

Monitoring and Forecasting Model State of the Telecommunications Network using Fuzzy Neural Networks



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ABSTRACT

At present, forecasting the state of Telecom networks is the most important task of network administration. Characteristic features of the network are the high dynamics of processes that occur in it, as well as the structural complexity of connections between nodes. They determine the need to use tools that are highly adaptable and resistant to external influences to assess the state of the network. Neural networks can be used as such tools. The neural network performs logical inference based on the fuzzy logic apparatus, otherwise there is no new knowledge and uses it in further work. Such systems are successfully used in many fields (machine learning, facial recognition, medicine, signal processing, military, and others), they allow you to get the desired results without human involvement and with little computational cost.

Key words : telecom network, monitoring, forecasting, fuzzy neural network.

1. INTRODUCTION

The analysis showed that in most cases the scope of application of neural networks as elements of monitoring, remote control and administration systems is very limited. Thus, in [4], a study of the issue of modifying existing network management systems was conducted. It is proposed to use a probabilistic neural network to solve problems of classifying and predicting the state of the transport environment in the network, which allows using the UE service-oriented architecture for organizing access to services. In [5], we consider models based on hybrid neural networks that allow us to evaluate and predict the state of computer networks. The results of experiments have shown that the proposed models provide high accuracy of classification of the current and predicted state of the computer network. An experimental evaluation of models that are designed to monitor and predict the state of computer networks, which are based on co-ordinated self-explanatory and hybrid neural networks, has been carried out. The article [6] proposes a method for predicting computer network States based on

biometric algorithms [1-4]. The estimation of methods for solving the problem of predicting the state of a computer network is given. Examples of phase images obtained in various conditions of operation of a computer network are considered. The concept of phase state and trajectory of computer network parameters is introduced. It is shown that with the help of phase trajectories, it is possible to identify the state of computer network computers and predict the appearance of a critical state. The results of the analysis of forecasting methods for complex technical objects, which include a computer network, show that the proposed method of verification of phase images loads the highest final score for predicting the States of a computer network. In [7] proposed an intelligent system for decision support (of IPR) on the basis of a comprehensive approach to the problem of diagnostics data network (MPD), including the use of methods of SIG-field and statistical analysis of network traffic to detect network anomalies (AI) and fuzzy intelligent (expert) system (NIS) response to emergency situations, as well as the creation of models, algorithms, and software (SW) maintenance and professional activity of specialists in management of data networks. We have developed models of signature and statistical network traffic analyzers and SYSTEMS for responding to abnormal situations in IPD; a method for machine diagnostics of IPD. A set of algorithms and programs was implemented: monitoring the state of MPD elements, statistical analysis and detection of network anomalies (MA), NOS; an ISPR based on fuzzy logic was created to diagnose MPD at a separate network level; a system of ISPR efficiency indicators was developed [8-14]. Thus, the analysis of the works shows that neural networks have great opportunities to solve this problem. At the same time, known models of neural networks cannot be directly used for this purpose. Therefore, there is a question of creating a tax model that allowed us to solve this problem [15].

2. MATERIALS AND METHODS

The network management process consists of implementing a set of impacts on the managed object, which are selected from a set of possible impacts based on the management program and information received about the object's behavior and environmental conditions to achieve a given goal. There are six functional groups of tasks of the telecommunications

network management system defined by *ISO/ITU-T* standards [6].

Group 1: network configuration management – these tasks consist of configuring the parameters of network nodes: switches, routers, network adapters and network interfaces, as well as software.

Group 2: error handling – this task group includes identifying, determining, and eliminating the consequences of network failures and failures.

Group 3: performance and reliability analysis – the tasks of this group are related to the assessment of such parameters as system response time, bandwidth of a real or virtual communication channel, intensive traffic in certain segments and channels of the network, the probability of data distortion during their transmission through the network, as well as the network availability coefficient. Network performance and reliability analysis functions are needed for both operational network management and network development planning [16].

Group 4: security management-the tasks of this group include controlling access to data when it is stored and transmitted over the network. Basic security controls include user authentication procedures, assigning and verifying network resource access rights, managing permissions, and so on.

Group 5: network tracking – the task of this group is to record the usage time of various network resources – devices, channels, and transport services.

6th group: identification and prediction of network state. A modern network is a complex technical system whose state is described by multidimensional vectors. It is difficult for administrators to work with such multidimensional data [17]. Therefore, it is necessary to use subsystems for monitoring and identifying network States as part of the Telecom network management systems, which collect, process, store and display information about the state of all components of the telecommunications network in real time [18]. A high-quality forecast allowed administrators to prepare the network in time to prevent congestion, errors, and other emergency situations. Thus, the development of methods that allow us to generate a qualitative forecast of the onset of critical events in the network is an urgent task. In the process use various methods and approaches to research [19-21]. Among the General scientific approaches, the following can be distinguished: 1) the system approach involves the study of quantitative and qualitative regularities of probabilistic processes in the system; 2) system UMNO-structural approach involves considering the system as a whole, which is developing dynamically, the division of the system into components and structural elements and consideration of their interaction; 3) the historical approach is to consider each phenomenon in the relationship of its historical forms; 4) structural approach allows to explain the structure of the phenomenon under study; 5) a comprehensive approach is to consider phenomena in their interdependence in the context of different Sciences that study these phenomena and others. There are a large number of methods for solving the forecasting problem, but not all of them are capable of forming a qualitative forecast of the state of a complex technical system. In General, forecasting methods are understood as a set of thinking techniques, methods that allow us to make a reliable judgment

about the future development of the object based on the analysis of information about the forecast in the object. To make a forecast, you must use several forecasting methods and compare the results obtained. Let's take a look at some of them [21-24].

The method of time extrapolation examines historical data. Predicting state parameters in the form of a temporary extrapolation of characteristics uses one parameter as an argument: time. In addition, the method of time extrapolation includes heuristic elements, which consist in developing a mathematical model and analyzing the results of forecasting. This results in a certain degree of subjectivity, which affects the final result [25].

Spatial extrapolation associated with the prediction in the feature space. The essence of the spatial extrapolation method is to extend the conclusion obtained from the analysis of one part of the process to another part or to the process as a whole. This method works under one condition – the law of changing the state in the past must be preserved in the future. Therefore, making any changes to the system will entail correcting many laws of changing the state of the telecommunications network, which is quite a time-consuming task. And those laws of state change that were obtained before the system was changed will become invalid. The advantages of the spatial extrapolation method can also be attributed to the absence of the need to develop cumbersome forecast models based on the results of observations.

If we model the functioning processes of a telecommunications network, then the first task will be a detailed description of the studied vulcanization system *by means of mathematical and physical modeling*. This is extremely difficult due to the heterogeneity and complexity of the system under study, which entails large-scale calculations. In addition, the process modeling method will not be effective in situations that require a quick response to changes in the system state [26].

To implement *heuristic methods* in a parametric system, it is necessary to use the knowledge of several experts, which will also create difficulties in quickly reacting to changes in the state of the telecommunications network. It will take a long time to study a large number of examinations. The use of *logical methods* will also not bring the desired result, since the problem of the research area does not mean a solution based on certain logical actions. *Regressive methods* also require cumbersome computational actions, since they require detailed research of the dependencies between variables that affect the state of the computer network [27]. When solving the problem *by the method of neural networks*, there is no need to study the processes of the state of the telecommunication network. A prerequisite is a set of parameters required for training a neural network. In our case, a set of input parameters is a set of functions that depend on a variety of unpredictable factors. It should be noted that the solution of the problem posed by the practical implementation of the software model of this method looks possible.

The method of causation, from a mathematical point of view, is the most interesting method. This method takes into account a set of factors that affect the density of communication nodes in the network in the future. Therefore, this is the most accurate method. It can be applied in practice using

high-performance computing tools for calculations both for small local area networks and for global networks with good design results. The causal relationship method is one of the best in creating a coherent mathematical method for quantifying forecasting. For short - term forecasting, the linear method is acceptable; for long-term forecasting, the nonlinear method is acceptable [28].

Expert forecasting methods are based on the processing of opinions and judgments of specialists-experts in a particular field of knowledge, which are obtained in the process of various specialized procedures for collecting them. Most of the currently known expert forecasting methods have been developed due to the need to choose optimal solutions for specific projects. At the same time, the methods need to be adapted to specific tasks of predictive and programmatic work. According to the method of using information received from expert specialists, there are such groups of expert forecasting methods: methods of direct estimates and methods with feedback. The difference between them is that in the first case, the obtained expert information is processed and issued directly as a result. In the second type of methods, the result is obtained in the process of several approximations, and at each step, the experts are influenced by the results of processing the previous one, that is, feedback with the experts is carried out. Taking into account the continuous growth and complexity of NN tasks being solved by automated communication management systems, increasing computing performance and increasing requirements to the quality of service, there is an interest in predicting the behavior of a telecommunications network. But, due to the different nature of the PRresponse to the requirements of telecommunications network services, even the best methods discussed above can not fully provide reliable forecasts for the necessary parameters. Since there are currently quite a large number of forecasting methods, and each method usually contains a certain number of design parameters, it is necessary to compare models from different classes, assuming that each of them is optimal in its own class. To solve this problem, you must first find some of the best models for each class in terms of the selected criteria. In turn, this task leads to the need to create a software package that searches for optimal predictive models in a certain set. To determine the type of forecasting in an automated control system, you can use a graph tree for selecting a forecasting method, where all possible classes of models of predicted parameters (States) and their corresponding forecasting methods are specified. This article examines the research for predicting network performance [29].

Based on the fact that the prediction problem is a special case of a regression task, where there is a dependency of the dependent variable from the independent, under specified conditions, the solution may be the use of types of neural networks (NS): multilayer perceptron, radial basis network, generalized regression network, the network Voltaire and of the network of Elman [8]. The analysis of the use of NM in solving forecasting problems indicates the expediency of using time series calculation, which will be based on the Elman neural network, which is one of the types of recurrent network [30]. The Elman network consists of a multilayer perceptron with feedback. This function allows you to take

into account previous actions and accumulate information to support management decision - making based on time series forecasting. That is, the prediction of time series is reduced to interpolation (determination intermediate value) of a function of several x variables and the solution of the problem approximation (i.e., leading to a simplified mean) multidimensional functions as an integral effect on the prediction quality. The Elman network consists of three layers – the input (distribution) layer, the hidden and output (finishing) layers. In this case, the hidden layer has feedback on itself. For figure 1 the scheme of the Elman neural network is presented [9, 10].

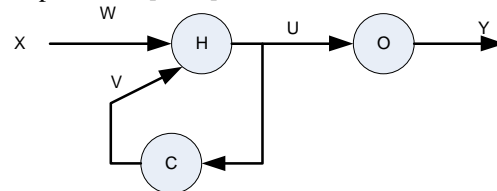


Figure 1: Diagram of the Elman neural network

Figure 1 shows us the diagram of the Elman neural network. Unlike the usual direct propagation network, the input image of a recurrent network is not a single vector, but a sequence of vectors $x(1), x(2), \dots, x(n)$ input images that are fed to the input in the specified order, while the new state of the hidden layer depends on its previous States. The Elman network can be described by the following relations in matrix form:

$$Y_t = F(U \times F(W \times X_t + V \times C_t)) \quad (1) \quad C_t = F(W \times X_{t-1} + V \times C_{t-1}) \quad (1)$$

where: X_t – input signal;

Y_t – output of the neural network;

C_t – the state of the context at iteration t to enter X ;

W - weight matrix of the input layer;

V – weight matrix of feedback from the hidden layer;

U - weight matrix connecting the output of the hidden layer and the input of the output layer;

X_{t-1} – signal on the previous iteration;

C_{t-1} - context state in the previous iteration;

F is the vector activation function;

H is the hidden layer of neurons, where each input X is connected to each neuron of the hidden layer;

O – output layer of neurons.

The same gradient methods are used for training Jerzy Elman's models [10] as for conventional direct distribution networks. It is calculated using a modified reverse propagation method, which is called the reverse propagation method with network deployment in time [11]. As in the reverse propagation method for direct propagation networks, the process of calculating the gradient (weight changes) occurs in three stages:

Direct pass – calculating the state of layers;

Reverse pass – calculating the error of layers;

Calculation of weight changes based on data obtained at the first and second stages [31].

Monitoring and forecasting the state of a telecommunications network involves studying a whole group of issues related to the network infrastructure (routers, switches), traffic structure, network load, configuration, security, quality of service, and so on. All of these components directly or

indirectly affect network performance, which is determined by the network management strategy. The network can be considered as a set of its e-calls: information directions $\{a-b, \dots, j\}$, routes $\{M\}$, nodes $\{V\}$, channels $\{K\}$, and service quality characteristics $\{Q\}$. Therefore, as the input of NM, we will have a set of network direction parameters in the form of an input signal $X(t) = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$, where x_1 is the traffic type

(speech, video, data transmission), which is passed; x_2 – the amount of service traffic between nodes; x_3 – capacity of the information section; x_4 – packet delay in the information field; x_5 is the value of JIT information on the era direction; x_6 – the quality of routes between the nodes; x_7 – the number of packet error rate (IPER); x_8 – the number of packets what was lost (IPLR). The input signal is monitoring information from the elements of the telecommunications network on the NMA fuzzy model is usually used for its processing [12, 13, 14]. Then network management can be represented as $U = \{U^{a-b}\}$, where $\{a-b\}$ is the information direction $a-b$, which consists of the end nodes a and b (sender and destination), as well as a set of nodes that form the transmission channels between a and b .

The proposed model for monitoring the management of a telecommunications network defines a list of parameters of the state of the information direction, which should be used for forecasting. Output of the neural network $Y(t)$ it is an output neuron (adder) that calculates the corresponding values of deviations of the normal state neuron detected by neurons – the value of network performance S_m , which will depend on the set of components. This deviation will characterize the speed of network performance changes over time, so that the network administrator can respond to critical situations. This output signal will also be processed by fuzzy set methods [12, 13, 14], and its value will take a clear form.

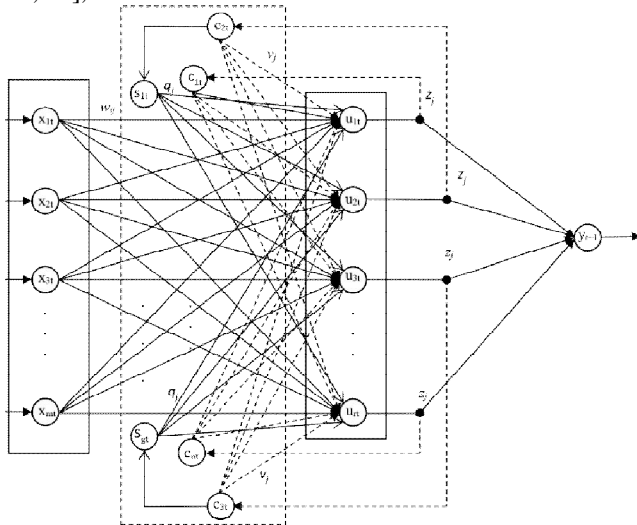


Figure 2: Elman Network for predicting route congestion

Figure 2 shows us Elman neural network. When predicting the performance of data transmission routes in the network, the problem of so-called "dead neurons" may arise. One of the limitations of any competing layer is that some neurons may not be involved. That is, neurons that have initial weight vectors are significantly further away from the

input vectors and never win the competition, regardless of the duration of training. As a result, such vectors are not used in training and the corresponding neurons never win (dead). Therefore, in order to provide an opportunity to defeat other neurons, the training algorithm provides for the possibility of losing the "winning neuron" of its activity. For this purpose, the activity of neurons is recorded on the basis of calculating the potential of each neuron in the process of predicting the performance of data transmission routes and training of the neuron.

3. CONCLUSION

The article presents a monitoring model and a method for predicting the performance of data transmission routes in a telecommunications network, which is based on a modified Elman recurrent neural network using two neurons in the feedback layer. In contrast to the existing methods of forecasting, the developed method took into account the features of the network based on the calculation of the potential of network neurons. This method allows you to increase the accuracy and speed of forecasting the performance of routes in the network by increasing the network bandwidth and reducing the computational complexity of the neural network. The work of the Elman network algorithm with stochastic time efficiency is considered, which minimizes the value of the network state function until it reaches the specified minimum value by repeated training. That is, the Elman neural network will change weights to minimize the error between anticipating the network and the prediction goal. The problem of so-called "dead neurons" is considered, where the activity of neurons is recorded on the basis of calculating the potential of each neuron in the process of predicting the performance of data transmission routes and training of the neuron. It is shown that it is advisable to use the least squares method to determine the effectiveness of time series forecasting methods. The forecast quality was evaluated using the proposed method of forecasting. Further research will focus on the development of decision support methods for predicting the state of a telecommunications network with the choice of a forecasting method, which specifies all possible classes of models of predicted parameters (States) and their corresponding forecasting methods.

By adapting the developed method of predicting the performance of data transmission routes in a telecommunications network, it can be applied to predict the state of a computer network, predict economic processes and in other areas of application, where it is possible to separate the factors that affect the system.

REFERENCES

1. Akhmadulina A.T., Skryniknikova O.V. // **Innovative economy: prospects for development and improvement.** - 2016.- No. 2 (12) .- P. 10-15. (In Russian)
2. Baranova I.V. **Types and criteria for evaluating the effectiveness of unitary enterprises** // Siberian

- Financial School.- 2011.- No. 4 (87) .- P. 43-50. (In Russian)
3. Bogataya I.N. **Improving internal risk control and management in commercial organizations.** In the collection: Development of finance, accounting and auditing in modern management concepts. Materials of the I international scientific and practical conference. 2018.- P. 286-290. (In Russian)
 4. Vorobyov Yu.N. **Technological transformation of the economy and its impact on the financial and economic security of business entities.** In the collection: Financial and economic security of the Russian Federation and its regions. Proceedings of the II International Scientific and Practical Conference. 2017.- P. 11-14. (In Russian)
 5. Vygolko TA **Analysis of economic power in the works of JK Galbraith** // Bulletin of the Institute of Economic Research. 2016. №4 (4). URL: <https://cyberleninka.ru/article/n/analiz-ekonomicheskoy-vlasti-v-rabotah-dzh-k-gelbrejta> (In Russian)
 6. **The public sector in the Russian economy** // Bulletin on the development of competition, March 2019 [Electronic resource] - Access mode: <http://ac.gov.ru/files/publication/a/21642.pdf> (In Russian)
 7. Gubareva, A.O., Gurkina, D.A. **Plyusy gosudarstvennoj sobstvennosti.** URL: <https://moneyprofy.ru/pljusy-gosudarstvennoj-sobstvennosti/> (In Russian)
 8. Gubina O.V., Ivanova N.A., Gerasimova S.V. **Assessment of the quality of the financial results of the organization.** In the collection: Problems of managing sustainable development of business structures in various fields of activity Collection of scientific papers of the International Economic Forum. Edited by N.A. Lytneva. 2017.- P. 67-74. (In Russian)
 9. Dementyev V.V., **The Problem of Power and Political Economy** / V.V. Dementev // European vector of economic development. - 2012 - N0.2 (13). - pp. 183-189. (In Russian)
 10. Zavarin D.A. **Types of ownership in modern Russia** // Science among us 2 (2) 2017 nauka-sn.ru - p. 67 – 71 (In Russian)
 11. Zavarin DA **Innovative geodetic GNSS technologies for determining spatial characteristics** / DA Zavarin, OK. Kraeva, N.D. Porscheva // Vuzovskaya Nauka - Region: Proceedings of the XV All-Russian Scientific Conference. - Vologda: VOU, 2016. p. 296–298. (In Russian)
 12. Lytneva N.A. **Development of the system of state and municipal administration in the context of public sector reform** / A. Polyenin, E. Bobrova, T. Golovina, M. Goncharova, I. Dokukina, S. Dolgova, E. Kyshtymova .A., Makarova Yu.L., Lytneva N.A., Popova O.V., Rudakova O.V., Tychinskaya I.A., Shipunov A.S. Collective Scientific Monograph / Edited by A.V. Glade. Oryol, 2017. -228 p. (In Russian)
 13. Lytneva N.A., Daniy I.S. **Methodology for analyzing the directions of optimizing municipal budget expenditures** // Basic Research.- 2017.- No. 7.- P. 162-166. (In Russian)
 14. Tesalovsky A., **Accuracy of the description of cadastral accounting objects in three-dimensional space** / A. A. Tesalovsky, Yu. S. Gorshkova, MV Konovalova, LA Sizova // Vuzovskaya Nauka - Region: Proceedings of the XIV All-Russian Scientific conferences. - Vologda: VOU, 2016. p. 183–185. (In Russian)
 15. Cheglakova S.G. **Analytical tools of resource management in ensuring the economic security of an economic entity** // Economics and Entrepreneurship .- 2018.- No. 1 (90) .- P. 617-621. (In Russian)
 16. Ellman M. (1989). **Socialist Planning.** Cambridge University Press. p. 327.
 17. Engels F. (1970). **Socialism: Utopian and Scientific.** Marx/Engels Selected Works, Volume 3, p. 95-151; Publisher: Progress Publishers.
 18. Gregory Paul R., Stuart Robert C. (2003). **Comparing Economic Systems in the Twenty-First Century.** Boston: Houghton Mifflin. p. 27.
 19. Tupper A. (2006). **«Public Ownership»** URL: <https://www.thecanadianencyclopedia.ca/en/article/public-ownership>.
 20. Aharonovich, A. R., Sergeevich, S. M., Nisonovich, S. M., & Vyacheslavovna, D. S. (2019). **Entrepreneurship of regional innovation systems of Russia and Belarus as a factor of socio-economic transformation in the national economy.** Academy of Entrepreneurship Journal, 25(Special Issue 1).
 21. Aharonovich, A. R., Sergeevich, S. M., & Vyacheslavovna, D. S. (2019). **Institutional framework for entrepreneurship of regional innovation systems of the union state.** Academy of Entrepreneurship Journal, 25(Special Issue 1).
 22. Krugilin, S. (2018). **Silvicultural growth models of the formation of Quercus Robur in the black earth zone conditions of the steppe of the South of Russia.** World Ecology Journal, 8(3), 23-45. <https://doi.org/https://doi.org/10.25726/NM.2019.49.29.002>
 23. Taran, S., & Kolganova, I. (2018). **Optimization of park plantings in the regions of Rostov-on-Don and Novocherkassk by introducing into gardening species of the genus ACER L.** World Ecology Journal, 8(3), 56-70. <https://doi.org/https://doi.org/10.25726/NM.2019.31.46.004>
 24. Abramov, R. A., & Sokolov, M. S. (2016). **Theoretical and methodological aspects of the formation of anti-corruption mechanisms in the system of higher education of the Russian Federation.** International Journal of Environmental and Science Education, 11(15), 7431–7440.
 25. Abramov, R. A., Sokolov, M. S., & Derevianko, S. V. (2019). **Research of properties of modern construction materials based on industrial waste, waste wood and metallurgical industries.** Key Engineering Materials, 802, 113–124. <https://doi.org/10.4028/www.scientific.net/KEM.802.113>
 26. Shashkova, A. (2019). **Regulating principles of disclosure of information to shareholders under G20 / OECD principles.** In Proceedings of the 33rd

- International Business Information Management Association Conference, IBIMA 2019: Education Excellence and Innovation Management through Vision 2020 (pp. 1931–1936).
27. Gennadievich, B. A. (2020). **Machine learning and data mining activity results when using projectiles in different sports**. International Journal of Advanced Trends in Computer Science and Engineering, 9(3), 3157–3160.
<https://doi.org/10.30534/ijatcse/2020/103932020>
 28. Natalia K. Kondrasheva, Anzhelika M. Eremeeva, Konstantin S. Nelkenbaum, Oleg A. Baulin & Oleg A. Dubovikov (2019) **Development of environmentally friendly diesel fuel, Petroleum Science and Technology**, 37:12, 1478-1484,
DOI: 10.1080/10916466.2019.1594285
 29. Klyuev S.V., Bratanovskiy S.N., Trukhanov S.V., Manukyan H.A. **Strengthening of concrete structures with composite based on carbon fiber** // Journal of Computational and Theoretical Nanoscience. 2019. V.16. №7. P. 2810 – 2814.
 30. Srivastava, V. K. L., Chandra Sekhar Reddy, N., & Shrivastava, A. (2019). **An effective code metrics for evaluation of protected parameters in database applications**. International Journal of Advanced Trends in Computer Science and Engineering, 89(13), 81–86.
<https://doi.org/10.30534/ijatcse/2019/1681.32019>
 31. Ssentumbwe, A. M., Man, B., & Lee, K. H. (2019). **English to luganda SMT: Ganda noun class prefix segmentation for enriched machine translation**. International Journal of Advanced Trends in Computer Science and Engineering, 8(5), 1861–1868.
<https://doi.org/10.30534/ijatcse/2019/08852019>