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FORECAST ANALYSIS OF TRAFFIC LOAD IN TELECOMMUNICATION SYSTEMS BY ANFIS, FFNN AND GRNN[19]

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Abstract: *In this paper the research objective is the traffic load forecasting of the stations (customer service queries) in Markov chain M/M/c. In connection with the predictive analysis, an approach for regression modeling based on Adaptive Neuro-fuzzy Interface Systems (ANFIS), Feed-Forward Neural Networks (FFNN) and Generalized Regression Neural Networks (GRNN) was performed. About the educational and engineering purposes, students and developers have the opportunity to solve scenarios of approximation tasks for different variations of the traffic indicators Average Arrival Rate and Service Time with application of Hybrid, Backpropagation and other training algorithms. The procedures showed a high degree of approximation between observed and predicted values in the synthesis of predictive neural models.*

Keywords: *Markov chain M/M/c, Predictive Analysis, Customer Service Queries, ANFIS, FFNN, GRNN.*

INTRODUCTION

The principle tendencies and challenges in the modern communications networks and services could be expressed in characterized requirements, multimedia services, precision management, predictable future, intellectualization and stronger emphasis on security and safety. Artificial Intelligence (AI) has become an integral part of all sectors of human reality: industrial, economic, educational and others (Guibao X., M. Yubo M., & Lialiang L., 2018). The integration of AI in the development of applications for these purposes in modern communications is an essential building aspect. Some of the options concerning AI application possibilities are related with Software Defined Networking (SDN) architecture, Network Function Visualization (NFV), Network Monitor and Control (Latah M., & Toker L., 2018).

The major aspects of communication systems and intelligent transport systems are as follows:

- forecasting of load on structural nodes which serve the incoming traffic and comprehensive analysis of the network traffic;
- an adequate planning of system resources and enhances quick action in processing of requests, thereby improving service quality end queue processing.

The problem is especially relevant in mobile networks where are used Multivariate LSTM Forecast Models for predict future network conditions in connection with real-time users (Nekovee M., Sharma S., Uniyal N., Nag A., Nejabati R., & Simeonidou D., 2020). In another study a scalable Gaussian process regression framework is used for traffic prediction about load-aware network managements in 5G wireless systems (Zhang K., Chuai G., Gao W., Liu X., Maimaiti S., & SI Z.,

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2019). A method based on wavelet transformation for the network traffic time series decomposition, Least Squares Support Vector Machine (LSSVM), Particle Swarm Optimization (PSO) and Gauss-Markov algorithms to predict components and estimation of the prediction models was proposed (Xu Y., Lin F., Xu V., Lin J., & Cui Sh., 2019). In (Tian Zh., 2020) a possibility to predict the self-similar network traffic with high burstiness was solved by the covariation orthogonal and the artificial neural network predictions. A similar approach using combination of Recurrent Neural Networks (RNN) and Longshort-Term-Memory (LSTM) is applied on the autonomous prediction of traffic demand in cellular network communications (Jaffry Sh., 2020).

The paper presents the models for predictive analysis of Traffic load in simulated modeling of Teletraffic systems were created by ANFIS, FFNN and GRNN hybrid approach on MATLAB software. The models were evaluated on the base of some criteria, respectively Root Mean Square Error (RMSE), Mean Squared Error (MSE), Spread indicator and other.

EXPOSITION

Simulation Modeling of Teletraffic Systems by Java Modeling Tool

Java Modeling Tool includes a packet of several simulators for modeling of telecommunication systems and analytic investigation of processes. The instruments of the medium allow for the users to acquire data for a number of parameters such as Response Time, Residence Time, Utilization, Throughput, the moments of arriving and release of requests from the system with adjusted:

- intensity of incoming calls;
- limitation and non-limitation of the queue;
- quantity of server units for information processing.

A Markov chain has been modeled M/M/c with fixed server station (c = 15) without restriction of calls in the queue (Fig. 1). All procedures have been implemented with defined factors:

- "Avg. Arrival Rate (x1)" – assigned average arrival rate of requests toward operator server stations;
- "Avg. Service Time (x2)" – assigned average time for processing of incoming requests,

as well as response M/M/c, respectively "Avg. Cust. N in Station (y)" – an average number of customers in the queue and an average traffic queries processing.

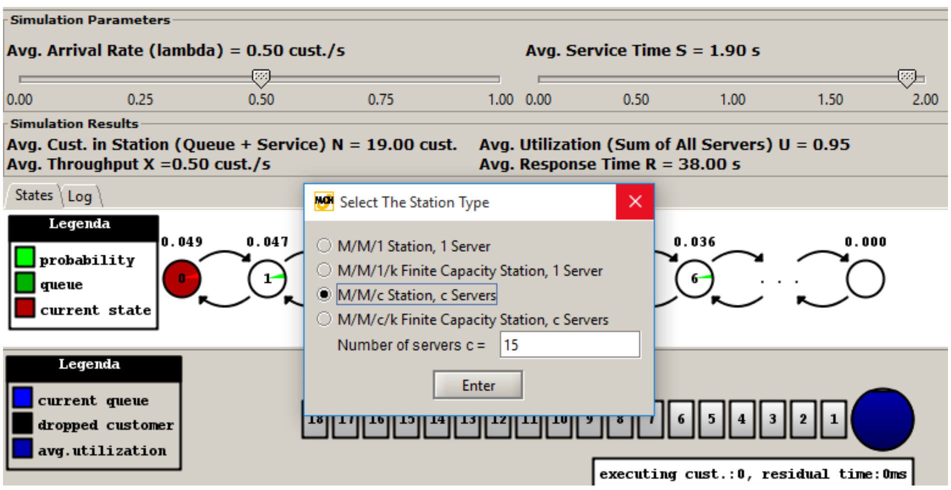


Fig. 1. JMT in simulation modeling of M/M/c chain

A series of simulations have been carried out with observation of several different scenarios concerning system's behavior with regard to specifics of selected equipment to be used for the purposes of predictive analysis. Here were specified information sets for educational purposes and verification in assessment and synthesis of models.

Investigation and Analysis of Adaptive-Neuro-Fuzzy Interface System for Predictive Analysis in MATLAB

In the next stage there were undertaken procedures for investigation and synthesis of neuro-fuzzy architecture for prediction of the load in the server stations, which handle incoming traffic with M/M/c.

An ANFIS model was developed in MATLAB medium with set functions for transformation of input variables in accordance with six levels of scenario, of loading of the modeled teletraffic system and a linear type of output. The model is presented in Fig. 2.

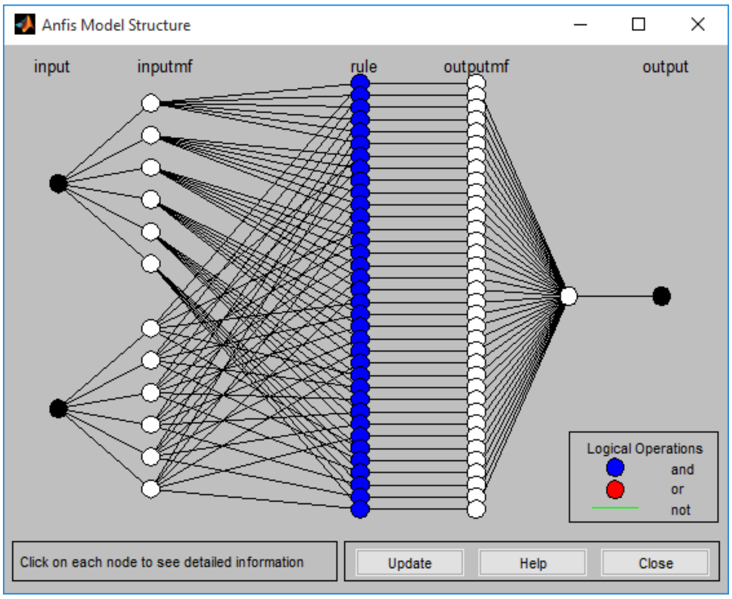


Fig. 2. ANFIS architecture for predictive analysis of server stations'load at M/Mc chain

Selection of final model involves the application of two training approaches - Hybrid and Backpropagation, with eight types of functions for belonging of input variables, respectively Avg. Arrival Rate and Avg. Service Time, concerning analysis and evaluation of the RMSE indicator. The training and verification sets in ratio 2:1 were applied in the model selection procedures. Table 1 contains the summarized results with reference to the change of the introduced criterion.

Table 1. Results in ANFIS model selection

Membership functions of input variables	**Training algorithms**	
	Hybrid	**Backpropagation**
trimf	1.6454e-07	0.0772660
trapmf	1.6926e-07	0.0021534
gbellmf	1.6697e-07	0.0157870
gaussmf	1.6701e-07	0.0264870
gauss2mf	**1.6277e-07**	0.0039852
pimf	1.6926e-07	0.0021534
dsigmf	1.6998e-07	0.0036605

There have been registered differences in the levels of errors during training between the algorithms used, which are higher for the reverse error propagation approach (Table 1). Here the minimum error threshold equals 0.0021534, and is found with trapezoidal and Pi-shaped type of function. Maximum value of RMSE = 0.0264870 is found by defining Gaussian function of belonging of input variables. However, the case is different with the hybrid approach in which the least value of 1.6277e-07 and the highest value of 1.6998e-07 of RMSE correspond to combined Gaussian function for belonging, and function which represents the difference between two sigmoidal functions. Judging from the indicators obtained for the purpose of analysis, the most appropriate is the ANFIS with “gauss2mf” type of functions for belonging of input variables.

About the ANFIS model is presented a Decision surface, which illustrates variations in teletraffic load with respect to the variations of average intensity of request arrivals and their average processing time (Fig. 3). Tests have been carried out with training data and verification data for the purpose of analysis objectivity (Fig. 4). With reference to procedures test data are designated with blue whereas predictive values, obtained by employing the neuro-fuzzy model, are indicated in red. A high level of approximation between specified groups of results is observed, which verifies the adequacy of the model.

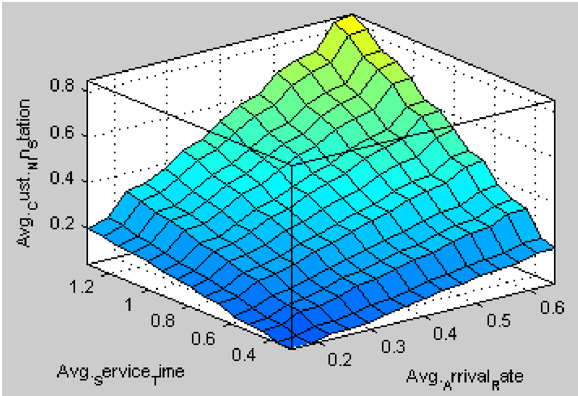
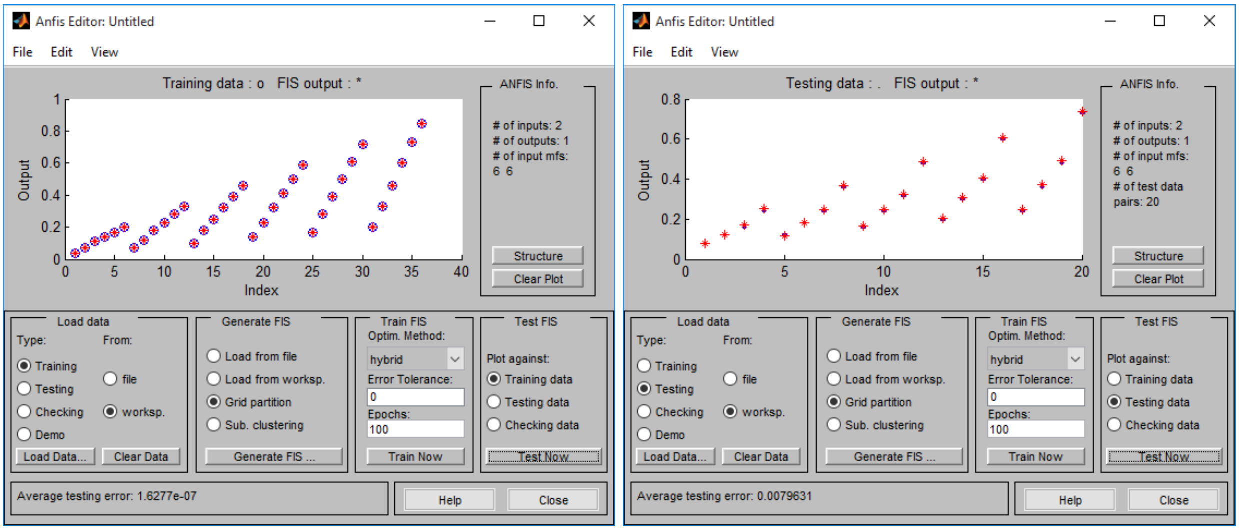


Fig. 3. Decision surface of solution for the selected ANFIS architecture for predictive analysis of traffic load stations in M/M/c chain



a) b)

Fig. 4. Test of ANFIS for predictive analysis of loading of server stations with M/M/c with a) train set and b) test set

Synthesis of FFNN Model for Predictive Analysis by MATLAB Software

In connection with the approximation task there have been carried out some activities related to training, validation and testing of FFNNs – 50% : 25% : 25%. The synthesis of model is based on the assessment of quality criteria MSE (Mean Squared Error) and variation range of network errors.

Table 2 contains data concerning quality indicators fixed in the process of experimentation with the quantity of neurons in the hidden layer of testing neural networks.

Table 2. Results in FFNN model synthesis

Hidden neurons	Quality criteria	
	MSE	Error variance
5	1.6975e-04	-0.0068 to 0.0307
6	0.0021	-0.0797 to 0.0563
7	6.5616e-04	-0.0404 to 0.0025
8	8.6803e-04	-0.0552 to -0.0101
9	3.2254e-04	-0.0124 to 0.0349
10	7.4122e-04	-0.0264 to 0.0608
11	7.4642e-04	-0.0403 to 0.0308
12	0.0346	-0.0546 to 0.3538
13	0.0082	-0.1681 to 0.0376
14	0.0013	-0.0748 to 0.0204
15	0.0014	-0.0570 to 0.0497
16	6.0944e-04	-0.0491 to 0.0119
17	0.0011	-0.0659 to 0.0293
18	1.0374e-04	-0.0191 to 0.0122
19	0.0120	-0.0462 to 0.1744

Within the frame of the defined interval of increase in calculation units, in the intermediate network layer there have been achieved lowest 1.0374e-04 and maximum 0.0346 values of the indicator MSE, respectively with 18 and 12 hidden neurons. Concerning specified architectures network errors fall within the defined limits:

- -0.0191 to 0.0122 for the best synthesized model, shown in Fig. 5;
- -0.0546 to 0.3538 concerning the network with established least appropriate applicability in the process of functional approximation.

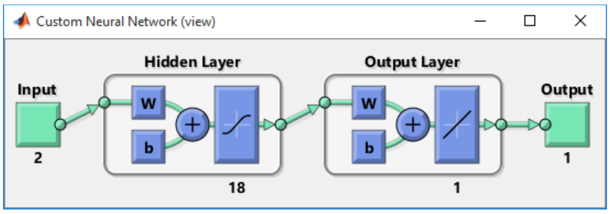


Fig. 5. Synthesized FFNN architecture for predictive analysis of server stations' load at M/M/c chain

The synthesized three layer model, which in terms of its structure contains intermediate and output layer with set tangent-sigmoidal and linear type of activation functions, has been assessed for its high level adequacy. Additional regression type analysis (Fig. 6 - the regression line resulting from training) has been carried out, based on which there have been drafted regression dependences for training, validation and test procedures. Some very good correlation ratios have been found at levels of 0.99, which is indicative of the high rate of approximation between observed and expected results.

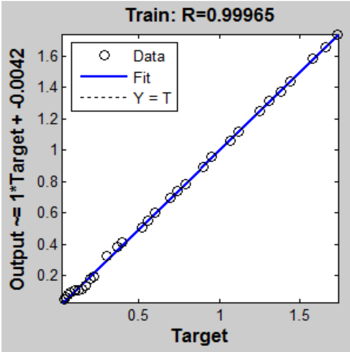


Fig. 6. Linear regression line for the process of training of the selected FFNN model for predictive analysis of traffic load in M/M/c chain

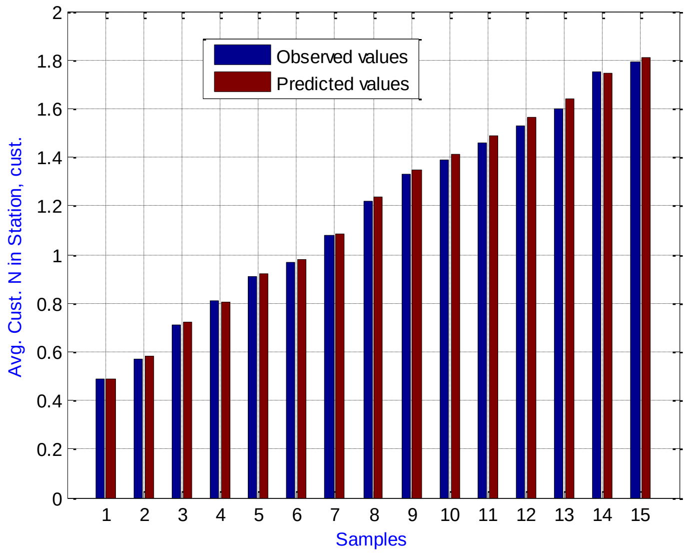


Fig. 7. Verification process of selected FFNN model for predictive analysis of server stations' load at M/M/c chain

Verification has been done with application of selected FFNN architecture using teletraffic data beyond the scope of training, validation and testing. Here were observed levels of network errors within the range from -0.0416 to 0.0070. Figure 7 present the both levels of loading in the process of simulation and the predictive loading of the system while servicing traffic flow, either of which display good level of approximation.

Synthesis of GRNN Architecture for Predictive Analysis in MATLAB Environment

There have been analyzed GRNN architectures for regression modeling with regard to "ÿ" parameter within applied ratio between training set and verification set, respectively 2:1. This type of models are variants of neural networks which feature radbas functions (RBFMs). Here the process of synthesizing can be carried out with respect to either an individual or a group of predictive variables. Their typical characteristic feature is that there is no distinction of phases in synthesizing and training of architectures; in other words, they take place within the frame of one and the same process. With GRNNs training is effected through the Single-pass (One-pass) algorithm. Table 3 contains the MSE values which are registered according to the rise of the "spread of radial basis functions" indicator; with width of radbas functions within the range from 0.15 to 0.8. GRNN test models for parametric approximation are presented in Fig.8. The architectures consist of:

- Input Layer;
- Radial Basis Layer also referred to as Hidden Layer wherein radbas functions for activation are used; these are normally spread functions or Gaussian functions;

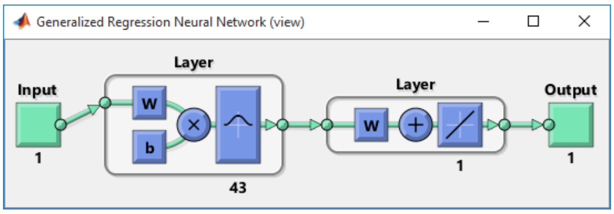
- Specific Linear Layer, also referred to as Summarion Layer, with application of "purelin" type of activation;
- Output Layer.

Table 3. Results in GRNN model synthesis in individual input variables

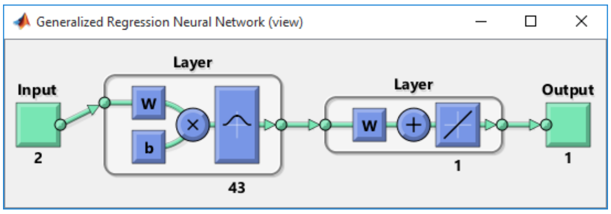
Spread indicator	Input variables		
	X_1	X_2	X_1 and X_2
0.15	0.0093	0.0013	9.2562e-04
0.20	0.0207	0.0029	0.0021
0.25	0.0397	0.0056	0.0040
0.30	0.0598	0.0093	0.0068
0.35	0.0841	0.0144	0.0105
0.40	0.1084	0.0209	0.0153
0.45	0.1309	0.0289	0.0212
0.50	0.1508	0.0384	0.0283
0.55	0.1680	0.0491	0.0366
0.60	0.1827	0.0608	0.0460
0.65	0.1952	0.0731	0.0561
0.70	0.2057	0.0856	0.0669
0.75	0.2147	0.0981	0.0780
0.80	0.2224	0.1102	0.0892

Three MSE ranges can be specified according to presented tabular results:

- 0.0093 to 0.2224 according to first informative indicator (Fig. 8.a);
- 0.0013 to 0.1102 with networks using input variable x_2 (Fig. 8.a);
- 9.2592e-04 to 0.0892 with application of both independent predictive teletraffic parameters (Fig. 8.b).



a)



b)

Fig. 8. GRNN models with a) one and b) two input variables for traffic load prediction of the server stations in M/M/c chain

For all reviewed cases there has been observed a tendency of exponential growth of MSE with substantial difference in the minimal levels of the error, which are established for a value of the indicator „spread = 0.15“. Highest effect has been observed in employing a combination of the informative indicators Avg. Arrival Rate and Avg. Service Time, whereas the lowest is observed in individual application of factor x_1.

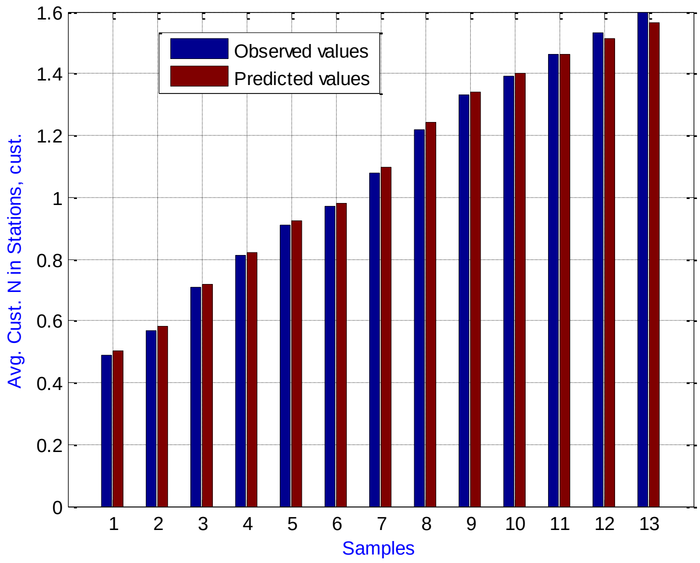


Fig. 9. Diagram of observed and predicted values in verification of the selected GRNN model of predictive analysis of traffic load of server stations in M/M/c chain

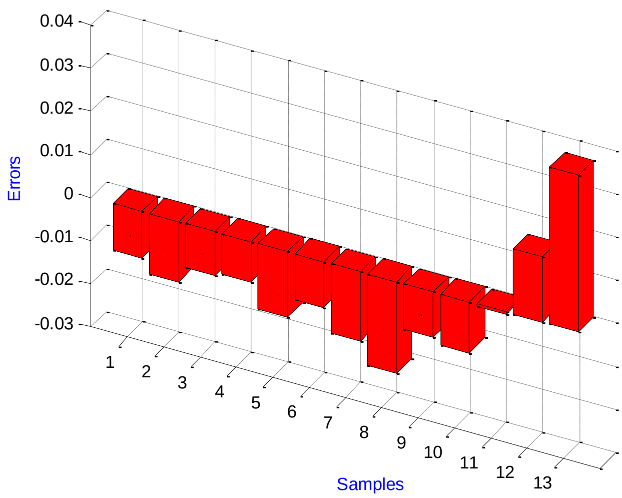


Fig. 10. 3D diagram of errors resulting from verification for the synthesized model GRNN for predictive analysis of load of server stations in M/M/c chain

Part of the processes of investigation and quality assessment involve calculation and output of variations of network errors with predictive analysis regarding average load at each of the major server stations of the investigated teletraffic system. A major finding is the relatively large level of approximation between observed levels and those obtained in the predictive analysis of load, as shown in Fig 9, which is indicative of the correct selection of GRNN with an option for applying an input set of x_1 and x_2. Error diagram refer to the verification procedures of GRNN architectures for regression modelling is given on Fig. 10. Network errors resulting from verification are limited within the interval from -0.0213 to 0.0363.

CONCLUSION

The results presented in here indicate very good applicability of the regression modeling equipment. In addition, the introduced approach through ANFIS, FFNN and RGNN can be adapted to telecommunications systems or network segments without regard to the type of connection, the range and their purpose and any kind of information content. The linear regression models were synthesized with levels of R2 over level 0.90 which also could be included in the course of the study. Indicated activities are introduced in technical subjects during training of future professionals who will work in the field of telecommunication and information systems in the industry.

REFERENCES

Guibao X., M. Yubo M., & Lialiang L. (2018). Inclusion on artificial intelligence in communication networking and services. *International Telecommunication Union Journal*, 1(1), 33-38.

Latah M., & Toker L. (2018). Artificial intelligence enabled software defined networking: A comprehensive overview. *IET Networking*, 1-25.

Nekovee M., Sharma S., Uniyal N., Nag A., Nejabati R., & Simeonidou D. (2020). *Towards AI-enabled microservice architecture for network function virtualization*. Paper presented at the IEEE International Conference on Communications and Networking (ComNet), 28th-30th October 2020, Hammamet.

Zhang K., Chuai G., Gao W., Liu X., Maimaiti S., & SI Z. (2019). A new method for traffic forecasting in urban wireless communication network. *EURASIP Journal on Wareless Communition and Networking*, 66, 1-12.

Xu Y., Lin F., Xu V., Lin J., & Cui Sh. (2019). Wireless traffic prediction with scalable Gaussin process: Framework, algorithms and verification. *IEEE Journal of Selected Areas in Communications*, 37(6), 1291-1306.

Tian Zh. (2020). Network traffic prediction method based on wavelet transformation and multiple models fusion. *International Journal of Communication Systems*, 33(11), 1-7.

Jaffry Sh. (2020). *Cellular traffic prediction with recurent neural networks*. Paper presented at the 5th International Symposium on Telecommunication Technologies (ISTT), 9th-11th November 2020, Shah Alam.