



TECHNICAL UNIVERSITY OF GABROVO
Faculty of Electrical Engineering and Technologies

Mag. Eng. Teodora Valentinova Zhorova

**TRAFFIC MONITORING IN COMMUNICATION SYSTEMS
WITH ARTIFICIAL INTELLIGENCE**

AUTHOR'S SUMMARY

of a dissertation

for acquiring the educational and scientific degree "Ph. Doctor"

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Doctoral program: Communication Networks and Systems

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Scientific supervisor: Assoc. Prof. Ivelina Stefanova Balabanova, PhD

Reviewers: Prof. Stanimir Mihaylov Sadinov, PhD

Prof. Valentina Ilieva Markova, PhD

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The dissertation work was discussed and directed for official defense at a session of the Extended Department Council of the Department of Communication Engineering and Technologies at the Faculty of Electrical Engineering and Electronics of the Technical University – Gabrovo, held on 19.03.2026.

The dissertation work contains 193 pages. The scientific content is presented in an introduction, four chapters and a conclusion, and includes 151 figures and 41 tables. 161 literary sources are cited. The numbering of the figures, tables and equations in the Author's abstract is consistent with that in the dissertation work.

The development of the dissertation work was carried out in the Department of Communication Engineering and Technologies at the Faculty of Electrical Engineering and Electronics of the Technical University – Gabrovo.

The official defense of the dissertation will take place on June 12, 2026 at 11:00 am in Room 2215, University campus no. 2 "Bazhdar" of the Technical University - Gabrovo.

Acknowledgements: I'd like to express my sincere condolences to Assoc. Prof. Ivelina Stefanova Balabanova, PhD for support and cooperation about dissertation work development.

Author: Mag. Eng. Teodora Valentinova Thorova

Title: TRAFFIC MONITORING IN COMMUNICATION SYSTEMS WITH ARTIFICIAL INTELLIGENCE

Circulation: 5 pcs.

Publisher: University Publishing House "Vasil Aprilov" at Technical University of Gabrovo

GENERAL CHARACTERISTICS OF THE DISSERTATION

Relevance of the problem

In recent years, the revolutionary development of Artificial Intelligence and Machine Learning has created a fundamental analytical framework, providing for the growing need to support and alleviate the labor intensity in all activities and processes of technological development of the human factor in various fields. The need and requirements for platforms with Artificial Intelligence are growing to effectively optimize the parameters of transmission media to reduce interference and increase the coverage range. Other requirements are associated with improving the functionality of Deep Packet Inspection functionality (DPI) systems in the following areas:

- Processing of Big Data clusters;
- Identification of the interruptions in traffic flows;
- Detection of a wide range of cyber threats such as DDoS attacks, etc.;
- Analyzing packet transmission characteristics and identifying information with compromised data integrity, etc.

A significant technical aspect concerns improving the mechanisms and stages of design, operation and optimization of network infrastructures with a high degree of scalability. There is a need to support the activities of Quality Assurance procedures (QA) specialists in terms of identifying defects, establishing recurring patterns in manipulations with information content, generating predictive models of behavior, etc.

The above facts confirm the relevance of searching for innovative opportunities for functional upgrading of QoS and QoE services through the integration of AI-based tools, applications and models in the "Planning" stage when designing communication routes and ICT communications infrastructures.

Purpose and objectives of the dissertation work

The aim of the dissertation is "Development of methodology and hybrid analytical modules for Quality of Service (QoS) and Quality of Experience (QoE) intelligent analysis and assessment, based on artificial intelligence, machine learning and deep learning approaches, designed for adaptive monitoring, diagnostics and prediction of noises and traffic characteristics of the transmission communication environment, while simultaneously ensuring cybersecurity and information security of network and communication resources". The scope of the implementation of the set goal includes the following main tasks:

1. To conduct a selection of technical approaches for extracting unified informative features when processing interference and transmitted network traffic in a communication environment in the course of training and verification of recognition and predictive analysis models.
2. To synthesize algorithms for simulation modeling of telecommunication systems with waiting and Descriptive analysis of the parameters forming the specification of the transmission medium.
3. To derive analytical models and investigate the interrelationship between factors in object-oriented predictive analysis of performance indices defining the qualities of transmission media when transmitting packets.
4. To adapt and select methods and algorithms for optimization in procedures for searching for an optimum in function minimization, identified with parameters for increasing the speed and volume of traffic served in the communication environment.
5. To develop approaches for recognizing and classifying random noises that occur in communication channels, which have negative effects on the quality of transmitted information, through Artificial Intelligence and Machine Learning tools.
6. To select and verify Artificial Intelligence models for predicting amplitude noise variance arising in the structure of transmission media when transmitting analog and digital signals in electronics and communications.

7. To synthesize approaches incorporating Artificial Intelligence tools for regression modeling in approximating selected performance indices of the transmission medium in communication infrastructures with waiting.
8. To develop approaches for monitoring traffic transmitted between network segments in terms of detecting the state of malicious attacks and data breaches based on Artificial Intelligence, Machine Learning and Deep Learning approaches.
9. To develop approaches for identifying the allocation of network resources for broadband access in urbanized city environments to corporate clients using Artificial Intelligence, Machine Learning and Deep Learning analytical tools.
10. To conduct a comparative analysis and prepare a comprehensive assessment of the effectiveness of techniques and algorithms created on the basis of Artificial Intelligence, Machine Learning and Deep Learning devices for diagnosing network traffic and access to Internet service.

Research methods

The research methodology includes the development of analytical components for cluster analysis, classification and recognition, function minimization through optimization methods and algorithms, regression diagnostics and modeling based on Artificial Intelligence, Machine Learning and Deep Learning technologies.

Scientific novelty

The scientific novelty in applied research is associated with the adaptation of classical Artificial Neural Networks, traditional Machine Learning methods, Deep Learning principles, conventional and non-conventional optimization techniques to create of hybrid analytical tools for monitoring and diagnosing transmission media in communication nodes and information systems.

Applicability

The focus of the proposed hybrid analytical modules with AI, ML and DL devices is to support the activities of network administrators in various phases of planning and resource management, as well as improving the quality of service in communication infrastructures. The complex purpose within the scope of potential users should be separated into the following categories:

- information service centers, mobile operators, providers of broadband access to Internet service in monitoring the transmission environment, related to diagnostics of disturbances, forecasting and optimization of metrics to increase the capacity and speed of traffic load;
- industrial production and corporate network segments in improving the resilience, efficiency and flexibility of implemented information security systems against cyber threats and malicious intrusions into managed digital resources.

Approval of the dissertation work

The main aspects of the research, familiarizing the scientific community with the results achieved in the dissertation work, are reflected in seven scientific papers at national and international forums. The publications presented at foreign international conferences with referencing and indexing of the scientific content in the Scopus database are two in the scope of "Environment. Technology. Resources" - Latvia, and "Electronics, Engineering Physics and Earth Science" - Greece. Part of the scientific papers discussed at seminars Department of Communications Equipment and Technologies, are presented in organized symposia at TU - Gabrovo - "International Scientific Conference" UNITECH "" and "Student Scientific Session", respectively three publications. Awarded by two presented papers at the "Scientific Conference of the University of Ruse "Angel Kanchev" and the Union of Scientists - Ruse" in the section "Communication and Computer Engineering" is "Internet Traffic Analysis by FFNN, k-Nearest Neighbors and Decision Tree Approach".

The presented results were realized in connection with the implementation of three internal university projects in specialized research laboratories at the Department of Communications Equipment and Technologies at Technical University of Gabrovo.

Structure and volume of the dissertation work

The dissertation is structured in an introduction and four chapters, a list of abbreviations and acronyms, scientific-applied and applied contributions, publications, participation in the projects, conclusion and bibliography.

Chapter 1 summarizes scientific papers and studies on the analysis of the state of the problem posed in the dissertation. Existing approaches and system solutions in noise detection, traffic flow diagnostics, optimization and cybersecurity techniques are studied. The specified objects are analyzed in the context of solving classification tasks and tasks and predictive analysis using Artificial Intelligence, Machine Learning and Deep Learning technologies.

Chapter 2 introduces approaches for detecting “noises in communication channels” and “superposed noises on transmitted analog and digital signals”. Based on an analysis of the functionality of AI and ML tools, models for identifying and predicting the amplitude noise variance of some of the most common random noises occurring during signal transmission in communication media are synthesized.

In Chapter 3, approaches for regression modeling based on Classical Regression analysis and Artificial Neural Networks regarding traffic performance indices "System Throughput" and "System Response Time" are proposed. An optimization problem has been solved by integrating a set of Non-linear optimization techniques and Genetic algorithm regarding the metric "System Response Time".

In Chapter 4, methodology for cyber threats detection about transmitted UDP traffic between corporate clients based on AI and DL tools is developed. Methodological verification is applied in scenarios with different sets of traffic metrics and traffic types, respectively “DoS attack effects”, “Normal traffic” and “Data breaches”. An approach for diagnosing WEB traffic to corporate clients in active time zones is proposed.

CONTENTS OF THE DISSERTATION

Chapter I: Investigation of aspects and techniques for intelligent analysis, applied in transmission media assessment

1.1. Data Mining tools for intelligent data analysis in data sets processing.

The concept of technological development of the modern world in the direction of arithmetic progression is strongly based on "Artificial Intelligence (AI)". AI is increasingly entering all technical areas of human daily life, business, economics, information technology and major areas of industry.



Fig. 1.10. Classification of Machine Learning techniques

Machine Learning (ML) is defined as an AI subfield that combines information clusters and specialized algorithms for training in prediction or multivariate decision sets, presented in Fig. 1.10. In ML, there is no need for specific “Explicit Programming” procedures. Analytical “Deep Learning (DL)” tools or Deep Neural Networks (DNN) are considered as part of ML methods, where the term “Deep” is associated with “the depth of the layers of neural networks or the set of computational units in the structural multilayer hidden layers”.

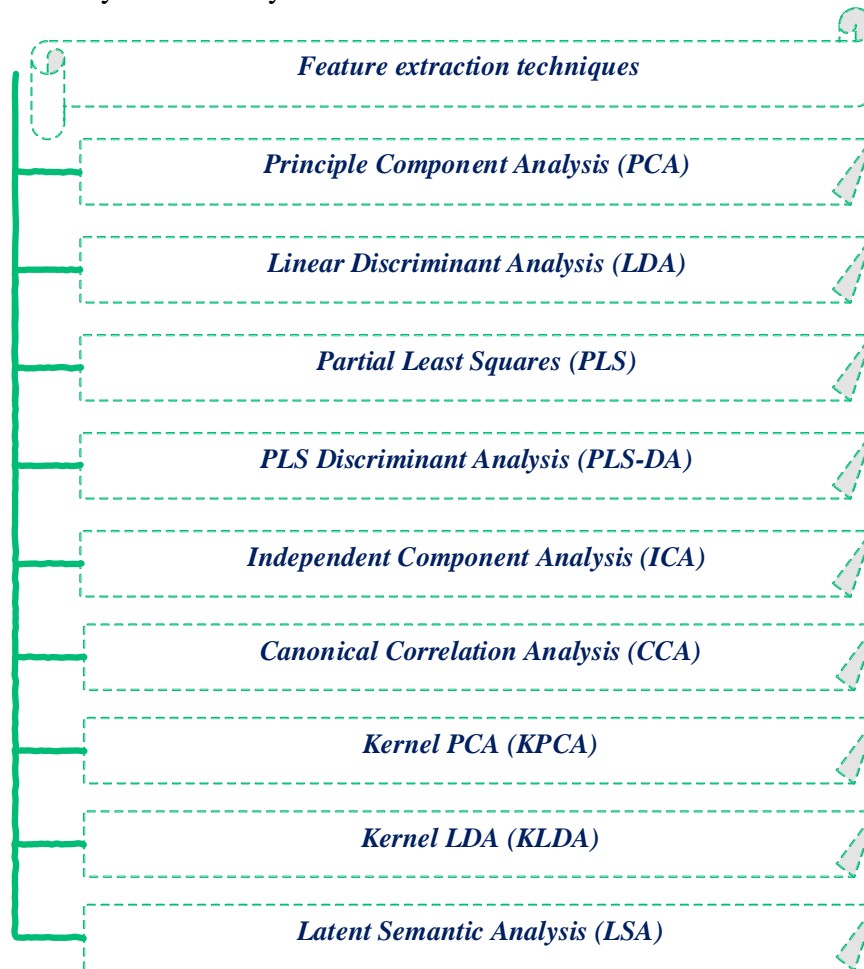


Fig. 1.13. Feature extraction techniques in AL and ML objects processing

The selection and implementation of appropriate approaches for extracting informative features (Fig. 1.13) when processing target objects as one of the vital phases in AI and ML tasks for classification, clustering, and predictive analysis are essential for achieving a good technical framework with high efficiency.

1.2. Assessment of the impact of disruptive influences in the structural transmission media and communication channels.

Noise as disturbing phenomena in communication, electronic and electrical systems can be divided and categorized in different ways, criteria or signs. The main part of scientific research distinguishes two groups “Internal Noises” and “External Noises”. The first includes: “Thermal Noise” and “Imperfections”, while the second includes: “Natural Origins”; “Electromagnetic Interference”; “Radio Frequency Interference” and “Crosstalk”. According to some studies, random effects in communication channels can be defined in specific categories, respectively “White Noise”; “Pink Noise” and “Blue Noise”. As for the different forms of representation and study of signals, they refer to the theoretical ones: “Time”; “Spatial”; “Frequency”; “Autocorrelation” and “Wavelet”. The presence of noise in electronic and communication systems of different types, purposes and scope is associated with a number of effects, shown on Fig. 1.15. One of the ways to limit these impacts is to apply analytical tools for predictive analysis of noise levels, shown in Fig. 1.17.

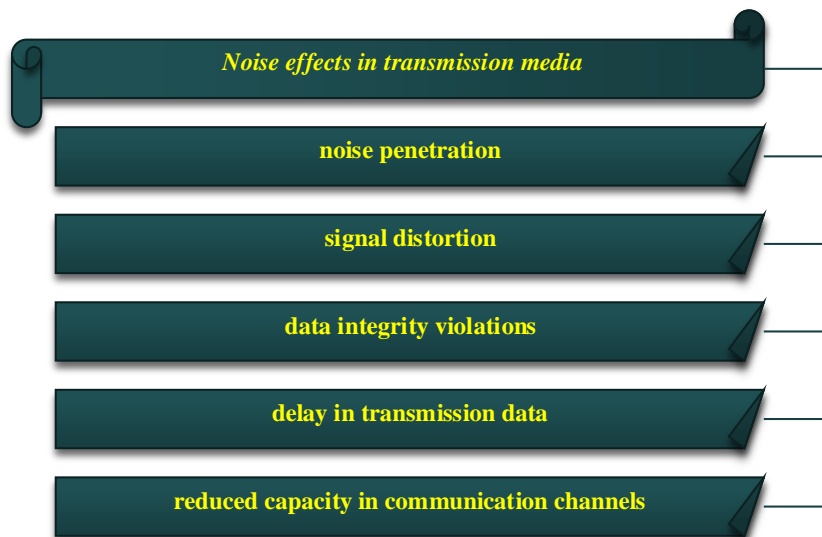


Fig. 1.15. Noise effects in transmission media

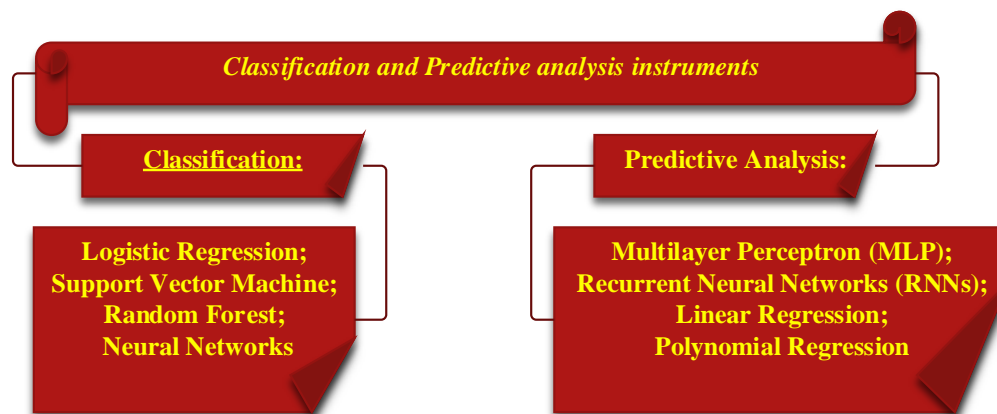


Fig. 1.17. Analytical tools for classification and predictive analysis

Widely used analytical tools are Artificial Neural Networks. In research, there is a particular emphasis on "Deep Learning Principles" or DNNs. Popular in this regard are Long Short-Term Memory or LSTM DNNs. Often the use of the aforementioned neural structures is associated with hybrid approaches with Convolutional Neural Networks (CNN).

1.3. Tools for intelligent analysis of the state and parameterization of transmission media in communication systems.

Complex monitoring of network traffic is one of the main activities regulated in the policies for access to information clusters through the WEB space of private and corporate clients. By definition, it is defined as a multifaceted process for effective management of traffic flow, carried out by:

- "Internet service providers";
- "Network administrators in institutions";
- "Client companies";
- "Various regulatory authorities in the field of information services".

The following aspects can be defined as the main complex directions in the analysis and evaluation of Internet traffic, as follows:

- "Productivity increase";
- "Effective access technology, protection methods";
- "Ensuring the servicing of large traffic flows and the buffer accumulation of information arrays".



Fig. 1.19. Intelligent instruments categories for network traffic state analysis

The vast majority of existing studies concern the detection and identification of the type of anomalies and violations in the integrity of the transmitted information, using different categories of tools for this purpose (Fig. 1.19). Recurrent Neural Networks (RNN) and one of their main varieties LSTM networks are applied in the estimation of traffic characteristics in sub-network encoders. Convolutional neural networks CNN are also a frequently used neural apparatus in the role of methods for preventing cyberattacks.



Fig. 1.20. QoS aspects in private and corporate clients

The processes related to traffic diagnostics and detection of anomalies from the effects of malicious software with the help of networks based on Gradient Descent and Momentum algorithms can also be mentioned. The problem of identifying violations in network traffic is the subject of comprehensive systems in government, administrative and industrial centers in relation to the public services offered by them, systematized in Fig. 1.20. Another aspect is associated with improving scalability in integrated system solutions with machine learning in online diagnostics of network traffic.

1.4. The role of Artificial Intelligence in information security and cybersecurity.

The concept of “Cybersecurity” distinguishes the following main areas: “Network security”, “Application security”, “Information security”, “Operational security” and “Resource recovery after emergency and disaster situations”. The integration of Artificial Intelligence tools in the field of Cybersecurity includes the procedures of “Detection”, “Prediction”, “Analysis” and “Threat mitigation”. The construction of AI-based public security management platforms is becoming a basic prerequisite for prevention against the types of attacks used in malicious intrusions into network and communication infrastructures, as shown in Fig. 1.28 and Fig. 1.30.

Within the scope of the corporate business organization, AI can be successfully used in a number of areas. Organizations regulating standardization frameworks provide corporate business organizations with criteria for building sustainable and robust security systems based on the following AI profiles:

- Govern – providing a set of legal and technical aspects;
- Identity – maintaining an up-to-date inventory of information content;
- Protect – tracking and personalization of user activities;
- Detect – identifying workloads, critical applications, resource constraints;

- Respond – taking adequate technical measures;
- Recover – restoration of information and communication resources in the event of incidents of varying complexity and type.

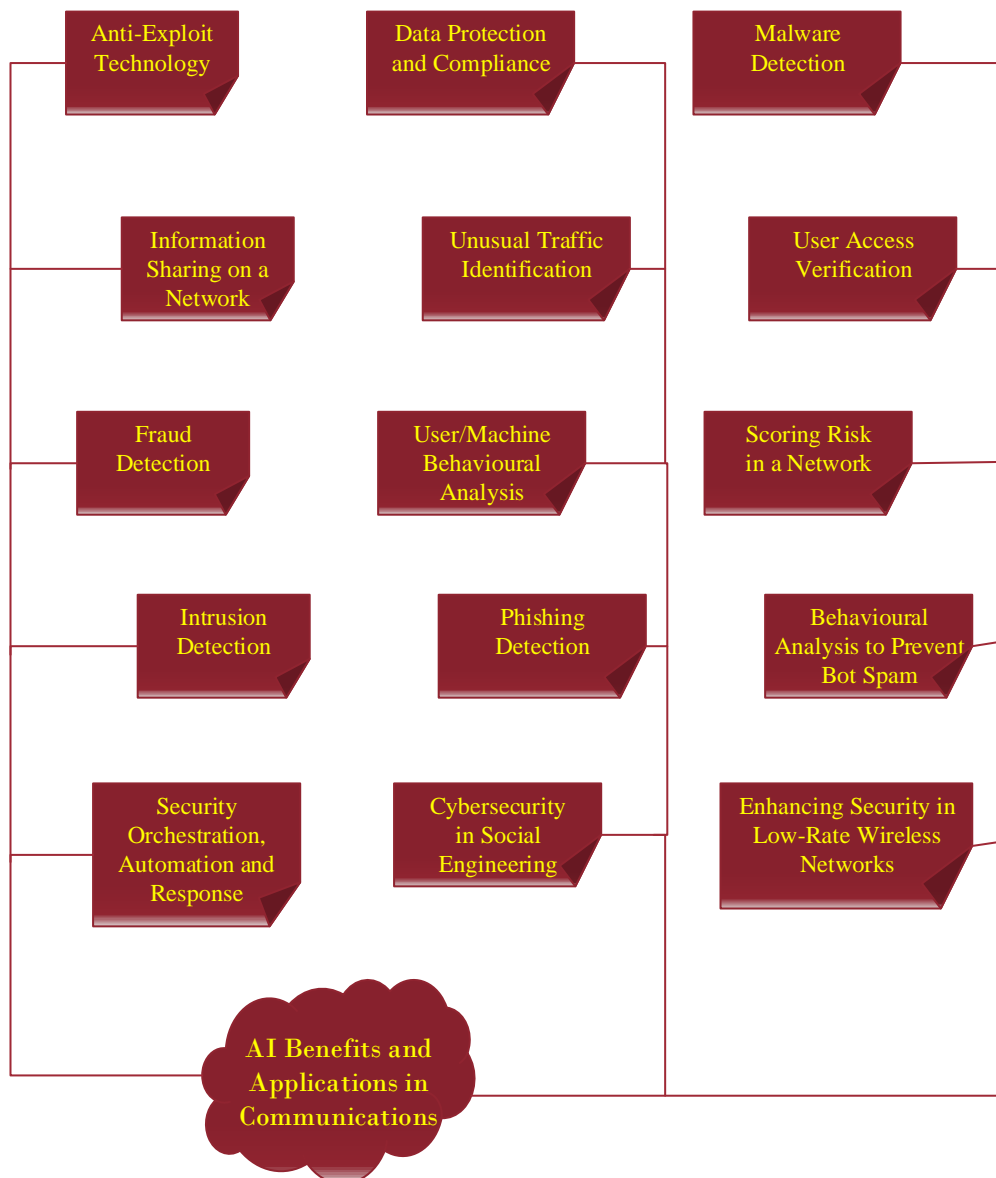


Fig. 1.28. Advantages and applications in the use of AI in Cybersecurity

There are a number of risks associated with AI-driven information resources and data warehouses in the process of creating models for preventing cyberattacks in industrial ICT infrastructures. In terms of the actions of attackers, there are two main types of attacks, which can be categorized as follows:

- Input Attacks: Along with the input training data, the attacker aims to integrate a model that changes the correct functionality and crashes the AI system:
 - ✓ Indistinguishable Perturbation: Attackers commit undetectable perturbations;
 - ✓ Content-Preserving Perturbation: Attackers make changes to the information distribution without changing the content;
 - ✓ Non-Suspicious Input: Attackers can change the point of entry without raising suspicion of malicious access;
 - ✓ Content-Constrained Input: Attackers can change the penetration position as long as this procedure involves introducing a malicious load on the system's resources;

- ✓ Unconstrained Input: Attackers can perform intrusions from arbitrary locations in the system.
- Poisoning attacks: Here the attacker seeks to disrupt AI models that are already in the training phase.

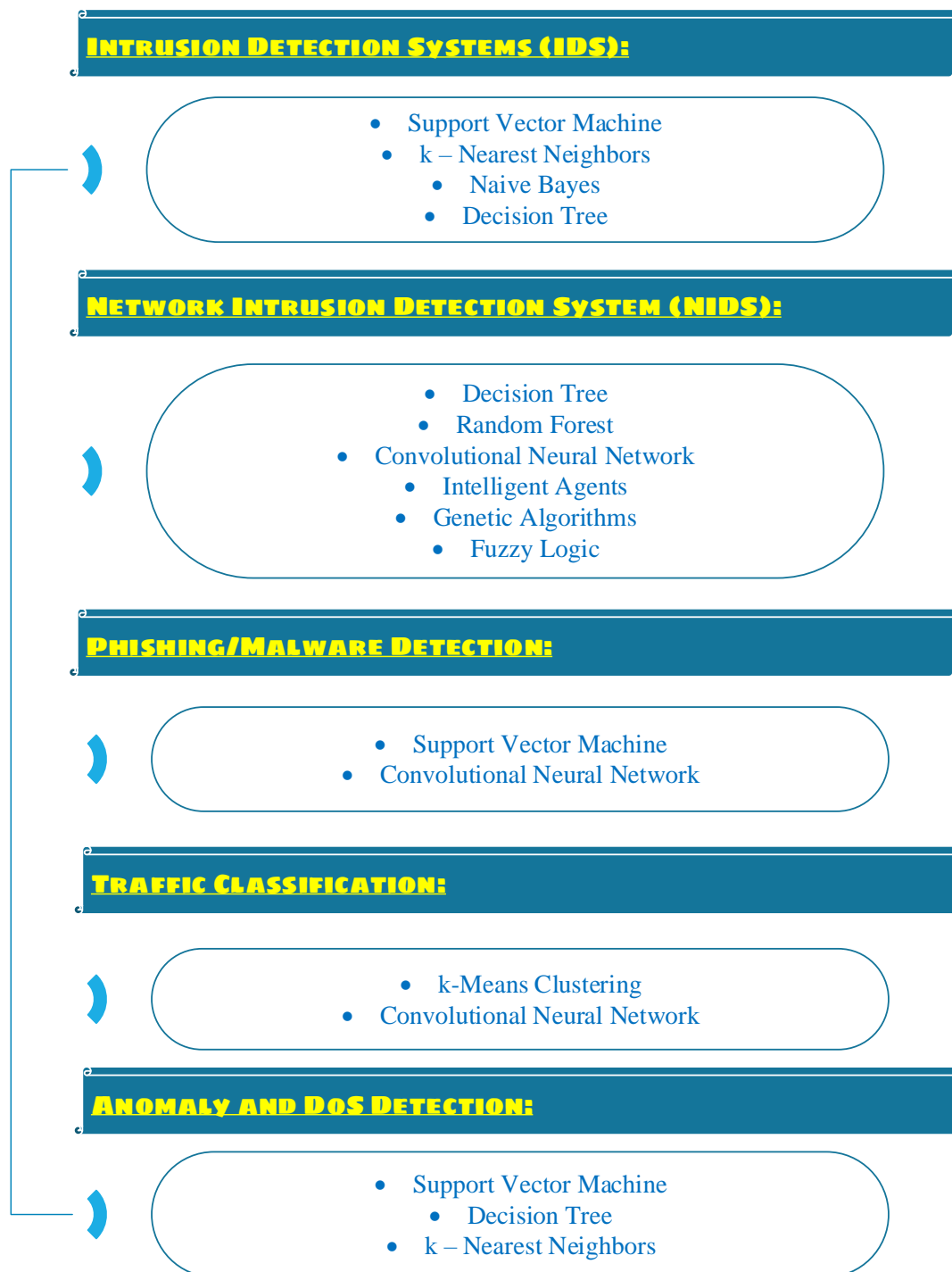


Fig. 1.30. AI techniques in Cybersecurity systems

1.5. Conclusions to Chapter I.

- Based on analysis, the need to integrate Artificial Intelligence and Machine Learning techniques in supporting the processes for simulation modeling of teletraffic systems during data transmission has been confirmed;
- A classification has been made based on an evaluation of the models, methods, algorithms and phases of the different types of tools forming the Machine Learning concept;

- Approaches for extracting informative features when processing registered quantitative parameters of objects, processes and systems with a focus on diagnostics through AI and ML have been systematized;
- An assessment of the technical means for classification and predictive analysis of noises in transmission media in communication systems has been carried out;
- Based on the analysis, a categorization of intelligent tools for analyzing the state of network traffic in information and communication infrastructures has been made;
- Based on the analysis, the need for conventional and non-conventional optimization methods and algorithms to improve the behavior, resilience and performance of communication systems has been identified;
- The need to implement Artificial Intelligence tools for network security diagnostics and identification of cyber threats targeting the resources of corporate information and communication systems has been confirmed.

Chapter II: Analysis of noise effects in network packet transmission

2.1. Research and synthesis of SVM and k-NN classifiers for identification of Gaussian White Noise and Periodic Random Noise.

C-SVM is based on a “Capacity” metric, whose smaller values allow control of the acceptable boundary between the discrete decision boundary and the area with incorrectly classified standards. In the course of research, the influence of high levels of C-parameter has been demonstrated. Compared to the reported Capacity = 10,000 in this case for the specified functions Linear, Polynomial and Sigmoid, significantly lower final accuracies were observed, respectively 59.500 %, 68.900 % and 50.00 0 %. However, with the Kernel function “Radial Basis Function (RBF)” satisfactory accuracies were achieved for the training set 86.863 % and 87.795 %, selected with the highest degree of suitability.

Nu-SVM is a classification type based on an adjustable Nu-parameter with a variation in the interval from 0 to 1. The specified index is associated with the lower bound of the number of standards representing the support vectors, and the upper bound of the part of the number of standards located on the incorrect side of the Hypersurface. For the specific SVM type of classification models Minimum overall accuracy was found to be 68.900 % (Nu = 0.400) when using Linear function, followed by the better reported level 86.850% (Nu = 0.500) at Sigmoid Kernel type. The advantages of Nu -SVM become pronounced with Polynomial function and with a clear advantage of RBF type, where strongly positive indications of Overall accuracy of 95.300 % and 97.900 % were reached with Nu = 0.100 (Fig. 2.4). In a sequential order of the defined Kernel functions for C-SVM and Nu-SVM classifiers, “1468, 1279, 800 and 1482” and "603, 168, 158 and 748" Complex Support Vectors were established.

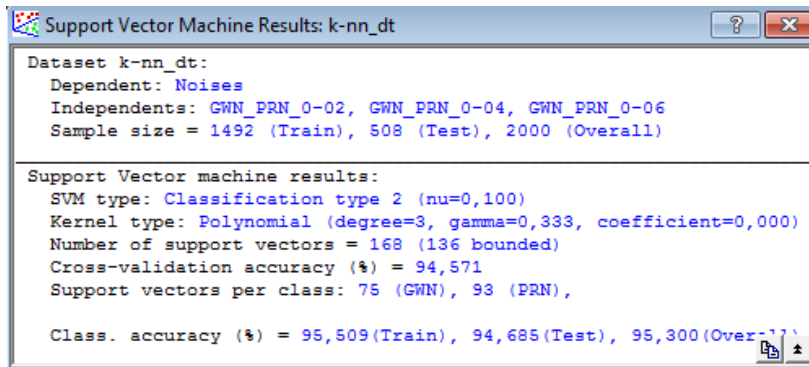
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Support Vector Machine Results: k-nn_dt
Dataset k-nn_dt:
  Dependent: Noises
  Independents: GWN_PRN_0-02, GWN_PRN_0-04, GWN_PRN_0-06
  Sample size = 1492 (Train), 508 (Test), 2000 (Overall)

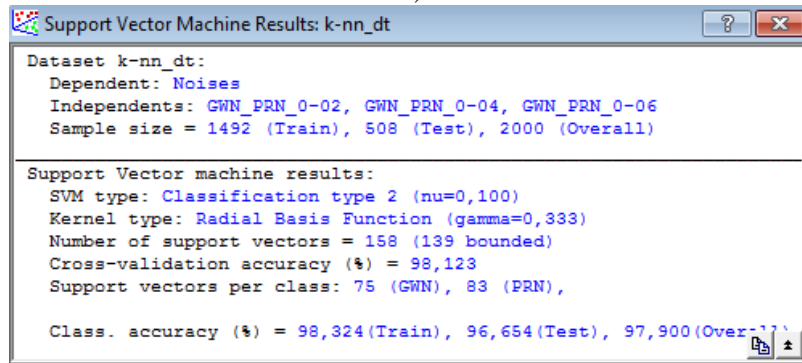
Support Vector machine results:
  SVM type: Classification type 2 (nu=0,400)
  Kernel type: Linear
  Number of support vectors = 603 (603 bounded)
  Cross-validation accuracy (%) = 68,164
  Support vectors per class: 299 (GWN), 304 (PRN),
  Class. accuracy (%) = 68,834(Train), 69,094(Test), 68,900(Over-11)

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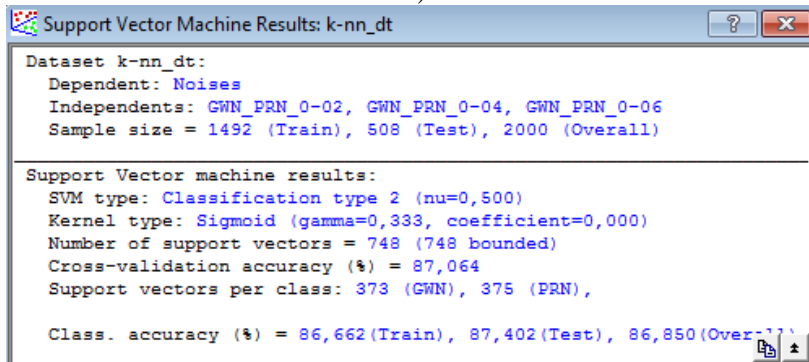
a)



b)

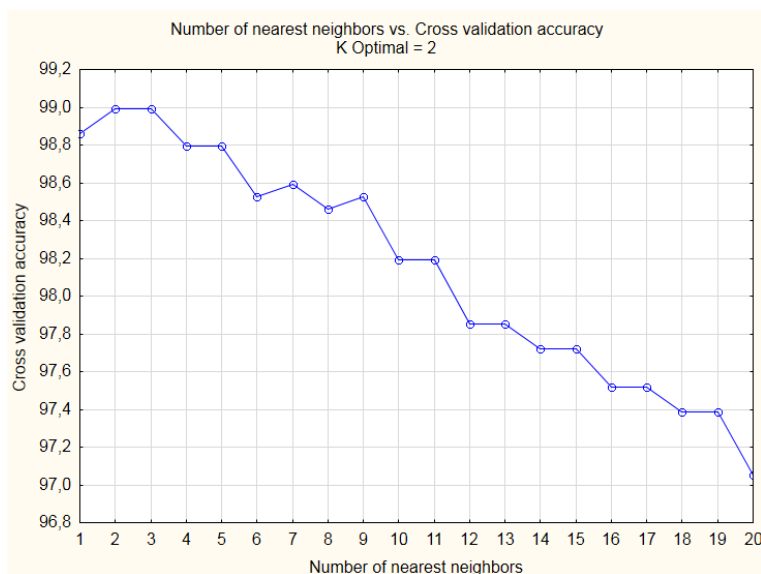


c)

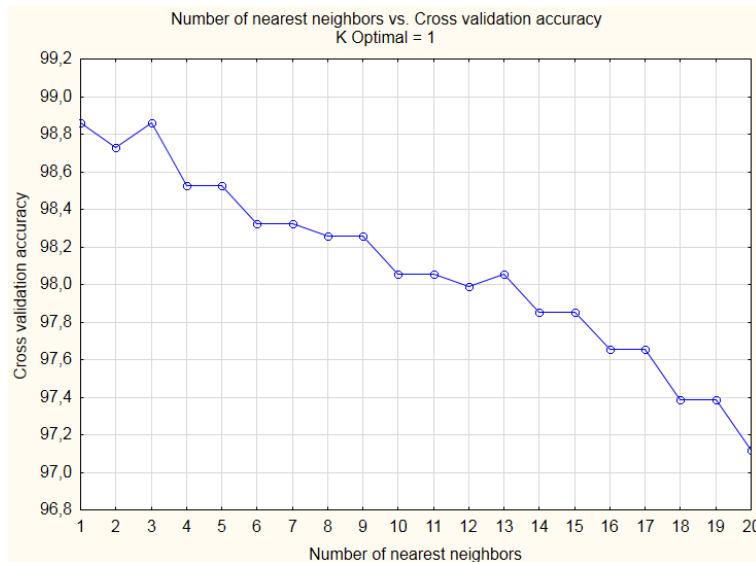


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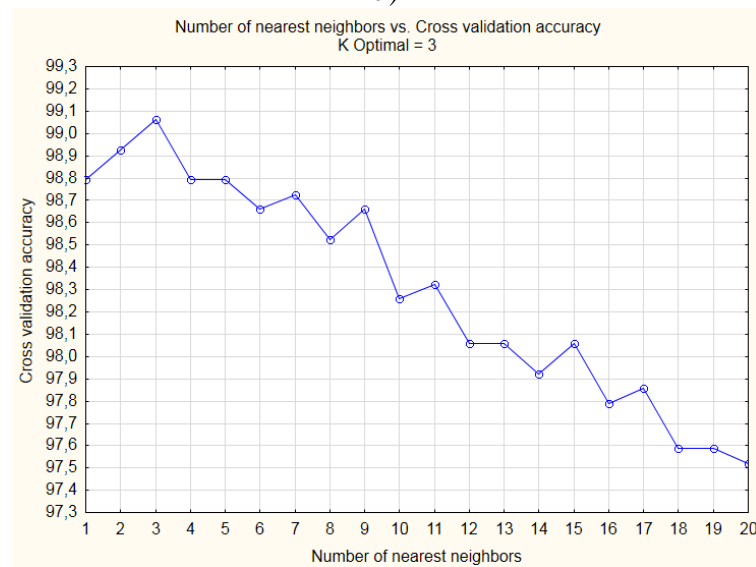
Fig. 2.4. Nu -SVM classifiers with a) Linear, b) Polynomial, c) RBF and d) Sigmoid Kernel functions



a)



b)



c)

Fig. 2.6. Iterative monitoring of k -NN models created in a) Euclidean , b) City block and c) Chebychev distances for recognizing GWNs and PRNs

The procedures for assessing the quality of the created k -NN classification models, presented in Fig. 2.6, when given in sequential order metric units for distance, recommended in scientific research when solving classification problems for the cases of " $n < 10$ ". The obtained empirical degrees of the accuracy criterion, iteratively tracking the behavior of the applied Cross-validation approach, determine the behavior of k -NN classification models with established advantages over SVMs, regardless of the used ones. According to the presented analysis, there is a certain advantage over SVM of k -NN, where the highest adequacy is assigned to the basic Euclidean distance.

2.2. Research on neuro-fuzzy classifiers for identification of Gaussian White Noise and Periodic Random Noise based on FFT spectral characteristics .

The effectiveness of neuro-fuzzy classifiers with identical membership functions of input variables for the training processes using the "Backpropagation algorithm" and "Hybrid techniques with Least square and Backpropagation algorithms" has been evaluated. Particular emphasis is placed on the "Root Mean Square Error (RMSE)" indicator. An advantage of the Hybrid approach compared to the Backpropagation method has been experimentally registered. Minimum readings of the effectiveness criterion 0.020000 and 0.007005 were found at a fixed "dsigmf" for the

"Backpropagation technique" and "gbell" type of membership function of the applied spectral features for Hybrid training. The highest error levels 0.048338 and 0.058642 were found at the membership function "trimf" within the framework of both training approaches.

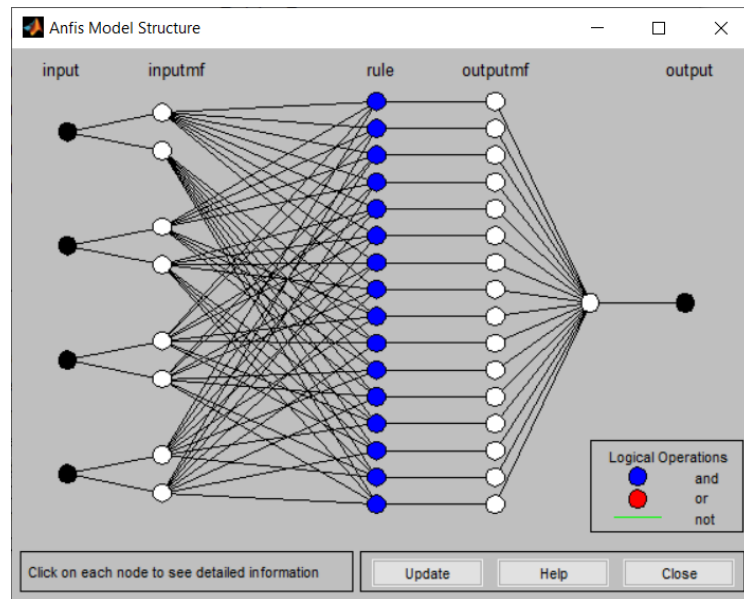
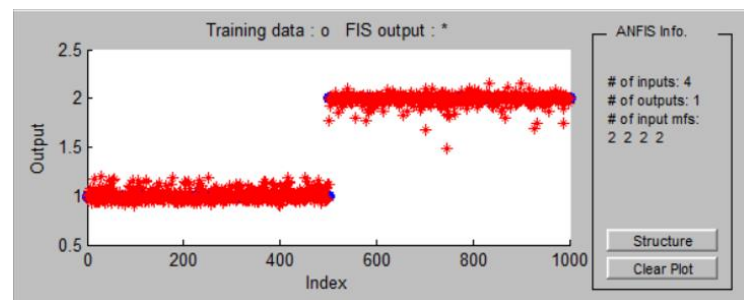
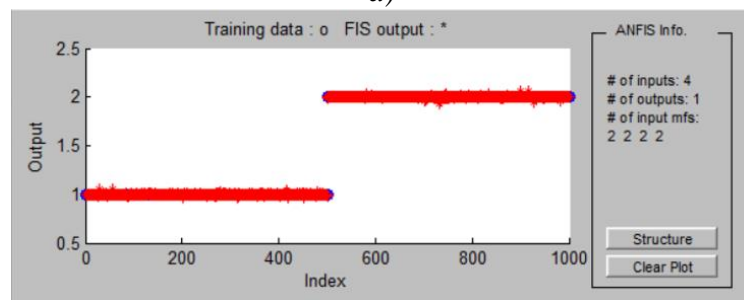


Fig. 2.21. Neuro-fuzzy classifier GWN and PRN identification



a)



b)

Fig. 2.24. Test process verification of neuro-fuzzy classifiers with a) lowest and b) highest quality metrics in Hybrid and Backpropagation learning algorithms

The correctness of the choice of the neuro-fuzzy model on Fig. 2.21 with the "gbell" membership function of input variables is clearly confirmed by the significantly higher degree of grouping of the verification standards on Fig. 2.24, confirming the significantly lower degree of the reported error 0.0069997. A classification accuracy corresponding to 100.0% was achieved for the specified neuro-fuzz structure.

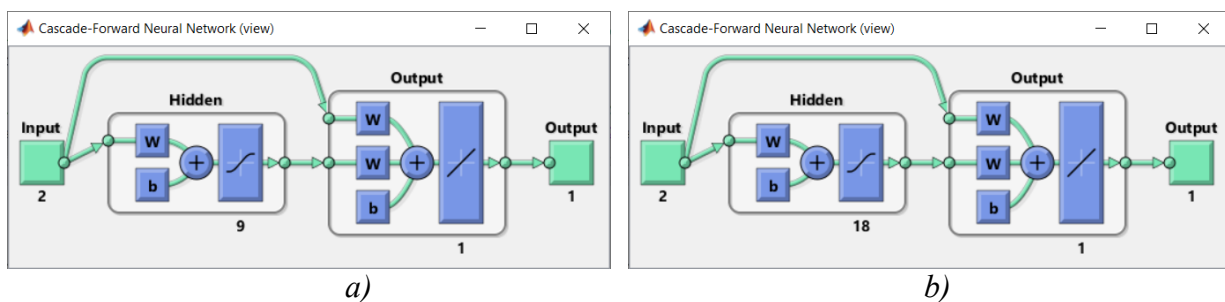
2.3. Synthesis of CFNNs structures for predictive amplitude analysis of Periodic Random Noise based on extracted statistical indicators "RMS" and "SD".

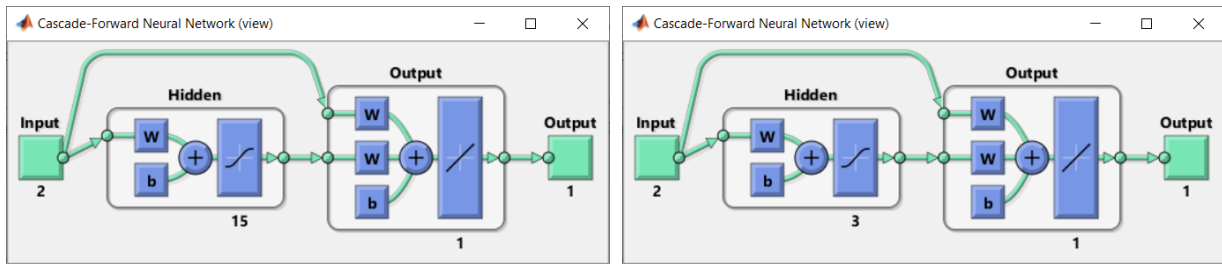
An analysis of the quality of “Cascade-Forward Neural Networks (CFNNs)” predictive models was performed for a pair of input analytical indices “RMS and SD”, extracted during primary processing of Sine, Square, Triangle and Sawtooth waveforms with superposed Periodic Random Noise. According to Table 2.8 regarding the first two test signals – Sine and Square signals, with the presence of PRN, the highest error values of the order of “ 10^{-4} ”, respectively $1.7728e-04$ and $1.5808e-04$ for architectures with 18 and 8 neurons in the intermediate network layers were observed. While in the procedures related to the amplitude variations of Periodic Random Noise added to Triangle and Sawtooth signals, better maximum levels of MSE were reported at the corresponding degree “ 10^{-5} ”. The highest error rates were achieved here, $MSE = 2.3040e-05$ for CFNN when including 17 and $MSE = 2.4337e-05$ for a predictive model with 16 hidden structural neurons.

Table 2.8 . Results in the selection procedure of CFNNs for amplitude level variance prediction of PRN to analog and digital signals

Hidden neurons	MSE for Sine with PRN	MSE in Square with PRN	MSE about Triangle with PRN	MSE in Sawtooth with PRN
3	4.5050e-07	1.6201e-05	2.7307e-06	3.7010e-07
4	1.1481e-04	2.2175e-05	6.1414e-07	1.7660e-06
5	1.4655e-06	5.1361e-06	8.5244e-07	1.6841e-06
6	1.2891e-06	1.3236e-05	2.4050e-06	3.7491e-06
7	5.0314e-06	1.4740e-05	2.5050e-06	4.2153e-07
8	3.2265e-07	1.5808e-04	2.6565e-06	9.8543e-06
9	2.5875e-07	4.2886e-06	1.4770e-07	4.9312e-06
10	3.6273e-07	2.6949e-06	1.2471e-05	5.1917e-06
11	4.9705e-07	6.9126e-07	2.0770e-06	3.3378e-06
12	1.9296e-06	7.1500e-06	3.1081e-06	7.4629e-06
13	7.5288e-07	6.0046e-06	3.4242e-06	9.9613e-06
14	2.4697e-06	6.2643e-06	2.2480e-07	9.4128e-07
15	1.6811e-05	3.7231e-06	1.1510e-07	1.3057e-05
16	1.2469e-06	2.0272e-05	9.6236e-06	2.4337e-05
17	1.6221e-06	2.1184e-05	2.3040e-05	4.6365e-06
18	1.7728e-04	6.6411e-07	1.0771e-06	5.7096e-06
19	9.1631e-06	1.3891e-04	3.7065e-06	5.0842e-06
20	3.0148e-06	2.0975e-04	1.2703e-05	2.4016e-05

Regarding the task of predictive analysis, the final CFNN s with 9, 18, 15 and 3 computing units in the hidden layers, shown in Fig. 2.31, were determined as the most suitable. The neural architectures regarding the object PRN effects are distinguished by achieved better levels of the basic MSE indicator in descending order compared to those obtained for signals at UWN. In a sequential order, satisfactory values $MSE = 2.5875e-07$, $MSE = 6.6411e-07$, $MSE = 1.1510e-07$ and $MSE = 3.7010e-07$ were registered for the studied Sine, Square, Triangle and Sawtooth waveforms with the registered presence of PRNs .





c)

d)

Fig. 2.31 . Cascade-Forward Neural structures for amplitude variance prediction in waveforms with PRN effects - a) “Sine with PRN”, b) “Square with PRN”, c) “Triangle with PRN” and d) “Sawtooth with PRN”

2.4. Research on FFNNs for predicting amplitude variations of Constant White Noise based on extracted statistical indicators "Min" and "Max".

FFNNs was performed when training with a Bayesian Regularization algorithm. Identical neural structures were created with fixed “hyperbolic tangent sigmoid” and “linear” transfer functions of the neurons in the hidden and output layers in a fixed range from 3 to 20, the results of which are summarized in Table 2.9.

Table 2.9. Study of FFNN in BR training for predictive analysis of the amplitude levels of UWN to Sine and Square, Triangle and Sawtooth signals

Hidden neurons	MSE in test samples		Hidden neurons	MSE in test samples	
	Son with UWN	Square with UWN		Triangle with UWN	Sawtooth with UWN
3	1.49445e-5	5.01191e-6	3	4.31698e-4	6.57935e-6
4	3.15040e-5	2.26269e-6	4	4.65051e-4	1.55920e-5
5	3.15040e-5	7.69753e-7	5	6.64184e-3	1.87699e-5
6	3.62525e-5	1.34544e-6	6	3.73203e-4	2.29972e-5
7	2.57697e-5	7.03414e-6	7	1.14863e-4	1.14334e-5
8	2.92002e-5	4.79208e-6	8	2.01085e-3	1.16126e-5
9	5.44664e-5	8.07133e-6	9	1.61300e-4	7.32980e-6
10	4.38610e-5	4.62541e-6	10	3.78390e-3	1.41347e-5
11	4.58814e-5	9.06271e-7	11	3.93365e-2	1.13889e-5
12	1.77804e-5	4.76656e-6	12	3.71264e-3	1.93207e-5
13	2.27808e-5	1.75893e-6	13	1.75104e-3	1.04982e-5
14	7.67937e-5	9.01756e-7	14	7.20549e-4	3.08972e-5
15	2.11002e-5	6.76589e-6	15	9.85018e-4	1.85419e-5
16	2.13257e-5	3.32387e-6	16	1.49009e-4	9.21799e-6
17	2.81509e-5	7.71967e-6	17	8.78740e-4	8.00949e-6
18	4.43218e-5	1.57173e-6	18	9.86971e-5	1.26585e-5
19	3.91506e-5	3.59555e-6	19	7.50651e-4	1.13836e-5
20	2.33375e-5	3.40613e-6	20	6.29804e-3	2.96661e-5

Within the scope of the activities carried out, a minimization of the adopted basic criteria for model selection was achieved, as follows:

- MSE = $1.49445 \cdot 10^{-5}$ for a structure with an initial number of computing units regarding Sine with UWN;
- MSE = $7.65753 \cdot 10^{-7}$ for a model with 5 hidden neurons for Square with UWN;
- MSE = $1.49445 \cdot 10^{-5}$ for a neural structure with 18 intermediate neurons included in conjunction with Triangle with UWN;
- MSE = $1.49445 \cdot 10^{-6}$ for a predictive model with a fixed number of computational units in the hidden layer regarding Sawtooth with UWN.

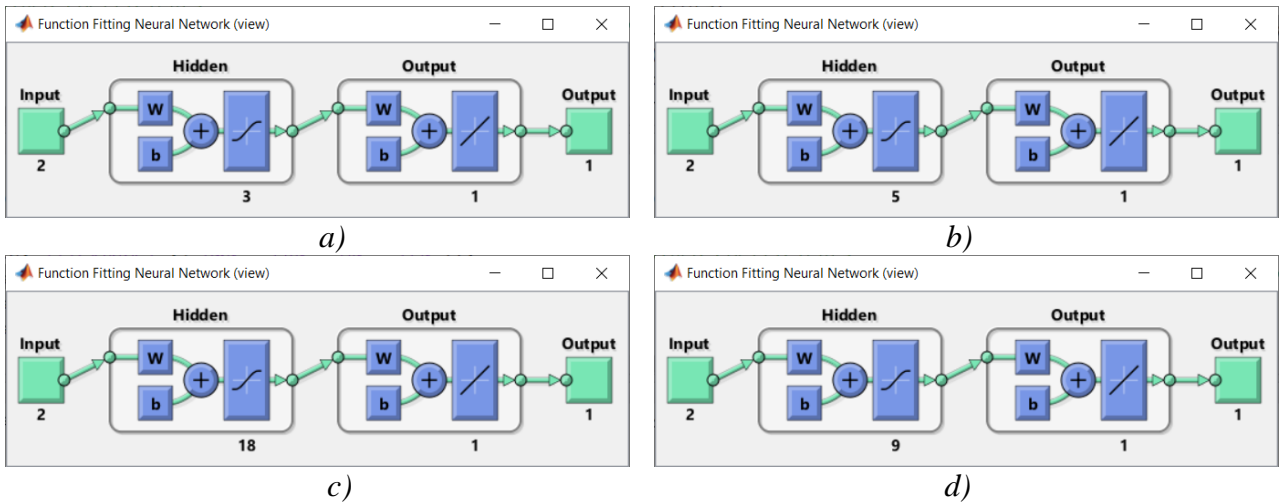


Fig. 2.34. FFNN for variance predictive analysis about Uniform White Noise to a) Sine, b) Square, c) Triangle and d) Sawtooth waveforms

Maximum error readings were found for predictive neural structures containing 14, 9, 11, and 14 hidden neurons in sequential order of the declared signal categories given in Fig. 2.34.

2.5. Evaluation of GRNNs in predictive analysis of amplitude level variance of Periodic Random Noise with extracted statistical metrics "SD" and "RMS".

Following a similar analogy as that applied in the selection of “Feed-Forward Neural Networks (FFNNs)”, a selection of “Generalized Regression Neural Networks (GRNN)” for regression diagnostics was carried out in Table 2.10. A common trend for all analyzed GRNN models is the observed gradual, moving towards exponential, increase in the MSE criterion. Regardless of the category of the signals studied, a minimum Spread indicator of the Kernel function in the second structural layers. Here the minimum MSE levels reached are equal to $9.5632 \cdot 10^{-7}$, $9.1807 \cdot 10^{-7}$, $1.4335 \cdot 10^{-6}$ and $7.6517 \cdot 10^{-7}$ for signals with sine, square, triangle and sawtooth waveforms with reflected influence of PRN.

Table 2 .10. Analysis of GRNN architectures for regression modeling about amplitude variance in Sine and Square, Triangle and Sawtooth waveforms with superposed PRN

Spread	MSE of observations in the test subset		Spread	MSE of observations in the test subset	
	Sine with PRN	Square with PRN		Triangle with PRN	Sawtooth with PRN
0.050	9.5632e-07	9.1807e-07	0.050	1.4335e-06	7.6517e-07
0.075	1.4661e-06	3.1523e-06	0.075	2.2448e-06	1.6920e-06
0.100	2.1596e-06	6.3159e-06	0.100	4.0874e-06	3.1820e-06
0.125	3.3734e-06	9.6002e-06	0.125	6.5746e-06	5.1112e-06
0.150	4.9466e-06	1.2671e-05	0.150	9.4332e-06	7.2785e-06
0.175	6.7363e-06	1.5503e-05	0.175	1.2665e-05	9.5648e-06
0.200	8.6902e-06	1.8148e-05	0.200	1.6357e-05	1.1926e-05
0.225	1.0815e-05	2.0757e-05	0.225	2.0595e-05	1.4378e-05
0.250	1.3142e-05	2.3498e-05	0.250	2.5440e-05	1.6978e-05
0.275	1.5706e-05	2.6492e-05	0.275	3.0935e-05	1.9793e-05
0.300	1.8542e-05	2.9806e-05	0.300	3.7121e-05	2.2876e-05
0.325	2.1672e-05	3.3473e-05	0.325	4.4038e-05	2.6264e-05
0.350	2.5115e-05	3.7514e-05	0.350	5.1730e-05	2.9984e-05
0.375	2.8886e-05	4.1951e-05	0.375	6.0241e-05	3.4054e-05
0.400	3.2999e-05	4.6810e-05	0.400	6.9618e-05	3.8494e-05
0.425	3.7468e-05	5.2122e-05	0.425	7.9910e-05	4.3324e-05
0.450	4.2306e-05	5.7924e-05	0.450	9.1170e-05	4.8565e-05
0.475	4.7529e-05	6.4249e-05	0.475	1.0345e-04	5.4240e-05
0.500	5.3153e-05	7.1132e-05	0.500	1.1683e-04	6.0373e-05

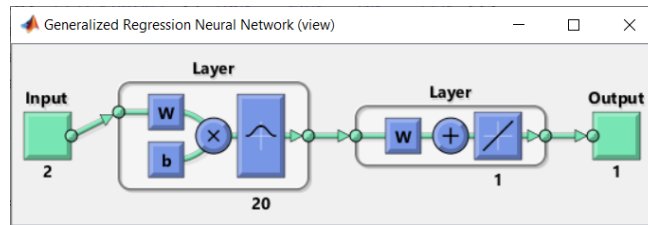


Fig. 2.37. Model of GRNN regression modeling structures about the amplitude variance in PRN this Sine, Square, Triangle and Sawtooth waveforms

In connection with additional analysis of the functionality of the model in Fig. 2.37, a family of linear regression dependencies for the network outputs was constructed. A complete overlap of the experimental and theoretical regression lines was found for all groups of signals. The obtained "Correlation coefficients" were $R = 0.99986$ for Sine and Square, $R = 0.99978$ for Triangle and $R = 0.99989$ for Sawtooth signal with the presence of PRN.

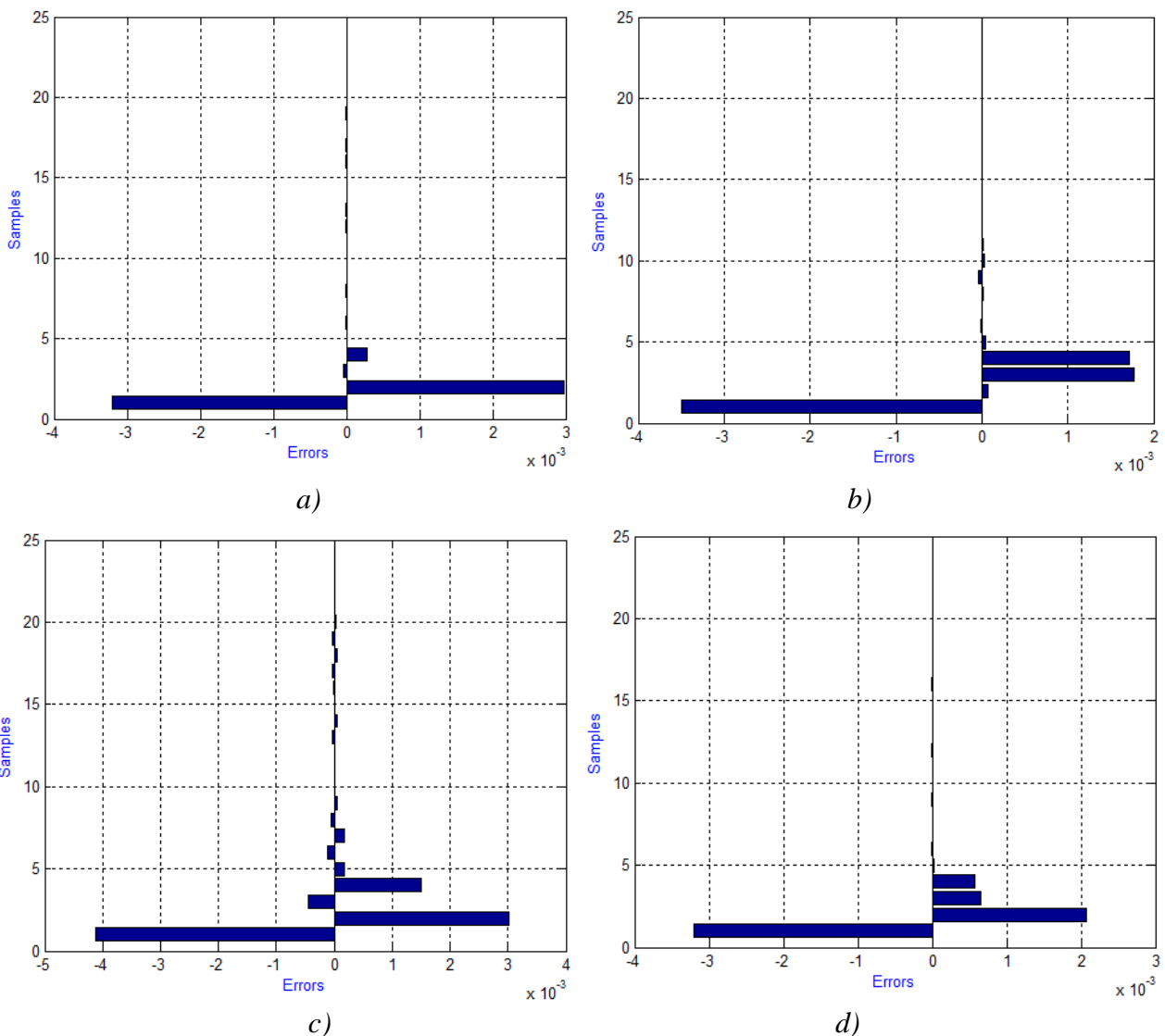


Fig. 2.39. Residuals plot of amplitude noise variance of PRN this a) Sine, b) Square, c) Triangle and d) Sawtooth waveforms with the application of GRNNs

Residuals plots were constructed with respect to the test signals on Fig. 2.39. A limited change in the network errors was observed, respectively "-0.0032 to 0.0030", "-0.0035 to 0.0018", "-0.0041 to 0.0030" and "-0.0032 to 0.0021". As a general trend, negligible low levels of "Residuals" are

observed. An exception was found for the first, second, third and fourth benchmarks of verification of GRNNs for predictive analysis of amplitude variations of Uniform White Noise to analog and digital signals.

2.6. Conclusions to Chapter II.

- Gaussian White Noise and Periodic Random Noise in simulated communication transmission media has been proven with an established quality advantage of k-NN;
- The effectiveness of the selected classification model with the highest reliability PNN over Neuro-fuzzy classifiers, CFNNs, Probabilistic Neural Networks and Naïve Bayes algorithm for GWN and PRN recognition has been confirmed;
- An approach has been developed for identification of GWN and PRN impacts using Support Vector Machine method, ANFIS with a hybrid learning algorithm based on obtained FFT spectral characteristics;
- Based on analysis, the effectiveness of Generalized Regression Neural Networks for recognizing GWN and PRN noises based on obtained FFT spectral characteristics with different window functions has been proven;
- MSE minimization was achieved in a proposed approach for predicting amplitude levels of UWN and PRN superimposed on analog and digital signals, with preliminary statistical processing and regression modeling models based on CFNNs;
- Amplitude variance of UWN and PRN to analog and digital signals with limiting the ranges of variation between theoretical and predictive noise levels has been proven.

Chapter III: Predictive analysis of transmission media performance in ICT - based infrastructures simulated

3.1. Derivation of analytical models for predicting performance indices of transmission media with Regression analysis .

A regression task for transmission media performance indices “System Throughput (ST)” and “System Response Time (SRT)” with an input index “System Demand (SD)” against the modeled ICT infrastructure using the MoM algorithm is considered. The applied regression diagnostics consists of assessing the adequacy of mathematical regression models of linear (3.1) and polynomial type (3.2) with the STATISTICA product, with the following indicators introduced:

- x_1 – controllable factor SD, s;
- y_1 and y_2 – output dependent variables ST and SRT.

$$y = b_0 + b_1 x_1 \quad (3.1)$$

$$y = b_0 + b_1 x_1 + b_{11} x_1^2 \quad (3.2)$$

The suitability check of theoretical models (3.1) and (3.2) in Fig. 3.3 and Fig. 3.4 shows high values of the adopted basic metric for model selection “Coefficient of Determination R^2 ”. The analysis against the linear model for traffic indices ST and SRT is identified with achieved $R^2 = 0.99573178$ and $R^2 = 0.99395010$ on Fig. 3.3. The regression processes against the polynomial model on Fig. 3.4 are characterized by a minimal excess of the observed R^2 , respectively $R^2 = 0.99999789$ for y_1 and $R^2 = 0.99998982$ for the factor y_2 . All experimental regression coefficients b_i are assessed as significant, relative to the accepted level of significance $\alpha = 0.05$.

Regression Summary for Dependent Variable: y (system_throughput)						
R= ,99786361 R ² = ,99573178 Adjusted R ² = ,99564286						
F(1,48)=11198, p<0,0000 Std.Error of estimate: ,03997						
N=50	b*	Std.Err. of b*	b	Std.Err. of b	t(48)	p-value
Intercept			45,77744	0,029338	1560,353	0,00
x1	-0,997864	0,009430	-3,35135	0,031670	-105,820	0,00

a)

Regression Summary for Dependent Variable: y (system_response_time)						
R= ,99697046 R ² = ,99395010 Adjusted R ² = ,99382406						
F(1,48)=7886,0 p<0,0000 Std.Error of estimate: ,00026						
N=50	b*	Std.Err. of b*	b	Std.Err. of b	t(48)	p-value
Intercept			0,217351	0,000192	1132,956	0,00
x1	0,996970	0,011227	0,018391	0,000207	88,803	0,00

b)

Fig. 3.3. Regression results in test adequacy of model (3.1) for performance index a) System Throughput and b) System Response Time

Regression Summary for Dependent Variable: y (system_throughput)						
R= ,99999894 R ² = ,99999789 Adjusted R ² = ,99999780						
F(2,47)=1113E4 p<0,0000 Std.Error of estimate: ,00090						
N=50	b*	Std.Err. of b*	b	Std.Err. of b	t(47)	p-value
Intercept			44,68508	0,003606	12393,19	0,00
x1	-0,253550	0,002425	-0,85155	0,008143	-104,57	0,00
x11	-0,747174	0,002425	-1,37503	0,004462	-308,16	0,00

a)

Regression Summary for Dependent Variable: y (system_response_time)						
R= ,99999491 R ² = ,99998982 Adjusted R ² = ,99998939						
F(2,47)=2309E3 p<0,0000 Std Error of estimate: ,00001						
N=50	b*	Std.Err. of b*	b	Std.Err. of b	t(47)	p-value
Intercept			0,224490	0,000043	5162,663	0,000000
x1	0,111348	0,005324	0,002054	0,000098	20,915	0,000000
x11	0,889026	0,005324	0,008986	0,000054	166,991	0,000000

b)

Fig. 3.4. Regression results in assessment process of analytical model (3.2) for performance index a) S T and b) S RT

Finite regression models have been derived to predict the potential performance indices for the simulated ICT infrastructure based on a zero-order model (3.3) and (3.4) and a second-order model (3.5) and (3.6).

$$y_1 = 45.77744 - 3.35135x_1 \quad (3.3)$$

$$y_2 = 0.217351 + 0.018391x_1 \quad (3.4)$$

$$y_1 = 44.68508 - 0.85155x_1 - 1.37503x_1^2 \quad (3.5)$$

$$y_2 = 0.224490 + 0.002054x_1 + 0.008986x_1^2 \quad (3.6)$$

The inverse regression task is studied to obtain a model for predicting the variations of a specific performance index of transmission media "System Demand or "y" under input controllable factors ST or "x₁" and SRT or "x₂". The results of the performed linear regression in Fig. 3.7 show a high value of Coefficient of determination R² = 0.99994031, indicating that 99.994031% of the change in parameter "y" is due to the impact of the controllable factors "x₁" and "x₂". All the initial regression coefficients, as follows b₀ = 144.905, b₁ = -1.835 (reflecting the impact of x₁) and b₂ = -280.170

(related to the assessment of the impact of x_2), are determined as significant with respect to the established probability “p level” much smaller than the accepted level of significance $\alpha = 0.05$.

Regression Summary for Dependent Variable: y (QoS)						
R= ,99997016 R ² = ,99994031 Adjusted R ² = ,99993777						
F(2,47)=3937E2 p<0,0000 Std.Error of estimate: ,00142						
N=50	b*	Std.Err. of b*	b	Std.Err. of b	t(47)	p-value
Intercept			144,905	2,280890	63,5300	0,000000
x1	-6,16449	0,089758	-1,835	0,026725	-68,6791	0,000000
x2	-5,16703	0,089758	-280,107	4,865810	-57,5664	0,000000

Fig. 3.7. Linear regression results in test adequacy of model (3.7) for predicting performance index SD

The final form of the synthesized analytical model for predicting variations in the "System Response Time" metric should be written as follows:

$$y = 144.905 - 1.835x_1 - 280.170x_2 \quad (3.8)$$

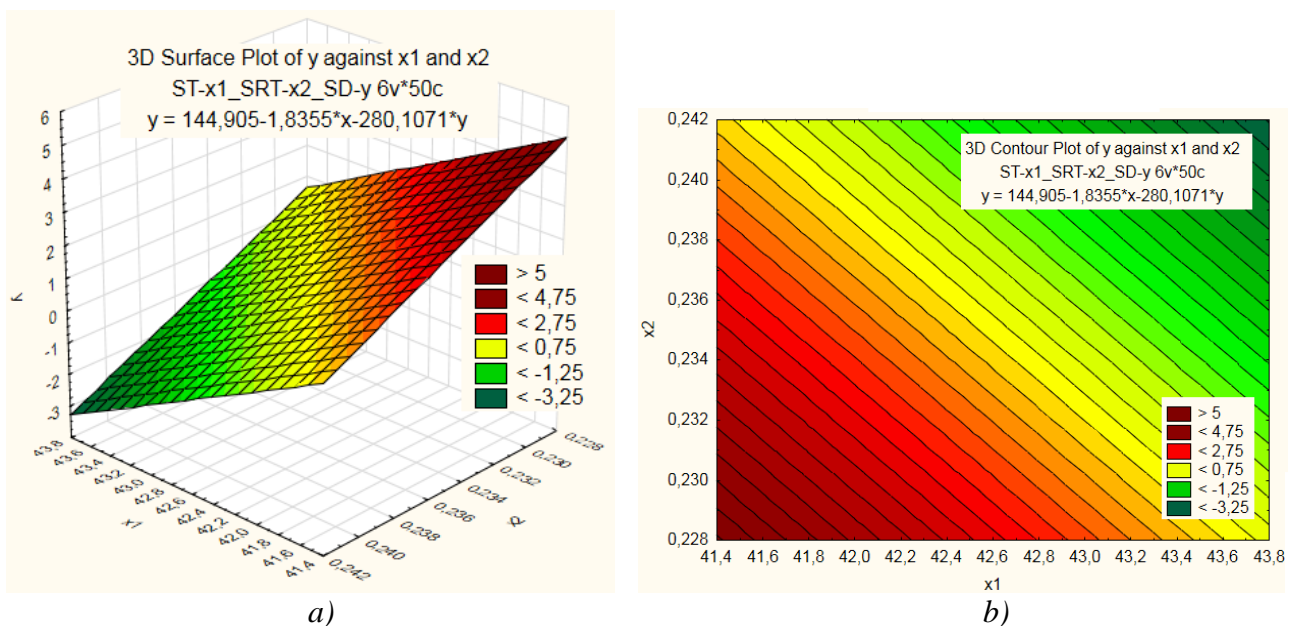


Fig. 3.9. Surface plot a) and Counter plot $y = f(x_1, x_2)$ b) for performance index of transmission media SD

The “Response Surface” $y = f(x_1, x_2)$ and the resulting section of the surface with a plane parallel to the plane x_1Ox_2 , i.e. the “Lines of uniform response” $y = f(x_1, x_2)$, were generated, shown in Fig. 3.9. The indicated response dependences confirm that a significant share of the upward changes in the output parameter SD are obtained at “medium and high levels of factor x_1 ” and “low and medium levels of factor x_2 ”.

3.2. Optimization task for finding an extremum regarding minimization of the performance index "System Response Time".

One of the essential aspects of improving the quality of service of information and communication units is associated with achieving a requirement for optimality by minimizing the complex performance index “SRT”. In this regard, algorithms and optimization methods can be applied to establish an optimum that satisfies the achievement of the specified criterion. Within the framework of the specific case, a regression model for calculating forecast levels of the index SRT relative to the input impact of a controllable factor SD, [s] is considered. By definition from optimization theory, the derived analytical model is considered as an "objective function or $f(x)$ " object of nonlinear minimization.

As a result of the optimization carried out with the sequential application of the “Interior point”, “SQP” and “Active-set” algorithms, an identical solution “-0.1143” was found, representing an optimum condition expressed in “coded” values of the set controllable factor SD. The optimal solution found guarantees the achievement of required minimum levels of the target traffic performance index SRT in the approximate order of “0.224373” for each of the optimization approaches. The correctness of the implemented optimization processes has been confirmed in relation to the matching positive degrees of the index “exitflag” for the “Interior point”, “SQP” and “Active-set” algorithms.

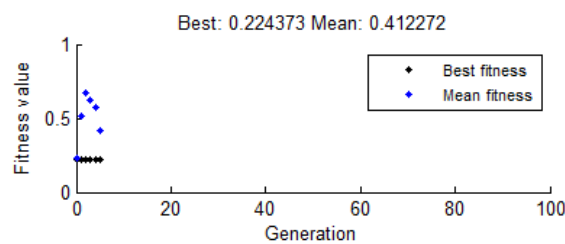
In order to expand the scope of the nonlinear optimization methodology with limitations of the applied approaches "Interior point", "SQP" and "Active-set" have been verified to find other optimization tools that confirm similar or similar efficiency. Optimization with the study of "Genetic Algorithm (GA)" has been introduced as an unconventional approach for nonlinear minimization of the traffic performance index "SRT " against a controllable factor “SD”.

GA specification was obtained, as well as the best (lowest) "Best: 0.224373" and average value found “Mean: 0.412272” of the objective function – the object of minimization, presented in Fig. 3.16. Within the procedures for reaching an optimal solution, five populations were generated. The initially created random generation consists of 2650, while the final population represents a set of 13050 points in the optimization parameter space.

```

GA_SRT.m x +
1 function [x,fval,exitflag,output,population,score] = GA_SRT(nvars)
2 %% This is an auto generated MATLAB file from Optimization Tool.
3
4 %% Start with the default options
5 options = gaoptimset;
6 %% Modify options setting
7 options = gaoptimset(options,'Display','iter');
8 options = gaoptimset(options,'PlotFcns',{ @gaplotbestf @gaplotbestindiv @gaplotc
9 [x,fval,exitflag,output,population,score] = ...
10 ga(@SRT,nvars,[],[],[],[],[],[],[],@ogrSRT,[],options);
  
```

a)



b)

Command Window				
Generation	f-count	Best f(x)	max constraint	Stall Generations
1	2650	0.224439	0	0
2	5250	0.224381	0	0
3	7850	0.224375	0	0
4	10450	0.224375	0	1
5	13050	0.224373	0	0

c)

Fig. 3.16. Specification a), quality indicators obtained b) and optimization process c) with application of Genetic Algorithm

The optimal solution found provides a "coded value: -0.1208", which is lower than the established coded level “x = -0.1143”, for controllable factor SD. While regarding the found “best

value of Fitness function: 0.2244”, there is a coincidence with the “best natural value of traffic index “SRT” derived during the minimization in the “Interior point”, “SQP” and “Active-set” approaches. The correctness of the performed optimization procedures has been confirmed – evidence of which is the positive value of the variable “exitflag” in Fig. 3.17. Fifty functional estimates of the set of points in the last generated population, where the smallest value of Fitness function was found, which tends to an optimal solution, are included.

Field	Value	Min	Max
x	-0.1208	-0.1208	-0.1208
fval	0.2244	0.2244	0.2244
exitflag	1	1	1
output	1x1 struct		
population	50x1 double		
score	50x1 double		

Fig. 3.17. Output indicators in Fitness function minimization with application of Genetic Algorithm

The verification performed shows the efficiency of the GA approach, successfully comparable to that achieved with “Interior point”, “SQP” and “Active-set”. Optimal solution (“x = -0.1143” and “x = -0.1208”) have been reached, at which a theoretical minimum level of the traffic index System Response Time is guaranteed. The estimated value from the minimization of SRT is approaches the lowest "Observed values" obtained in simulation modeling. This fact can be marked as an indication of high efficiency of all applied approaches in relation to the considered optimization task. The optimization goals of guaranteeing SRT levels satisfying the requirement for increasing the capacity of servicing system users within the scope of the simulated ICT infrastructure have been achieved.

3.3. Forecasting transmission medium performance indices with FFNNs under two input impacts and different training algorithms.

FFNNs were carried out in analyzing the applicability of the following training algorithms: Levenberg-Marquardt (LM); Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG), summarized in Table 3.4 and Table 3.5, with an adopted basic criterion (MSE). The following input and output parameters were introduced in the processes of synthesis of predictive models:

- Input variables – 1) SD, and 2) The values of the teletraffic indicator System Demand, raised to the second power;
- Output parameters - ST and SRT are defined.

Regarding the first set traffic index, maximum error readings were recorded, respectively MSE = 2.02598e-4, MSE = 1.64856e-10 and MSE = 2.43299e-3 successively for LM, BR and SCG training for structures with 9, 13 and 10 intermediate computational units. Satisfactory minimum MSEs were obtained for FFNN structures with set 4 (MSE = 3.17825e-10), 10 (MSE = 7.79211e-11), and 13 (MSE = 3.54521e-5), hidden neurons. According to the summarized results, the selected neural model with BR algorithm is evaluated with the highest degree of adequacy for predicting the variations of the traffic characteristic "System Throughput". Comparing the applied training algorithms, it was found that the SCG approach is characterized by the lowest efficiency for the specific analyzed traffic parameter.

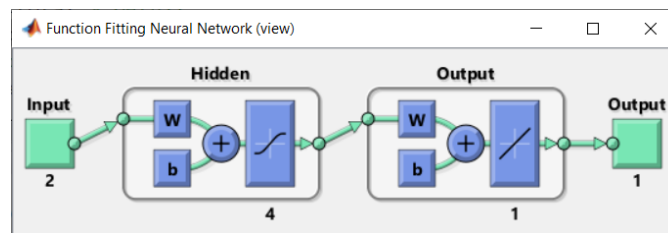
Table 3.4. Results in investigation of neural networks
System Throughput predictive analysis

Hidden neurons	LM	BR	SCG
	MSE in train process	MSE in train process	MSE in train process
3	1.14099e-9	1.57589e-10	7.01570e-5
4	3.17825e-10	1.19221e-10	7.82394e-5
5	2.09195e-9	1.20101e-10	6.55992e-5
6	2.09897e-6	1.25709e-10	7.80464e-5
7	8.42537e-9	1.53955e-10	8.78858e-4
8	5.79434e-7	9.02992e-11	9.09759e-4
9	2.02598e-4	1.41492e-10	4.08480e-4
10	2.67695e-7	7.79211e-11	2.43299e-3
11	1.00936e-6	1.21158e-10	1.52216e-3
12	1.89889e-4	1.19690e-10	1.70738e-4
13	3.52341e-6	1.64856e-10	3.54521e-5

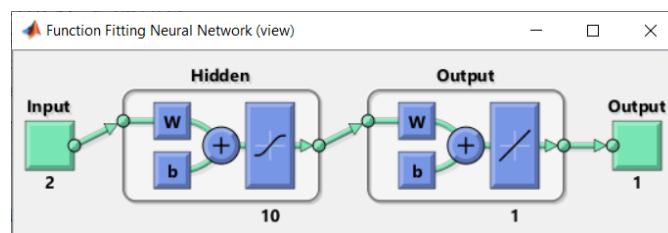
Regarding the synthesis of predictive models for the second set of teletraffic indicators, covering “Queue dwell times and processing of incoming requests (SRT)”, a certain trend of lower efficiency was observed for SCG compared to the other algorithms used. However, observing the initial degrees of the MSE quality criterion, here a pronounced adaptability of SCG is distinguished compared to the selection of neural models for “System throughput”, shown in Fig. 3.25.

Table 3.5. Evaluation results of neural networks for prediction of performance index System Response Time

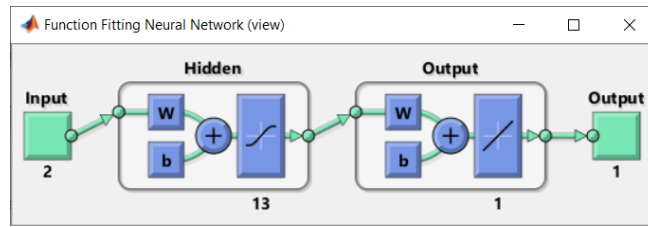
Hidden neurons	LM algorithm	BR algorithm	SCG algorithm
	MSE at testing	MSE in training	MSE at training
3	5.00144e-9	1.44758e-9	7.20825e-9
4	6.88759e-10	1.06745e-9	4.29007e-7
5	5.46010e-8	2.18784e-9	3.83399e-7
6	2.51603e-10	5.80534e-9	2.16496e-7
7	5.91742e-9	2.67628e-9	9.91093e-8
8	5.50524e-9	6.38057e-10	2.55897e-7
9	5.41969e-11	1.65099e-9	3.60012e-8
10	7.73573e-9	1.15110e-9	2.06796e-7
11	1.20022e-9	4.25863e-10	1.38354e-7
12	5.58102e-10	6.71894e-10	1.37807e-7
13	1.36464e-11	1.61493e-9	6.66151e-8



a)

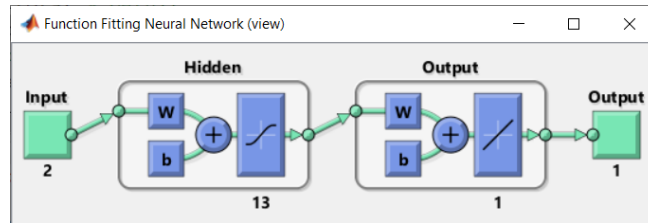


b)

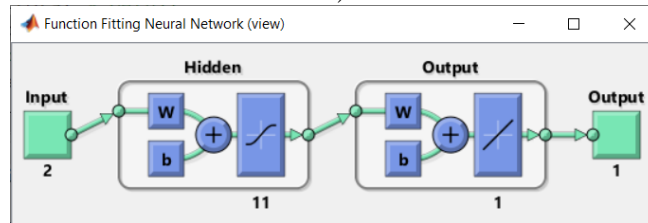


c)

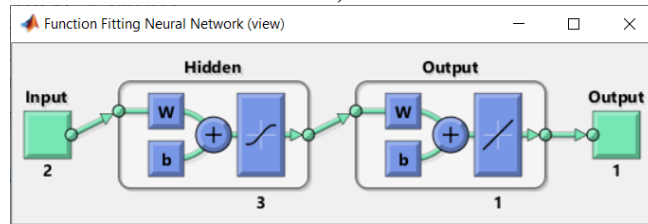
Fig. 3.25. FFNNs predictive models selected for performance index System Throughput in a) LM, b) BR and c) SCG learning algorithm



a)



b)



c)

Fig. 3.26. Selected FFNNs for predictive analysis of performance index System Response Time in a) LM, b) BR and c) SCG training algorithm

The largest errors $MSE = 5.46010e-8$, $MSE = 5.80534e-9$ and $MSE = 4.29007e-7$ were found for FFNNs with 5, 6 and 4 hidden neurons, respectively for LM, BR and SCG algorithms. Achieving the error minimization requirement are neural architectures with 13 for LM, 11 for BR and 3 structural intermediate neurons for SCG training – $MSE = 1.36464e-11$, $MSE = 4.25863e-10$ and $MSE = 7.20825e-9$, given in Fig. 3.26. Comparing the selected final FFNN models for predicting the Complex queueing time and service, the advantage of the LM learning algorithm over the BR and SCG approach is highlighted.

3.4. Predictive analysis of transmission medium performance indices under a combination of two input impacts using RBNN, GRNN and CFNN.

Radial Basis Neural Networks (RBNNs) is introduced. The registered output indicators MSE, MAE and RMSE when evaluating RBNNs are analyzed, simultaneously summarized for traffic indices ST and SRT in Table 3.7. The analysis of the behavior of the specified criteria covers RBNNs with a step increase in SI in the range 0.1 - 0.9. The following degrees satisfying the objectives of the study have been established:

- " 10^{-11} " for mean-squared errors and " 10^{-6} " at mean absolute error and root mean square error;
- " 10^{-15} " for MSE and " 10^{-8} " for MAE and RMSE;

of the applied input data in the training procedures. The recorded values of MSE, MAE and RMSE are characterized by an exponential increase up to levels of SI = 0.4. A certain establishment of the quantitative criteria with varying fluctuations has been observed:

- "8.1400e-11 to 8.9000e-11" for MSE, "7.7000e-6 to 8.2000e-6" for MAE, and "9.0000e-6 to 9.4200e-6" for RMSE in neural selection for ST;
- "2.5600e-15 to 2.7100e-15" regarding MSE, "4.3500e-8 to 4.5100e-8" for MAE and "5.0000e-8 to 5.2100e-8" regarding RMSE when selecting a forecast model for SRT;

to the final width of the radial basis function SI = 0.9. As a result of the activities performed, identical RBNN architectures were selected in Fig. 3.29 for predicting the performance indices ST and SRT at a minimum set width of the radial basis function SI = 0.1, in cases of achieving MSE = 7.7309e-12 and MSE = 2.2659e-16.

Table 3.7. RBNN for variable prediction of performance indices ST and SRT in two controllable factors

SI	MSE	MAE	RMSE	MSE	MAE	RMSE
	Throughput			Complex waiting time and service		
0.10	7.7309e-12	2.0281e-06	2.7805e-06	2.2659e-16	1.0985e-08	1.5053e-08
0.15	2.3484e-11	4.0773e-06	4.8460e-06	7.0014e-16	2.2364e-08	2.6460e-08
0.20	5.9231e-11	6.0761e-06	7.6962e-06	1.7846e-15	3.3327e-08	4.2245e-08
0.25	6.4694e-11	6.2573e-06	8.0433e-06	1.7846e-15	3.3327e-08	4.2245e-08
0.30	7.1730e-11	7.0615e-06	8.4693e-06	2.1609e-15	3.8694e-08	4.6485e-08
0.35	7.7241e-11	7.3046e-06	8.7887e-06	2.3329e-15	4.0039e-08	4.8300e-08
0.40	8.1960e-11	7.7676e-06	9.0532e-06	2.4844e-15	4.2629e-08	4.9844e-08
0.45	8.1520e-11	7.7370e-06	9.0288e-06	2.4698e-15	4.2454e-08	4.9697e-08
0.50	8.4402e-11	7.9536e-06	9.1870e-06	2.5663e-15	4.3712e-08	5.0659e-08
0.55	8.4309e-11	7.9503e-06	9.1820e-06	2.5637e-15	4.3698e-08	5.0633e-08
0.60	8.4188e-11	7.9454e-06	9.1754e-06	2.5581e-15	4.3630e-08	5.0578e-08
0.65	8.6694e-11	8.0451e-06	9.3110e-06	2.6415e-15	4.4207e-08	5.1396e-08
0.70	8.8591e-11	8.1885e-06	9.4123e-06	2.7021e-15	4.5046e-08	5.1981e-08
0.75	8.8577e-11	8.1878e-06	9.4115e-06	2.7017e-15	4.5041e-08	5.1978e-08
0.80	8.8570e-11	8.1875e-06	9.4112e-06	2.7010e-15	4.5034e-08	5.1971e-08
0.85	8.8576e-11	8.1883e-06	9.4115e-06	2.7006e-15	4.5010e-08	5.1968e-08
0.90	8.8721e-11	8.1890e-06	9.4192e-06	2.7064e-15	4.5021e-08	5.2023e-08

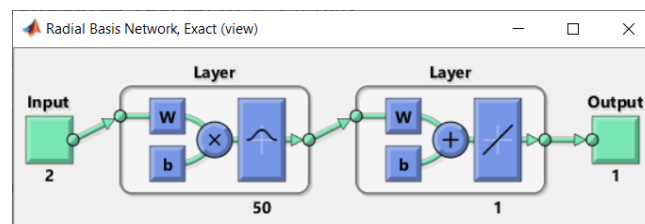
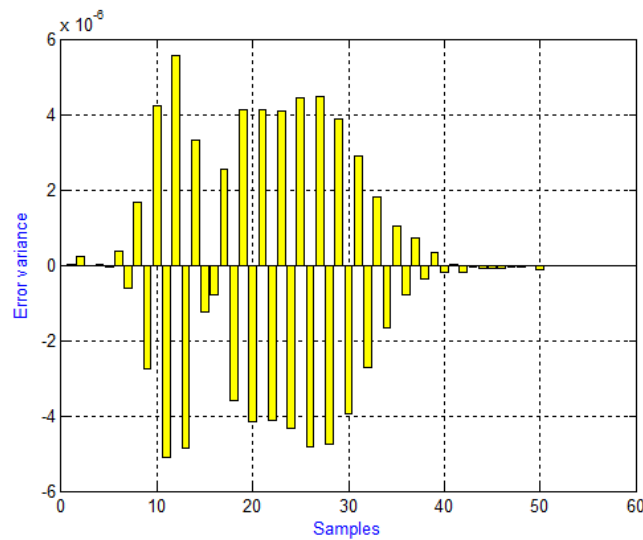


Fig. 3.29. RBNN for predictive analysis of performance indices ST and SRT

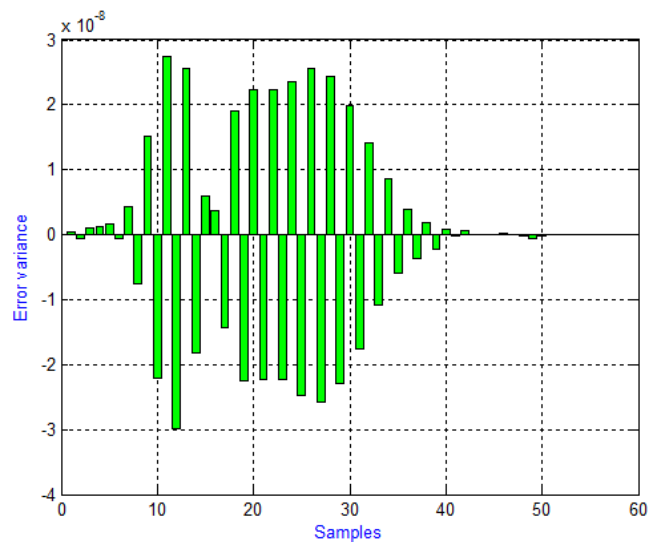
Residual diagrams for the synthesized RBNN forecast models were obtained when setting a minimum width in the structural radial-base layer in Fig. 3.30, whose variations fall within the following limits:

- "-5.1208e-06" to "5.5636e-06" when monitoring the ST index;
- "-2.9878e-08" to "2.7410e-08" relative to the SRT metric.

The recorded limits show a high level of efficiency when using RBNNs as analytical tools for regression diagnostics of transmission media parameterization.



a)



b)

Fig. 3. 30. Networks errors variance him/her RBNN in $SI = 0.1$ for predictive analysis of performance indices ST and SRT

The next phase of the approach integrates the four-layer GRNNs when setting an activation function in the radial-basis layer of Gaussian type in Fig. 3.31. The selection of predictive GRNN models is based on an evaluation of the MSE and MAE criteria with an exponential step increase of the SI metric in the radial-basis network layer, shown in table 3.8. An evaluation of the registered values of MSE and MAE for the two target teletraffic performance indices was made. For both predictive indicators, a general trend of exponential increase in errors with an upward smooth change of the functional parameter SI from 0.050 to 0.300 was established. The highest levels of the criteria by groups for ST , respectively $MSE = 0.02114$ and $MAE = 0.1144$, and SRT , as follows $MSE = 6.4204e-07$ and $MAE = 6.2290e-04$, were found at $SI = 0.300$. At a minimum set degree $SI = 0.050$, determined with the highest degree of suitability, the functions in the radial-basis structural layer of GRNN achieved the lowest levels $MSE = 1.01008e-04$, $MAE = 0.0042$ for "System Throughput" and $MSE = 2.9993e-09$, $MAE = 2.21640e-05$ for the traffic characteristic "System Response Time".

The third module of the approach consists of studies aimed at selecting CFNNs for the purposes of the prediction task in Table 3.9. This category of neural networks is considered as a variation of FFNNs with relevant structural differences related to the presence of a direct connection between the input and output layers and the inclusion of a second weight matrix to the output layer. Similar training procedures were applied using the LM algorithm with structural changes of the hidden neurons in the known range from 5 to 15 computational units in terms of complex analysis of quality indicators MSE and MAE.

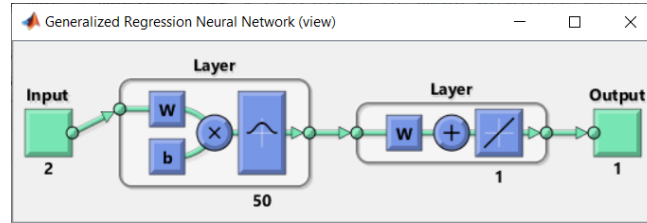


Fig. 3.31. Structure of GRNN model for predictive analysis of performance indicators ST and SRT

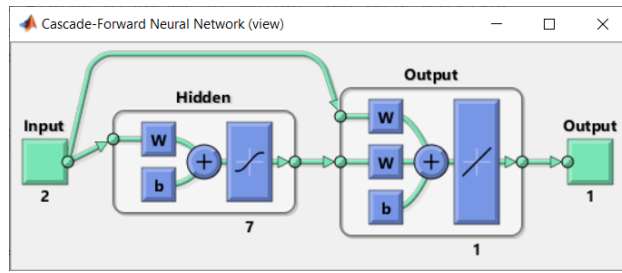
Table 3.8. Results in examining the quality of GRNN models for level prediction in performance indices ST and SRT

Spread index	System Throughput		System Response Time	
	M SE	MAE	M SE	MAE
0.050	1.0108e-04	0.0042	2.9993e-09	2.2164e-05
0.075	3.4460e-04	0.0091	1.0252e-08	4.8472e-05
0.100	8.1530e-04	0.0156	2.4299e-08	8.3690e-05
0.125	0.0016	0.0236	4.7319e-08	1.2712e-04
0.150	0.0027	0.0331	8.1474e-08	1.7830e-04
0.175	0.0043	0.0438	1.2892e-07	2.3670e-04
0.200	0.0064	0.0558	1.9185e-07	3.0184e-04
0.225	0.0091	0.0689	2.7244e-07	3.7342e-04
0.250	0.0124	0.0831	3.7294e-07	4.5111e-04
0.275	0.0165	0.0983	4.9550e-07	5.3435e-04
0.300	0.0214	0.1144	6.4204e-07	6.2290e-04

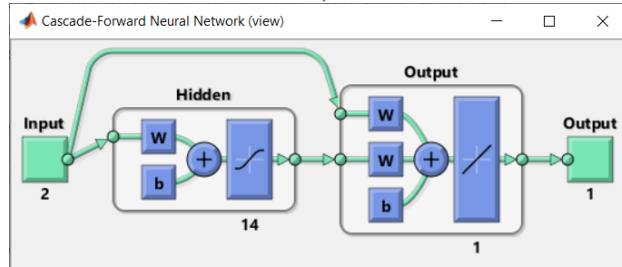
Table 3.9. Results in investigation of CFNNs for predictive analysis of performance index System Throughput and System Response Time

Hidden neurons	System Throughput		System Response Time	
	M SE	MAE	M SE	MAE
5	1.6415e-09	2.0126e-05	7.5662e-10	2.0018e-05
6	1.0022e-09	1.4178e-05	6.0152e-11	5.7154e-06
7	1.0782e-10	8.5520e-06	1.3590e-10	8.1408e-06
8	2.2607e-10	9.8568e-06	2.0148e-12	1.2498e-06
9	1.6997e-10	9.0878e-06	5.3233e-11	5.0956e-06
10	5.8023e-09	5.7095e-05	4.0863e-09	5.3444e-05
11	1.8411e-10	1.1316e-05	6.3765e-12	1.5975e-06
12	1.3511e-10	9.4508e-06	7.2580e-10	2.2891e-05
13	1.7786e-09	1.7127e-05	3.3792e-10	1.5585e-05
14	7.3851e-10	1.8198e-05	1.1041e-12	8.0021e-07
15	3.0354e-09	3.3020e-05	6.6437e-10	2.0675e-05

Neural architectures were found that achieved the requirements for minimization of the analyzed indicators, with 7 for the traffic characteristic ST and 14 intermediate neurons for the index SRT, given in Fig. 3.34. The achieved minimum error levels fall into successive orders “ $1.0782 \cdot 10^{-10}$ – MSE for y_1 ”, “ $8.5520 \cdot 10^{-6}$ – MAE for y_1 ”, “ $1.1041 \cdot 10^{-12}$ – MSE for y_2 ” and “ $8.0021 \cdot 10^{-7}$ – MAE for y_2 ”. The highest values of the quality criteria were established for the groups MSE = $5.8023 \cdot 10^{-9}$, MAE = $5.7095 \cdot 10^{-5}$ for the index ST and MSE = $4.0863 \cdot 10^{-9}$, MAE = $5.3444 \cdot 10^{-5}$ for “System Response Time”.

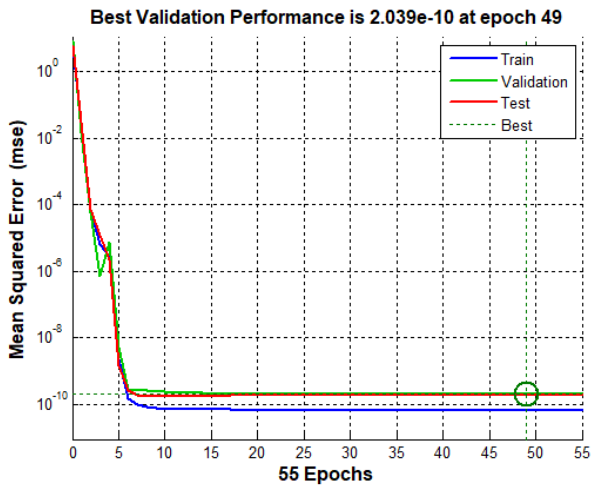


a)

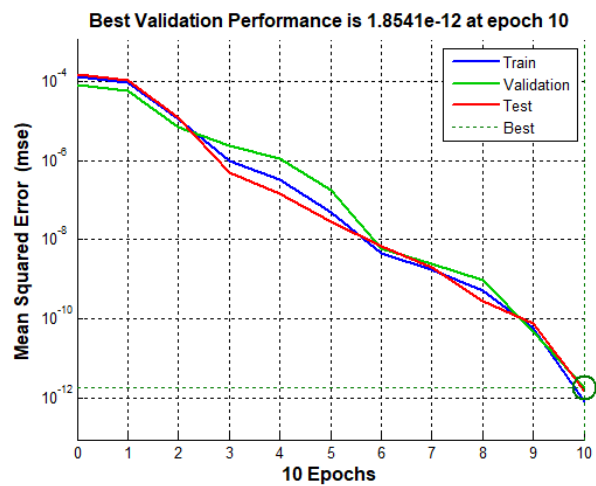


b)

Fig. 3.34. CRNNs for level prediction of performance indicators
a) System Throughput and b) System Response Time

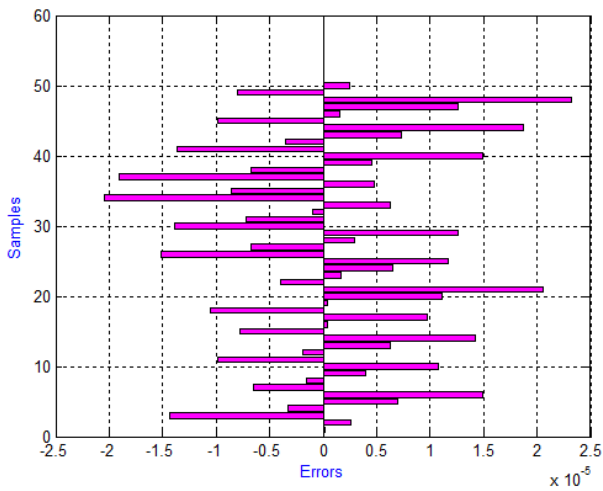


a)

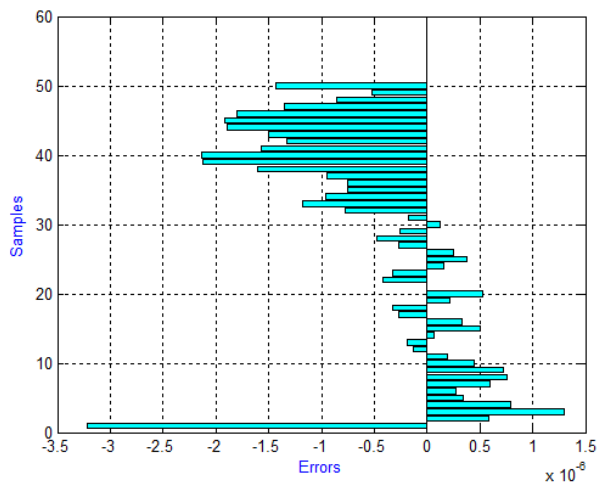


b)

Fig. 3.35. MSE for CRNNs synthesized for prediction of index ST and b) SRT



a)



b)

Fig. 3.36. Residuals plot in CFNN performance index prediction
of System Throughput a) and System Response Time b)

MSE criterion during training, validation and testing of the selected final CFNNs is analyzed in Fig. 3.35. There is a general trend of similarity in the direction of change of the output characteristics between the network processes. The training procedures take place within 55 for the ST prediction model and 10 iterations for the CFNN architecture associated with SRT index monitoring. The best "Validation Network Performance" $2.039e-10$ and $1.8451e-12$ was achieved at the 49th and 10th training cycles, respectively, for the networks for predictive analysis of traffic characteristics "Throughput" and "System Response Time". Considering the residual diagrams in Fig. 3.36, as well as comparing the overall behavior of the last two analytical tools for predictive monitoring, it is noted that the synthesized predictive Cascade-Forward models significantly outperform GRNNs.

3.5. Conclusions to Chapter III.

- ICT simulation modeling is proposed. Queueing network infrastructure for monitoring and administering network traffic;
- Based on regression diagnostics, an advantage of 2nd order models has been established in assessing the adequacy of derived linear and polynomial models for predictive analysis of traffic indices ST, SRT and SD of simulated ICT Queueing network infrastructure;
- The effectiveness of a proposed optimization approach with Interior-point, SQP, Active-set and Genetic algorithms for finding an optimum in minimizing System Response Time has been established. traffic metric to improve the speed of processing requests;
- A need to include a second controllable factor versus single input impact of controllable factor SD in a synthesized approach with integration of GRNNs and FFNNs for regression modeling of traffic parameters ST and SRT;
- Based on a verification of network performance, the advantage of LM over BR and SCG training algorithms has been proven in an approach with Feed-forward neural networks and two controllable factors for predicting ST and SRT;
- The effectiveness of a regression modeling approach in relation to variations in traffic indices ST and SRT is proven with an established advantage for network efficiency when integrating RBNN compared to GRNN and CFNN.

Chapter IV: Traffic state monitoring over corporate clients with AI and ML instruments

4.1. Diagnostics of the state of UDP network traffic with three-layer and multilayer neural architectures.

4.1.1. Parameterization of logged UDP traffic.

The modern concept of quality of service in communications when transmitting packets between network segments is based on the application of adequate intelligent analysis of the state of the transmission environment. The main emphasis is placed on network diagnostics to establish the "presence of attacks". One of the possibilities for this is that the procedure refers to the implementation of AI for analyzing the state of transmitted traffic of some commonly used network standards - TCP, UDP or ICMP. The task of recognizing categories of network UDP traffic to corporate clients is defined as follows:

- Normal traffic;
- Attacked traffic,

based on recorded traffic metrics (Fig. 4.1), as follows:

- Duration;
- Packet count;
- Byte count.

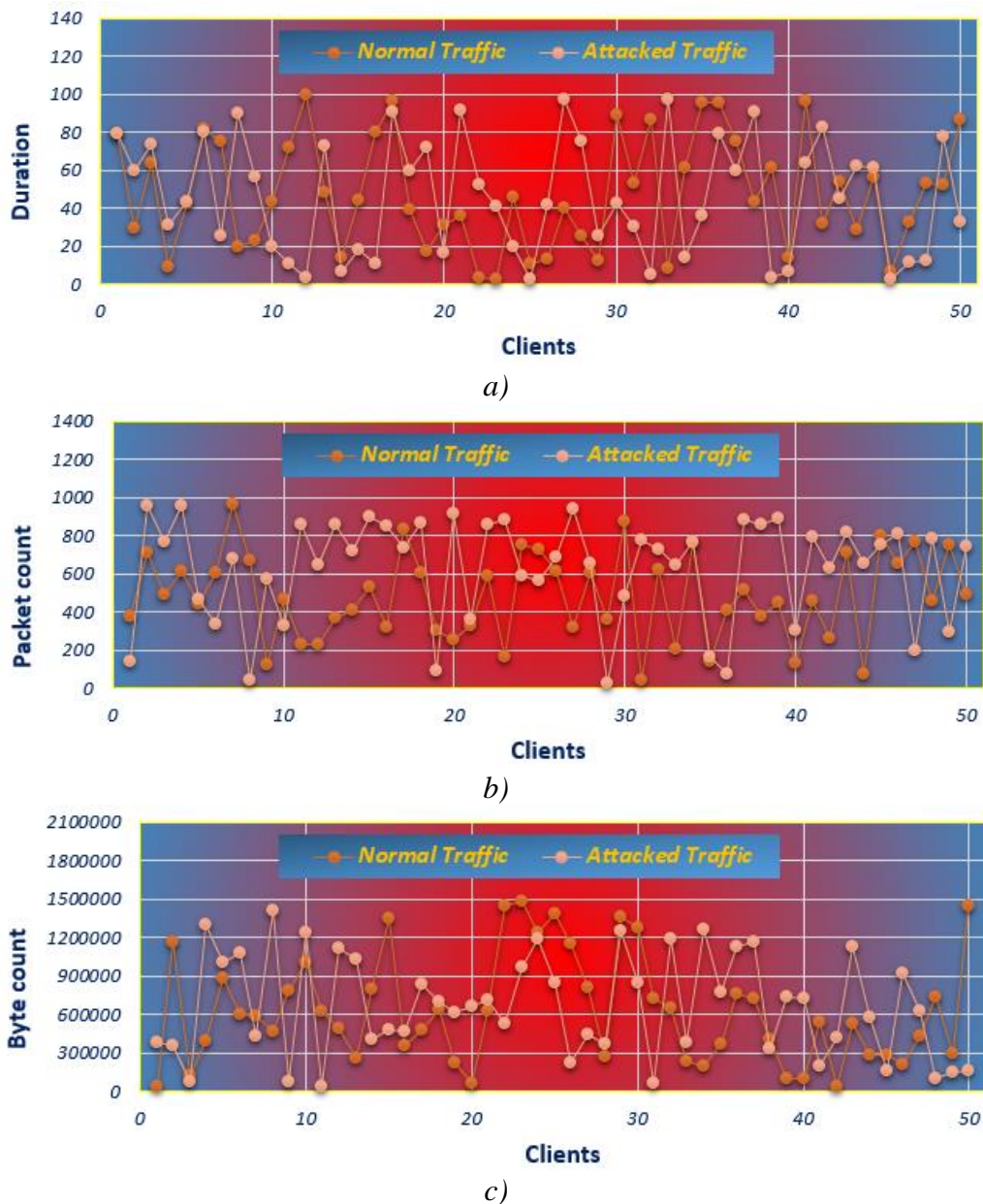


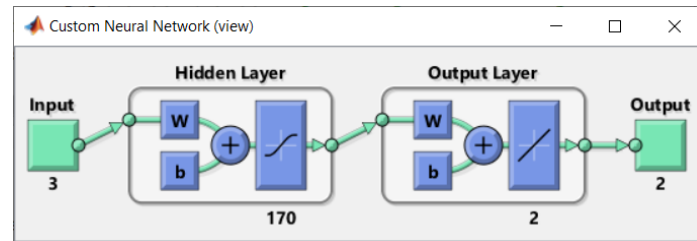
Fig. 4.1. Transmission parameters in UDP (User Datagram Protocol) network traffic – a) Duration, b) Packet count and c) Byte count

4.1.2. Monitoring the status of UDP network traffic with integration of Feed-Forward, Cascade-Forward networks with LM learning algorithm and Probabilistic Neural Networks.

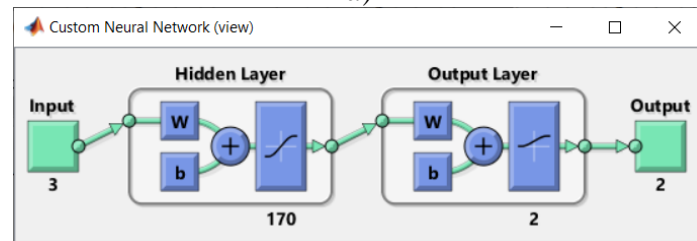
A methodology for diagnosing the state of transmitted UDP traffic to corporate clients with the inclusion of artificial neural networks with a number of computational neurons in the second structural layers identical to that established in the previous basic neural architecture has been developed, respectively 170 building neural units. The research procedures integrate the following neural devices:

- Feed-Forward structure when replacing the SCG training algorithm with LM training and using a “linear” transfer function in the output layer (Fig. 4.6.a);
- Feed-Forward model with LM algorithm when applying “log-sigmoid” activation type of neurons in the output layer (Fig. 4.6.b);
- Feed-Forward neural network in LM training when setting a “hyperbolic tangent sigmoid” activation function in the output layer (Fig. 4.6.c);
- Cascade-Forward Neural Network based on LM learning algorithm (Fig. 4.6.d).

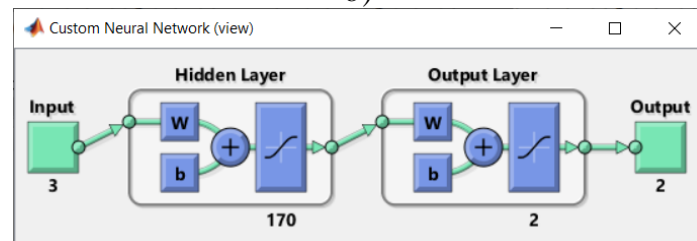
In the course of experimental studies of the test neural models in a sequential order, quantitative equivalents of "mean-squared error" were obtained, respectively $MSE = 0.1882$, $MSE = 0.1916$, $MSE = 0.1355$ and $MSE = 0.3015$. Relatively close classification accuracies were reported for the test neural recognition models, equal to 90.0% for "putelin", 85.0% for "logsig", 84.0% for "tansig" transfer function for FFNNs and again 90.0% for CFNN.



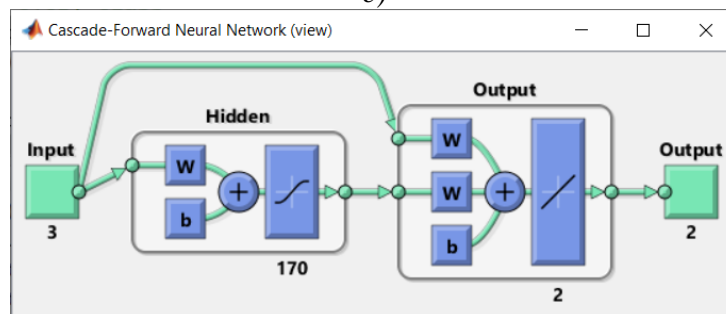
a)



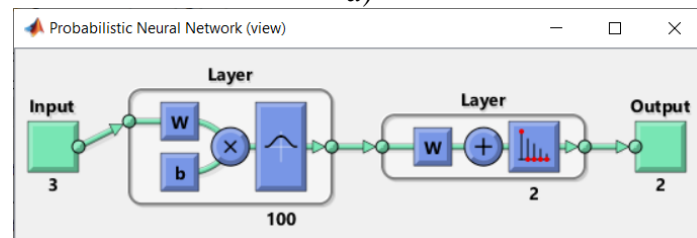
b)



c)



d)



e)

Fig. 4.6. FFNNs in a) "purelin", b) "logsig" and c) "tansig" output activation, d) CFNN and e) PNN for attack detection in UDP traffic transmission

Despite the recognition threshold of 90.0%, the levels of the registered values of the indicator "MSE" remain significantly high. This fact gives grounds for searching for another analytical tool with better performance, as was established for the case when including the four-layer Probabilistic Neural Networks in Fig. 4.6.e) at medium levels of the "Kernel function width in the radial-basis

layer". Here, a significant minimization of the criterion "mean square error" to the numerical equivalent $MSE = 0.0100$ and an increase in classification accuracy to 99.0% was found.

4.2. Detection of DoS attacks, integrity status and anomalies in transmitted network traffic for corporate clients.

Verification in a laboratory environment to confirm the functionality of the multilayer FFNNs in network traffic diagnostics for "Detection of cyber threats and network anomalies" was conducted. A specification with the preservation of the traffic index "Duration" and the introduction of the specific parameters of the transmission medium "Network Latency" and "Data Transfer Rate" was applied, shown in Fig. 4.12.

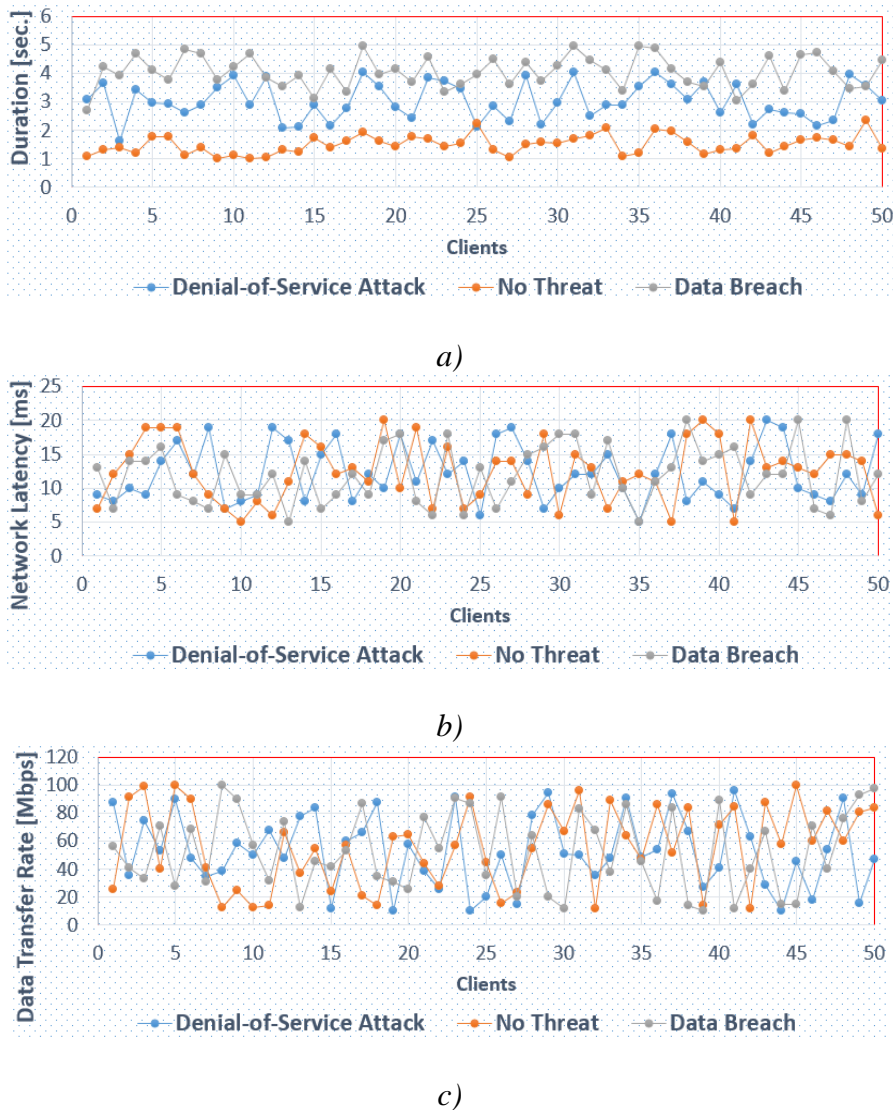


Fig. 4.12. Transmission media parameters a) "Duration ", b) "Network Latency" and c) "Data Transfer Rate" in scenarios of "DoS attack", "Normal traffic state" and "Data breach"

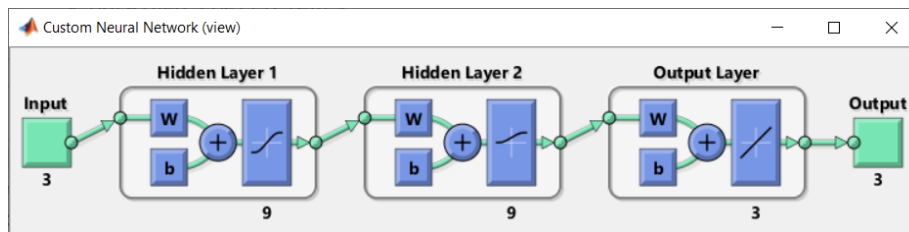
FFNNs and additionally introduced CFNNs neural structures in Table 4.4 and Table 4.5 was studied. After analyzing the quantitative indicators "mean square error" and "classification accuracy", neural architectures with a content of 9, 16, 20 and 17 neurons in the intermediate structural layers were selected, shown in Fig. 4.13. The accuracies of 90.0 %, 86.7 % and 91.7 % were achieved for feed-forward networks with "purelin", "logsig" and "tansig" output transfer functions, and 88.3 % for CFNN with the best validation performance. In the sequence of the indicated order, the minimum readings $MSE = 0.0628$, $MSE = 0.2056$, $MSE = 0.0681$ and $MSE = 0.0714$ were registered.

Table 4.4. Assessment metrics of multilayer FFNNs cyber threats, normal traffic state and data breach diagnostics

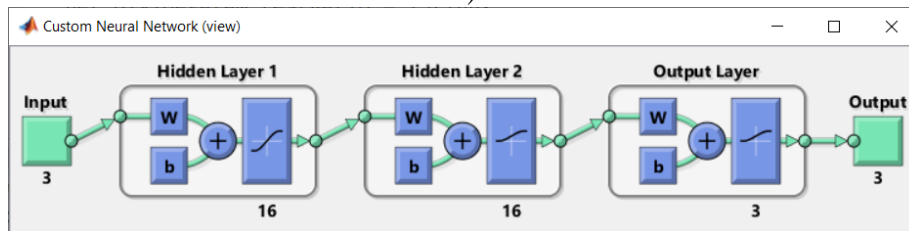
NEURONS IN THE FIRST HIDDEN LAYER	NEURONS IN SECOND HIDDEN LAYER	MSE	ACCURACY, %
“PURELIN” TRANSFER FUNCTION			
5	5	0.0814	76.7
6	6	0.0966	81.7
7	7	0.1276	66.7
8	8	0.1068	76.7
9	9	0.0628	90.0
10	10	0.1364	68.3
11	11	0.1076	75.0
12	12	0.1045	70.0
13	13	0.1001	85.0
14	14	0.0861	81.7
15	15	0.0936	75.0
16	16	0.0978	76.7
17	17	0.1361	75.0
18	18	0.1120	73.3
19	19	0.1338	70.0
20	20	0.0929	85.0
“LOGSIG” TRANSFER FUNCTION			
5	5	0.2151	80.0
6	6	0.2176	70.0
7	7	0.2269	60.0
8	8	0.2155	65.0
9	9	0.2325	70.0
10	10	0.2189	63.3
11	11	0.2265	
12	12	0.2112	80.0
13	13		78.3
14	14	0.2099	80.0
15	15	0.2073	83.3
16	16	0.2056	86.7
17	17	0.2240	60.0
18	18	0.2113	78.3
19	19	0.2237	58.3
20	20	0.2364	60.0
“TANSIG” TRANSFER FUNCTION			
5	5	0.0855	80.0
6	6	0.0838	83.3
7	7	0.1532	66.7
8	8	0.1595	63.3
9	9	0.0855	85.0
10	10	0.0837	80.0
11	11	0.0929	
12	12	0.1269	73.3
13	13	0.0964	75.0
14	14	0.0954	81.7
15	15	0.0595	85.0
16	16	0.0945	83.3
17	17	0.0946	85.0
18	18	0.0738	90.0
19	19	0.0913	81.7
20	20	0.0681	91.7

Table 4.5. Assessment metrics in multilayer CFNN's DoS attack, normal traffic state and data breach detection processes

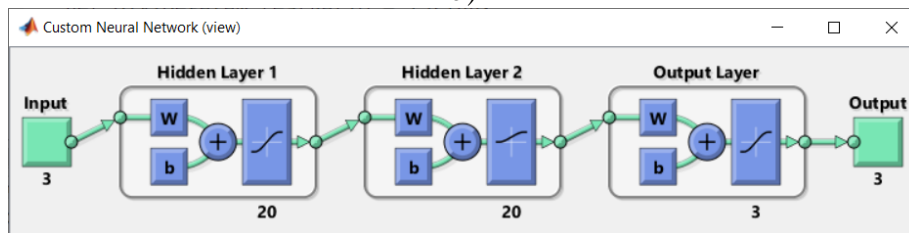
Neurons in the first hidden layer	Neurons in second hidden layer	Mean-squared error	Accuracy, %
5	5	0.0971	75.0
6	6	0.0920	83.3
7	7	0.0803	81.7
8	8	0.0856	83.3
9	9	0.0799	81.7
10	10	0.1152	71.7
11	11	0.0928	81.7
12	12	0.0882	80.0
13	13	0.1066	78.3
14	14	0.10 26	
15	15	0.0879	
16	16	0.0820	
17	17	0.0714	88.3
18	18	0.0869	83.3
19	19	0.0984	81.7
20	20	0.0914	85.0



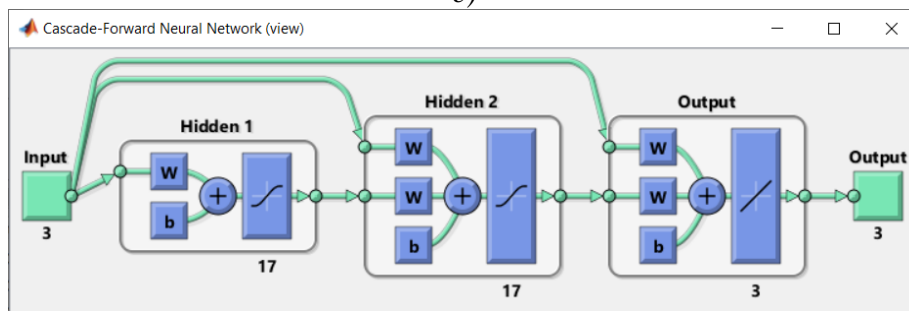
a)



b)



c)



d)

Fig. 4.13. Mullayer FFNNs with a) “purelin”, b) “logsig”, c) “tansig” output activations and d) CFNN “DoS”, “No Threat” and “Data Breach” detection

4.3. Diagnostics of WEB content distribution to corporate clients in urban areas during an active work time zone.

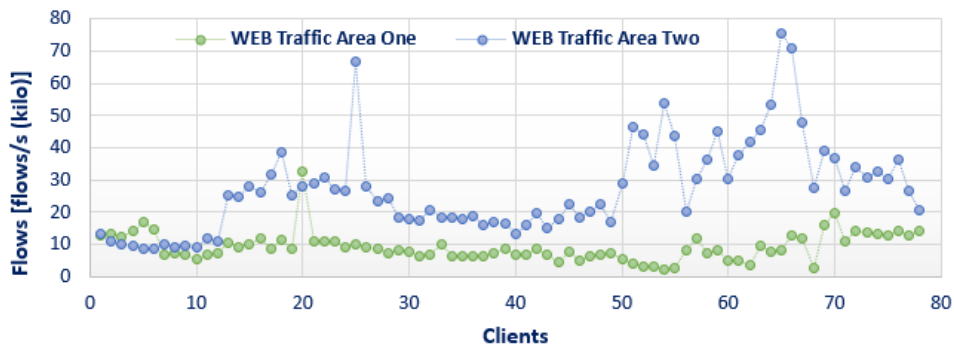
4.3.1. Parameterization of registered WEB traffic to corporate clients.

The task of identifying geographic areas of Internet traffic consumption for corporate clients according to data from the active noon time zone for areas of the city of Chicago (USA) is considered. The analysis is based on an assessment of the main parameters of the WEB traffic in fig. 4.17, as follows:

- Network streams, flows/s (kilo-);
- Mean packet size in IPv4;
- Mean packet size IPv6 ;
- Mean transition rate, pkts/s (kilo-).

Geographical consumption areas are defined Internet services , respectively:

- Class #1: Chicago city area “1”;
- Class #2: Chicago city area “2”.



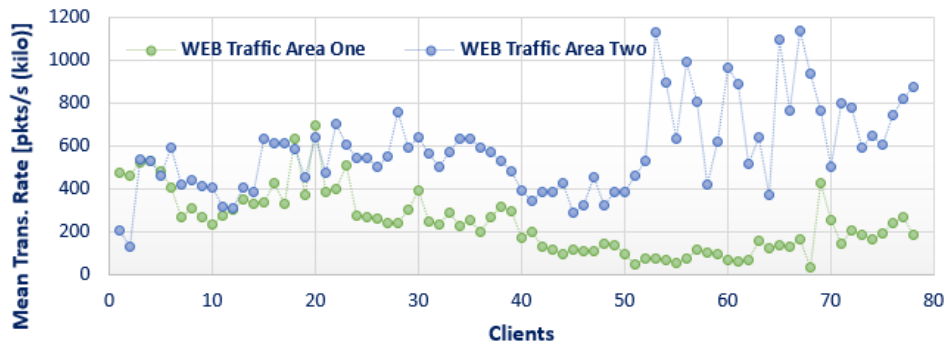
a)



b)



c)



d)

Fig. 4.17. Network traffic parameters registered in packet transmission a) traffic flows, b) packet size in IPv4, c) packet size in IPv6 and d) mean transition rate

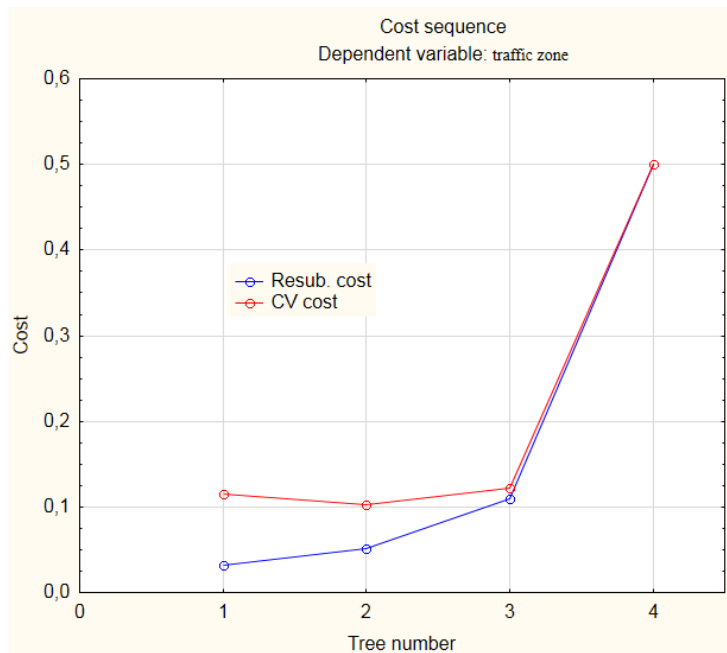
4.3.2. Research on Decision tree method models for identifying Internet consumption areas.

V-fold Cross-Validation and Resubstitution were estimated for the generated base architecture “Tree 1 (model with 7 end nodes)” and architectures with reduced structural nodes, given in Fig. 4.23:

- “Tree 2 (model with 4 end nodes)”;
- “Tree 3 (model with 2 end nodes)”;
- “Tree 4 (model with 1 terminal node)”.

Tree sequence (traffidanni_zones)					
Dependent variable: traffic zone					
Optimal tree denoted by *					
	Terminal nodes	CV cost	CV std. error	Resubstitution cost	Node complexity
Tree 1	7	0,115385	0,025579	0,032051	0,000000
Tree 2	4	0,102564	0,024291	0,051282	0,006410
*Tree 3	2	0,121795	0,026185	0,108974	0,028846
Tree 4	1	0,500000	0,040032	0,500000	0,391026

a)



b)

Fig. 4.23 . Multivariate models for decision making assessment by cross-validation and resubstitution – a) table form and b) graphical form presentation

About the results an increase of accuracy from V-fold validation compared to the resubstitution approach with the exception of the latter structure has been established. The following levels of accuracy have been calculated for the considered models by the Decision tree method, respectively:

- “Tree 1 (base model without reduction of structural nodes)” – from V-fold cross-validation 88.4615% and 96.7949% with resubstitution;
- “Tree 2” – 89.7436% by cross-validation and 94.8718 using resubstitution;
- "Tree 3" – from V-fold cross-validation 87.8205 % and 89.1026 % for resubstitution;
- “Tree 4” – accuracy equal to only 50.00% for the two applied approaches for assessing classification quality.

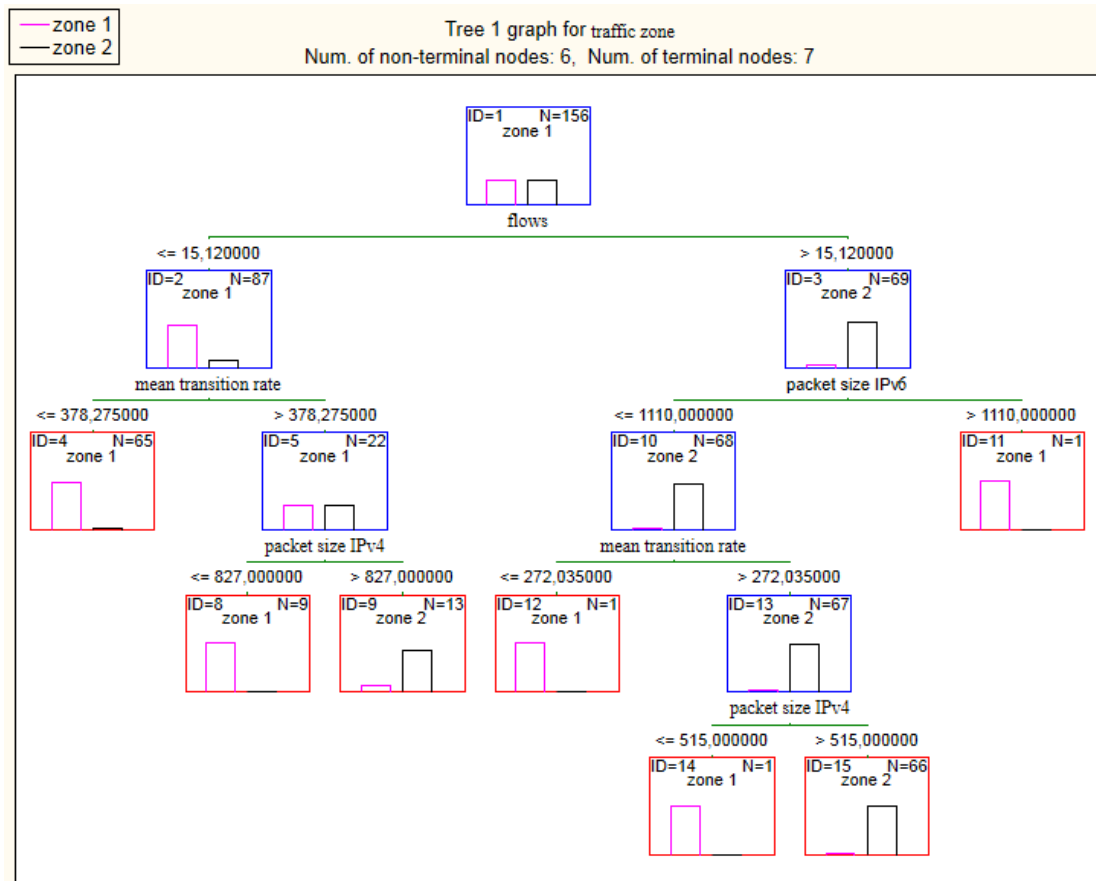


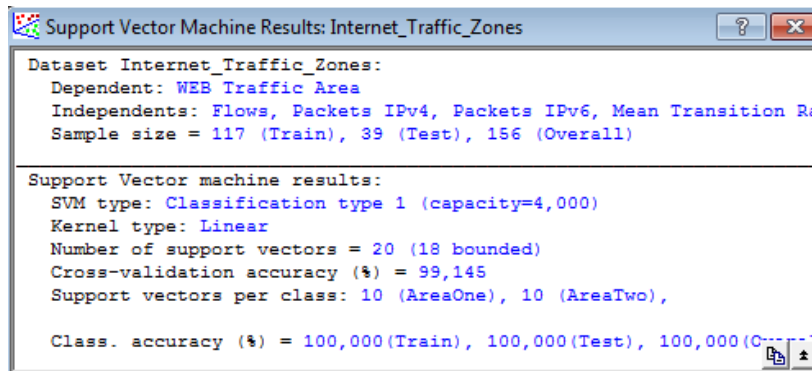
Fig. 4.24 . Multivariate model for decision making in categorization of WEB traffic areas on the basis of statistical traffic metrics

Based on the specified quantitative indicators, an “approximately expected accuracy” can be given for categorization based on traffic data that were not used in training and testing the models – 92.6282% for “Tree 1”, 92.3077% for “Tree 2” architecture and 88.4615% for the “Tree 3” model determined as the optimal model. Considering the obtained final levels and observing the requirement for maximum accuracy, the generated basic tree architecture without removing branches for categorization of Internet consumption areas was selected in Fig. 4.24. The structure contains six internal and seven external nodes and was built without excluding any of the input features after a preliminary assessment of their significance.

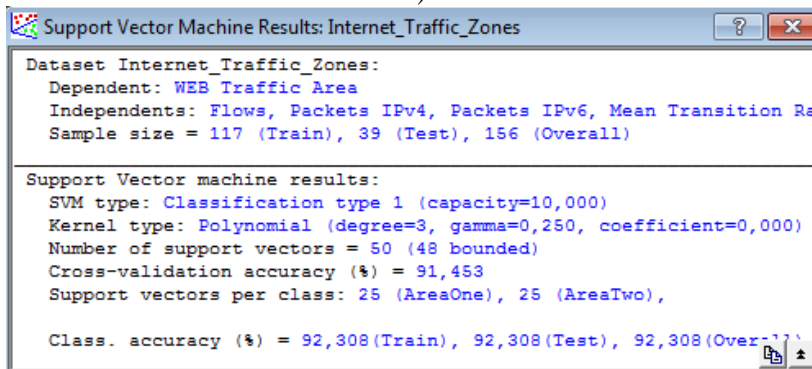
4.3.3. Analysis and evaluation of models using the Support Vector Machine method for recognizing Internet consumption areas.

Support Vector Machine method has been conducted in the context of the task of diagnosing regions of consumption of accessible WEB content in urban environments. Two categories of SVM

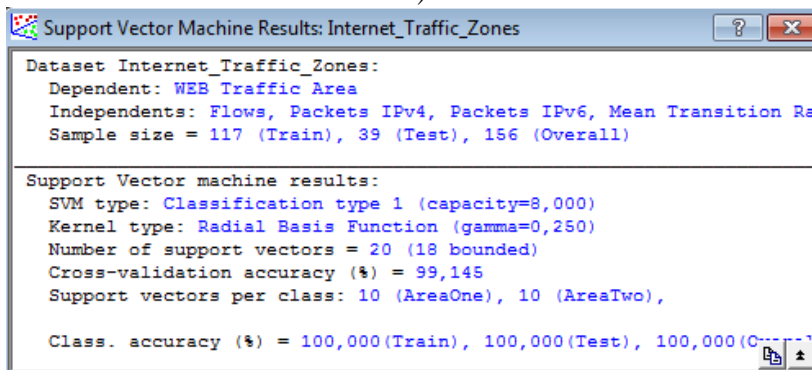
classifiers have been adapted , respectively C-SVM and Nu-SV M. for “Linear”, “Polynomial”, “RBF” and “Sigmoid” type of Kernel functions on Fig. 4.25 and Fig. 4.26.



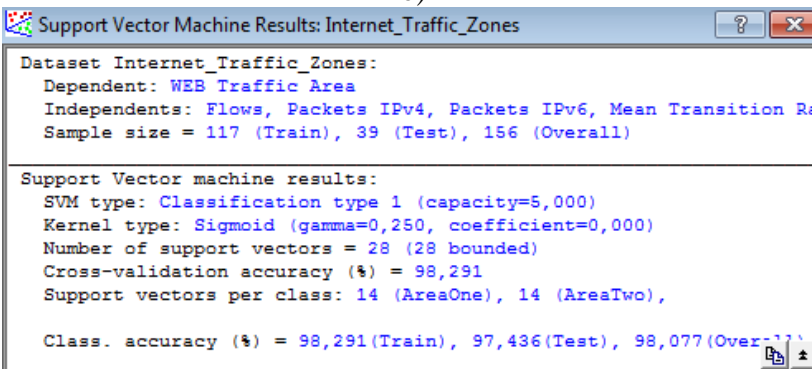
a)



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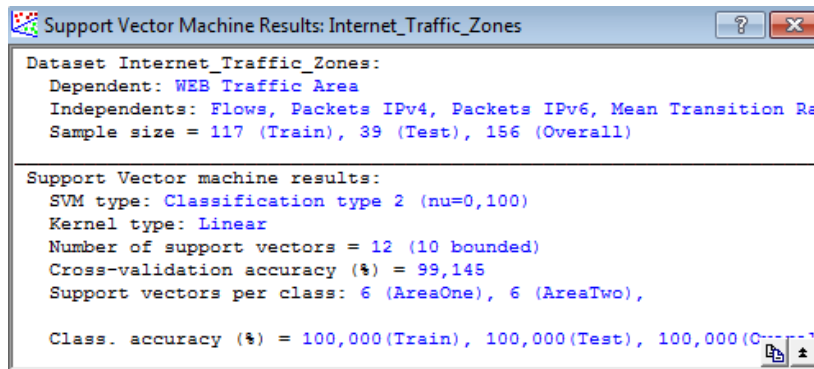


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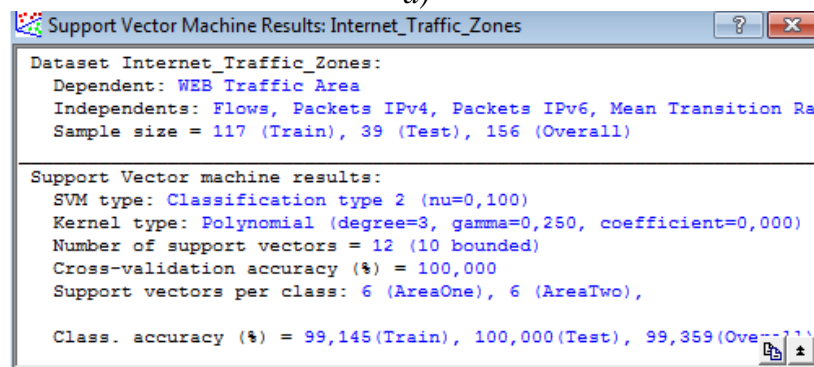
Fig. 4.25. C-SVM classifiers for recognition of WEB traffic areas

The Support vectors for constructing the "Hypersurface" separating the target output groups in the classification space were analytically determined, respectively "20", "50", "20" and "28". The

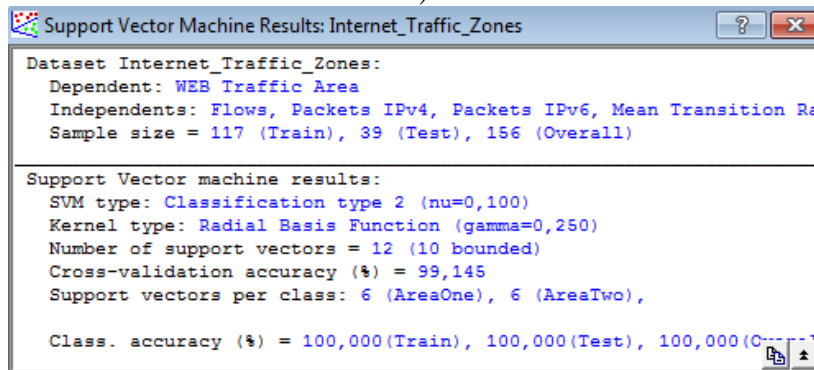
lowest final accuracy was found to be 92.308 % for the C-SVM model with the applied Kernel “Polynomial” function. A complete correct recognition of 100.0 % of the standards participating in the training and testing sample was achieved, coinciding for the cases of “Linear” and “RBF”, while for “Sigmoid” Kernel type the accuracy is 98.077 %.



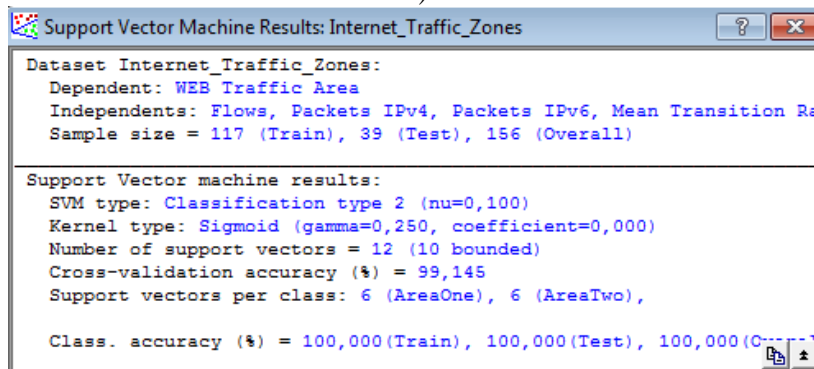
a)



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Fig. 4.26. Nu-SVM classification models for WEB traffic areas identification

The possibility of adapting Nu-SVM classification models has been evaluated with some advantage with respect to similar types of Kernel functions. Maximum recognition threshold of 100.0 % is reached for “Linear”, “Radial Basis Function” and “Sigmoid” functions. The final accuracy obtained with the Nu-SVM model with the “Polynomial” Kernel type set to 99.359 %.

4.3.4. Analysis of the effectiveness of linear and quadratic discriminant classifiers for diagnosing WEB traffic to corporate clients.

A “Linear” and “Quadratic” types of discriminant classifiers has been made, summarized in Table 4.12. Listed in sequential order: “Linear”, “Diagonal Linear”, “Pseudo - Linear”, “Quadratic”, “Diagonal Quadratic” and "Pseudo - Quadratic" classification models have been evaluated. The results of the studied discriminant models were evaluated, showing good and close efficiency above 85.0%. The lowest classification accuracy of 87.82 % was reported for the cases of "Diagonal Linear" and "Diagonal Quadratic" discriminant type. The best adequacy to the specificity of the classification task was established with the “Pseudo-Linear” model, expressed with a quantitative estimate of 90.38 %.

Table 4.12. Metrics for evaluating Discriminant Classifiers
WEB content distribution zones

Type of Discriminant classifier	Cross validation error	Cross-validation accuracy, %
Linear	0.1026	89.74
DiagLinear	0.1218	87.82
PseudoLinear	0.0962	90.38
Quadratic	0.1154	88.46
DiagQuadratic	0.1218	87.82
PseudoQuadratic	0.1026	89.74

A set of specific statistically calculated parameters was derived in the course of the study of the Discriminant Classifiers of Fig. 4.31, as having the highest ("Pseudo-Linear") and the lowest achieved efficiency ("Diagonal Quadratic"). The composition of specific variables, including "Gamma", "Delta", "Sigma", “Mu”, etc., was analyzed.

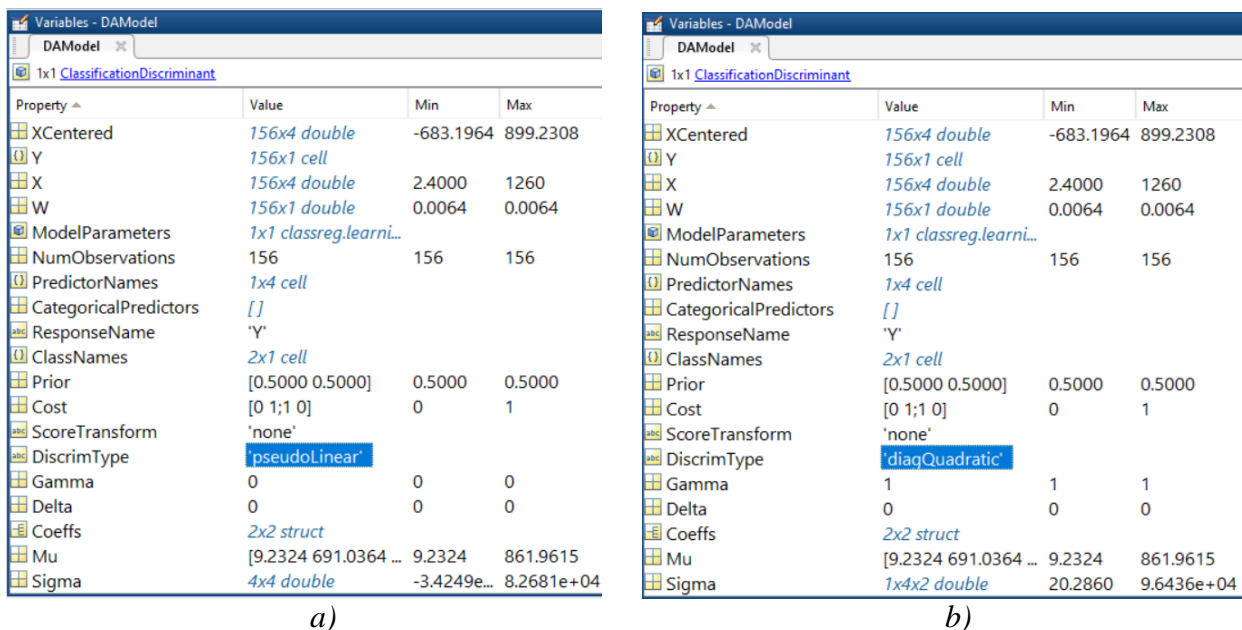


Fig. 4.31. Statistical metrics in the investigation of a) “Pseudo-Linear” and b) "Diagonal Quadratic" discriminant model

4.3.5. Synthesis of multilayer FFNNs with a “hyperbolic tangent sigmoid” transfer function in the output neurons for WEB traffic diagnostics.

A systematization and evaluation of the variations of the selected criteria "Accuracy", "MSE" and "MAE" was carried out when analyzing the effectiveness of FFNNs based on applied ratios between the computational units in structural hidden layers, respectively "1:1", "1:2" and "2:1", presented in Table 4.17 to Table 4.19.

In relation to the first applied ratio between the neurons in the first and second hidden layer, a minimum of 56.5% and a maximum accuracy of 100.0 % were recorded for models with 10 and 7 to 9 intermediate computational units. The mean-squared error was found to be the lowest 0.0017 and the highest value 0.2628, respectively, for 8 and 10 hidden neurons. The minimum and maximum MAE found are equal to 0.0200 and 0.2684, established for the same FFNNs regarding the previous quality indicator. According to the presented results, a neural architecture with the presence of 8 neurons in the structural hidden layers was selected, shown in Fig. 4.40.a).

Table 4.17. Evaluation of FFNNs in deep learning WEB traffic areas identification in ratio between neurons in hidden layers 1:1

No.	Hidden layer #1	Hidden layer #2	Accuracy, %	MSE	MAE
1.	3	3	95.7	0.0397	0.1007
2.	4	4	78.3	0.1134	0.1821
3.	5	5	65.2	0.1855	0.2070
4.	6	6	95.7	0.0393	0.0627
5.	7	7	100.0	0.0151	0.0436
6.	8	8	100.0	0.0017	0.0200
7.	9	9	100.0	0.0222	0.1061
8.	10	10	56.5	0.2608	0.2684
9.	11	11	95.7	0.0463	0.0669

Table 4.18. Investigation of FFNNs in deep learning WEB traffic areas recognition in ratio between neurons in hidden layers 1:2

No.	Hidden layer #1	Hidden layer #2	Accuracy, %	MSE	MAE
1.	3	6	95.7	0.0531	0.0609
2.	4	8	95.7	0.0451	0.0641
3.	5	10	47.8	0.2681	0.2848
4.	6	12	95.7	0.0558	0.0900
5.	7	14	87.0	0.1142	0.1811
6.	8	16	43.5	0.4134	0.4874
7.	9	18	100.0	0.0263	0.1145
8.	10	20	95.7	0.0244	0.0616
9.	11	22	95.7	0.0317	0.1211

Regarding the second considered ratio, two architectures were found, in which accuracy below the level of 50.0 % was obtained, as follows: 43.5% with 8 in the first and 16 neurons in the second hidden layer and 47.8% for FFNN with 5 in the first and 10 hidden neurons in the second layer. A single achievement of complete correct recognition of the processed information traffic samples was noted - accuracy 100.0 %, with a structure with 9 and 18 neurons in the first and second intermediate layers. Within the described case, minimum MSE = 0.0263 and MAE = 0.1145 were also registered. Maximum levels of mean-squared error 0.4134 and average absolute error 0.4874 were observed for the neural architecture with “8 in the first and 16 neurons in the second intermediate layer”. The analysis of the results shows the advantage of FFNN with nine in the first and eighteen intermediate

neurons in the second hidden layer (Fig. 4.40.b)). However, considering the many times lower degrees of MSE and MAE in the first considered case in the procedural synthesis, its use turns out to be more appropriate.

Table 4.19. Examine the quality of FFNNs in deep learning WEB traffic areas identification in ratio between neurons in hidden layers 2:1

No.	Hidden layer #1	Hidden layer #2	Accuracy , %	MSE	MAE
1.	6	3	52.2	0.2394	0.2468
2.	8	4	87.0	0.0774	0.1402
3.	10	5	39.1	0.3102	0.3378
4.	12	6	95.7	0.0327	0.0792
5.	14	7	91.3	0.0859	0.1137
6.	16	8	95.7	0.0506	0.1303
7.	18	9	91.3	0.0671	0.1124
8.	20	10	82.6	0.1600	0.2364
9.	22	11	100.0	0.0073	0.0345

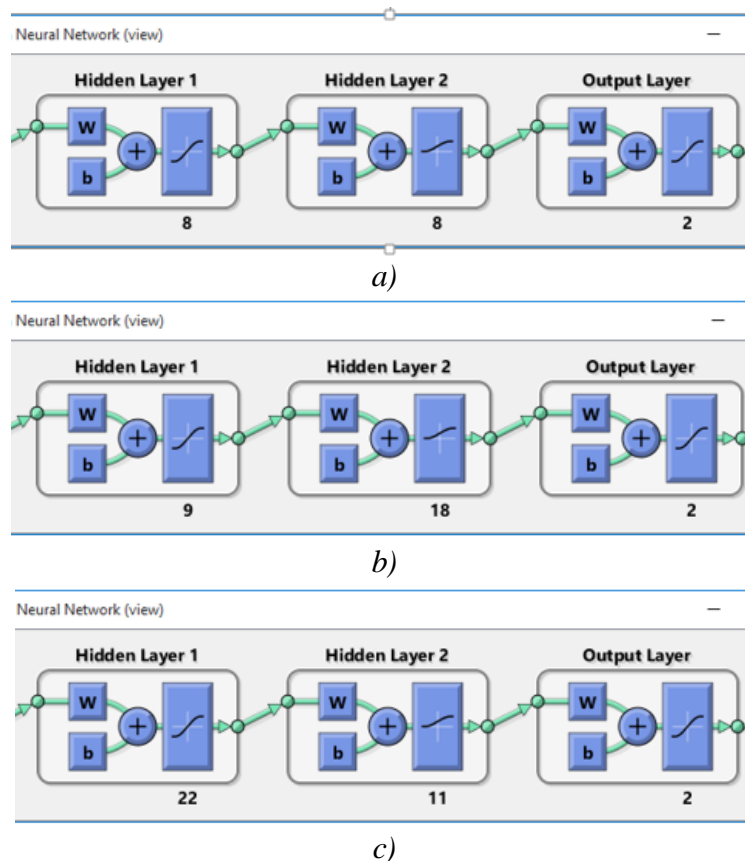


Fig. 4.40. Selected FFNNs for WEB traffic areas identification in ratios between neurons in hidden layers a) "1:1", b) "1:2" and c) "2:1"

According to the last applied quantitative ratio between the neurons in the hidden layers, a combination was again established, in which the correct identification of the target areas of corporate Internet consumption was achieved. This is an FFNN with the presence of 22 and 11 neurons, respectively in the first and second hidden layers of Fig. 4.40.c). With respect to the indicated neural structure, the lowest levels of MSE = 0.0073 and MAE = 0.0345 were registered. The highest upward variations of the errors MSE = 0.3102 and MAE = 0.3378 were found in an architecture in which 10 computing units were used for the first and 5 intermediate neurons for the second hidden layer. Of

the considered cases of neural synthesis, the lowest classification accuracy was found here, falling in the order of 39.1 %.

Comparing the error rates, it can be said that FFNNs with a ratio of "2:1" have better qualities than those built on the basis of a ratio of "1:2". Evaluating the synthesized final models of traffic zone identification, the architecture with an identical number of neural computing units in the intermediate layers is determined as the model with the highest network performance .

The network error diagrams were generated in Fig. 4.42, representing the variations of the differences between the theoretically assumed and the results calculated using the synthesized multilayer models when manipulating the data included in the test dataset.

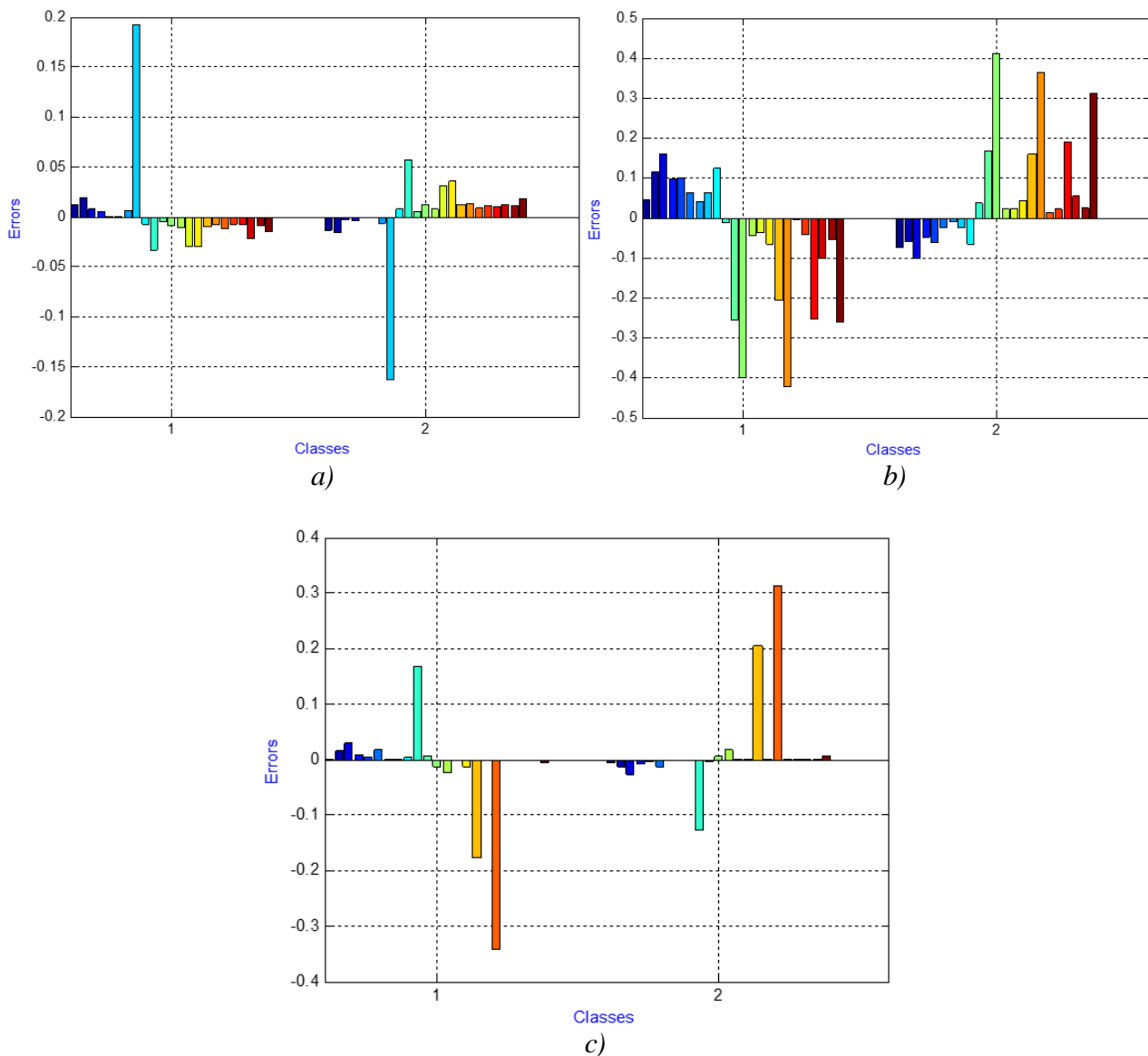


Fig. 4.42. *Errors diagrams for selected FFNNs about WEB traffic areas recognition in ratios between neurons in hidden layers a) "1:1", b) "1:2" and c) "2:1"*

In the analyzed multilayer neural models for identifying areas of corporate Internet consumption, the following variation ranges were established, as follows:

- -0.1627 to 0.1928 for FFNN with a "1:1" ratio between neurons in the intermediate layers;
- -0.4241 to 0.4119 regarding the model when setting 9 in the first and 18 computational units in the second hidden layer;
- -0.3428 to 0.3130 for the multilayer neural architecture with a hidden layer ratio of "2:1" used.

According to an assessment of the observed variations in network errors, the advantage of the model with an identical number of neurons in the two intermediate layers stands out, followed by neural architectures with an applied ratio of "1:2" and "2:1". The presented errors confirm the advantages of the first alternative for the distribution of neural computing units for the considered identification task.

4.4. Conclusions to Chapter IV.

- An approach is proposed for diagnosing network traffic and detecting attacks when transmitting UDP packets to corporate clients with the inclusion of Feed-Forward in SCG and LM training with different output activations, Cascade-Forward and Probabilistic neural machines with an established advantage of PNN;
- The effectiveness of introduced Machine Learning approaches based on Discriminant Analysis, Naïve Bayes Algorithm, Decision Tree and k – nearest neighbors in detecting attacks on transmitted UDP traffic was analyzed with a relatively low accuracy threshold of about 67.0%;
- Deep Learning was evaluated using Feed-Forward architectures with an identical number of neurons in the hidden layers and different output activation functions for recognizing UDP traffic under attack, with a significant advantage over using ML tools being established;
- A verification of the adequacy of the principles of "Deep Learning" was carried out in an introduced approach for diagnosing the served network traffic between corporate clients in order to detect cyber threats and network anomalies;
- FFNN, k-NN, CART Decision tree, SVM and Naïve Bayes models was carried out using STATISTICA and MATLAB for the classification of geographic areas of Internet consumption in an urbanized city environment with the highest efficiency achieved with the Naïve Bayes Algorithm;
- Feed-Forward with different output activations, have been studied. and Probabilistic neural networks for analyzing the distribution of WEB content to corporate clients with the highest accuracy achieved 100.0% with PNN;
- An approach is proposed for different ratios between neurons in the intermediate layers in Deep Learning Multilayer Feed-Forward for identification of Internet service access zones to corporate clients in an urbanized urban environment with the highest efficiency established at a ratio of 1:1 for tangent-sigmoidal and linear output activation functions.

CONCLUSION

The dissertation proposes a complex strategy for monitoring and diagnosing noises , parameterization and network resources of transmission media , as well as assessing the state and consumption of the served streams of transmitted packet data. Systematic activities have been carried out to adapt, modify and develop hybrid analytical modules for data mining with the implementation of a significant spectrum of tools based on AI, ML and DL technologies.

The proposed strategy is characterized by a wide potential integration, both in local systems with relatively autonomous functioning, and in large-scale telecommunication systems and information and communication infrastructures for administering network traffic from the planning stage to operation. The absence of a regulated commitment to specific technical requirements for: "structural communication segments"; "transmission media type"; "path length"; "network communication management standards"; "number of users served" and "broadband access technology", forms the basis for a high degree of technical implementation.

There are significant opportunities for integration targeting small, medium and large corporate clients and administrative centers and clusters in the field of information services, Internet service providers and network operators. Future technical prospects for improving the scope of research can be summarized in the following areas:

- inclusion of additional objects and processes in the context of classification and predictive analysis tasks in terms of cybersecurity management when ensuring access to electronic resources and services;
- expanding the scope of the used optimization methods and algorithms for searching for extrema in relation to complex performance indices of the transmission environment and assessing the traffic load of the serving network servers, distribution units and system modules.

CONTRIBUTIONS OF THE DISSERTATION WORK

Scientific-applied contributions:

- The advantages of the developed approach with C-SVM, Nu-SVM, k-NN, ANFIS, CFNN, PNN and Naïve Bayes classifiers for recognizing Gaussian White Noise and Periodic Random Noise with FFT and without prior spectral analysis in simulation-modeled transmission media are proven;
- amplitude variance prediction of Uniform White Noise and Periodic Random Noise over analog and digital signals in a simulated communication environment has been established ;
- System Throughput and System Response Time are proposed by Regression analysis and GRNN, FFNN with LM, BR and SCG learning algorithms, RBNN and CFNN with proven effectiveness with controllable factors;
- A methodology has been developed, evaluated and implemented regarding the effectiveness of Interior-point, Sequential Quadratic Programming , Active-set and Genetic algorithms for optimization of the network environment parameter System Response Time in a simulated ICT infrastructure;
- normal and network traffic attacks based on the UDP communication protocol has been proven;
- Methods for implementing analytical tools FFNN, k-NN, CART Decision Ttree, SVM, Naïve Bayes, PNN and Multilayer FFNNs with different ratios between neurons in hidden layers and transfer functions in network output layers for identification of WEB traffic in urban area.

Applied contributions:

- spectral analysis and descriptive statistics for feature extraction in the synthesis of classification and prediction models has been established;
- A program implementation and experimental studies with a simulation modeling algorithm are proposed and queuing is proven. teletraffic systems performance in user service;
- The effectiveness of Descriptive analysis has been confirmed for metric assessment of incoming network traffic in packet transmission diagnostics.

LIST OF PUBLICATIONS ON THE DISSERTATION WORK

1. Balabanova I., **Zhorova T.**, Georgiev G., "Internet Traffic Analysis by ANFIS, k-Nearest Neighbors and Decision Tree Approach". Proceedings of the University of Ruse, vol. 61, book 3.2, FRI-2G.302-1-CCT2-01, pp. 44-51, 2022. ISSN: 2603-4123 (online), ISSN: 1311-3321 (print), ROAD Database. Best Paper Award!
2. Balabanova I., **Zhorova T.**, "Traffic Information Analysis Using Deep Learning Artificial Neural Networks". Proceedings of International Scientific Conference UNITECH'22, 18 – 19 November 2022, Gabrovo, Bulgaria, pp. I-173 - I-178, 2022.
3. Balabanova I., **Zhorova T.**, Georgiev G., "Amplitude Noise level Prediction in Signals with Noises by Statistics Extraction and CFNN Techniques". AIP Conference Proceedings - 2nd International Conference on Electronics, Engineering Physics and Earth Science, EEPES'23, vol. 3063, issue 1, pp. 1-10, 2024. ISSN: 0094243X, ISBN: 978-073544856-8, DOI: 10.1063/5.0196146, Scopus SJR 0.152 (2023).
4. Balabanova I., **Zhorova T.**, Georgiev G., "Internet Traffic Zone Identification by Backpropagation and Probabilistic Neural Networks". Proceedings of 14th International Scientific and Practical Conference "Environment. Technologies. Resources", vol. 2, pp. 12-17, 2023. ISSN; 2256-070X, ISBN: 978-171387488-1, DOI: 10.17770/etr2023vol2.7265, Scopus.
5. Balabanova I., Georgiev G., **Zhorova T.**, "WEB Traffic Monitoring by Descriptive Statistics and Multilayer Neural Networks". Proceedings of the University of Ruse, 27-28 October 2023, Ruse, Bulgaria, vol. 62, book 3.2, FRI-2G.302-1-CCT2-08, pp. 125-133, 2023. ISSN: 2603-4123 (online), ISSN: 1311-3321 (print), ROAD Database.
6. **Zhorova T.**, "Synthesis of Predictive Models for Network Traffic with FFNNs and Training Algorithms Selection". Proceedings of International Scientific Conference UNITECH' 23, 17 - 18 November 2023, Gabrovo, pp. I-211 - I-216, 2023.
7. **Zhorova T.**, Kosev K., Petkova A., Penchev I., Ganchev Ts., "Monitoring of Network Traffic Parameters with Artificial Intelligence". Proceedings of " Student Scientific Session 24", 18 October , Gabrovo , Vol. I, pp. 78- 83 , 2024, ISSN: 1313-3055.

PARTICIPATION IN INTERNAL PROJECTS

1. Project No. **SRP2025-6 "TRANSMISSION MEDIA INVESTIGATION AND BUSINESS PROCESSES MODELING WITH MACHINE LEARNING IN COMMUNICATIONS"** to Faculty of Electrical Engineering and Electronics with scientific supervisor Assoc. Prof. Ivelina Stefanova Balabanova, PhD for 2025.
2. Project No. **2406E "NETWORK TRAFFIC AND DATA ACCESS MONITORING BY BIOMETRIC DIAGNOSTICS WITH ARTIFICIAL INTELLIGENCE"** to Faculty of Electrical Engineering and Electronics with scientific supervisor Assoc. Prof. Georgi Ivanov Georgiev, PhD for 2024.
3. Project No. **2305E "ICT-BASED SYSTEMS DEVELOPMENT FOR TRAFFIC AND USER ACCESS INVESTIGATION AND MONITORING WITH ARTIFICIAL INTELLIGENCE"** to Faculty of Electrical Engineering and Electronics with scientific supervisor Assoc. Prof. Georgi Ivanov Georgiev, PhD for 2023.

TRAFFIC MONITORING IN COMMUNICATION SYSTEMS WITH ARTIFICIAL INTELLIGENCE

Mag. Eng. Teodora Valentinova Zhorova

ABSTRACT

Dissertation integrates complex methods for adapting Artificial Intelligence instruments in the context of considered scenarios for monitoring and diagnostics of the network resources in communication systems. The scientific research scope is aimed at Hybrid analytical models developing by Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) for noise impact analysis, performance indices, transmission media security and traffic services assessment. Objects of research about the state of communication channels are Gaussian White Noise, Periodic Random Noise and Uniform White Noise as independent and present effects to Analog and Digital signals. The specified types of interference are analyzed on the basis of synthesized AI and ML classification and predictive models about their Noise amplitude variance analysis in the conditions of a simulated network environment. The transmission media state in ICT infrastructures simulated with queue management systems of Incoming and Outgoing traffic streams is evaluated with the inclusion of Statistics, AI and ML techniques for Regression modeling and diagnostics. Predictive analysis and Non-linear optimization objects are the specific metrics of the network environment such as "System Throughput" and "System Response Time". Technical approaches with AI and DL modules for ensuring Cybersecurity and Information Security are proposed when servicing UDP network traffic between corporate clients. The verification of the developed modules for network diagnostics is based on the states of "Denial-of-Service Attack", "No Threat" and "Data Breach". A methodology for monitoring the state when prioritizing WEB traffic in active time zones for corporate clients based on hybrid AI, ML and DL modules, applicable to the structures of Media Service Providers and WEB Traffic Data Providers has been introduced.

Keywords

Artificial Intelligence; Machine Learning; Deep Learning; Analytics; Noise Effects Assessment; Traffic Diagnostics; Optimization of Transmission Media; Cybersecurity and Information Security.