x_{ip}, x_{iq}), i = 1, 2, 3, \dots, N\}$ system and optimal output of $\{(y_i), i = 1, 2, 3, \dots, N\}$ for all dependent two-variable samples [8].

Each term of Kolmogorov-Gabor polynomial contributes differently and the GMDH network removes the terms that do not contribute significantly layer by layer using self-organizing arithmetic. The goal of modeling can be reached if the function f is planned according to minimum squares error as given in (3).

$$\text{Min} \sum_{k=1}^N [(f(x_{ip}, x_{iq}) - y_i)^2] \quad (3)$$

A. Application of GMDH to Nonlinear Function Approximation

Numerous applications of GMDH are reported in literature to be a promising function approximation tool. Unlike other nonlinear predictors that suffer long training times, difficulties in determining optimum network parameters, and the black box nature, GMDH modeling offers the advantages of faster model development requiring little user intervention, faster convergence during model

synthesis without the problems of getting stuck in local minima and easy of hardware implementations [9].

In a related development, [10] applied GMDH-based model to traffic flow forecasting. The model was simulated in MATLAB environment and the results indicated that the average relative error of prediction was only 3.35% which demonstrated that GMDH is a suitable data-fitting tool. Likewise, [11], investigated water demand forecast using MLP neural network and GMDH with genetic learning algorithm. The comparison reveals that the GMDH neural network results are close to the actual data and it outperformed the MLP neural network

Reference [12] examined the use of two enhanced versions of GMDH networks for modeling MR200 damper system identification. Firstly, two-tier architecture was used where the predicted values in the first tier are fed to the network for a second tier training. Secondly, a hybrid of GMDH and stepwise regression in which feature selection is done by stepwise regression prior to GMDH training. Modeling the MR200 damper was done in forward and inverse modes where force and voltages are being predicted respectively. The GMDH-based model with stepwise regression when compared with polynomial classifier, MLP and ANFIS modelling, was found to offer significant reduction of about 40% in RMSE for both forward and inverse models.

Also, [13] used GMDH neural network to model economic performance of some European countries. The result of the forecasts agreed with the trend of European Commission 2013 forecasts for continuous economic growth of the countries. Reference [14] modelled gold-price forecast using GMDH neural network and Multilayer Perceptron (MLP) neural network. In terms of RMSE, and mean absolute error (MAE) criteria, GMDH enjoys lower error means compared to MLP network.

In a related development, a short-term electrical energy forecast was proposed by [15] using GMDH-type neural network. Root mean square error (RMSE), goodness of fit (R^2) and mean absolute percentage error (MAPE) were used as performance indices to test the accuracy of the forecast. Results showed that the GMDH-type neural network model prediction is better than linear regression analysis model.

This research work proposes the use of GMDH as an abductive network regressor technique to the problem of MSS busy hour traffic demand forecasting in a GSM/GPRS network. The abductive network model automatically selects only influential input parameters (KPIs) and expresses the input-output relationship in polynomial form.

III. METHODOLOGY

To evaluate the performance of the MSSs, busy hour traffic data was collated from network management system (NMS) of one of the GSM network service providers in Abuja, Nigeria [16]. For proper network dimension, measurement of traffic data should be taken during busy hour when congestion is expected to be at its peak. The traffic data KPIs used for core network busy hour traffic analysis in this work is shown in Table I with their target-values [17].

TABLE I: OPERATOR METRIC TARGET VALUES¹

MSS KPI	TARGET (%)
Call assignment success rate (CASR)	≥ 98
Paging success rate (PSR)	≥ 96
Hand over success rate (HOSR)	≥ 96
A-interface Utilization	≤ 70

To select the prediction model in inputs, correlation coefficient which is defined as a number or function indicating the degree of correlation between two variables say X and Y was used. In this work, the variables of interest are busy hour traffic as the target or output versus any other KPIs. Correlation analysis examines each pair of measurement to determine whether the two tend to move together. It ranges between 1 for high positive correlation to -1 for high negative correlation, with 0 indicating a purely random relationship. Equation (4) defines correlation coefficient as.

$$\text{Correl}(X, Y) = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} \quad (4)$$

This equation is used to select the MSS KPIs in Table I that have good correlation with busy hour traffic on the four MSS for busy hour traffic congestion analysis and optimal network dimension. The Summary of correlation test analysis is shown in Table II.

TABLE II: SUMMARY OF CORRELATION TEST

MSS	CASR	PSR	OG HOSR	A-Interface utilization	BHCA utilization
MSS01	0.3	0.4	-0.1	0.8	0.5
MSS02	1	0.9	1	0.8	0.7
MSS03	0	-0.6	-0.5	0.7	0.8
MSS04	0.3	-0.4	-0.2	0.5	1
Average	0.4	0.1	0.1	0.7	0.8

Table II shows that only A-Interface utilization and BHCA utilization has strong correlation with BH traffic in all the MSSs while other KPIs failed the test.

The BH traffic, busy hour call attempt (BHCA) utilization and A-interface utilization of each of the four MSSs was exported to Microsoft excel file from the network NMS and the file was imported in to GMDH shell environment in XLS format to train and validate the model for predicting the busy hour congestion of the MSSs using k-fold cross-validation to split the whole dataset into ratio 40:60 for training and testing respectively to create polynomial network.

The GMDH shell software [18] used in this work is the classical implementation of Ivkhenenco's GMDH algorithms. It automatically synthesizes network models from a database of input-output pairs. The model emerging from the shell synthesis process is a robust and compact input-output transformation in the form of a layered

abductive network of functional elements as shown in Fig. 2.

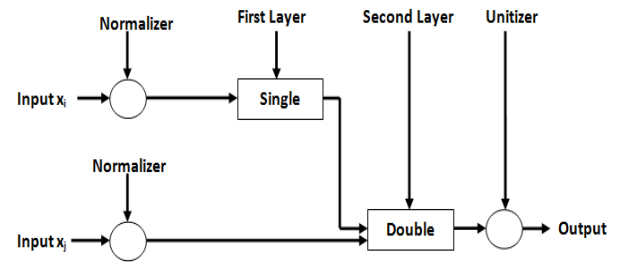


Fig. 2. A two-input, two-layered GMDH shell

A. Data Processing

The dataset used in this work consist of 54,000 recordings of BH traffic data from a live GSM/GPRS network. After removal of outlier data [19], 572 numbers of recordings were obtained. The busy hour traffic carried by these four MSSs during two-year period is shown in Fig. 3.

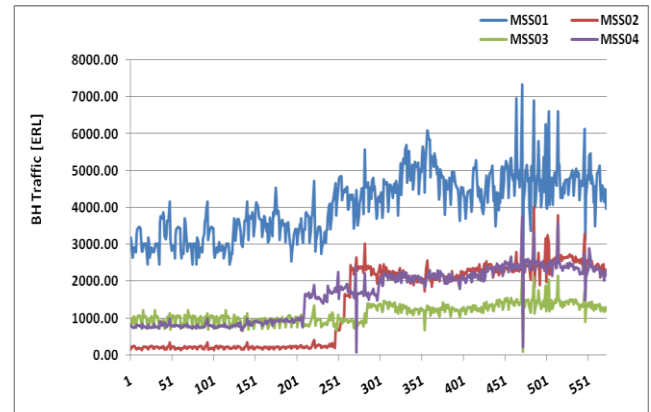


Fig. 3. Daily Busy Hour Traffic Trend of MSS

To maintain a good Grade of Service (GoS), 30 busiest traffic days of the year are used when performing busy hour traffic analysis for one year [3] in order to cater for most scenarios of carried traffic experienced by MSSs during the period. Hence, we used 60 busiest traffic days in this work since we are analysing two-year data.

Fig. 4 shows the plot of the measured busy hour traffic for the MSSs, indicating 60 busiest hour traffic demand pattern for the two years period.

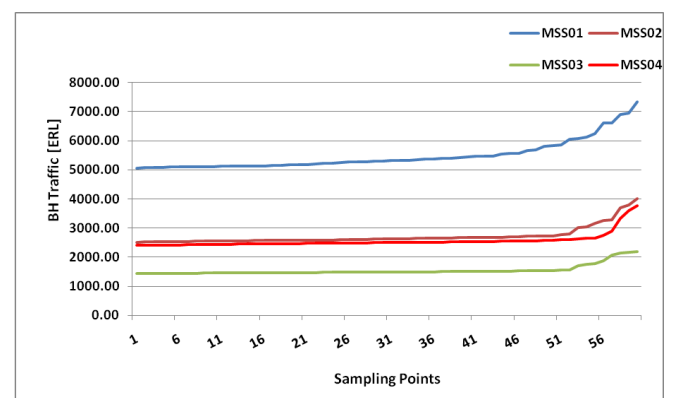


Fig. 4. Traffic Demand Pattern for 60 Busiest Traffic Days

¹Source: Anonymous (2012) [16]

In this work, two different experiments were conducted as follows:

- In the first experiment, busy hour traffic demand of seven-day to thirty-day ahead $d(t)$, $(t+24)$, $d(t+48)$, ..., $d(t+144)$ is investigated. Where d stands for day and t represent the first busy hour of the cell.
- For the second experiment, busy hour traffic demand for two-month to three-month ahead $d(t+1416)$, $d(t+1440)$, $d(t+1896)$ is investigated.

Thus, after specifying the two data sets, a training set was created and used for the GMDH shell to determine the coefficients of the polynomial for each of the cells.

B. Statistical Performance Evaluation Criteria

The three standard statistical performance evaluation criteria for the model are as follow:

- Mean absolute percentage error (MAPE) is a quantity used to measure how close predictions are to the eventual outcomes. The mean absolute error between the measured y_i and the predicted $\hat{y}_i$ congestion is defined in (5) as.

$$\mu = \frac{100\%}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (5)$$

where N is the total number of measured samples.

- Root Mean Percentage Square Error (RMSPE) which measures the mean deviation (error) of the congestion values to the predicted values and is expressed in (6).

$$RMPSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N}} * 100\% \quad (6)$$

The RMSPE aggregates the magnitudes of the errors in predictions for various times into a single measure of predictive power which is a good measure of accuracy.

- R-square (R^2) is the square of the correlation between the actual values and the predicted values. R-squared is a statistical measure of how close the data are to the fitted regression line. It measures how successful the fit is in explaining the variation of the data- the goodness of fit and is given in (7).

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y}_i)^2} \quad (7)$$

where, $\bar{y}_i$ is the mean of the measured congestion.

R^2 can take on any value between 0 and 1, but can be negative for models without a constant, which indicates that the model is not appropriate for the data. A value closer to 1 indicates that a greater proportion of variance is accounted for by the model.

IV. RESULTS AND DISCUSSION

The strong correlation between busy hour traffic and busy hour call attempt (BHCA) utilization and A-interface utilization in Table II established the validity of using both the BHCA and A-interface utilization as inputs to the GMDH model so as to predict the busy hour traffic - the target of GMDH model.

Fig. 5 – 8 showed the plots comparing the actual measured 60 busiest hour traffic and the forecasted value for MSS01, MSS02, MSS03 and MSS04.

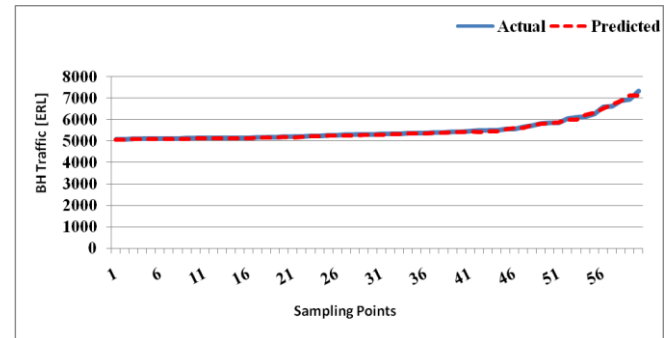


Fig. 5. Actual Vs Predicted Busy Hour Traffic Demand Pattern of MSS01

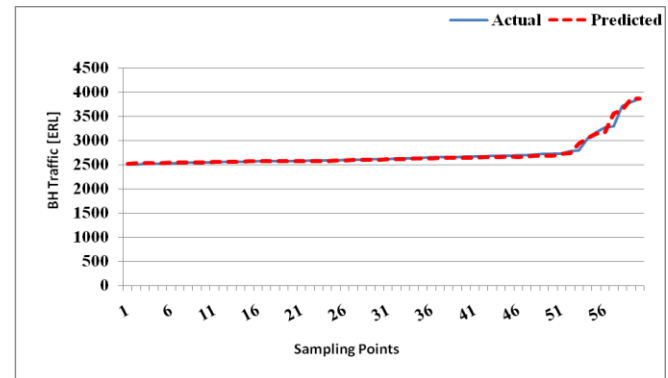


Fig. 6. Actual Vs Predicted Busy Hour Traffic Demand Pattern of MSS02

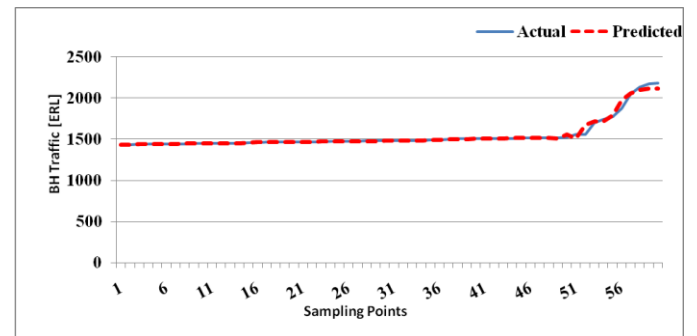


Fig. 7. Actual Vs Predicted Busy Hour Traffic Demand Pattern of MSS03

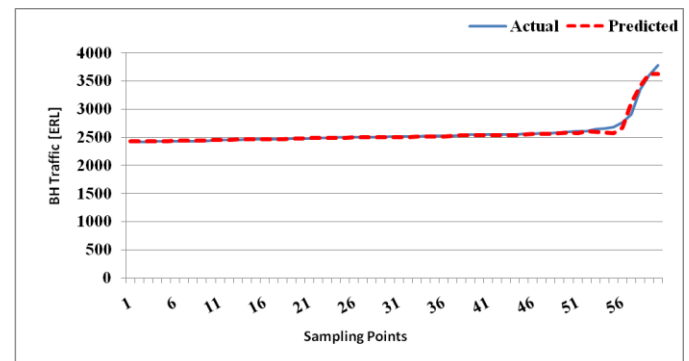


Fig. 8. Actual Vs Predicted Busy Hour Traffic Demand Pattern of MSS04

The Fig 5 - 8 showed that the predicted traffic closely followed the actual traffic. This implies that the proposed model is able to accurately predict the busy hour traffic with high R^2 and a low MAPE.

The summary of the forecasted traffic statistical indices for 7-days to 30-days and 2-months and 3-months busy hour traffic ahead for the four MSSs are shown in Table III and Table IV respectively.

TABLE III: STATISTICAL INDICES FOR SHORT-TERM BUSY HOUR TRAFFIC PREDICTION

MSS ID	Number of day	MAPE	RMSPE	SIGMA	R_SQUARE
MSS01	7	0.3	0.45	0.45	0.96
	12	0.18	0.27	0.27	0.98
	30	0.41	0.72	0.72	0.98
MSS02	7	0.13	0.16	0.16	0.98
	12	0.12	0.16	0.16	0.98
	30	0.87	1.57	1.57	0.94
MSS03	7	0.08	0.1	0.1	0.96
	12	1.45	2.13	2.13	0.86
	30	0.52	1.07	1.07	0.96
MSS04	7	0.13	0.16	0.16	0.98
	12	0.09	0.12	0.12	1
	30	0.68	1.34	1.34	0.94

TABLE IV: STATISTICAL INDICES FOR MID-TERM BUSY HOUR TRAFFIC PREDICTION

MSS ID	Number of day	MAPE	RMSPE	SIGMA	R_SQUARE
MSS01	60	0.41	0.72	0.72	0.98
	90	0.52	0.85	0.85	0.98
MSS02	60	0.87	1.56	1.56	0.94
	90	0.89	1.58	1.58	0.94
MSS03	60	0.58	1.37	1.37	0.96
	90	0.58	1.37	1.37	0.96
MSS04	60	0.68	1.34	1.34	0.94
	90	0.51	1.39	1.39	0.94

The proposed GMDH model accurately predicts changes in actual busy hour traffic thus the reason for the low MAPE and RMSPE obtained as shown in Tables III and IV. Fig. 9 shows the RMPSE performance comparison of the proposed short-term and mid-term for the four MSSs.

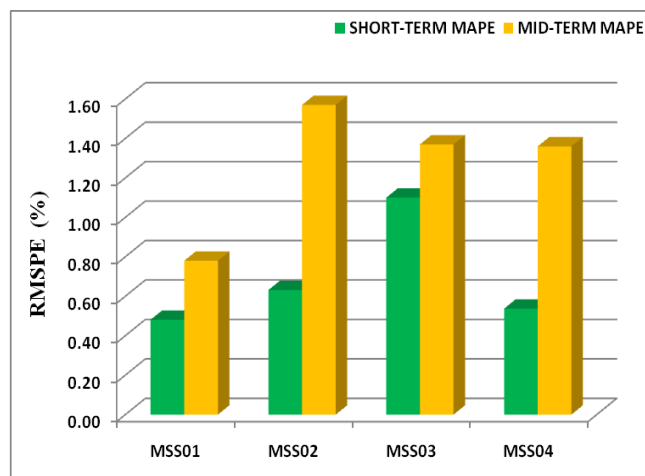


Fig. 9. Statistical Indices Performance Comparison of the MSSs

Fig. 9 showed that the short-term yields a better performance in all the MSSs in terms of RMSPE.

The lower RMSPE observed in the short-term prediction suggest that the two-year data period used in this work is ideal for daily and weekly predictions which are necessary for efficient operation and management of existing network resources. Fig. 10 shows the overall performance of the two predictions as an average for the four MSSs.

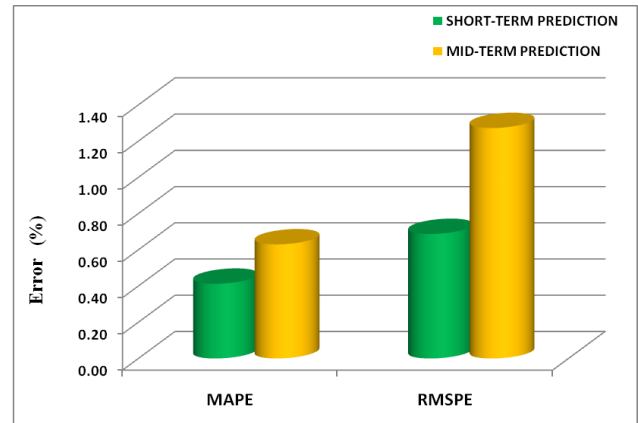


Fig. 10. Performance Comparison of the Proposed Short-term and Mid-term Models

Fig. 10 revealed that the Short term predicts busy hour traffic better in all MSSs compared to mid-term prediction.

V. CONCLUSION

Mobile Soft Switch (MSS) busy hour traffic prediction was undertaken based on data from a live GSM/GPRS network and correlation analysis was used to established that the busy hour call attempt (BHCA) utilization and A-interface utilization exhibit significant positive linear correlation of 0.7 and 0.75 respectively with BH traffic which is the model target and as such they are used as the inputs of the model while the effects of other KPIs during BH are negligible. The use of GMDH model provided accurate prediction of both short-term and mid-term busy hour traffic demand in GSM/GPRS MSS, hence, an effective tool for network optimization.

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