PREDICTION OF MACROCELL TRAFFIC CONGESTION USING A HYBRID OF POLYNOMIAL NEURAL NETWORKS AND GENETIC ALGORITHMS

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Abstract-- This work used a hybrid of Group Method of Data Handling (GMDH) neural networks and Genetic Algorithm (GA) to optimize busy hour traffic congestion prediction model in cellular macrocell. The optimized model was implemented in MATLAB environment using call setup success rate (CSSR) and busy hour (BH**)** traffic of the macrocell as input to the model and traffic channel (TCH) congestion of the macrocell as the target. The GA was used for the optimal layer selection pressure of GMDH neurons and on the average improved the prediction accuracy of GMDH model by reducing its mean absolute percentage error (MAPE) by 80%.

Index Terms— Call Setup Success Rate; Genetic Algorithm; Gradient Descent; Group Method of Data Handling, and Traffic Channel Congestion

I. INTRODUCTION

The challenge of improving network quality and at the same time increasing capacity in mobile cellular network has resulted in traffic congestion and consequently degradation of quality of service (QoS) due to inadequate provision of the needed network resources during busy hour or under-utilization of the available resources as a result of improper network planning. To cope with the demand, cellular network elements are dimensioned on continuous bases using network management system (NMS) statistics; drive test trailing and customer feedbacks.

Traffic congestion during busy hour (BH) affects cellular network QoS and real live traffic data analysis and modeling are required to mitigate the congestion. The busy hour of a network is the time when the network processes the highest traffic in a day and it is used to measure network performance, determine the robustness of a network and its dimension [1]. To measure the network performance, the pattern of busy hour traffic is considered for congestion evaluation [2] using key performance indicators (KPIs).

KPIs that are used for traffic profile in mobile network at cell level are: busy hour Traffic (in Erlang), Call Setup Success Rate (CSSR), Handover Success Rate (HOSR), Stand-alone Dedicated Control Channel (SDCCH) congestion and Traffic channel (TCH) congestion, Call Drop Rate (CDR) and busy hour (BH) traffic load [3]. In this work, real live traffic data which consist of the KPIs from integrated GSM/GPRS network was used for traffic congestion modeling. The modeling was based on network management system (NMS) statistics data spanning three years period from four congesting cells on the network.

Four types of Artificial Intelligent models that were used for BH traffic congestion prediction in [4] are Radial Basis Function Neural Network (RBF-NN), Multilayer Perceptron Neural Network (MLP-NN), Group Method of Data Handling (GMDH) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The performance of these models were compared and the GMDH model was found to offer better prediction results in terms of root mean squared percentage error (*RMSPE*) and mean absolute percentage error (MAPE).

GMDH was developed as a model for obtaining high order input- output relationship in time-series problems by identifying non-linear relationships between inputs and outputs data [5]. GMDH is an inductive feed-forward neural network that consists of large number of layers and each layer contains many neurons. All neurons in GMDH shell have two inputs and one output as shown in Fig. 1.

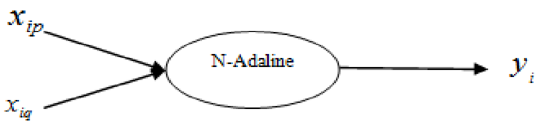

Fig. 1: A Single GMDH Neuron Model

GMDH neuron model can be expressed mathematically as a second order polynomial network (PNN) model with base function as in (1):

$$y_i = f(x_{ip}, x_{iq})$$

$$y_i = a_0 + a_1 x_{ip} + a_2 x_{iq} + a_3 x_{ip} x_{iq} + a_4 x_{ip}^2 + a_5 x_{iq}^2 \quad (1)$$

Equation (1) can be expressed in matrix form as (2):

$$A\mathbf{a} = Y \quad (2)$$

where

$$A = \begin{bmatrix} 1 & x_{ip} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ . & . & . & .. & . & . \\ . & . & . & .. & . & . \\ 1 & x_{Np} & x_{Nq} & x_{Np}x_{Nq} & x_{Np}^2 & x_{Nq}^2 \end{bmatrix}$$

The **a** in (2) represents the coefficient of the base function and can be expressed as **a** = $\{a_0, a_1, a_2, a_3, a_4, a_5\}$ which is the vector of the coefficients to be determined for the partial quadratic polynomial and $Y = \{y_1, y_2 . . . y_N\}^T$.

Solving (2) for **a** leads to (3):

$$\mathrm{a} = (A^T A)^{-1} A^T Y \quad (3)$$

Note that from (1) the least-squares errors r^2 can be expressed as (4):

$$r^2 = \frac{\sum_{i=1}^{N} (y_i - f(x_{ip}, x_{iq}))^2}{\sum_{i=1}^{N} y_i^2} \quad (4)$$

The use of (3) to determine the vector of coefficients in (1) is done recursively for each neuron in the hidden layers of the GMDH network and is susceptible to round off errors like any other neural networks because it is not derivative free [6], [7] and hence the solution found by GMDH is not optimal. To avoid GMDH model falling into local optimum, GA is chosen for the optimization of GMDH model parameters in this study. The essence is to obtain a more accurate model which will give a better prediction and hence a better tool for network planning and optimization.

The application of GA for solving real-live problems is a brilliant extension of Charles Darwin's theory of evolution as a powerful meta-heuristic optimization methods based on the concept of biological evolutionary processes. Unlike other optimization techniques, GA depends only on a cost-function to assess the fitness of a particular solution to a problem [8] using operators borrowed from natural genetics.

This work tuned the standard GMDH model for optimum TCH congestion prediction in GSM/GPRS network resources using GA and compared the performances of the tuned model (G-GMDH) to standard GMDH model using MAPE, RMSPE and neural network model error as statistical indices.

II. LITERATURE REVIEW

Recently, GAs have been used to tune each neuron of GMDH model searching for its optimal set of connections with the preceding layer. GAs as stochastic methods are commonly used in the training of neural networks in terms of associated weights or coefficients and have successfully performed better than traditional gradient-based techniques [9].

The work of [10] investigated the performance of three different methods of developing structure of GMDH neural network using GA and SVD for design and optimization of cooling systems. The result showed that such application led to much simpler GMDH polynomial equations and hence better modeling of the systems compared to conventional GMDH neural network.

In a related development, [11] developed a hybrid of GMDH and differential evolution (DE) population-based algorithm (DE-GMDH) for modeling and prediction of tool-wear in end-milling operations. Comparison of DE-GMDH and GA -GMDH results showed that the proposed algorithm performs favorably with GA-GMDH and hence can be applied to real-life prediction and modeling problems.

Similarly, [12] worked on GMDH type neural network and evolutionary algorithms (EAs) for modeling the effects of intake valve-timing (Vt) and engine speed (N) of a spark-ignition engine using some experimentally obtained training and test data. The results of EA- GMDH showed the superiority of the GMDH type models over feedforward neural network models in terms of the statistical measures in the training data, testing data and the number of hidden neurons.

[13] presented a new method of building the GMDH with multilayer iterative adaptive (MIA) algorithm by genetic selection of parents for each new neuron and with cloning of the best neuron so that any new neuron can be connected to the output of any already existing neuron. The genetically modified GMDH network with cloning outperforms other population-based algorithms when demonstrated on some tasks from the Machine Learning Repository.

Combinatorial GMDH GA (COMBI GMDH-GA) algorithm was designed by [14] for solving inductive modeling tasks with very large numbers of input variables. The result showed that the algorithms develop model of optimal structure faster than any other variants of GMDH because of its ability to avoid exhaustive search.

Likewise, [15] modeled and predicted the brake pedal system under random braking condition based (GMDH) and genetic algorithm (GA). The GA is used in the GMDH to enable each neuron search for its optimal set of connections with the preceding layer. The results obtained with this hybrid approach were compared with different nonlinear system identification methods. The experimental results showed that the hybrid approach performs better than the other methods in terms of root mean square error (RMSE) and correlation coefficients.

All the reviewed works showed good performance and differ in terms of the tuning parameters and their applications. In this work, GMDH neurons layer selection pressure is used to tune GMDH parameters.

A. GMDH NEURONS LAYER SELECTION PRESSURE TUNING

According to [10], the three different methods of developing structure of GMDH neural network are:

Pre-specified-network method: this method pre-specifies the number of layers in the network and number of neurons in each layer.

Error-driven method: the numbers of layers and the number of neurons in each layer of the GMDH network is determined using error threshold in (4). This method allows addition of some input variables or generated neurons in different layers to be included in subsequent layers.

Increasing-selection-pressure method: in this method, the number of neurons in each layer and the number of layers in network is determined only by selection pressure.

Increasing-selection-pressure method is used in this work for the formulation of the GMDH fitness function because it is easier to implement as it does not require knowledge of the structure of the GMDH network that will evolve after the modeling unlike the other methods. The steps required for the increase-selection-pressure are as follows.

Step 1: Let $N = n$ 1 neurons in the first layer from the vector of input variables Vec. of Var. = {x_1, x_2, x_3,..., x_m} , where n is the number of input. Set

$$SP_k = 1 \tag{5}$$

k=1; Set selection pressure

Step 2: $N_k(N_k - 1)/2$ neurons is constructed according to all possibilities of connection by each pair of neurons in the layer. This can be achieved by forming the quadratic expression $f(x_{ip}, x_{iq})$ which approximates the output y in (1) with least-squares errors of (4) either by solving (4) or (5).

Step 3: $SP_k = SP_{k-1} - 0.1$ is set (increase the selection-pressure) and m_k neurons is selected whose errors according to (4) are less than a certain value calculated from (6):

$$\bar{r}^2 = SP_k \left(\frac{\sum_{j=1}^{v} r_j^2}{v} \right) \tag{6}$$

where

$$v = INT\left(SP_k \frac{N_k(N_k - 1)}{2} \right)$$

Step 4: $k = k + 1$ and $N_k = m_{k-1}$. If $N_k \neq 1$ then go to Step 2. Otherwise END.

Selection-pressure is a critical parameter that must be carefully tuned when using increase-selection-pressure method. If this pressure is set too high the genetic algorithm will converge quickly but possibly to a local optimum, while if it is set too low the system will converge only very slowly, if at all. It is an important decision that has a significant influence on the structure of the network that must be carefully chosen so that the coefficients of the GMDH network are determined properly.

IV. EXPERIMENTAL SETUP AND METHODS

The experimental setup for collecting and processing the traffic data used in this work is shown in Fig. 2. The setup comprises of base station subsystem (BSS) and network subsystem (NSS) connected to standalone system called network management system (NMS).

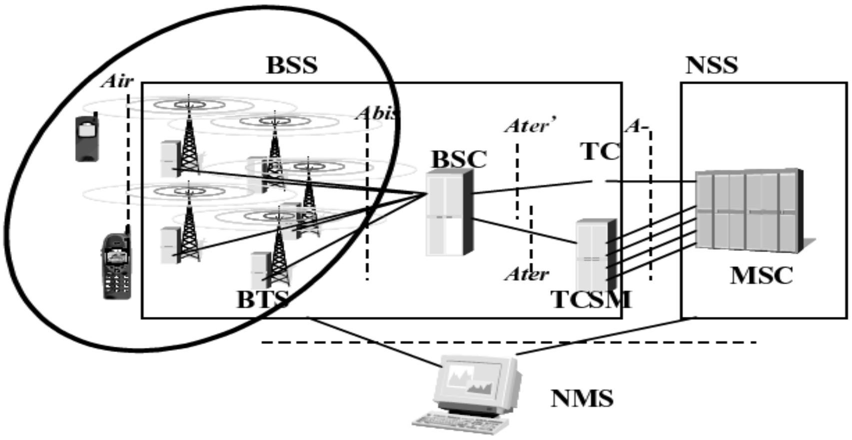

Fig. 2: System for collecting traffic data

NMS is the functional entity from which the service provider monitors and controls the entire network. The data used in this work was extracted from the NMS with the help of Ericsson Business intelligent (BI) tools installed on the standalone computer and exported to Microsoft Excel environment and part of the processed data for the four cells is shown in Table I.

Table I: Traffic Data for the Macrocells

CELL01 DATA			CELL02 DATA			CELL03 DATA			CELL04 DATA		
CSSR	TRAFFIC	TCH CONG	CSSR	TRAFFIC	TCH CONG	CSSR	TRAFFIC	TCH CONG	CSSR	TRAFFIC	TCH CONG
57.92	29.88	2.67	89.77	19.64	8.47	97.52	13.70	2.20	97.03	13.80	2.40
56.90	30.73	2.98	88.09	19.19	10.86	97.52	13.70	2.25	97.18	12.67	2.45
58.71	23.73	3.01	92.43	18.85	5.61	97.41	15.12	2.31	96.92	13.94	2.69
42.35	17.75	3.90	70.63	18.83	50.35	97.33	14.08	2.43	95.92	16.00	3.40
46.00	19.74	3.97	84.01	18.69	50.57	97.33	14.08	2.45	95.48	13.44	4.03
46.34	17.54	5.12	89.33	18.59	9.49	97.33	14.08	3.27	95.58	17.01	4.09
47.26	19.31	7.73	77.06	18.58	26.72	96.64	12.88	3.34	94.89	16.66	4.61
48.62	19.75	8.84	47.49	18.57	52.70	97.34	15.24	3.38	94.45	17.23	5.08
87.69	13.55	11.27	89.74	18.30	9.20	94.94	7.94	3.53	93.06	16.77	5.18
86.46	16.98	12.98	84.99	18.24	12.32	94.94	7.94	3.66	94.09	17.12	5.20
86.18	18.44	13.37	87.71	18.19	10.72	96.32	15.44	3.69	93.59	17.99	6.06
82.75	13.57	15.17	81.82	17.67	18.17	96.32	15.44	3.78	95.16	17.70	6.34
83.14	15.97	16.23	82.41	17.60	16.97	96.32	15.44	3.96	92.45	11.92	6.38
75.70	15.01	23.58	79.96	17.58	19.91	94.87	17.69	4.83	92.45	11.92	6.40
75.46	13.43	24.00	93.84	17.51	3.94	96.02	15.88	5.04	92.45	11.92	6.63

74.70	15.14	24.44	88.35	17.36	9.21	96.10	13.27	5.21	92.86	16.08	7.25
69.86	18.54	29.68	84.98	17.28	9.74	96.10	13.27	5.32	92.40	15.20	7.49
69.34	18.83	30.43	90.29	17.27	7.98	96.22	15.53	5.33	91.44	15.47	9.48
67.96	17.93	31.39	94.92	17.23	3.38	95.73	21.04	6.19	91.44	15.47	9.71
…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…
65.80	18.87	32.10	80.58	17.21	10.31	95.42	15.26	6.69	91.42	15.36	11.06

To develop a good prediction model for the congestion, the selection of the input variables must be closely associated with the TCH congestion values and there must be a strong linear correlation between the traffic parameters (CSSR, HOSR, DCR, SDCCH congestion and busy hour BH traffic) and TCH congestion. Correlation test showed that traffic channel (TCH) congestion depend only on call setup success rate (CSSR) and BH traffic at cell level. An average correlation coefficient value of 0.9 was observed between TCH congestion and CSSR while 0.6 was observed between TCH congestion and BH traffic [16].

For the standard GMDH model, BH traffic, CSSR and TCH congestion pairs of each cell was fit into GDMH shell which create a second order polynomial network. The traffic data was imported in to GMDH shell environment in CSV/XLS/XLSX format to train and validate the model for predicting the busy hour congestion of the cell using k-fold cross-validation to split the whole dataset into ratio 60:40 for training and testing respectively.

For the G-GMDH, open source codes available online in Matlab for optimizing GMDH model whose inputs variable are not more than five is modified and adapted for the optimization [17]. In the code, 0.6 was chosen as selection pressure which is obtained after adapting the fitness function into GA.

The Genetic Algorithm for the tuning of GMDH parameters was implemented using the Matlab R2013a platform and executed on a Personal computer HP 650 that run on Window 8 with Intel ® core (TM) i3 2348M cpu@2,30GHz and Installed Memory (RAM): 8.00GB.

The performances of the models developed in this study were evaluated based on three common standard statistical performance evaluation criteria- mean absolute percentage error (*MAPE*), root mean square percentage error (*RMSPE*) and neural network model error [15], [18] as in (7) – (9):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{abs(Y_i - Z_i)}{Y_i}\times 100\% \qquad (7)$$

where n is the number of variables, Y is the actual output and Z is the predicted output.

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Z_i)^2} \times 100\% \qquad (8)$$

For an optimized neural network structure, the model error could be approximated [19] by (9):

$$Model\_error \approx \sqrt{\sigma^2}\,\frac{\sqrt{n_{eff}}}{\sqrt{N}} \qquad (9)$$

where σ^2 is variance, n_{eff} denotes effective neural network parameters (weights and biases) that are optimized during training and testing and N gives the number of data samples.

Note that the model error in (9) decreases with an increase in the number of data samples, *N*.

V. RESULTS AND DISCUSSION

Using the modified Matlab codes, the plots of the optimized prediction against the actual TCH congestion for G-GMDH are shown in Fig. 3 - 6.

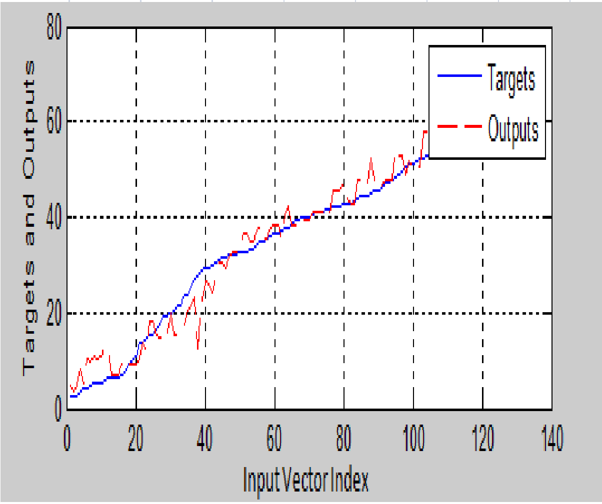

Fig. 3: Target and Prediction Output for CELL4

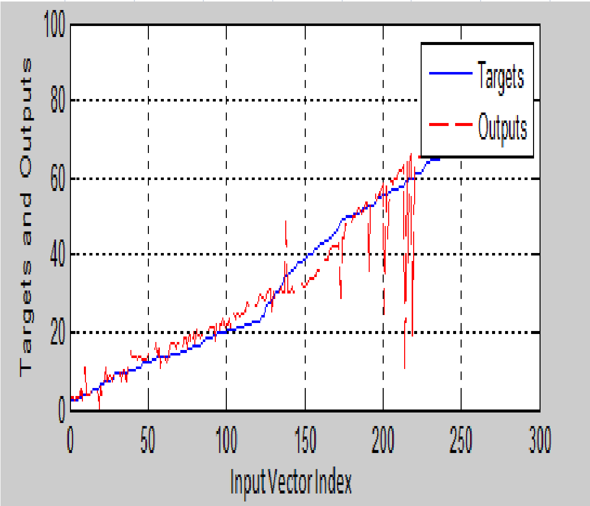

Fig. 4: Target and Prediction Output for CELL3

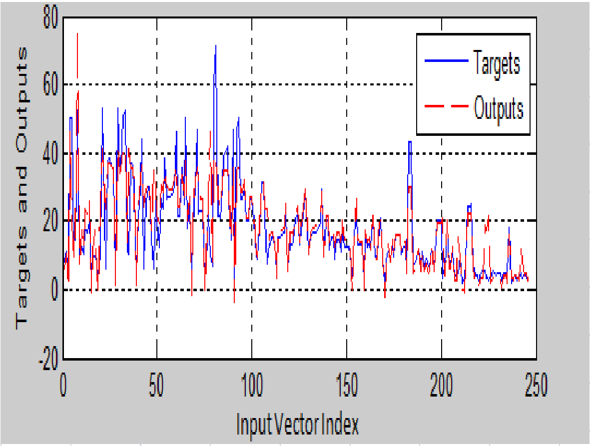

Fig. 5: Target and Prediction Output for CELL2

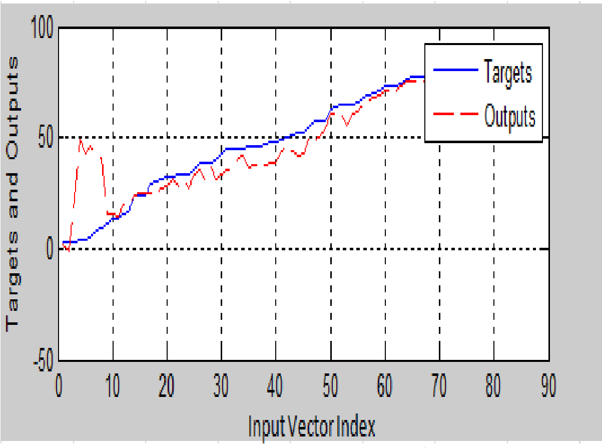

Fig. 6: Target and Prediction Output for CELL1

The summary of the GMDH and G-GMDH models statistical performance indices is shown in Table II and Table III respectively for the macrocells 1-4.

Table II: Statistical performance indices of GMDH model

Site	MAPE	RMSPE
CELL 1	2.65	3.91
CELL 2	3.83	4.6
CELL 3	0.67	0.94
CELL 4	2.13	4.77
Average	2.32	3.56

Table III: Statistical performance indices of G-GMDH model

Site	MAPE	RMSPE
CELL 1	0.38	10.85
CELL 2	0.31	6.8
CELL 3	0.29	6.25
CELL 4	0.3	3.75
Average	0.32	6.92

It is observed from Table II that the prediction performance of GMDH model is best in CELL 3 in terms of both MAPE and RMSPE.

Also, from Table III, the prediction performances of G-GMDH model is best in CELL 4 in terms of both MAPE and RMSPE closely followed by CELL 3.

However, according to (9) the prediction accuracy should be better in CELL 3 then follow by CELL 2, CELL 1 and CELL 4 given the number of the preprocessed data samples for each macrocell as shown in Table IV. This shows that the GMDH model prediction error do not obey (9) but G-GMDH prediction obeyed (9) for all the cells except CELL 4 which may be due to the deviation of the cell KPIs from their optimal values as a result of the noise that affected CELL 4 traffic data.

Table IV: Number of Sample Data for each Macrocell

Site	Number of Data Samples
CELL 1	83
CELL 2	246
CELL 3	279
CELL 4	130

The performance of the G-GMDH model compared with standard GMDH model result is shown in Fig. 7.

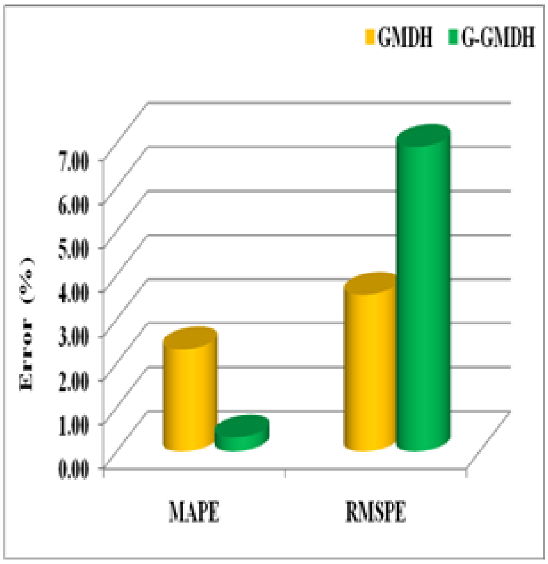

Fig. 7: Comparisons of G-GMDH and GMDH Models

Fig. 7 shows that G-GMDH model performance is only better than standard GMDH model in terms of MAPE while the GMDH model performance is better in RMSPE. The percentage reduction in MAPE after the tuning of GMDH layer select pressure by GA is shown in Table V.

Table V: Percentage improvement of GMDH Model by GA

Site	MAPE
CELL 1	86.15
CELL 2	57.03
CELL 3	91.92
CELL 4	85.52
Average	80.16

From Table V, GA was able to improve the prediction accuracy of GMDH model by 80% as a result of tuning the layer selection pressure of the model. Hence, G-GMDH model is better than GMDH model in terms of MAPE for predicting TCH congestion during busy hour which is in agreement with the related applications in [9] and [15].

VI. CONCLUSION

When modeling traffic congestion using the standard GMDH model there is the need to fine-tune the model parameters using genetic algorithm (GA) to enhance the performance of the model. The use of the hybridized G-GMDH model for prediction of the TCH congestion in this work was shown to provide a significant improvement over the standard GMDH model which demonstrated that GA can be used effectively to optimally tune GMDH parameters for a more accurate prediction.

It was also discovered that the G-GMDH model prediction error agrees with the model error approximation of [19] for an optimized neural network structure. Hence, the model obtained in this study is expected to play an important role in the planning and optimization of GSM/GPRS network resources for improved quality and increased capacity.

REFERENCES

[1] E.O. Oladeji, E.N. Onwuka and M.A. Aibinu, “Determination of Voice Traffic Busy Hour and Traffic Forecasting in Global System of Mobile Communication (GSM) in Nigeria,” 2013 IEEE 11th Malaysia International Conference on Communications 26th - 28th November 2013, Kuala Lumpur, Malaysia.

[2] S. Kyriazakos, G. Karetsos, E. Gkroustiotis, C. Kechagias and P. Fournogerakis, “Congestion Study and Resource Management in Cellular Networks of present and Future Generation,” IST Mobile Summit 2001, Barcelona, Spain, 9-12 September 2001.

[3] A. Adegoke , I. Babalola, and W. Balogun, "Performance Evaluation of GSM Mobile System in Nigeria," Pacific Journal of Science and Technology, pp. 436-441, 2008

[4] O. Aliyu, O. U. Okereke, and E. C. Anene, “Teletraffic Congestion Prediction in GSM/GPRS Macrocells Using Artificial Intelligence Techniques,” Unpublished Doctoral Seminar III, Presented at the Electrical and Electronics Engineering Department, Abubakar Tafawa Balewa University, Bauchi, Nigeria, October, 2016b.

[5] B. Koo, S. Lee, W. Kim, and J. H. Park, “Comparative Study of Short-term Electric Load Forecasting, 2014 Fifth International Conference on Intelligent Systems,” Modeling and Simulation

[6] M. A. Ahmadi, M. Golshadi, “Neural Network Based Swarm Concept for Prediction Asphaltene Precipitation due Natural Depletion,” *J. Pet. Sci. Eng*. **2012**, *98–99*, 40–49.

[7] J.I.E. Lin, C.T. Cheng, K.W. Chau, “Using Support Vector Machines for Long-Term Discharge Prediction,” Hydraulic *Sci. J.* 2006, *51*, 599–612.

[8] M. Abbod, and K. Deshpande, “Using Intelligent Optimization Methods to Improve the Group Method of Data Handling in Time Series Prediction,” School of Engineering and Design, Brunel University, West London, UK Uxbridge, UK, UB8 3PH.

[9] Z. N. Nariman, A. Darvizeh, M.E. Felezi, and H. Gharababaei, “ Polynomial Modelling of Explosive

Compaction Process of Metallic Powders Using GMDH-type Neural Networks and Singular Value Decomposition," Model Simulation Mater SciEng 2002, 10(6):727–44.

[10] S. K. Hannani, M. Fardadi, and R. Bahoush, "Optimization and Design of Cooling Systems using a Hybrid Neural Network and Genetic Algorithm Methodology," *Center of Excellence in Energy Conversion, School of Mechanical Engineering, Sharif University of Technology, Tehran, Iran*, 2004 WIT Press, www.witpress.com, ISBN 1-85312-705-1.

[11] G. C Onwubolu, " Design of Hybrid Differential Evolution and Group Method of Data Handling for Inductive Modeling," International Workshop on Inductive Modeling, IWIM 2007, Prague, Czech; September 23-26, 2007 .

[12] K. Atashkari, N. N. Zadeh, M. Gölcü, A. Khalkhali, and, A. Jamali, "Modelling and Multi-objective Optimization of a Variable Valve-timing Spark-ignition Engine Using Polynomial Neural Networks and Evolutionary Algorithms," Energy Conversion and Management Journal 48(3) 1029-1041.

[13] M. Jirina and M. Jirina Jr., " GMDH Method with Genetic Selection Algorithm and Cloning," Neural Network World 5/13, 451-464.

[14] V. Stepashko, and O. Moroz, " Hybrid Searching GMDH-GA Algorithm for Solving Inductive Modeling Tasks," IEEE First International Conference on Data Stream Mining & Processing 23-27 August 2016, Lviv, Ukraine.

[15] J. Bae, S. Lee, D.H. Shin, J. J Lee and J.H. Kim , "Nonlinear Identification of Electronic Brake Pedal Behavior Using Hybrid GMDH and Genetic Algorithm in Brake-By-Wire System," Journal of Electrical Engineering Technology 2017; 12(?): 1921-718, http://doi.org/10.????/JEET.2017.12.1.1921, ISSN (Print) 1975-0102, ISSN (Online) 2093-7423.

[16] O. Aliyu, O. U. Okereke, E. C. Anene, and U. U Abraham, "Traffic Congestion Analysis in Mobile Macrocells**,"** International Conference on Information and Communication Technology and Its Applications (ICTA 2016), Federal University of Technology, Minna, Pages 243-249

[17] S. Mostapha, and K. Heris, " Implementation of Group Method of Data Handling in MATLAB," YPML113, Copyright (c) 2015, Yarpiz (www.yarpiz.com) .

[18] O. Nelles, " Nonlinear System Identification: From Classical Approaches to Neural Networks and Fuzzy Models," Springer Science & Business Media, Berlin, Germany, 2001.

[19] R. F. Turkson, F. Yan, M.K.A. Ali, B. Liu, and J. Hu, " Modeling and Multi-Objective Optimization of Engine Performance and Hydrocarbon Emissions via the Use of a Computer Aided Engineering Code and the NSGA-II Genetic Algorithm, " Journal of Sustainability **2016**, 8, 72; doi:10.3390/su8010072,