<u>TECHNICAL UNIVERSITY OF GABROVO</u>

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DETECTION AND ANALYSIS THROUGH COMMUNICATION CHANNELS OF THE PHYSICAL CHARACTERISTICS OF METALS BY USING OF ULTRASONIC SENSORS

A U T H O R ' S   S U M M A R Y

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The materials related to the dissertation are available for those who are interested in Room 3209, University Campus №3 of the Technical University of Gabrovo.

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I. GENERAL CHARACTERISTICS OF DISSERTATION

Relevance of the problem:

Measurements of force loads applied to metal parts, structures and equipment through intelligent sensor networks is an urgent task for modern industry. Some areas may be mentioned, such as:

- ❖ Mechanical Engineering and Metallurgy in the manufacture and testing of metal components and functional structures;
- ❖ Construction and construction-repair activities;
- ❖ Shipbuilding and Automotive;
- ❖ Railway transport;
- ❖ Control of aircraft;
- ❖ Agricultural activities and Agriculture;
- ❖ Development of products, components and complex systems for testing biomedical equipment intended for various sectors of medicine;
- ❖ Communications during laying, construction and maintenance of communication cable routes, monitoring of mechanical loads at base and mobile stations, etc.

Given the undesirable overlap of various interferences and noises in the communication channels, an important task related to the quality of recorded measurement information is to ensure the data transfer from the input nodes with functional transducers of the used sensor networks and systems. This is necessary in connection with the adequate functioning and adaptability of the subsequent system modules for visualization and correct analysis of the processed information arrays of procedures for parametric remote monitoring. For this purpose, it is necessary to use appropriate statistical tools and apparatus for noise reduction, diagnostics of the type and degree of impact, as well as forecast analysis of its quantitative measurability in relation to the analyzed measurement information.

Another important point is related to determining the volume of traffic from sensor data and specific parametric information, which can be served by the information and communication modules in their design and optimization of their system resources. In this regard, approaches for qualitative and quantitative analysis can be modified and created by adapting methods and algorithms from applied statistics and artificial intelligence. Here arises the need to search for and determine appropriate types of artificial neural networks, training algorithms and parameters, criteria for their evaluation and verification procedures, confirming the reliability of the choice of a particular device.

Methods of the research:

In order to achieve the goal and the tasks set in the research, the technology of artificial intelligence and classical regression analysis is applied in extracting knowledge from data when processing measuring sensory information in connection with applied load forces, unwanted noise and passing traffic in communication channels.

Newnesses:

A methodology for identification of working measuring transducers, types of interfering influences and quantification of forces of influences on tested metal samples and estimated serviced traffic from measuring and service data based on artificial intelligence and different training algorithms is proposed.

Aim and tasks of the dissertation:

The aim of the dissertation is to develop a software monitoring system for measuring and researching applied forces on metal parts, objects and structures to ensure the transmission medium and processing of incoming traffic of registered measurement data sensory data integrating the concept of qualitative and quantitative of information through artificial intelligence.

In connection with the defined goal of the dissertation, the following tasks are set for implementation:

1. To train and synthesize artificial neural networks of simulated noise effects superimposed on the transmission of signals in communication channels for communication in a simulation environment at Levenberg-Marquardt training when experimenting with activation functions.
2. To select models for identification of added impacts in digital signal transmission in electronics, automation and communications based on artificial neural networks when operating with Levenberg-Marquardt training algorithm by experimenting with activation functions.
3. To conduct training procedures on artificial neural networks with the right propagation of signals and back propagation of the error in Scaled Conjugate Gradient training algorithm for recognizing the type of interference in communication channels.
4. To design and test the performance of a system for measuring forces applied to tested metal parts, including signal processing and statistical analysis units based on the concept of a "virtual laboratory".
5. To create neural models for recognition of working measuring means for registration of forces on metal objects on the basis of SCG and LM training algorithms in selection of the input variables applied to the models.
6. To synthesize and verify models for predictive analysis of applied force effects on metal parts, created on the basis of artificial intelligence in Levenberg-Marquardt training algorithm.
7. To derive linear regression models for predictive analysis of applied forces on metal objects with different number of included working measuring transducers.
8. To derive mathematical models of different degrees on the basis of regression analysis to predict the amount of processed requests with packet information and the time for their service in simulated telecommunications systems.
9. To implement procedures for creation, evaluation and verification and generalized regression neural networks and FCNN architectures for forecast analysis of the potential number of client requests with packet data when experimenting with the used controllable factors.
10. To synthesize FFNN neural models for predictive analysis of potential processed traffic from client requests with packet data at different combinations of controllable factors and training algorithms - Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient.

Area and object of the study about dissertation:

The dissertation considers these tasks as a single set of consecutive studies aimed at creating, synthesizing and deriving models for identification and predictive analysis in the operation of simulation and actual experimental data. The following **subject area of research** is considered: "industrial directions for testing of metal objects with integration of information and communication technologies".

Accordingly, the area defined in this way is focused on the following **object of study**: "system for testing metal objects subjected to different loads, and ensuring the processes of signal transmission in terms of minimizing noise and random effects and planning the volume of processed applications, containing measurement and specific information".

Approbation of dissertation:

The main stages of the dissertation are presented at international scientific conferences at the Technical University of Gabrovo, Technical College of Lovech, International Scientific Conference on Communications, Informatics, Electronics and Energy Systems "CIEES", international journals "Journal of Engineering Science and Technology Review" and Advances in Intelligent Systems and Computing, indexed to international **Scopus** and **IEEE** databases.

II. SHORT CONTENT OF DISSERTATION

CHAPTER I: SENSOR TECHNICAL EQUIPMENT AND AI BASED MODELS FOR ANALYSIS OF ANALYSIS OF TRANSMITTED SIGNALS AND PARAMETRIC INFORMATION

1.3. Applied technical approaches for digital signal processing and noise reduction in communication channels

Signal processing can be considered as a set of processes of sequential conversion of signals in order to reduce the effect of noise and improve quality. Different processing methods are applied, which can be divided into the following categories:

- Analog Signal Processing (ASP);
- Digital Signal Processing (DSP);
- Processing of continuous signals over time;
- Processing of discrete signals over time;
- Nonlinear Signal Processing (NSP).

In turn, DSP methods are divided into:

- Non-parametric methods:
  - Analysis in the frequency domain;
  - Time domain analysis.
- Parametric methods:
  - Models with sinusoidal functions;
  - Stochastic models.
- Hybrid methods:
  - Combined and Innovative methods;
  - Recursive methods.

DSP technical approaches include a wide range as some of the better known ones are presented in fig. 1.11.

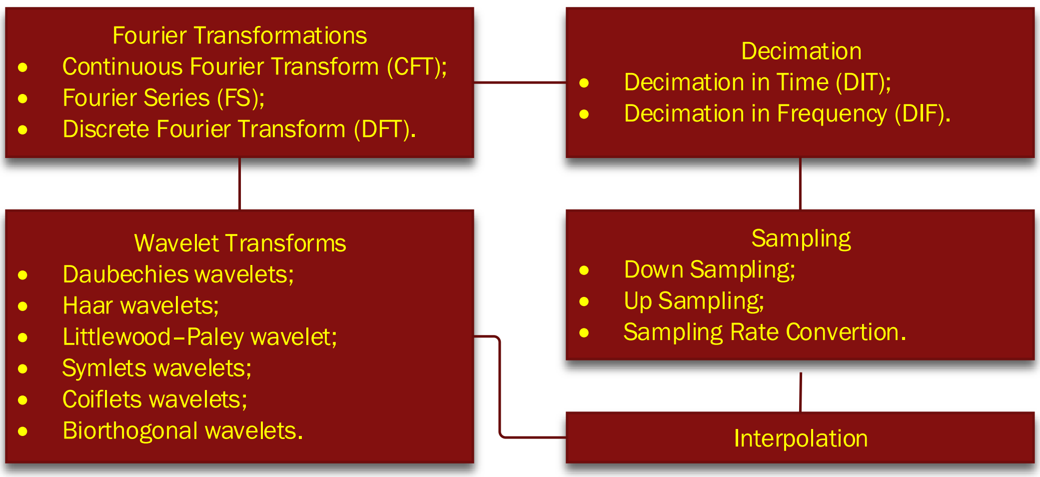


Fig. 1.11. *Some more well-known technical approaches to digital signal processing*

A significant problem in communications is the noise generated in the communication channels during the transmission of signals leading to significant changes in their form, whether analog or digital. White Noise (WN), Correlated Noise (CN) and other types of effects can occur and be superimposed.

This requires the application of various filtration methods, which can be grouped into two main categories:

- Infinite Impulse Response filters - IIR units (filters with infinite impulse response);
- Finite Impulse Response filters - FIR units (filters with final impulse response),

which are presented in fig. 1.12.

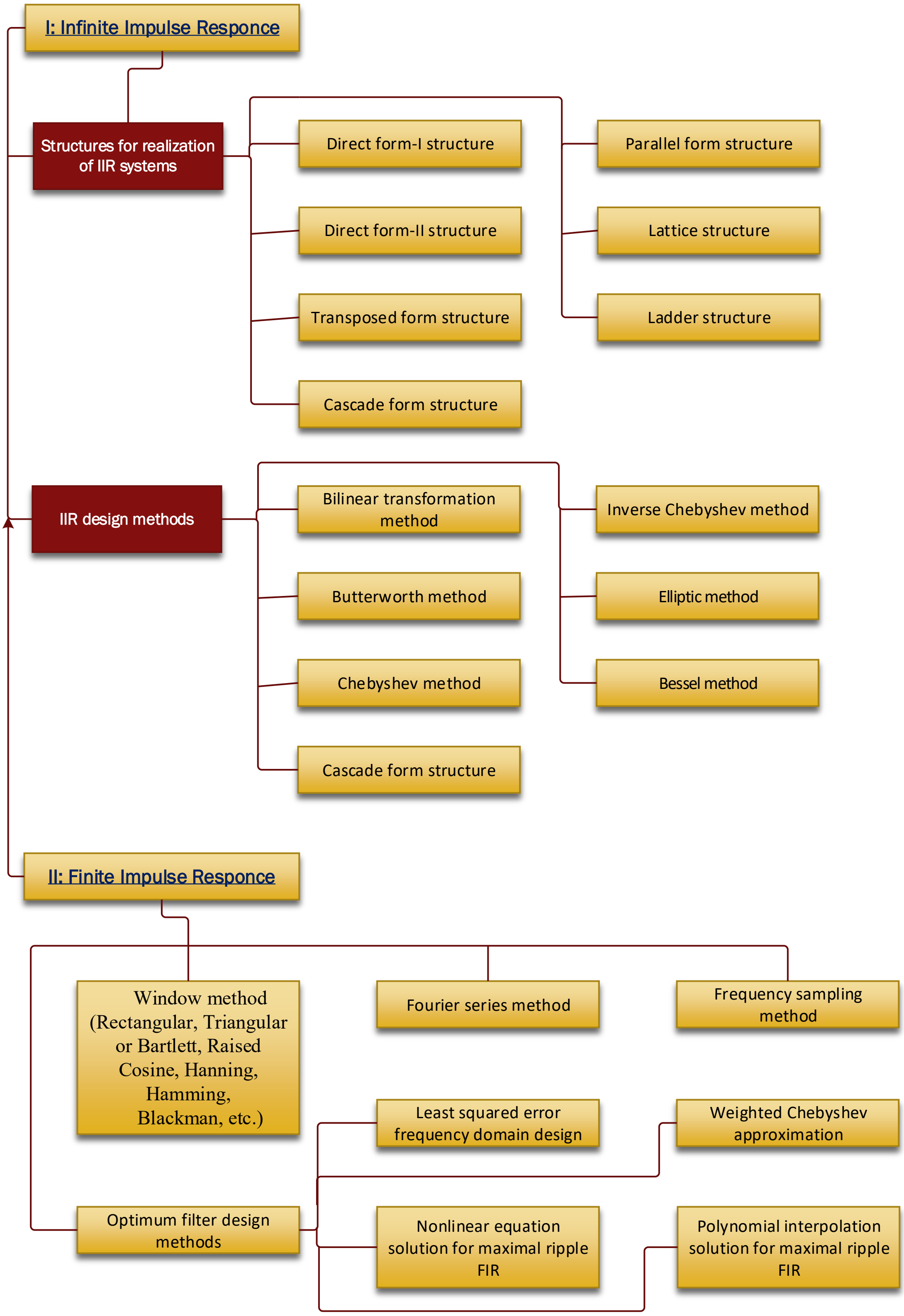


Fig. 1.12. *Methods for designing IIR and FIR filter sections*

Another possibility to reduce the effect of noise and improve the quality of transmitted signals in severely affected communication channels is associated with the use of:

- synchronous detection methods;
- technical approaches for extended spectral analysis;
- complex periodic signals;
- wavelet transformation.

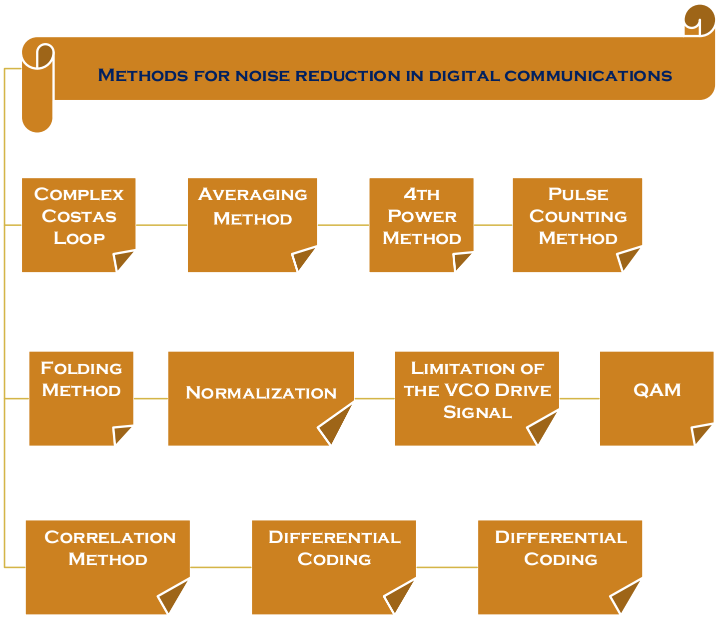


Fig. 1.13. *Noise suppression methods in system devices in communications*

Improving the specific signal-to-noise ratio through the synthesis of linear prediction filters and adaptive digital filters is also seen as a technical tool in this direction. The application of technical approaches to stabilize the minimum root mean square error achieves satisfactory levels of all noise levels in different categories of communication systems. The combination of technologies for multiple access to the communication channels TDMA, OFDMA, FDMA in the implementation of iterative communication receivers can achieve significant suppression of nonlinear distortions. The effect of undesirable disturbances can also be compensated by a method combining the approaches - Discrete Cosine Transform (DCT) and Discrete Sine Transform (DST).

From a different point of view, a significant problem in a number of communication devices is related to limiting their sensitivity to noise. This requires the use of methods to achieve this effect. For the purpose of Fig. 1.13 a systematization has been made, mainly affecting the field of digital communications.

1.5. Measurement of force effects. Sensor elements

1.5.1. Areas of application of force measurements on objects

Measurements of forces on details and the development of technologies in terms of the technical sensor elements and measuring instruments used are becoming more widespread in various fields of industry. The problem is particularly affected during the separate stages of steel production and testing in large metallurgical companies and enterprises. Apart from steel production, other industrial areas that can be mentioned are:

- *Agricultural industry;*
- *Sophisticated systems for testing loads in large-scale complex metal structures and structures such as bridges and cranes;*
- *Automotive industry - trucks and platforms;*
- *Rail transport - testing of propulsion mechanisms, detection of ignition in diesel engines of locomotives, etc.*

A current field of application, which deals with the task of monitoring power loads and integration of measuring sensors, is medicine in connection with the production of a series of medical devices and systems. Here you can specify:

- *Outpatient drug dosing systems;*
- *Precision equipment for surgical interventions;*
- *Saline pumps;*
- *Load various components of complex medical equipment.*

Another modern and interesting field of application is *biomedical research* in determining the degree of strength in the analysis of fingerprints by touch and pressure, assessment of cell resolution, pressure monitoring in a variety of technical research tools.

1.5.2. Criteria for selection, calibration and sensitivity of sensors for measuring force effects

The selection of a specific type of force sensors needs to be taken into account, both with the specifics of the test object and the environment of the experiment, and with some basic basic criteria, respectively:

- *Output signal at the rated load;*
- *Max. Nonlinearity;*
- *Slip at the contact interface;*
- *Mass of sensor element.*

At the next stage, criteria can be defined for the selection of a complete system for changing the forces of impact on objects, shown in fig. 1.17.

An essential aspect related to the reliability of the measurement data and the accuracy of the measurements is the correctness of the sensor calibration, which goes through three stages:

- Specifying the calibration
- Undertaking the calibration;
- Analysis of the calibration data.

The first of the stages regulates the following current issues:

- Calibrate in situ or in a laboratory?
- Calibrate the whole system or just the transducer?
- Whether to request adjustment?
- What is the required uncertainty level?
- What is the direction of force and the operating range of force?
- What are the end-loading conditions in the application?
- What is the temperature range for the application?

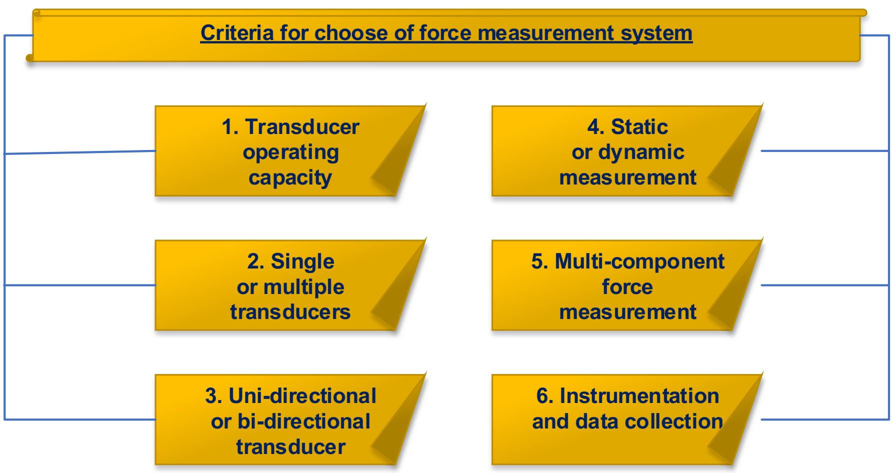


Fig. 1.17. *Criteria for selection of measuring system for monitoring of force impacts on sites*

The set of types of output voltages to be measured and recorded, as well as taken into account in power sensor calibration procedures, may include the following:

- standard uncertainties associated to the standard weight;
- weights creep;
- resolution of the system;
- hysteresis;
- sensor without load;,
- repeatability of the measurement of weights;
- environment temperature.

According to the literature, the following types of Force Calibration Machines can be used for the purposes of the calibration process, respectively:

- Deadweight;
- Hydraulic amplification;
- Lever amplification;
- Comparator with one or three reference force transducers.

An important feature of the sensory elements used in installations for monitoring the forces of impact on tested metal objects is "Sensitivity". The indicated quality indicator of the measuring procedures can be significantly influenced by the following factors:

- Improper geometric positioning of the sensor element during installation;
- Non-optimal location of the sensors;
- Change the properties of the elements;
- Presence of parasitic loads, etc.

In these cases there is a need to place compensating components in the moments of deformation and bending.

1.5.3. Categorization of sensors for monitoring and registration of force impact

The research gives grounds for the formation of standard categories of sensory technical means for measuring force according to various features, but in general the categorization given in fig. 1.18.

1.6. System technical solutions for measuring force loads on metals and measuring technical means

According to the measuring devices for monitoring and recording of force loads are divided into the following categories:

- „Direct Measurements ”to which they belong:
  - ✓ Force transducers;
  - ✓ Load cells;
  - ✓ Dynamometers.
- "Indirect measurements" to which may be attributed: Sensors called strain gauges, which are usually mounted to mechanical systems.

The following industrial areas concerning the measurement of forces on metal structures and structures can be defined:

- Determining the forces of the machine in the process of rolling steel industry;
- Optimal and controlled application of pressing forces on metal plate and sheet material;
- Machines for testing materials used in mechanical testing, used for the initial production and control of subsequent operations with products;
- Mechanical testing of steel materials and construction products used in construction;
- Application of tensile forces on paper, plastic, rolls of film and laminate;
- Cutting forces on metal plate and sheet material;

- Determining the forces of the hook and rope at anchor for ships and tankers;
- Overload control in towers and overhead cranes and elevators;
- Determining the forces applied to the wheels of the truck on paved roads;
- Measurement of the forces coming to the feet of the tower of oil refineries;
- Forces applied to regulate the voltage of cables during their laying and installation;
- Forces applied during underwater laying of tubular equipment.

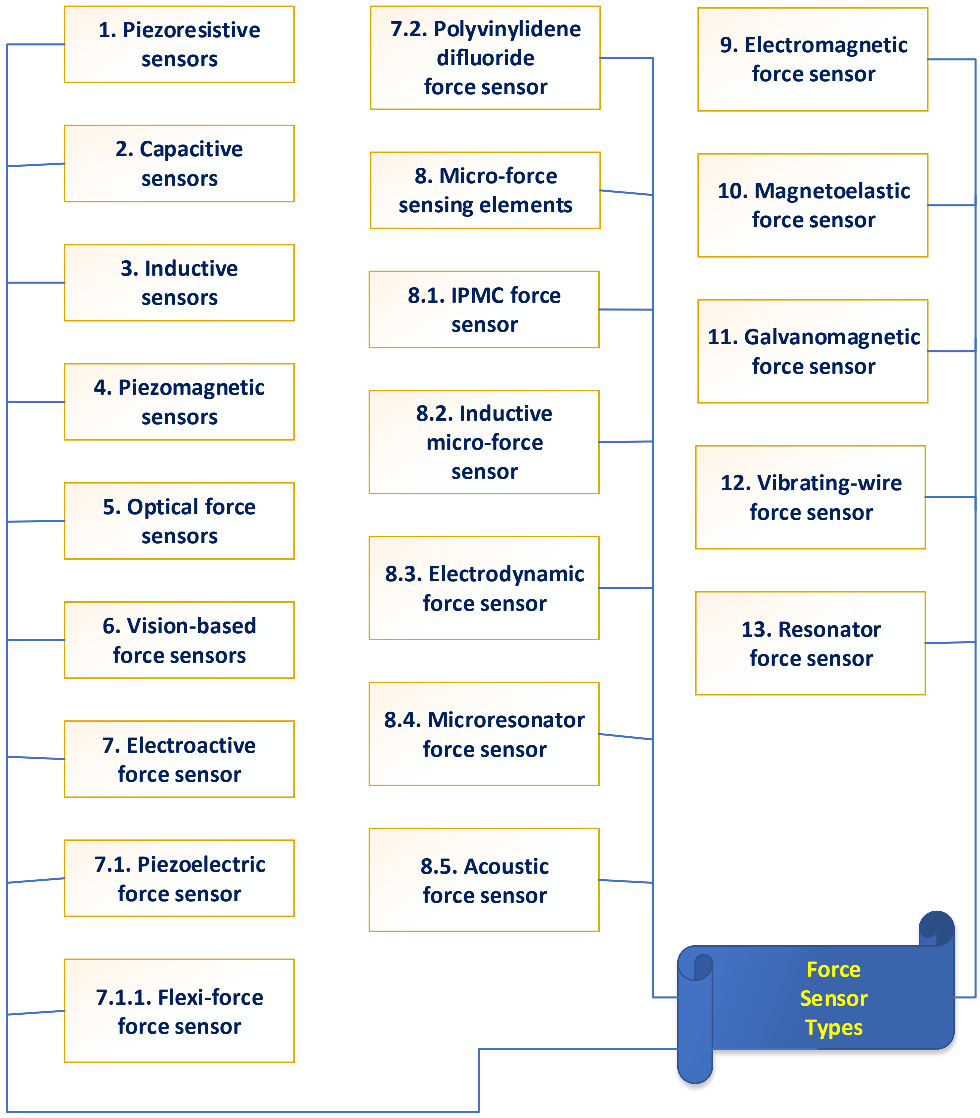


Fig. 1.18. *Categories of sensors for monitoring and recording of forces*

With respect to measuring instruments for indirect measurements can be divided into "metal" and "semiconductor". Metal utensils, in turn, are divided into the following groups:

- Thin wire strain gauges;
- Foil strain gauges;
- Metal film strain gauges.

They are suitable for monitoring long-term dynamic loads, while semiconductors for recording loads applied in a limited area due to their high sensitivity.

There are a number of scientific studies that focus on monitoring and measuring the induced deformations and the associated applied forces of loads. The use of the following technical means is considered:

- Photogrammetric strain measurement systems;
- Foil strain gauges;

- Fiber Optical strain gauges like FSG and FBG sensor elements,

through which forces of the order of 26 kN are registered. Another publication discusses a computer-based system known as the "Computerized Dynamometer" allowing the inclusion of 8 sensors based on load cell type S. The hardware includes:

- Mechanical dynamometer;
- Digital dynamometer with internal sensors;
- Digital dynamometer with external sensors.

Sensor data were collected via an electronic board with a USB driver, ADC, multiplexer, amplifiers and filter units next to the sensors used [63]. Wearable ground reaction force (GRF) measuring system using biaxial force sensors based on an optical sensor mechanism was designed in [64]. Here, the physical interference between two axes of the custom sensor has been minimized by the independent sensor by applying a cantilever structure to both axes and the hysteresis and repeatability of the specialized sensor. An experimental scenario for measuring a pair of applied forces and vibrational effects is discussed in [65]. The measurements were performed by:

- pressure sensor matrices;
- acceleration sensors.

Another study is aimed at evaluating systems for measuring the impact on metal objects using technical approaches using:

- Polyvinylidine fluoride (PVDF) force transducers, кwhich were subsequently modified as Superimposed PVDF force/strain gauges;
- Miniature piezo-electric load cells, having quartzdynamic transducer.

Strain gauges have been used to monitor the static and dynamic response of metal structures. The measuring instruments were positioned in different places inside the structures and a DAC USB system was used to monitor their condition. In another study an Arduino based measuring system was implemented, operating with:

- Mechanical gauges;
- Optical gauges;
- Electrical gauges, as follows;
  - ✓ Capacitive gauges;
  - ✓ Inductive gauges;
  - ✓ Photoelectric gauges.

Another study is related to the development of a microgripper system, allowing the determination of two basic parameters, respectively "position" and "force", in connection with the testing of different types of conductors. The system has components for capturing and releasing test objects, two groups of tenzoresistive transducers, helping to read the specified non-electrical quantities. An analysis of the static and dynamic characteristics of the measuring technical means used has been performed. In another research a strain gauge transducer was modeled for the mechanical loading of Components of Symmetrical Coulters in agriculture. Appropriate procedures have been carried out in relation to adequate positioning of technical measuring instruments and improvement of sensory characteristics such as "sensitivity", "linearity", "minimization of error", "extension of the measuring range" and "more efficient reading of the load spectrum".

The object of research in connection with the measurement of force and application of strain gauges can be not only stationary metal objects and equipment, but also completely different environments such as the fluid-wall interaction of open water channels. Regarding the collection of sensor data, a set of six technical elements was used, subjected to mechanical bending between two position points. In the considered system there is an application of the apparatus of regression analysis for determination of the interrelation between the load and the instrumental signals. The approach described can be used for sensory calibration procedures. Another study addressed the task of analyzing the mechanical properties of polymeric materials and their characteristics to assess the applied force according to the required flexibility criteria. The mechanical properties of the test materials - high density polyethylene, phenol-formaldehyde and natural rubber, were tested by force deformations in the range from 1 to 20 N using measuring strain gauges.

The impact of forces of different sizes on parts and structures can be registered by applying a wide range of transducers. System solutions are developed with combined use of several types of technical means for measuring between resistive, inductive, capacitive, piezoelectric, electromagnetic, electrodynamic, magnetoelastic, galvanomagnetic, vibration, acoustic, gyroscopic, etc. One of the most commonly used sensor types is strain gages. Strain gauge transducers are divided into metal and semiconductor. They are compared according to various criteria such as measuring range, sensitivity, resistance, resistance tolerance and dimensions. They are mainly connected in DC bridge measuring circuits in different configurations with one working, two working in adjacent arms, two working in opposite arms and four working converters.

Research examines various system solutions for measuring forces. Automated wireless network monitoring systems related to the measurement of intense elastic surface deformations in serviced plastic-coated metal pipelines are widespread. In another study a multi-channel measuring system for evaluation of sensory elements for deformation based on USB communication interface was designed. The test modules are equipped with an 8-bit microcontroller, an amplifier with adjustable gain, a Bessel low-pass filter and an analog-to-digital converter controlled by SPI and other control signals.

1.8. Applications of forecasting analysis devices in information and communication systems in forecasting analysis tasks

According to research, the forecast analysis based on artificial intelligence in the field of communications concerns two main areas:

- *Direction №1*: the declining influx of users of services in the mobile telecommunications industry due to interruptions or unforeseen events in mobile and cellular communications [104-111];
- *Direction №2*: the overall traffic from incoming customer requests in services in the telecommunication and LTE networks.

The main mathematical tools used for quantitative forecasting in relation to the defined target areas can be divided into three main categories (Fig. 1.21), respectively:

- *Machine learning;*
- *Applied statistics;*
- *Artificial neural networks.*

1.9. Artificial neural networks in the processing and reduction of noise effects in information and communication systems

Research regarding the processing and analysis of signals in information and communication systems in various fields of industry is mainly related to the recognition of the following objects:

- Speech signals;
- Sound signals;
- Biomedical signals,

in channels representing a transmission medium with the presence of noise. The tools that are applied for identification are:

- Deep Neural Networks (DNN);
- Hidden Markov models;
- Multivariate Analysis of Variance (MANOVA);
- Multi-layer Perceptrons and other.

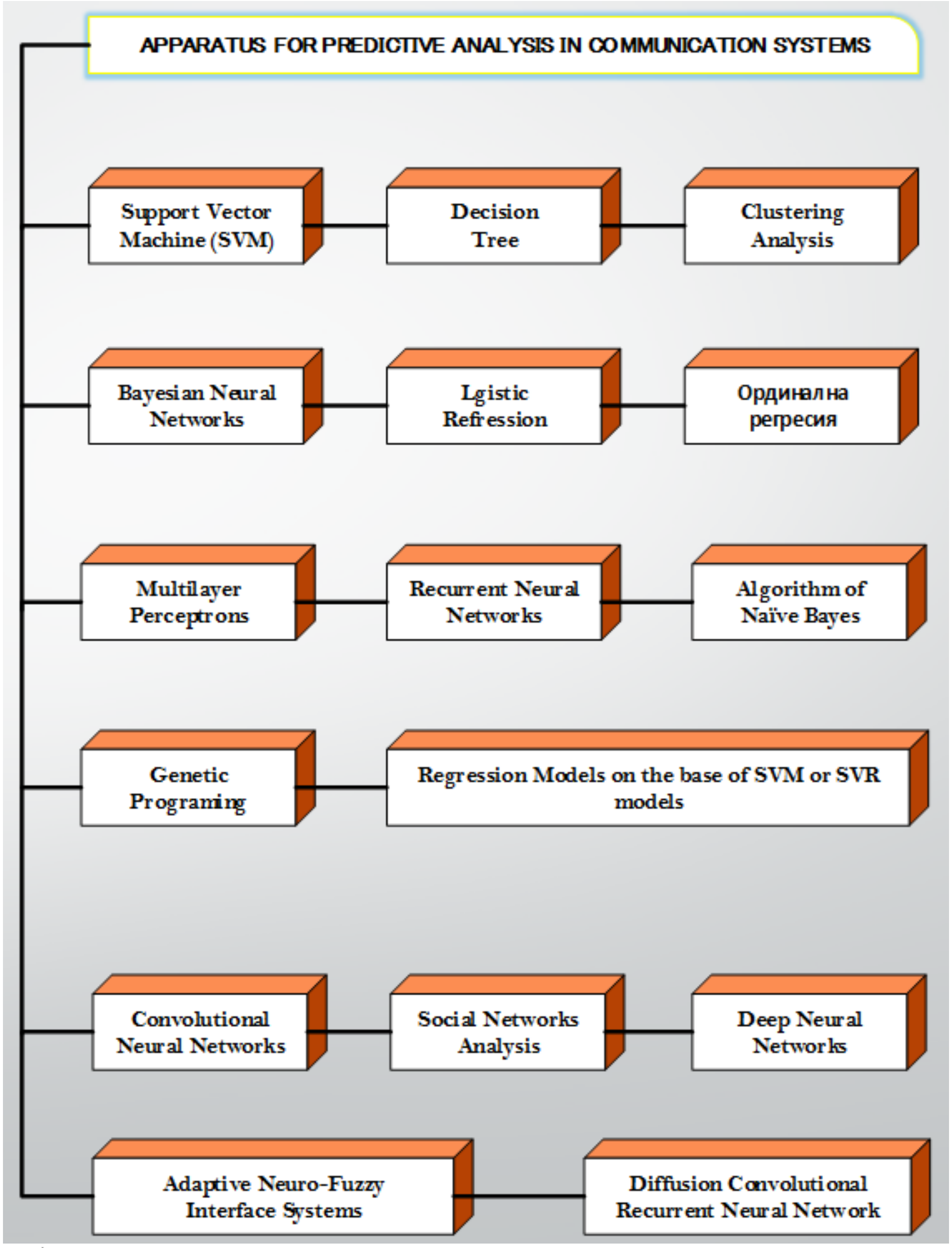


Fig. 1.21. Apparatus for predictive analysis in communications

According to other studies concerning the processes of noise assessment and reduction, there is the applicability of specialized approaches and algorithms, among which can be specified, respectively:

- Independent Component Analysis, Recursive Least Squares (RLS), and Recurrent Neural Networks in automated speech recognition systems;
- Support Vector Machine (SVM) method, k-means cluster analysis, k - Nearest Neighbors (k-NN), in optical communications;
- DNNs and Convolutional Neural Networks in Orthogonal Frequency-Division Multiplexing (OFDM) and Two-Dimensional Magnetic Recording (TDMR) systems;
- RNN neural architectures in combination with Long Short Term memory (LSTM) - a variant of RNNs, and Gated Recurrent Unit (GRU-GRU) in Micro-Electro-Mechanical System Inertial Measurement Units (MEMS-IMU);
- Deep-Learning Neural Networks (DLNNs) in the development of biomedical electronic devices;

- Principal Component Analysis, CNN, Feed-Forward Neural Networks in case of parameter reduction:
  - ✓ Signal-to-Noise Ratio (SNR);
  - ✓ SNR RMS (Root Mean Square) parametric values;
  - ✓ Peak SNR;
  - ✓ Structural Similarity Index Measure (SSIM),
- in image diagnostic systems;
- Linear regression analysis, Discriminant analysis, Naïve Bayes algorithm, Decision tree method, Adaptive neural-fuzzy interface systems in electronics.

Conclusions to the first chapter

- ❖ The peculiarities of the main types of interfaces and standards for transmission of sensor and parametric information in the implementation of sensor modules and multifunctional boards in electronics and communications are considered;
- ❖ A general functional classification of the sensory elements used in different fields of industry and technology is made according to the excitatory factors and the principle of transformation. The main types of characteristics that can be studied in the study of sensory functionality are defined;
- ❖ A classification of intelligent communication applications and technologies has been compiled and a comparative analysis has been made between WAN and LAN technologies, as well as with regard to basic IEEE standards for data transmission;
- ❖ Basic technical measuring means for monitoring and registration of measurements of force loads on metals, details and constructions and sensor systems for measuring loads in different spheres of industry, as well as the essence, specifics and features of the apparatus of artificial neural networks have been studied;
- ❖ The areas of application of methods, algorithms and approaches of mathematical and applied statistics, machine learning and artificial intelligence, defined for predictive analysis in telecommunication systems in relation to users of communication services and processed traffic, are defined;
- ❖ An analysis of the methods and technical approaches for digital signal processing and filtering and the role of artificial intelligence in reducing noise to signals in information and communication systems in various fields.

CHAPTER II: RECOGNITION OF NOISES AND SIGNALS WITH NOISES IN SIMULATION MODELING COMMUNICATION CHANNELS

2.2. Noise identification models based on artificial neural networks with backpropagation training

2.2.1. Investigation and synthesis of artificial neural networks for noise recognition in Levenberg-Marquardt training algorithm

A study is presented in connection with the possibility of applying the device of artificial neural networks on some of the most common types of noise accompanying the process of transmission of analog and digital signals in communication channels. The analysis applies to the following types of noise:

- ➢ Gaussian White Noise - GWN;
- ➢ Periodic Random Noise – PRN.

For this purpose, a simulation of the test noises at fixed identical values of the standard deviation for GWN and the spectral amplitude at PRN, respectively 0.02, 0.04 and 0.06, was made using the software product LabVIEW. Following the analogy of the indicated levels of the simulation parameters, an information sample was formed, which included 2000 observations with three informative features, respectively GWNs - 1000 standards, and PRNs - 1000 samples.

An approach for synthesis of architectures based on three-layer architectures of artificial neural networks with direct signal propagation and error back propagation is introduced. Regarding the objectives of the study, procedures are envisaged using the Levenberg-Marquardt algorithm when experimenting with training parameters (goal, leaarninig rate, min_grad, etc.) with successive growth of neurons in the intermediate (hidden) layer in the range of 5 to 20 neurons . The training and selection of artificial neural networks for the recognition of GWNs and PRNs is also associated with setting different types of output activation:

- linear – purelin type;
- hyperbolic tangent sigmoid – tansig type;
- log-sigmoid– logsig type.

With linear activation, a minimum of 98.3% and a maximum of 100.0% accuracy were recorded for 5 and 15 intermediate neurons. The error ranges from 0.0118 at 15 to 0.0441 at 5 hidden neurons. Regarding tangent-sigmoidal initial activation, the lowest accuracy of 98.3% was observed in 10 and 20 hidden neural units, while the highest 100.0% was reached in 8 and 13. The second quality criteria showed a change from 0.0021 to 0.0140, respectively at 13 and 19 neurons in the intermediate layer. In connection with the last applied type of output activation, low and high accuracy are observed with an approximate difference of about 50%, with the second levels predominating. There was also a clear significant increase in times the root mean square error over the whole range of hidden neural units compared to tansig and purelin types. A minimum of 47.7% and a maximum accuracy of 100% were recorded for 8 and 10 hidden neurons, for which MSE = 0.2500 and MSE = 0.1255 were achieved.

Table 2.1. Results of recognition of GWNs and PRNs with artificial neural networks with linear output transfer function

Hidden neurons	Accuracy, %	Mean-Squared Error
5	94.0	0.0441
6	97.0	0.0310
7	97.7	0.0255
8	97.3	0.0284
9	98.3	0.0224
10	97.3	0.0282
11	99.7	0.0201
12	98.0	0.0265
13	97.3	0.0256
14	98.3	0.0251
15	100.00	0.0118
16	99.7	0.0188
17	98.3	0.0235
18	99.3	0.0170
19	99.0	0.0173
20	98.7	0.0219

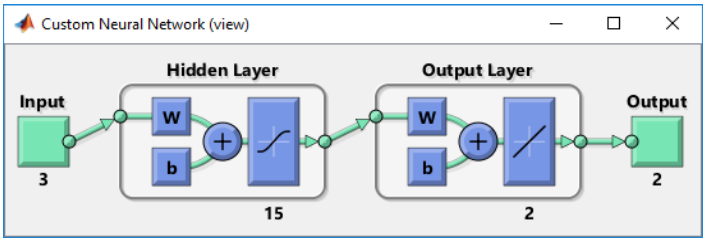
Table 2.2. Results of recognition of GWNs and PRNs groups of signals with artificial neural networks with tangent-sigmoidal output transfer function

Hidden neurons	Accuracy, %	Mean-Squared Error
5	99.3	0.0078
6	99.3	0.0115
7	99.0	0.0065
8	100.0	0.0074
9	98.7	0.0102
10	98.3	0.0115
11	99.3	0.0107
12	98.7	0.0121
13	100.00	0.0021
14	98.7	0.0126
15	99.3	0.0069
16	99.7	0.0091
17	99.7	0.0069

18	98.7	0.0140
19	99.7	0.0130
20	98.3	0.0137

Table 2.3. Results of recognition of GWNs and PRNs groups of signals with artificial neural networks with log-sigmoid output transfer function

Hidden neurons	Accuracy, %	Mean-Squared Error
5	94.3	0.1498
6	98.0	0.1357
7	98.7	0.1904
8	47.7	0.2500
9	99.3	0.1276
10	100.00	0.1255
11	48.3	0.2500
12	56.0	0.1807
13	99.3	0.1289
14	49.3	0.1904
15	99.7	0.1268
16	99.3	0.1281
17	99.7	0.1262
18	52.0	0.1864
19	99.7	0.1255
20	99.7	0.1276



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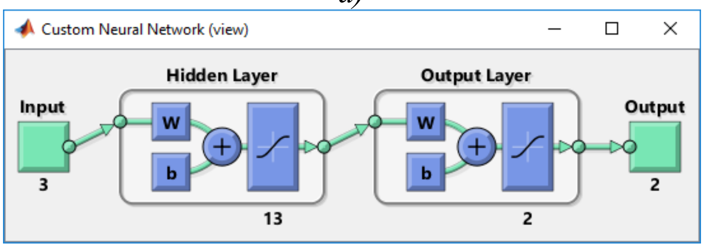
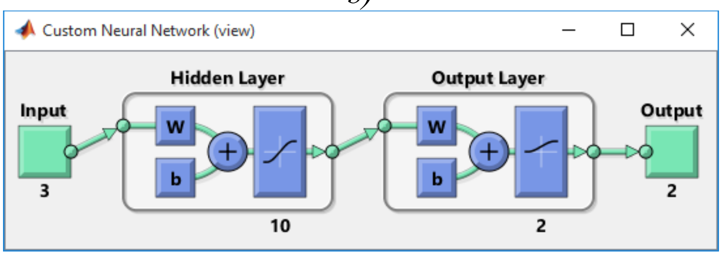


b)



c)

Fig. 2.4*. Selected neural networks for recognizing GWNs and PRNs at output a) linear, b) tangent sigmoid and c) log-sigmoid activation function*

There is a tendency of advantage of the tangent sigmoid over the linear and especially over the logarithmic-sigmoidal activation function given the obtained lower values of the criterion "root mean square error". Figure 2.4 presents the experimentally selected networks with 15, 13 and 10 intermediate neurons with the best performance.

2.3. Models for recognizing digital signals with the presence of noise through artificial neural networks with backpropagation training

2.3.1. Investigation and synthesis of artificial neural networks for noise identification of digital signals

At the next stage of the analysis, rectangular signals with the presence of GWN and PRN were simulated at the levels of the configuration parameters 0.02, 0.04 and 0.06. A similar approach is applied here with regard to the assessment of the quality of classification and the activities for selection of neural networks for identification. In fig. 2.12 and fig. 2.13 oscillograms of the target signal groups for analysis are presented, while the results of the study are presented from table 2.4 to table 2.6.

According to the application of the linear activation function at the output of the neural networks, high variations of the accuracy were obtained, varying from 93.3% to 100.0% for 6 and 16 neural computing units. The values of the root mean square error do not fall below the level of 0.0150 as the lowest MSE = 0.0155 and the highest MSE = 0.0747 were observed, respectively at fixed 16 and 6 neurons in the structural hidden layers of the studied networks.

Table 2.4. Results of recognition of rectangular signals with GWN and PRN with artificial neural networks with linear output activation function

Hidden neurons	Accuracy, %	Mean-Squared Error
5	96.0	0.0355
6	93.3	0.0747
7	97.0	0.0511
8	95.7	0.0396
9	98.7	0.0294
10	98.7	0.0227
11	98.7	0.0264
12	98.0	0.0352
13	99.3	0.0191
14	98.7	0.0240
15	99.0	0.0234
16	100.00	0.0155
17	97.3	0.0332
18	99.7	0.0160
19	96.3	0.0273
20	99.0	0.0241

Table 2.5. Results of recognition of rectangular signals with GWN and PRN with artificial neural networks with tangent sigmoid output activation function

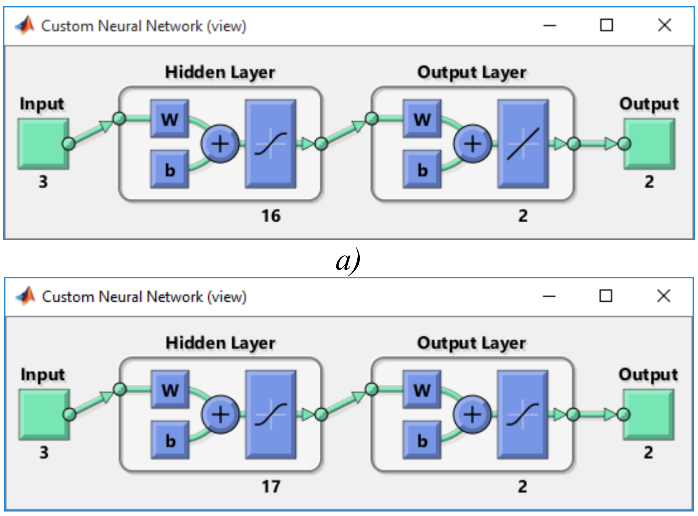
Hidden neurons	Accuracy, %	Mean-Squared Error
5	91.7	0.0608
6	99.0	0.0076
7	99.3	0.0072
8	99.00	0.0084
9	98.3	0.0142
10	98.0	0.0162
11	99.3	0.0063
12	97.7	0.0186
13	98.3	0.0158
14	98.3	0.0144
15	99.0	0.0117
16	99.7	0.0057
17	100.0	0.0049
18	99.7	0.0171
19	99.0	0.0136
20	98.7	0.0159

In the course of the experiment with tansig initial activation type, a minimum indication of accuracy of 91.7% was found in 5 hidden neurons, and for the rest of the test interval the criterion changed from 97.7% at 12 to its highest value of 100.0% at 17 neuron. Mean square error levels range from 0.0186 to 0.0049 for 12 and 17 neurons in the latent layer except for recorded MSE = 0.0608 for 5 intermediate neurons.

Analyzing the results contained in Table 2.6, a similar trend is observed for strongly increased mean square error rates compared to purelin and tansig in the indicated course of change of hidden neurons, established in the previous part of the research focused only on noise analysis in simulated communication environment. Here, too, deterioration of precision for specific intermediate neurons is observed, although there are no such clearly distinguished groups of "low" and "high" variations of the indicator with a significant difference, ie. there are intermediate levels - for example 60% at 11; 70.7 at 13; 76.7 at 12; 83.7 in 8 intermediate neurons, etc. There is an inverse relationship between the decrease in accuracy from 100.0% to 70.7% with an increase in computational neurons for a limited part of their range - from 9 to 13. The lowest level of quality criterion 49.3% was registered in an architecture with seventeen intermediate neurons. The root mean square error varies from 0.1260 for the case of the highest accuracy to 0.2009 at 11 neurons in the hidden network layer.

Table 2.6. Results of recognition of rectangular signals with GWN and PRN with artificial neural networks with log-sigmoid output activation function

Hidden neurons	Accuracy, %	Mean-Squared Error
5	95.7	0.1427
6	89.0	0.1917
7	95.3	0.1445
8	83.7	0.1960
9	100.0	0.1260
10	98.3	0.1330
11	60.0	0.2009
12	76.7	0.1603
13	70.7	0.1963
14	99.0	0.1285
15	98.7	0.1284
16	52.3	0.1868
17	49.3	0.1889
18	74.3	0.1612
19	99.0	0.1282
20	57.3	0.1831



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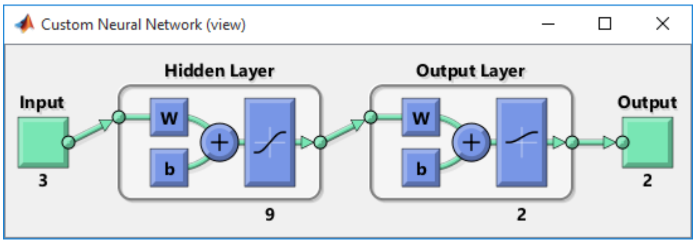


c)

***Fig. 2.14**. Selected neural networks with a) linear, b) tangent-sigmoid and c) log-sigmoid output activation function for recognition of square signals with GWN and PRN*

Architectures of networks with 16, 17 and 9 intermediate structural neurons were found, meeting the need to maintain optimality between the expected high accuracy while recording the minimum MSE reading given in fig. 2.14.

2.4. Research and selection of FFNN neural architectures to identify noise impacts and digital signals with superposed noise based on Scaled Conjugate Gradient training.

2.4.1. Synthesis of feed-forward neural networks in SCG algorithm for recognition of simulated GWN and PRN interfering effects in communication channels.

Another potential possibility for neural synthesis is associated with a change in the training algorithm and the type of initial activation function such as:

- Levenberg-Marquardt was replaced by Scaled Conjugate Gradient (SCG) training;
- Softmax type activation is set in the structural output neurons.

The specificity of the entered parameters determines the initial results from the application of the neural apparatus to be accepted as "probability" and not as "numerical interpretation".

Table 2.7 contains the results obtained in the study of FFNNs using SCG for the detection of random noise effects - GWN and PRN, with a set change in the calculated structural units in the hidden layers from 3 to 31. Criteria to be evaluated are “accuracy” and "Cross-Entropy (CE)" recognition. Satisfactory levels of accuracy above "0.99" were found for the analyzed interval of intermediate neurons. The lowest found accuracy is 92.8% in the baseline architecture of the study, while the highest value of the criterion 99.8% was recorded for the cases of 11, 13, 15, 21, 25, 27 and 33 neurons in the intermediate layer of FFNNs. In this case, the choice of the final type of identification model is based on the achieved minimum entropy "5.58345e-0" for an architecture with 25 neurons, shown in fig. 2.24.

Table 2.7. Results of selection of FFNNs in SCG training for GWN and PRN identification

Hidden neurons	*Accuracy, %*	*Cross-Entropy indicator*
3	92.8	2.46521e-0
5	99.0	4.29463e-0
7	99.7	4.84113e-0
9	99.7	4.59377e-0
11	99.8	6.07409e-0
13	99.8	6.76620e-0
15	99.8	6.12029e-0
17	97.2	1.97068e-0
19	99.2	3.74847e-0
21	99.8	6.06058e-0
23	99.2	4.04383e-0
25	**99.8**	**5.58345e-0**
27	99.8	5.77250e-0
29	99.7	6.64407e-0
31	99.2	4.01312e-0
33	99.8	6.61422e-0

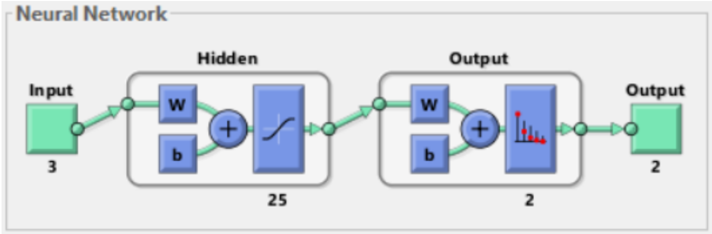


Fig. 2.24. *Selected FFNN neural architecture in the course of SCG training to identify GWN and PRN impacts*

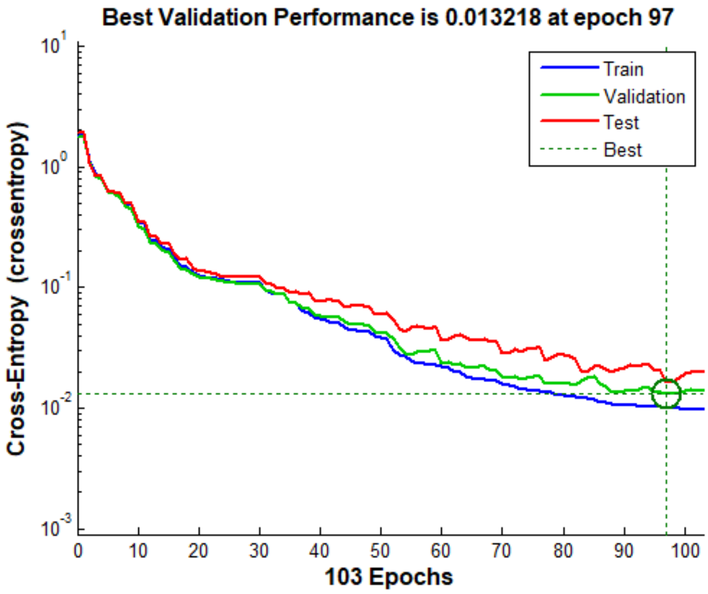


Fig. 2.25. *Cross-Entropy in the synthesized FFNN neural architecture in the course of SCG training for identification of GWN and PRN impacts*

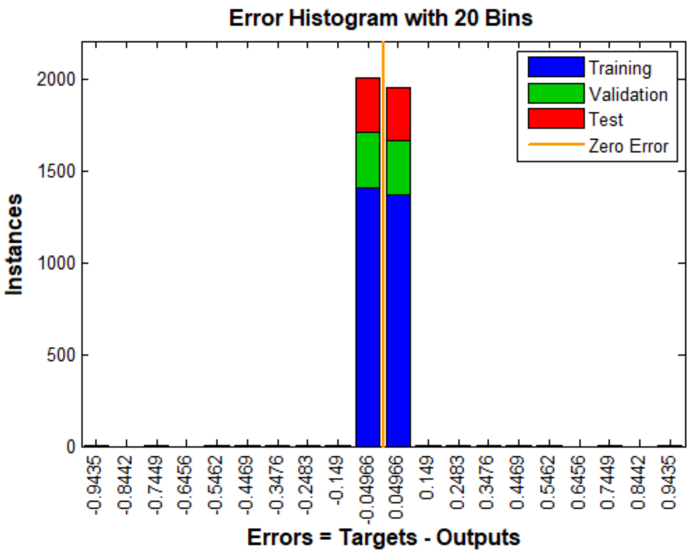


Fig. 2.26. *Error diagram for the selected FFNN neural architecture in the course of SCG training to identify GWN and PRN impacts*

The tendency of such and gradually decreasing change of the CE indicator from training, validation and testing in fig. 2.25 testifies to the correctness of the applied processes. The overall training process covers 103 iterations as the "best validation performance" was found in the 97th training cycle.

A histogram of the network errors is shown in fig. 2.26, for which there is a close location of the indications from the main network processes regarding the data from the test sample to the level of the basic zero error. According to the presented dependence, the errors from the application of the model fall within the range of levels "-0.04966" and "0.04966".

2.4.2. Selection of FFNNs in SCG algorithm for identification of simulated digital signals with superimposed GWN and PRN random effects in communication channels.

Given the positive indications of adapting SCG training in the analysis of simulated interfering effects of the environment in communication channels, the task of recognizing noises that are superimposed on transmitted digital signals was moved. In this regard, Table 2.8 summarizes the accuracy data and the CE criterion for the same range of hidden neurons as in the previous study. Regarding architecture, a minimum accuracy of 69.3% was observed for 3 units of calculation and CE = 1.27713e-0. Approximate levels of accuracy of "91.0%", "94.0%", "96.0% to 98.8%" were found during the training of FFNNs with increasing neurons in the intermediate layer, the maximum of which refers to an architecture with 31 hidden neurons and CE = 3.86609e-0.

Table 2.8. Results of a study of FFNNs in SCG training
for digital signal recognition in the presence of GWN and PRN

Hidden neurons	***Accuracy, %***	***Cross-Entropy indicator***
3	69.3	1.27713e-0
5	98.2	3.11645e-0
7	97.4	2.69296e-0
9	91.6	2.21454e-0
11	93.9	1.35195e-0
13	98.7	5.49103e-0
15	97.0	2.46378e-0
17	97.8	2.37423e-0
19	96.7	1.84056e-0
21	97.2	2.20736e-0
23	98.6	3.33221e-0
25	99.3	5.61578e-0
27	97.8	2.85755e-0
29	97.9	2.70141e-0
31	**98.8**	**3.86609e-0**
33	98.3	3.30483e-0

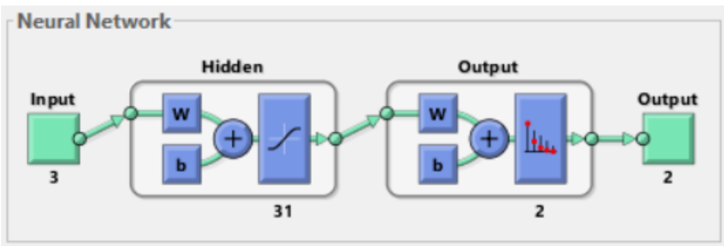


Fig. 2.27. *Synthesized FFNN neural architecture in SCG training algorithm for digital signal recognition in the presence of GWN and PRN*

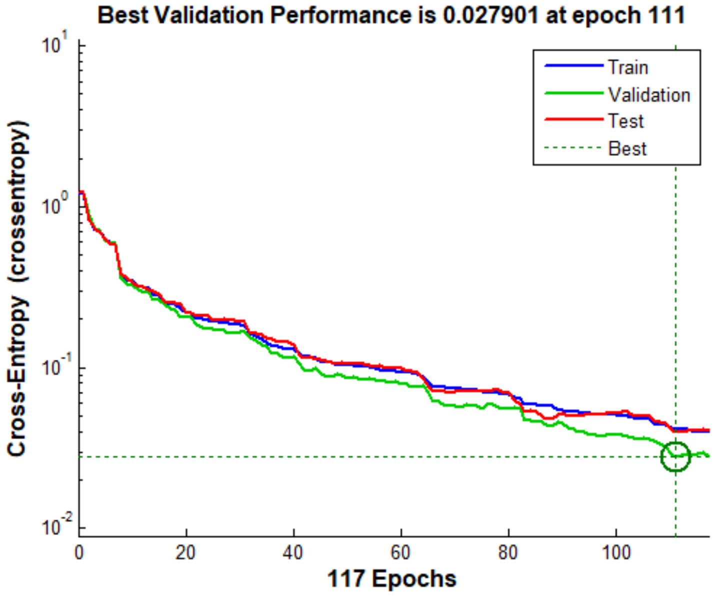


Fig. 2.28. *Cross-Entropy for the selected FFNN neural architecture in SCG training algorithm for digital signal recognition in the presence of GWN and PRN*

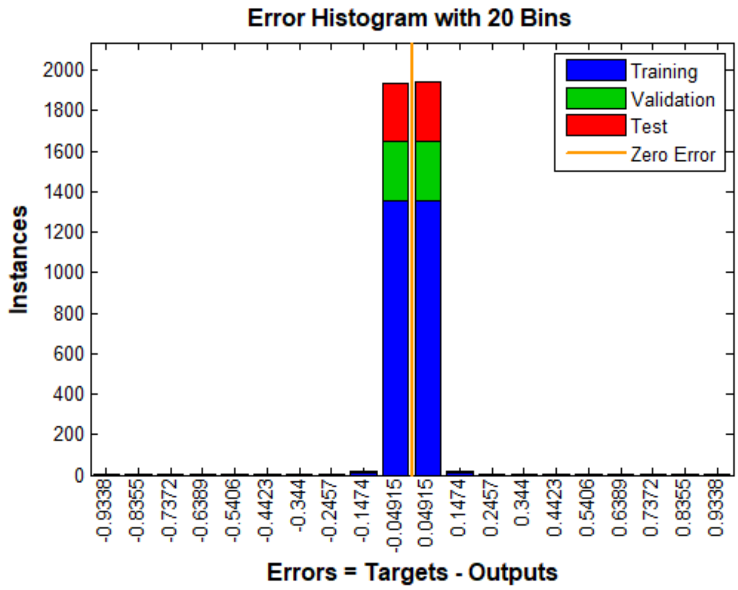


Fig. 2.29. *Error diagram for the selected FFNN neural architecture in SCG training algorithm for recognizing digital signals in the presence of GWN and PRN*

The synthesized best model for identification of rectangular signals with influence of Gaussian and Periodic noise is shown in fig. 2.27. In connection with the model, a percentage ratio of 70:15:15% was used between the data from the input set, divided randomly. Figure 2.28 shows the behavior of the network during training, validation and test procedures. A similar and downward change in CE was observed, defined as the absence of an indication for neuronal retraining. Within 111 of the total number of 117 training cycles, the best network productivity of 0.027901 was achieved.

The estimated error variation range observed next to the zero error level in fig. 2.29, from the integration of the model for the purposes of the considered task is ± 0.04915. Regarding the operation with a minimal part of the training data, the expected errors fall to ± 0.1474.

Conclusions to the second chapter

- An approach has been developed for the study and selection of artificial neural networks with direct signal propagation through Levenberg-Marquardt (LM) and Scaled Conjugate

Gradient (SCG) training based on a gradient algorithm with reverse propagation of the error for recognizing noise and signals with presence of noise in regulation of activation functions in analysis of accuracy, mse, cross-entropy indicator, significance of correlation and generalized forecast results;

- Positive and negative aspects have been identified, as well as identical trends in terms of quality indicators from the application of linear, tangent-sigmoidal and logarithmic-sigmoidal activation function in the source layers in the selection of artificial neural networks in LM training, determining the lowest level the suitability of the latter type of function, despite the achieved positive indications in terms of accuracy and correlation;
- Architectures based on artificial intelligence and LM training algorithm for identification of simulated noises in communication channels for communication in linear, tangent sigmoid and log-sigmoid function of the output with obvious advantage of the hyperbolic tangent sigmoid tangent are synthesized and analyzed;
- Structures of artificial neural networks in LM training for recognition and classification of simulated digital signals with added effects of Gaussian constant noise and Periodic random noise were selected and evaluated according to accepted quality criteria based on experimental studies according to differently stated neurons in hidden layers and selection of the type of activation function with the best adequacy of the hyperbolic tangent sigmoid type;
- FFNN neural models have been developed and evaluated in the course of SCG training algorithm for identification of simulated individual and complex to digital signals random Gaussian and Periodic effects in information transmission in communication channels.

CHAPTER III: MODELS FOR QUALITATIVE AND QUANTITATIVE ANALYSIS OF INFORMATION BY TENSORESISTIVE TRANSDUCERS

3.1. System for studying the load of metal objects under the influence of forces based on strain gauges.

Field of interest for the practice in:

- the field of communications;
- sensor systems for data collection and analysis in relation to electrical and non-electrical quantities;
- automated information systems for monitoring technological objects and processes in the field of industry,

is the possibility to adapt the specified mathematical instruments in the areas of qualitative and quantitative analysis of information registered by strain gauges, with force loading of various metal objects.

In this regard, a concept of a communication system for research and analysis of the degree of loading of details under the influence of forces of different sizes, whose block architecture is shown in fig. 3.1.

Test experimental object of the study is a metal cantilever beam, on which forces are applied in a perpendicular direction. Two strain gauges are glued to the surface, located so as to provide the necessary temperature compensation without the need for an additional sensor element. The strain gauges are connected to adjacent arms of a standard DC bridge. As a result of the beam load, the electrical and mechanical parameters of the sensors are changed, as well as the voltage in the measuring diagonal of the bridge, the size of which is measured by a module of the NI 6002 module of the company National Instruments. Through LabVIEW virtual applications, the output voltage of the bridge is monitored using a configured serial communication channel between the NI 6002 and a personal computer, and filtered in real time via digital recursive (IIR) and non-recursive (FIR) units.

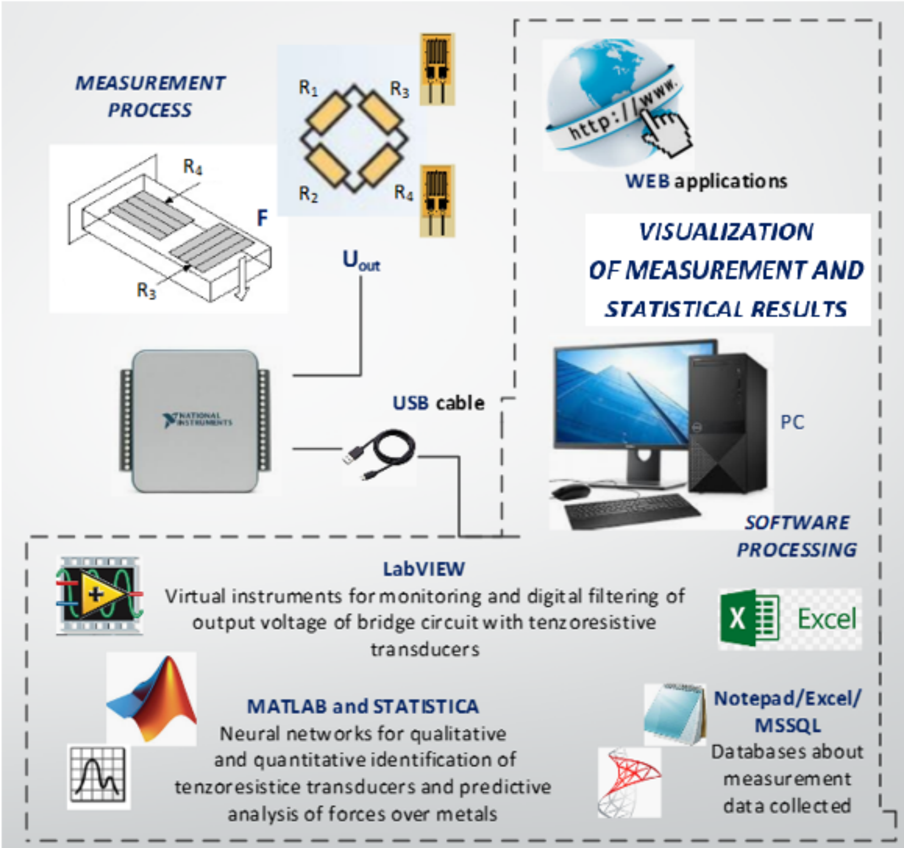


Fig. 3.1. *Architecture of a system for analysis of forces on metals by means of strain gauges*

It is possible to statistically analyze the registered data in relation to various indicators such as minimum, average and maximum values, standard deviation, maximum and minimum times and others. Based on experimentally derived mathematical regression models with the STATISTICA package, set in LabVIEW using a specified sub-virtual instrument, estimated values of the impact force in the cases of one or two strain gages used are calculated.

Using MATLAB scripts in LabVIEW, the parameters of pre-trained artificial neural structures are called and loaded:

- in the case of direct propagation of signals and back propagation of the error;
- Generalized Regression Neural Networks,

for identification of the included working sensor elements in the bridge circuit, currently used in measuring the input non-electric quantity - qualitative analysis of data from strain gauge sensors. This directly includes non-verbal models for predicting the load from the applied forces on the test metal object, ie. there is a task for quantitative analysis of data from strain gages.

Using the presence of a WEB server to the LabVIEW virtual environment, the possibility for remote access to the tools for:

- establishing and configuring the connection to the USB module, as well as monitoring the status of some of its analog inputs. In this case, this is the voltage in the measuring diagonal of the bridge circuit with the inclusion of narrow-resistor converters;
- processing and visualization of measurement and statistical results, as well as those from quality and quantitative analysis via the Internet environment.

The choice of the main Feed-Forward Neural Networks (FFNNs) was made according to the main advantage of minimizing the error after the course of each training iteration on the applied gradient algorithm.

3.2. Virtual tools for filtering and descriptive analysis of measurement data from working strain gauges in the study of force loads on metal objects

In connection with additional descriptive analysis of the registered force effects applied on experimental metal objects and proportional voltage levels in the measuring diagonal of the bridge circuit with the inclusion of strain gauges, an auxiliary virtual instrument was created. The user interface and the block diagram of the application are presented in fig. 3.4.

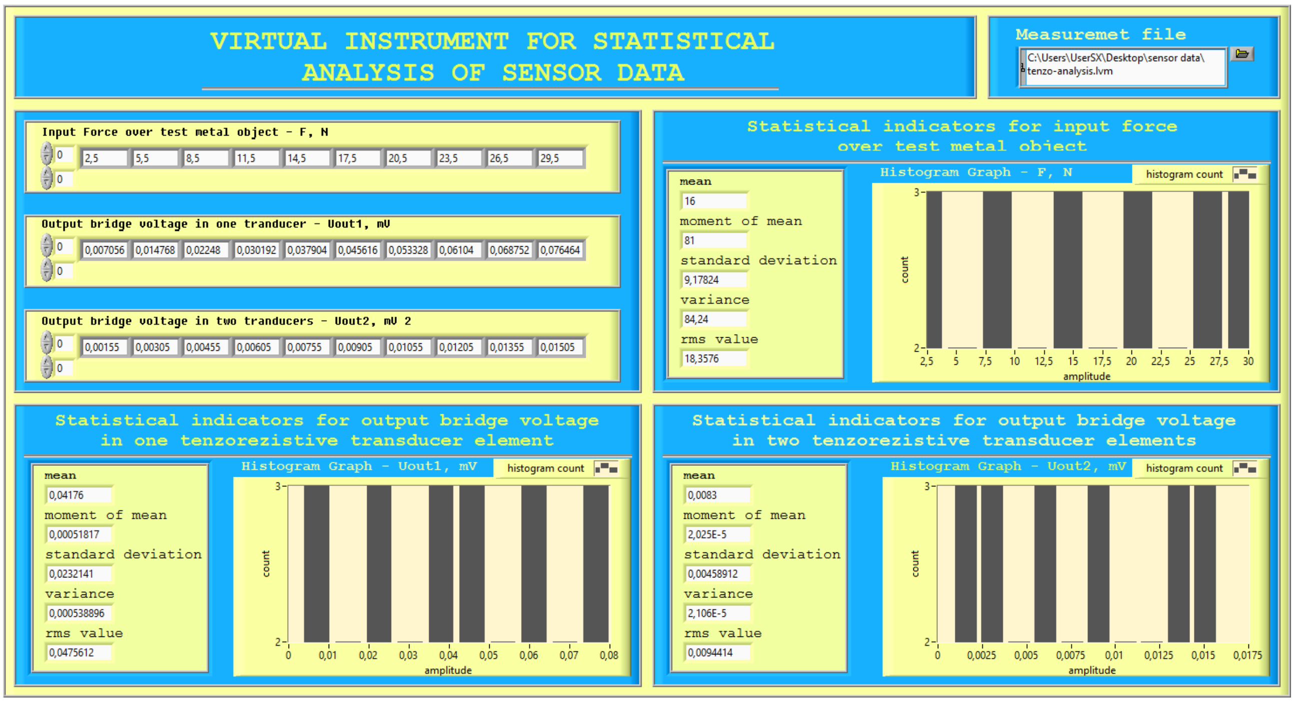
The selection of experimental data with the extension ".lvm" for subsequent analysis is done through a provided control element, the correctness of which can be pre-checked through Notepad and MS Excel environments. Digital data array indicators are designed to display:

- the applied load force F, N;
- the measured measuring voltage as a reaction to one sensitive element U_{out1}, mV;
- the measured voltage of the bridge circuit when two operating transducers are switched on U_{out2}, mV.

Functional histograms have been introduced for the indicated monitoring parameters, giving information about the levels of their change in the course of the experimental procedures, which can be further analyzed and evaluated.

The main role of the virtual application concerns the use of specified sub-virtual tools for extracting set statistical indicators, identical for the three studied values. The analysis covers the following parameters:

- Mean;
- Moment of Mean;
- Standard deviation;
- Variance;
- RMS value.



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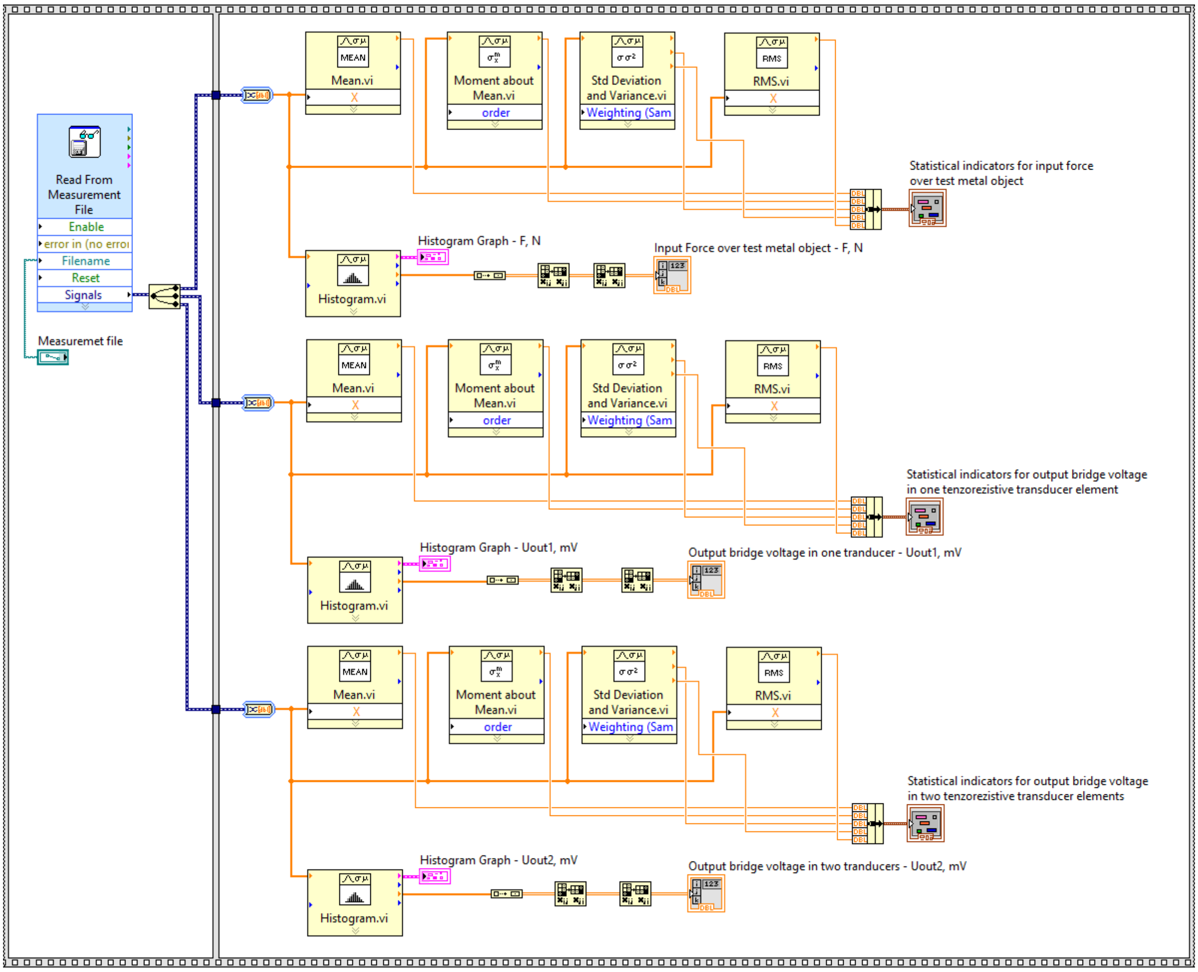


b)

Fig. 3.4. *Virtual application for statistical analysis of registered sensory data when loading metal objects*

3.5. Synthesis of artificial neural networks for identification of working transducers in the analysis of forces on metals in the bridge circuit of inclusion through FFNNs in SCG training.

Training of three-layer FFNNs neural architectures for quantitative identification of included working measuring strain gauges in load monitoring on metal objects was performed. The architectures are built on the basis of:

- input neural layer;
- hidden or also called intermediate layer when laying neural computing units with tangential-sigmoidal activation;
- output layer when setting the softmax activation function.

The training processes are based on the Scaled Conjugate Gradient (SCG) algorithm when submitting one and two input variables, respectively:

- "Uout" – the output voltage in the indicator diagonal of the bridge circuit for switching on sensor elements;
- "F and U_{out}" – combination of applied force on a prototype and respectively reported output voltage of a bridge circuit.

The following initial classification groups are defined:

- Class №1: Bridge circuit with one working tensoresistive element;
- Class №2: Bridge circuit with two working narrow resistor converters,

where combinations of probabilities at the respective levels are used to encode each output group - '1 0' for class №1 and '0 1' for class №2. A feature resulting from the use of the softmax type of activation is the interpretation of the initial network results not as "numbers" but as "probabilities".

An assessment of artificial neural networks was performed after training according to the achieved indicators:

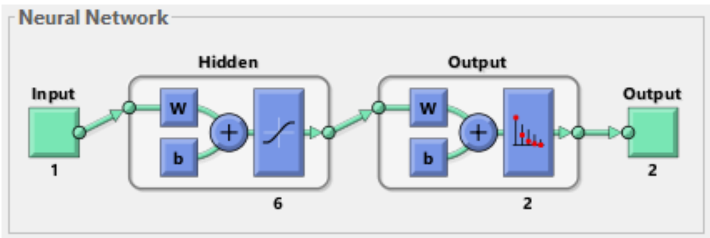
- ❖ “Classification Accuracy“;
- ❖ “Cross-Entropy”.

In relation to the defined classification groups, these indicators are analyzed according to the growth of neurons in the hidden layers in the range from 5 to 15. The results of the procedures are presented in Table 3.1. For the two cases studied, satisfactory levels of accuracy of about 90.0% and 100% were obtained for the majority of the analyzed models using one and two input variables. The lowest accuracy of 88.50% was registered with "U_{out}" for 7 intermediate neurons, while for "F and U_{out}" the minimum reading of the criterion found for 7 and 10 hidden neurons was 98.10%.

Table 3.1. Study of FFNN architectures for one and two input variables in SCG training

Hidden neurons	Accuracy, %	Cross-Entropy	Accuracy, %	Cross-Entropy
	U_{out}		F and Uout	
5	90.40	1.48916e-0	100.00	4.29507e-0
6	**90.40**	**1.10373e-0**	100.00	13.56822e-0
7	88.50	1.04975e-0	98.10	1.96157e-0
8	90.40	1.61987e-0	100.00	13.84607e-0
9	90.40	1.25043e-0	100.00	14.58822e-0
10	90.40	1.54694e-0	98.10	2.77515e-0
11	90.40	1.55780e-0	**100.00**	**2.94522e-0**
12	90.40	1.22658e-0	100.00	13.14914e-0
13	90.40	2.240027e-0	100.00	3.16867e-0
14	90.40	3.11792e-0	100.00	14.30631e-0
15	90.40	3.19195e-0	100.00	3.39250e-0

Based on the presented results, the best architectures shown in fig. 3.9, at 6 in single and 11 neurons in the intermediate layers at combined input. The models are based on tangent-sigmoidal and softmax activation functions in the output layers. The highest accuracy and lowest values of the Cross-Entropy indicator found here are 90.40% and 1.10373e-0 for the first and 100.00% and 2.94522e-0 for the second selected best architecture.



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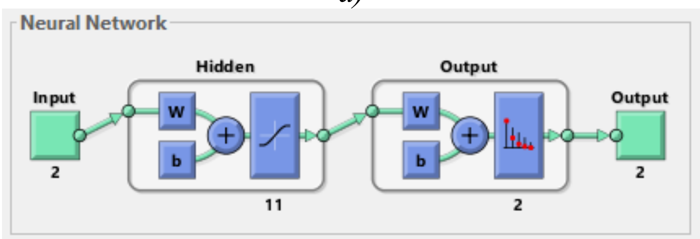


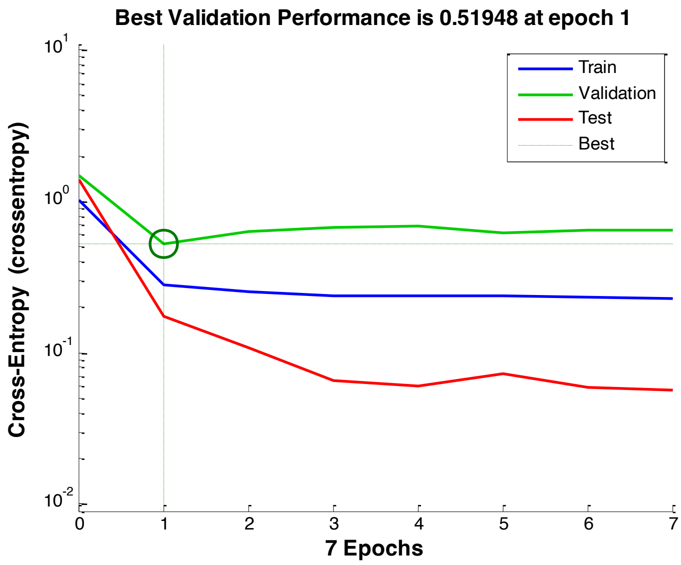
b)

Fig. 3.9. *FFNN for quantitative identification of strain gauges for a) one and b) two input variables*

An additional assessment and analysis of the qualities of the synthesized feed-forward architectures for quantitative identification of tensoresistive transducers was made in relation to:

- Cross-Entropy in relation to training, validation and test processes (Fig. 3.10);
- the output matrices of correct and incorrect classifications for the main network processes "training", "validation" and "testing", which are given in fig. 3.11.

With regard to the Cross-Entropy curves, there are no indications for retraining of the models for which similar variation trends have been observed. The best validation performances of 0.51948 were achieved at the 1^{-st} and 0.058209 at the 9th iteration during training with a duration of 7 and 15 cycles.



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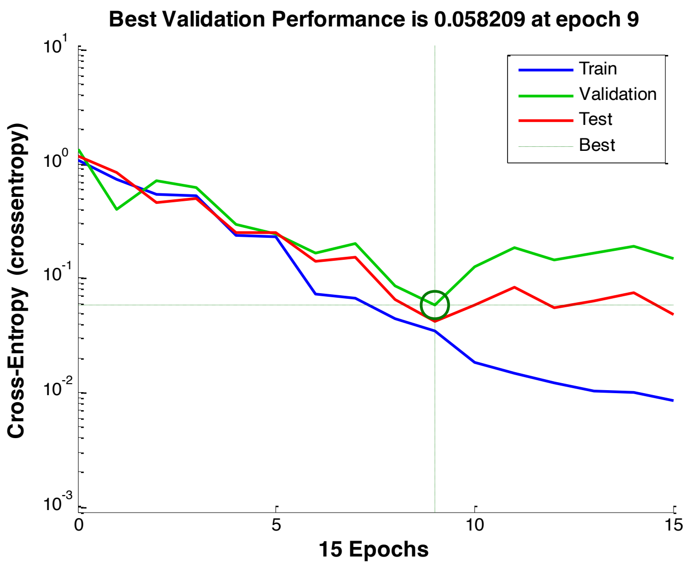


b)

Fig. 3.10. *Cross-Entropy for synthesized FFNNs for quantitative identification of strain gauges for a) one and b) two input variables*

a)

b)

Fig. 3.11. *Classification matrices for the synthesized FFNNs for quantitative identification of operating tensoresistive transducers for a) one and b) two input variables*

The classification matrices show the location of the standards with correct and incorrect affiliation to a given source group. Regarding the individual use of the "output voltage of the bridge circuit", accuracy levels of 91.7%, 75.0% and 100.0% were achieved, respectively in training, validation and testing. In the case of application of the "influencing input non-electrical quantity" as the second informative feature, identical accuracy of classification was found, equal to 100.0% are all the indicated processes, determining the advantages of the second neural model.

3.6. Investigation of neural models with backpropagation for identification of working transducers under the influence of forces on metals in Levenberg-Marquardt training

Actions have been implemented by analogy with the previous ones in the synthesis of models for qualitative analysis of information obtained from strain gages. The activities were applied to artificial neural networks with backpropagation (FFNNs) using the fastest learning algorithm, called the Levenberg-Marquardt algorithm (LM algorithm). The analyzed neural architectures consist of:

- input layer;
- intermediate layer with a given tangent-sigmoidal activation function;
- initial layer with linear activation function.

Tables 3.2 and 3.3 summarize data on quality criteria for the selection of neural models:

- accuracy of recognition and classification;
- mean-squared error.

Here again, the neural selection approach is followed by feeding one “F” and a combination of two input variables “F and U_{out}” to predict the operation of the strain gauge transducers. Architectures with variations of the intermediate neural units in the range from 5 to 15 were studied. The initial groups, respectively:

- „one working transducer“;
- „two working transducers“,

are defined by individual output neurons and discrete code combinations that determine their functional affiliation. In neural training, kits containing 52 information standards (26 for each test class) were used.

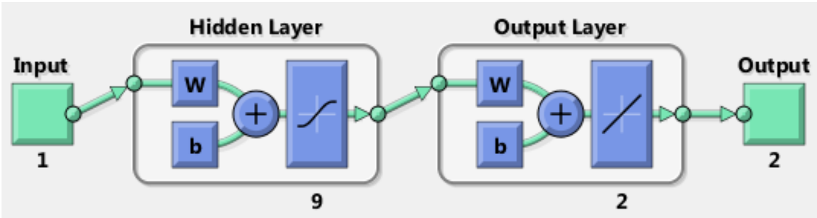
Table 3.2. Results in the study of artificial neural networks with one input variable in LM training

Hidden neurons	Accuracy, %	Mean-Squared Error
5	87.5	0.0973
6	62.5	0.1861
7	62.5	0.2590
8	87.5	0.1447
9	**100.0**	**0.0832**
10	50.0	0.3517
11	75.0	0.2813
12	62.5	0.4670
13	87.5	0.1331
14	75.0	0.1585
15	50.0	0.3843

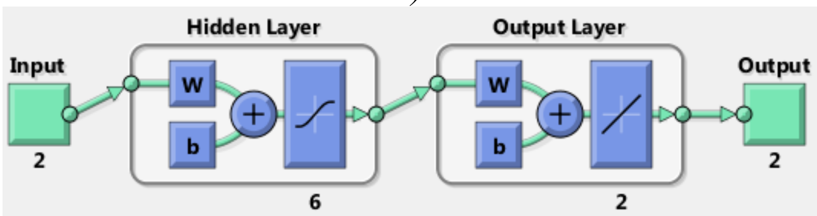
Table 3.3. Results in the study of artificial neural networks with two input variables in LM training

Hidden neurons	Accuracy, %	Mean-Squared Error
5	87.5	0.0349
6	**100.0**	**9.9631e-04**
7	87.5	0.0694
8	100.0	0.0065
9	100.0	0.0176

10	100.00	0.0029
11	100.0	0.0044
12	100.0	0.0349
13	87.5	0.1139
14	100.00	0.0124
15	87.5	0.0818



a)



b)

Fig. 3.13. *Synthesized models in LM training for identification of strain gauge transducers for a) one and b) two input variables*

As a result of the study, a relatively larger range of accuracy changes from 50.0% in 15 to 100.0% in 9 neurons was observed in the single-variable network. A similar conclusion can be made with respect to the second criterion, ranging from 0.0832 at 9 to 0.4670 at 12 hidden neurons. Compared to the neural models with two incoming input variables, a maximum accuracy of 100.0% was found for 6, 8-12 and 13 neurons. The minimum root mean square error is 9.9631e-04 at 6, while its highest levels reach 0.1139 at 13 neural units. The selected networks with the best indicators at 9 and 6 neurons in the hidden layers in the cases with one and two input variables are shown in fig. 3.13.

3.7. Predictive analysis of the force of loading on metals in a bridge circuit for the inclusion of strain gauges using FFNN architectures

FFNNs with linear output activation in LM training algorithm for approximation of the following transformation functions were studied:

- “$F = f(U_{out1})$”;
- “$F = f(U_{out2})$”;
- “$F = f(U_{out1}$ and $U_{out2})$”,

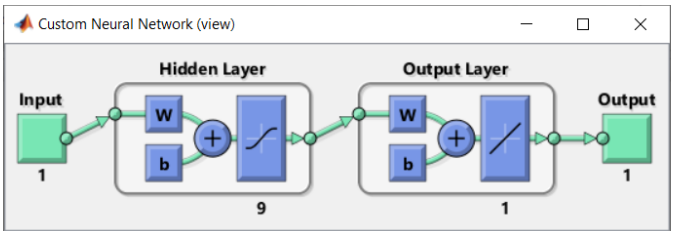
where U_{out1} and U_{out2} are the measured voltages of the bridge circuit of one and two operating sensing elements. The basic criteria for selecting a model for predictive analysis of the load on experimental metal samples is the root mean square error, analyzed by analogy with the previous problem when changing neurons in the hidden layer in the range 5 to 15. For neural selection processes, percentages were set between input data as follows: 50% for training, 25% for validation and 25% for test procedures.

Table 3.4. Investigation of FFNN architectures for approximation for one and two input variables

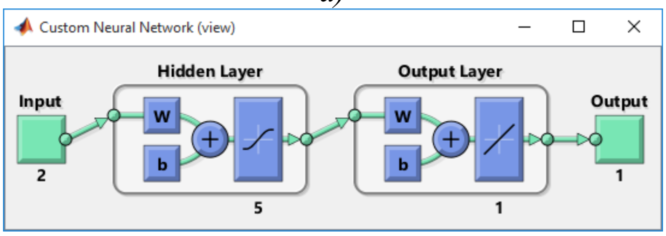
Hidden neurons	**MSE at U_{out1}**	**MSE at U_{out2}**	**MSE at U_{out1} и U_{out2}**
5	0.5971	8.0906	**0.0029**
6	1.9451	16.0860	0.0152

7	0.9674	0.5114	0.0722
8	**0.3302**	1.5668	0.6968
9	0.4279	**0.3582**	0.0885
10	11.9616	32.7781	0.4661
11	24.7131	2.3140	0.5848
12	2.9257	22.2944	0.6491
13	23.3295	33.2414	0.0052
14	19.8530	23.1725	0.5929
15	26.6503	27.7549	0.9412

Table 3.4 contains data on the recorded error values for the three studied types of neural architectures. When applying individual input variables “U_{out1}” and “U_{out2}”, minimum values of MSE = 0.3302 and MSE = 0.5114 were registered, respectively for 8 and 7 neurons in the intermediate layers. The maximum error levels found are 26.6503 at 15 and 33.2414 for 13 hidden structural units, respectively. Comparing the obtained errors with those of models with two input variables "U_{out1} and" U_{out2} "we see better qualities in the latter, where MSE changes at significantly lower levels in the final range from 0.0029 to 0.9412, respectively at 5 and 15 intermediate neuron.



a)



b)

Fig. 3.17. *Selected FFNNs for prediction of force effects on metals in switching on a bridge circuit with strain gages at the supply of a) "U_{out2}" and b) "U_{out1}" and "U_{out2}" input variables*

According to the results for the purposes of the forecast analysis, neural architectures with the presence of 8, 7 and 5 computing units in the hidden layer were selected, respectively when submitting “U_{out1}”, “U_{out2}” and “U_{out1} and “U_{out2}”. Figure 3.17 illustrates the models for informative features “U_{out2}” and “U_{out1} and “U_{out2}”.

3.8. Derivation of linear regression models for forecasting force effects on metals.

The first part of the research concerning the synthesis of models for quantitative analysis of the forces of impact on experimental metal samples consists in the application of the tool of regression analysis. In connection, two information categories are defined, including 26 records for each group with:

- output parameter “force F” with “y” entered;
- controllable factors of the site "registered output voltage from the bridge measuring circuit with the inclusion of one "U_{out1}" and two operating transducers "U_{out2}" with a label "x".

Regression procedures were applied to the experimental data in the product Statistica 10 to check the suitability of zero-degree models, and results with very good quality indications were observed, shown in fig. 3.29.

Regression Summary for Dependent Variable: y (danninew)
R= ,99948781 R?= ,99897588 Adjusted R?= ,99893320
F(1,24)=23411, p<0,0000 Std.Error of estimate: ,29978

N=26	b*	Std.Err. of b*	b	Std.Err. of b	t(24)	p-value
Intercept			-0,4749	0,122680	-3,8707	0,000730
x	0,999488	0,006532	394,7272	2,579826	153,0054	0,000000

a)

Regression Summary for Dependent Variable: y (danninew)
R= ,99943534 R?= ,99887101 Adjusted R?= ,99882396
F(1,24)=21234, p<0,0000 Std.Error of estimate: ,31475

N=26	b*	Std.Err. of b*	b	Std.Err. of b	t(24)	p-value
Intercept			-0,4334	0,128564	-3,3714	0,002529
x	0,999435	0,006859	788,5744	5,411632	145,7184	0,000000

b)

Fig. 3.29. *Regression results for models of a) 1 and b) 2 transducers*

$$y = -0.4749 + 394.7272x_1 \quad (3.1)$$
$$y = -0.4344 + 788.5744x_1 \quad (3.2)$$

Compared to the accepted baseline significance level α = 0.05, no significant experimental regression coefficients bi were found. The obtained Fisher's criteria F (1,24) = 23411 and F (1,24) = 21234, as well as their respective probabilities p <0.0000, determine the derived models regarding the forecasting of forces in productions with the inclusion of one (3.1) and two working sensitive sensor elements (3.2) as adequate and fully describing the experimental data in the course of the performed diagnostics. Regarding the coefficients of determination R2 compared to the obtained forecast models, close high levels were found, respectively R2 = 0.99897588 for one and R2 = 0.99887101 for two detecting strain gages, confirming the high quality of the forecast regression models.

3.9. Research and selection of models for predictive analysis in connection with force effects on metal objects on the basis of generalized regression neural networks in two operating transducers

Another type of artificial neural networks that can be used as a basis for creating models for predictive quantitative analysis of potential forces on metal objects is that of generalized regression neural networks (Generalized Regression Neural Networks - GRNNs). An approach in GRNN-based research is to perform architecture tests when specifying a different number of input variables. Initially, the behavior of neural networks when submitting one and a combination of these three informative features, respectively U_{out}, ΔR/R and Δl/l was analyzed. Significantly elevated MSE readings were obtained over the entire range of variation in the width of the radial-basis functions in both cases. As a result, models with three input variables were excluded. Neural architectures with different combinations of two features and those with individual variables were then evaluated sequentially. Negative trends were found in the use of "measured output voltage in the indicator diagonal of the bridge" and better but still unsatisfactory results when applying the other two individual information signs ΔR/R and Δl/l.

Table 3.6. Results of the synthesis of RGNN architectures
for the cases of one and a combination of two informative recognized

№	**Spread indicator**	**ΔR/R**	**ΔR/R и Δl/l**
		MSE indicator	
1.	0.80	22.3324	8.6830e-17
2.	0.81	22.9465	2.0387e-16
3.	0.82	23.5604	4.6403e-16
4.	0.83	24.1738	1.0255e-15
5.	0.84	24.7861	2.2032e-15
6.	0.85	25.3969	4.6084e-15
7.	0.86	26.0060	9.3955e-15
9.	0.87	26.6129	1.8693e-14
10.	0.88	27.2173	3.6335e-14
11.	0.89	27.8189	6.9071e-14
12.	0.90	28.4173	1.2853e-13
13.	0.91	29.0124	2.3436e-13

14.	0.92	29.6037	4.1908e-13
15.	0.93	30.1911	7.3556e-13
16.	0.94	30.7744	1.2682e-12
17.	0.95	31.3532	2.1493e-12

Table 3.6 contains summary data on architectures using one “ΔR/R” variable (fig. 3.32.a) and the combination of two input variables with the best quality indicators “ΔR/R and Δl/l” (fig. 3.32.a), 3.32.b), in order to better present the overall assessment process from a negative and a positive endpoint. In the synthesis procedures for the two types of generalized regression neural architectures, identical ranges of the width of the radial basis layer functions were used, as follows from "0.8" to "0.98" with a constant step of increasing the indicator "0.01". By analogy with FFNN research, the basic MSE criterion is analyzed here. In the course of the processes of model selection when applying one and a combination of two informative features, the same tendency of gradual increase of the root mean square error has been established. At the lowest value of "spread" the lowest MSE variations were observed. A very negative indication was observed in GRNN based on the variable “ΔR / R”, associated with a significant tens of times exceeding the levels of MSE compared to models with submitted “ΔR / R” and “Δl/l”. In an architecture with one informative feature, a minimum root mean square error of 22.3324 was found, while in a neural network with two input variables, the error was only insignificant at 8.6830e-17.

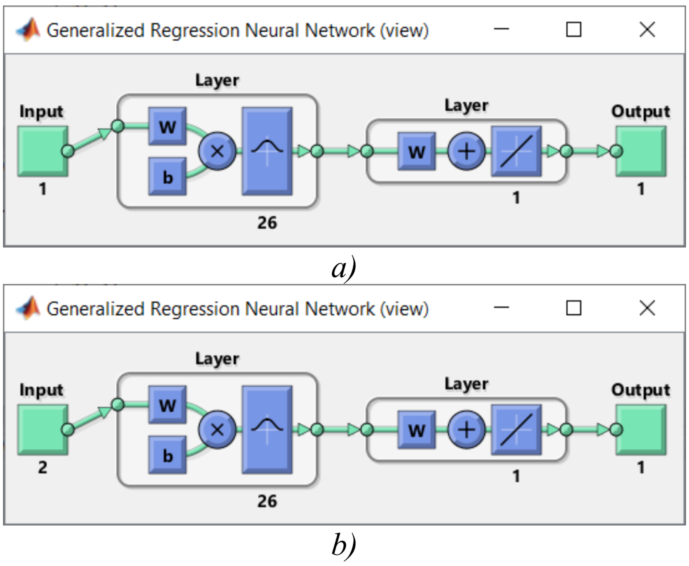


Fig. 3.32. *Investigated GRNN models for predictive analysis of force load in a) one and b) two input variables*

Regarding the objectives of the forecast analysis, an architecture of a generalized regression neural network with the most adequate MSE estimate was chosen when submitting the relative changes in resistance and length of sensitive sensor elements at the spread indicator level "0.8".

Conclusions to the third chapter

- Experimental system for monitoring, filtering, registration, research and statistical analysis of non-electric power impacts on tested metal objects and noise reduction with WEB access based on strain gauge transducers, multifunction module NI 6002, virtual platform LabVIEW, software digital filters and regression diagnostics has been developed;
- An approach for quantitative identification of the included working sensor transducers and forecast analysis of the power loads in testing of metal samples on the basis of processing and analysis of experimentally obtained data through artificial neural networks and regression analysis is systematized;

- ❖ Tests concerning the operability of the designed system were performed and experimental data were obtained, used as an information basis for the synthesis of models for qualitative and quantitative analysis of data from strain gauges;
- ❖ Architectures of artificial neural networks with direct signal propagation and error backpropagation were synthesized in Levenberg-Marquardt and Scaled Conjugate Gradient training algorithms, evaluated by a set of quality indicators, to identify the operational sensor elements to the bridge of their circuit. switching on when measuring forces;
- ❖ Neural backpropagation models have been created on the basis of a selection of input informative features for the purpose of predictive analysis of potential load forces during testing of strain gauge transducers on test metal objects;
- ❖ Linear mathematical models with the help of regression analysis and models based on generalized regression neural networks in different cases of input variables for predictive analysis of force effects in testing of test metal objects with inclusion of strain-sensitive sensing elements were derived.

CHAPTER IV: FORECAST ANALYSIS OF TRAFFIC IN IMITATED MODELED INFORMATION AND COMMUNICATION CHANNELS OF THE MARKOV CHAINS TYPE

4.1. Simulation modeling of teletraffic systems of the Markov chain type in connection with the synthesis of models for predictive analysis of system customer service

A series of studies were conducted in connection with simulation modeling of Markov chains M/M/1 and M/M/c/k at c = 15 and accumulation of several categories of experimental. With regard to the formed information sets, the aim is to obtain models for predictive analysis of the incoming and processed traffic with the help of a set of different mathematical devices. The procedures were performed according to defined factors or parameters in teletraffic simulation, as follows:

- ➢ Avg. Arrival Rate (x_1) – set average speed of receiving requests to the operating server stations;
- ➢ Avg. Service Time (x_2) – fixed average processing time of incoming requests;
- ➢ Max Station Capacity k, (x_3) – set the maximum number of calls in the queue,

as well as its responses to the object in Markov chains M/M/1 and M/M/c/k at c = 15, respectively:

- ➢ Avg. Cust. N in Station (y_1) – average number of users in the queue + average number of requests served;
- ➢ Avg. Response Time (y_2) – average time spent in the queue + average time for servicing requests.

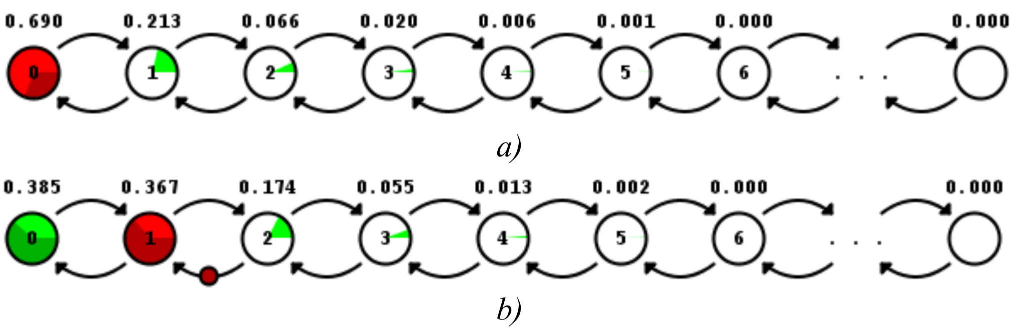


Fig. 4.1. *Transition diagrams in simulation modeling of the teletraffic system a) M/M/1 and b) M/M/c/k at c = 15*

Figure 4.1 presents diagrams of the transitions with respect to moment states in the simulation conditions of the studied Markov chains. In the course of the simulation processes, information sets of experimental data were set aside, respectively, both for training and for verification procedures regarding the verification of their adequacy.

4.3. Application of the regression apparatus for deriving models for predictive analysis with respect to the service of system users in the Markov M/M/1 chain

4.3.1. Verification of the adequacy of basic analytical models of zero, first and second degree regarding forecast analysis of traffic parameters

In the initial stage of the presented researches the possibility of deriving forecast models in connection with a teletraffic system with unlimited queue and one server station on the basis of the classical regression analysis was considered. For this purpose, the adequacy of the basic analytical linear and polynomial models given below was set:

$$y = b_0 + b_1x_1 + b_2x_2 \tag{4.1}$$

$$y = b_0 + b_1x_1 + b_2x_2 + b_{12}x_1x_2 \tag{4.2}$$

$$y = b_0 + b_1x_1 + b_2x_2 + b_{12}x_1x_2 + b_{11}x_1^2 + b_{22}x_2^2 \tag{4.3}$$

The analysis regarding the parameters of the object y_1 and y_2 was applied with the help of the software package STATISTICA 10. In fig. 4.3 shows the obtained final form of the extended matrix of the experiment, reflecting all possible interactions of the controllable factors. After defining the extended matrix, we proceeded to the application of the regression apparatus, the results of which are shown in fig. 4.4 and fig. 4.5.

Regression Summary for Dependent Variable: y1 (m-m-1)
R= ,75137946 R?= ,56457109 Adjusted R?= ,53818146
F(2,33)=21,394 p<,00000 Std.Error of estimate: 1,0366

N=36	b*	Std.Err. of b*	b	Std.Err. of b	t(33)	p-value
Intercept			-2,42048	0,550424	-4,39749	0,000108
x1	0,504320	0,114869	4,44143	1,011622	4,39040	0,000110
x2	0,556985	0,114869	1,88663	0,389085	4,84889	0,000029

a)

Regression Summary for Dependent Variable: y1 (m-m-1)
R= ,90029822 R?= ,81053688 Adjusted R?= ,79277471
F(3,32)=45,633 p<,00000 Std.Error of estimate: ,69438

N=36	b*	Std.Err. of b*	b	Std.Err. of b	t(32)	p-value
Intercept			0,92390	0,636538	1,45144	0,156391
x1	-0,445059	0,166183	-3,91953	1,463532	-2,67813	0,011587
x2	-0,604608	0,195959	-2,04794	0,663757	-3,08537	0,004172
x12	1,580058	0,245145	9,83642	1,526114	6,44540	0,000000

b)

Regression Summary for Dependent Variable: y1 (m-m-1)
R= ,94190570 R?= ,88718634 Adjusted R?= ,86838407
F(5,30)=47,185 p<,00000 Std.Error of estimate: ,55339

N=36	b*	Std.Err. of b*	b	Std.Err. of b	t(30)	p-value
Intercept			3,3100	0,757580	4,36915	0,000137
x1	-1,40401	0,361046	-12,3648	3,179645	-3,88873	0,000518
x2	-1,56469	0,315829	-5,3000	1,069781	-4,95424	0,000027
x12	1,58006	0,195369	9,8364	1,216242	8,08755	0,000000
x11	0,97480	0,341430	10,5565	3,697493	2,85506	0,007734
x22	0,98375	0,281281	1,9130	0,546966	3,49738	0,001487

c)

Fig. 4.4. *Regression results when checking the adequacy of models a) (4.1), b) (4.2) and c) (4.3) on parameter y1 for a Markov chain M/M/1*

The results show the lowest levels of the coefficients of certainty R^2 obtained for the linear models for predicting variations of "average number of requests in the queue + average number of requests served" and "average total time of stay in the queue and processing of requests" for a given server station. The following coefficients $R^2 = 0.56457109$ and $R^2 = 0.65195915$ were found for the responses of the object y_1 and y_2, defining model (4.1) as inadequate regarding the purpose of the study.

When using polynomial models of a corresponding degree, an increase in the levels of R^2 was observed in relation to the forecast parameters of the served traffic. From the analysis of the suitability of model (4.2) regression estimates of certainty of the order of levels of "0.81" and "0.83" were registered. With regard to the second degree model, it was found that 88.718634% of the change y_1 and 91.163600% of the variations of the initial parameter y_2 are the result of the influence of controllable factors. The remaining 11.281366% and 8.937000% of the change in teletraffic parameters are due to accidental disturbances.

Regression Summary for Dependent Variable: y2 (m-m-1)
R= ,80743987 R?= ,65195915 Adjusted R?= ,63086576
F(2,33)=30,908 p<,00000 Std.Error of estimate: 1,4225

N=36	b*	Std.Err. of b*	b	Std.Err. of b	t(33)	p-value
Intercept			-3,24818	0,755325	-4,30038	0,000142
x1	0,392648	0,102697	5,30762	1,388209	3,82336	0,000554
x2	0,705540	0,102697	3,66813	0,533926	6,87011	0,000000

a)

Regression Summary for Dependent Variable: y2 (m-m-1)
R= ,91477834 R?= ,83681942 Adjusted R?= ,82152124
F(3,32)=54,701 p<,00000 Std.Error of estimate: ,98912

N=36	b*	Std.Err. of b*	b	Std.Err. of b	t(32)	p-value
Intercept			1,20203	0,906727	1,32568	0,194333
x1	-0,430398	0,154226	-5,81791	2,084752	-2,79070	0,008793
x2	-0,301481	0,181860	-1,56741	0,945500	-1,65776	0,107139
x12	1,369801	0,227507	13,08885	2,173898	6,02092	0,000001

b)

Regression Summary for Dependent Variable: y2 (m-m-1)
R= ,95479631 R?= ,91163600 Adjusted R?= ,89690867
F(5,30)=61,901 p<,00000 Std.Error of estimate: ,75174

N=36	b*	Std.Err. of b*	b	Std.Err. of b	t(30)	p-value
Intercept			4,4735	1,029119	4,34688	0,000146
x1	-1,12033	0,319535	-15,1441	4,319322	-3,50613	0,001453
x2	-1,38837	0,279517	-7,2182	1,453222	-4,96704	0,000026
x12	1,36980	0,172907	13,0889	1,652178	7,92218	0,000000
x11	0,70134	0,302175	11,6577	5,022781	2,32097	0,027270
x22	1,11368	0,248942	3,3240	0,743015	4,47366	0,000102

c)

Fig. 4.5. *Regression results when checking the adequacy of models a) (4.1), b) (4.2) and c) (4.3) on parameter y2 for a Markov chain M/M/1*

Based on the accepted significance level $\alpha = 0.05$ and the established Fisher criteria F (5.30) = 47.185 and F (5.30) = 61.901, as well as their respective probabilities p less than α, for responses of the object y_1 and y_2 give grounds model (4.3) to be defined as the most complete describing the experimental data and the highest degree of adequacy. Regarding the model, the experimental regression coefficients b_0, b_1, b_2, b_{12}, b_{11} and b_{22} are defined as significant.

$$y_1 = 3.3100 - 12.3648x_1 - 5.3000x_2 + 9.8364x_1x_2 + 10.5565x_1^2 + 1.9130x_2^2 \qquad (4.4)$$

$$y_2 = 4.4735 - 15.1441x_1 - 7.2182x_2 + 13.0889x_1x_2 + 11.6577x_1^2 + 3.3240x_2^2 \qquad (4.5)$$

Based on the performed regression diagnostics, final models (4.4) and (4.5) are derived for predictive analysis of the target parameters of the processed traffic from a given structural server station y_1 and y_2, presented above. In connection with the qualities of the obtained forecast analytical models, it can be said that the expected levels of the coefficient of certainty R^2 around "0.91" in the forecast analysis of y^2 are considered satisfactory. When forecasting the quantitative changes of the traffic load - parameter y_1, due to the lower degrees of similarity between the theoretical and forecast results, there is a reason to look for more adequate mathematical tools for forecast analysis.

4.5. Synthesis of GRNN models for predictive analysis of the served user requests of server stations in the M/M/c/k chain with different input variables and training algorithms

In the next stage, we moved on to research aimed at regression modeling, analysis and evaluation of the effectiveness of one of the types of artificial neural networks, which are specified for the purposes of predictive analysis - generalized regression neural architectures. The object of forecast analysis is "the average number of requests to be called in the queue, added to the average number of processed requests from the system server station (parameter y_1)" is the Markov chain M/M/15/k. GRNNs were created and analyzed for strictly defined 45 structural units in the radial-base layers. The actual research processes were divided into three phases, consisting in the synthesis of GRNNs based on different amounts of learning variables, respectively:

- ❖ Single input effects;
- ❖ Combinations of two controllable factors;
- ❖ A set of three independent informative features.

Two baseline indicators, Mean Squared Error and Mean Absolute Error, were assessed, with a gradual increase in the spread indicator at identical levels from 0.15 to 0.95 for structural neurones with radial-base layers. The results of the analysis of neural functionality are summarized sequentially from Table 4.5 to Table 4.7.

Table 4.5. MSE and MAE indicators in the synthesis of generalized regression neural networks for forecasting the served requests in the Markov chain M/M/c/k when applying individual input variables

<table>
<tr><th rowspan="2">Spread indicator</th><th>MSE</th><th>MAE</th><th>MSE</th><th>MAE</th><th>MSE</th><th>MAE</th></tr>
<tr><th colspan="2">x1</th><th colspan="2">x2</th><th colspan="2">x3</th></tr>
<tr><td>0.15</td><td>0.0090</td><td>0.0642</td><td>0.0012</td><td>0.0180</td><td rowspan="7">5.1444e-04</td><td rowspan="7">0.0202</td></tr>
<tr><td>0.20</td><td>0.0202</td><td>0.1054</td><td>0.0028</td><td>0.0307</td></tr>
<tr><td>0.25</td><td>0.0371</td><td>0.1514</td><td>0.0054</td><td>0.0464</td></tr>
<tr><td>0.30</td><td>0.0591</td><td>0.1980</td><td>0.0091</td><td>0.0640</td></tr>
<tr><td>0.35</td><td>0.0843</td><td>0.2413</td><td>0.0140</td><td>0.0838</td></tr>
<tr><td>0.40</td><td>0.1100</td><td>0.2791</td><td>0.0203</td><td>0.1053</td></tr>
<tr><td>0.45</td><td>0.1344</td><td>0.3107</td><td>0.0282</td><td>0.1283</td></tr>
<tr><td>0.50</td><td>0.1564</td><td>0.3368</td><td>0.0375</td><td>0.1521</td><td>5.1758e-04</td><td rowspan="5">0.0203</td></tr>
<tr><td>0.55</td><td>0.1757</td><td>0.3581</td><td>0.0483</td><td>0.1761</td><td>5.2206e-04</td></tr>
<tr><td>0.60</td><td>0.1923</td><td>0.3755</td><td>0.0601</td><td>0.1995</td><td>5.2912e-04</td></tr>
<tr><td>0.65</td><td>0.2066</td><td>0.3897</td><td>0.0727</td><td>0.2222</td><td>5.3862e-04</td></tr>
<tr><td>0.70</td><td>0.2188</td><td>0.4015</td><td>0.0857</td><td>0.2435</td><td>5.5033e-04</td></tr>
<tr><td>0.75</td><td>0.2292</td><td>0.4113</td><td>0.0989</td><td>0.2633</td><td>5.6408e-04</td><td>0.0204</td></tr>
<tr><td>0.80</td><td>0.2382</td><td>0.4195</td><td>0.1118</td><td>0.2814</td><td>5.7987e-04</td><td>0.0207</td></tr>
<tr><td>0.85</td><td>0.2458</td><td>0.4264</td><td>0.1244</td><td>0.2979</td><td>5.9781e-04</td><td>0.0209</td></tr>
<tr><td>0.90</td><td>0.2525</td><td>0.4323</td><td>0.1364</td><td>0.3130</td><td>6.1805e-04</td><td>0.0211</td></tr>
<tr><td>0.95</td><td>0.2583</td><td>0.4374</td><td>0.1478</td><td>0.3267</td><td>6.4079e-04</td><td>0.0213</td></tr>
</table>

The application of individual input variables x_1 and x x_2 2 is associated with observed significant degrees of increase in quality indicators with increasing width of the radial-basis functions. The following variation ranges are registered for:

- ❖ MSE from 0.0090 to 0.2583 at x_1 and from 0.0012 to 0.1478 for the variable x_2 for the defined limit values of the spread indicator;
- ❖ MAE an indicator ranging from 0.0642 to 0.4374 for spread = 0.15 for factor x_1 and from 0.0180 to 0.3267 for spread = 0.95 for factor x_2.

Comparing the results with respect to the two types of test GRNN architectures, there is an advantage in the supply of x_1 over the control effect x_2. Significant improvement was found in models with input variable x_3. Here, the minimum mse and absolute errors obtained are 5.1444e-04 and 0.0202 for models for spread values “0.15”, “0.20”, “0.25”, “0.30”, “0.35”, “0.40” and “0.45”. Maximum MSE = 6.4079e-04 and MAE = 0.0213 were found at the highest limit of the spread indicator.

In connection with the training procedures of GRNNs when using combinations of two input input variables, the lowest quality indications were found for the pair “x_1 and x_2”. The MSE ranges from 0.020 to 0.1239 at spread levels of “0.20” and “0.95”, while the MAE varies from 0.0251 to 0.2973. Exceptions in the initial samples for the indicators are values of MSE = 8.5469e-04 and MAE = 0.0147 at the smallest fixed width of the radial-base functions, approaching the achieved positive close indications in combinations "x_1 and x_3" and "x_2 and x_3". ”. Quantitative ranges for MSE and MAE were obtained in the analysis of neural functionality, respectively:

- ❖ from 5.0812e-04 to 6.3866e-04 on the root mean square error and from 0.0201 to 0.0213 for the mean absolute error at a set value of spread = 0.15;
- ❖ from 4.8957e-04 to 6.3240e-04 for MSE, as well as from 0.0197 to 0.0212 in conjunction with the MAE indicator.

Significantly better performance in architectures with applied combinations of variables "x_1 and x_3" and "x_2 and x_3" compared to GRNNs with single input effects "x_1" and "x_2". There are also slight advantages in the neural networks trained on the basis of the second - "x_1 and x_3", over the other applied pairs of controllable factors.

Table 4.6. MSE and MAE indicators in the synthesis of generalized regression neural networks for forecasting the served requests in the Markov chain M/M/c/k in using combinations of two input variables

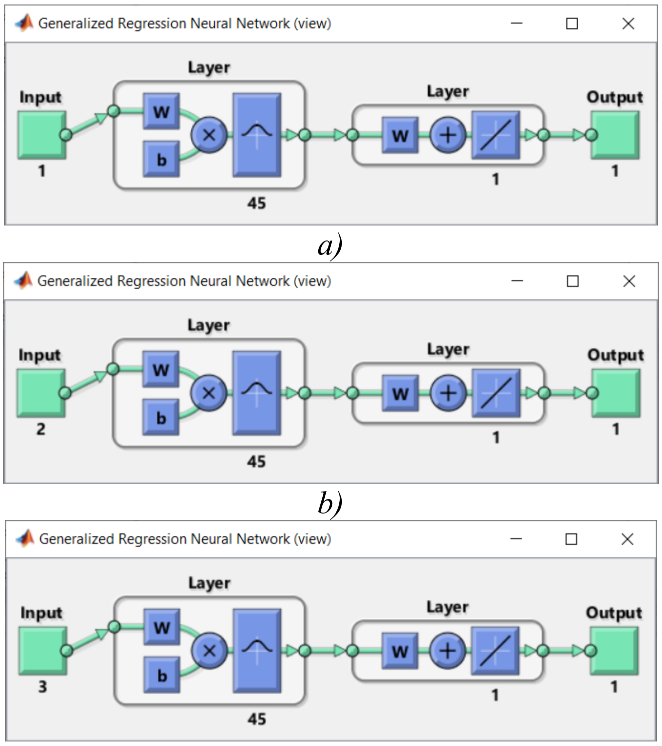
<table>
<tr><th rowspan="2">Spread indicator</th><th>MSE</th><th>MAE</th><th>MSE</th><th>MAE</th><th>MSE</th><th>MSE</th></tr>
<tr><th colspan="2">x_1 and x_2</th><th colspan="2">x_1 and x_3</th><th colspan="2">x_2 and x_3</th></tr>
<tr><td>0.15</td><td>8.5469e-04</td><td>0.0147</td><td>5.0812e-04</td><td>0.0201</td><td>4.8957e-04</td><td>0.0197</td></tr>
<tr><td>0.20</td><td>0.0020</td><td>0.0251</td><td>5.1088e-04</td><td rowspan="8">0.0202</td><td>5.0037e-04</td><td>0.0199</td></tr>
<tr><td>0.25</td><td>0.0039</td><td>0.0378</td><td>5.1216e-04</td><td>5.0541e-04</td><td>0.0200</td></tr>
<tr><td>0.30</td><td>0.0066</td><td>0.0527</td><td>5.1284e-04</td><td>5.0808e-04</td><td rowspan="6">0.0201</td></tr>
<tr><td>0.35</td><td>0.0102</td><td>0.0690</td><td>5.1317e-04</td><td>5.0936e-04</td></tr>
<tr><td>0.40</td><td>0.0149</td><td>0.0871</td><td>5.1335e-04</td><td>5.0970e-04</td></tr>
<tr><td>0.45</td><td>0.0207</td><td>0.1065</td><td>5.1397e-04</td><td>5.0993e-04</td></tr>
<tr><td>0.50</td><td>0.0277</td><td>0.1269</td><td>5.1600e-04</td><td>5.1138e-04</td></tr>
<tr><td>0.55</td><td>0.0359</td><td>0.1482</td><td>5.2030e-04</td><td>5.1515e-04</td></tr>
<tr><td>0.60</td><td>0.0451</td><td>0.1694</td><td>5.2723e-04</td><td rowspan="3">0.0203</td><td>5.2170e-04</td><td rowspan="3">0.0202</td></tr>
<tr><td>0.65</td><td>0.0554</td><td>0.1906</td><td>5.3666e-04</td><td>5.3091e-04</td></tr>
<tr><td>0.70</td><td>0.0664</td><td>0.2111</td><td>5.4833e-04</td><td>5.4245e-04</td></tr>
<tr><td>0.75</td><td>0.0778</td><td>0.2308</td><td>5.6206e-04</td><td>0.0204</td><td>5.5611e-04</td><td>0.0203</td></tr>
<tr><td>0.80</td><td>0.0895</td><td>0.2494</td><td>5.7783e-04</td><td>0.0206</td><td>5.7183e-04</td><td>0.0205</td></tr>
<tr><td>0.85</td><td>0.1012</td><td>0.2667</td><td>5.9575e-04</td><td>0.0208</td><td>5.8968e-04</td><td>0.0207</td></tr>
<tr><td>0.90</td><td>0.1127</td><td>0.2826</td><td>6.1597e-04</td><td>0.0211</td><td>6.0981e-04</td><td>0.0210</td></tr>
<tr><td>0.95</td><td>0.1239</td><td>0.2973</td><td>6.3866e-04</td><td>0.0213</td><td>6.3240e-04</td><td>0.0212</td></tr>
</table>

The last phase of the synthesis of GRNN models for predictive analysis consists in the evaluation of MSE and MAE indicators against a gradual increase of the spread parameter for the case of using three input variables. When submitting the input combination “x_1, x_2 and x_3” the best quantitative indicators were obtained in the course of the research, against which the specified GRNN architecture is evaluated with the highest degree of adequacy. Numerical ranges from 4.8341e-04 to 6.3031e-04 for MSE and from 0.0196 to 0.0211 for MAE criteria have been established.

Table 4.7. MSE and MAE indicators in the synthesis of generalized regression neural networks for forecasting the served requests in the Markov chain M/M/c/k in applying three input variables

Spread indicator	MSE	MAE
	x_1, x_2 and x_3	
0.15	4.8341e-04	0.0196

0.20	4.9686e-04	0.0199
0.25	5.0315e-04	0.0200
0.30	5.0649e-04	0.0201
0.35	5.0809e-04	
0.40	5.0848e-04	
0.45	5.0859e-04	
0.50	5.0985e-04	
0.55	5.1345e-04	
0.60	5.1987e-04	
0.65	5.2899e-04	
0.70	5.4050e-04	0.0202
0.75	5.5414e-04	
0.80	5.6983e-04	0.0205
0.85	5.8766e-04	0.0207
0.90	6.0776e-04	0.0209
0.95	6.3031e-04	0.0211



a) *b)* *c)*

Fig. 4.15. *Investigations of generalized regression neural networks for forecasting the served requests in the Markov chain M/M/c/k for a) one, b) two and c) three input controllable factors*

In fig. 4.15 illustrates the type of analyzed architectures of generalized regression neural networks for one, two and three input variables. Regarding the objectives of forecast analysis of the potential average traffic load of server stations in the M/M/c/k chain, models were selected for combinations “x_1 and x_2”, “x_1 and x_3”, “x_2 and x_3” and found with the most Better GRNN values for "x_1, x_2 and x_3" at the smallest width of the radial basis functions at the level of "0.15".

4.6. FFNN models for forecast analysis of the traffic load of server stations in the M/M/c/k chain with different input variables and training algorithms

4.6.1. Selection of FFNN architectures for predictive analysis of the average served traffic from structural server stations in the M/M/c/k chain

Based on the established advantages in obtaining predictive models through artificial intelligence, a basis for expanding research in this direction is formed. Activities for implementation and analysis of the functionality of other types of networks were carried out with the introduction of specified conditions and categories of neural learning. In this direction the task for synthesis of FFNN models at tangent-sigmoidal and linear activations for predictive analysis of the parameter “Avg. Cust. N in Station” by analogy with GRNN for different pairs of variables and three controllable factors of the object in the course of the following training gradient approaches:

- ❖ Levenberg-Marquardt algorithm;
- ❖ Bayesian Regularization training;
- ❖ Scaled Conjugate Gradient algorithm.

Table 4.8. Results in the study of FFNN models for predictive analysis of input variables x_1 and x_2 and different training algorithms

Input variables x_1 and x_2						
Hidden neurons	**Levenberg-Marquardt**		**Bayesian Regularization**		**Scaled Conjugate Gradient**	
	MSE in testing	**R in testing**	**MSE in testing**	**R in testing**	**MSE in testing**	**R in testing**
5	3.58376e-5	0.999956	1.62116e-5	0.999971	2.00065e-4	0.999805
6	1.95550e-5	0.999976	3.05737e-5	0.999974	1.12584e-2	0.986220
7	2.17066e-5	0.999962	1.87423e-5	0.999969	3.07503e-4	0.999364
8	1.25622e-5	0.999981	**7.87707e-6**	**0.999978**	4.15378e-3	0.994077
9	1.46942e-5	0.999978	2.88317e-5	0.999960	8.13698e-4	0.998838
10	3.57247e-5	0.999946	2.83059e-5	0.999971	1.62650e-2	0.979963
11	3.73982e-5	0.999944	2.07308e-5	0.999972	2.56892e-4	0.999629
12	1.184425e-4	0.999895	2.87987e-5	0.999973	2.79524e-2	0.982778
13	2.45482e-5	0.999989	4.27936e-5	0.999965	2.39668e-3	0.995858
14	4.49284e-5	0.999937	2.49110e-5	0.999975	1.773763-3	0.995772
15	4.14351e-5	0.999962	4.09594e-5	0.999973	5.27899e-4	0.999341

Accepted baseline criteria for performance evaluation are the "average error" and the "correlation coefficient", the first one being of greater importance. The indicators are reported according to the test processes of the target neuronal architectures with a defined quantitative change of the hidden neurons from 5 to 15 units. The data for the considered synthesis cases are systematized from Table 4.8 to Table 4.11.

Table 4.9. Results in the study of FFNN models for predictive analysis of input variables x_1 and x_3 and different training algorithms

Input variables x_1 and x_3						
Hidden neurons	**Levenberg-Marquardt**		**Bayesian Regularization**		**Scaled Conjugate Gradient**	
	MSE in testing	**R in testing**	**MSE in testing**	**R in testing**	**MSE in testing**	**R in testing**
5	4.39720e-5	0.999950	2.11298e-5	0.999984	3.08028e-3	0.997355
6	1.62596e-5	0.999967	3.75225e-5	0.999961	2.45964e-3	0.998581
7	9.70807e-6	0.999989	2.01365e-5	0.999975	2.09834e-3	0.998711
8	6.50901e-5	0.999921	1.96413e-5	0.999973	1.01533e-3	0.998663
9	4.76781e-5	0.999924	1.14102e-5	0.999984	3.00404e-3	0.996675
10	7.33183e-5	0.999784	**4.38308e-6**	**0.999976**	9.57688e-3	0.995464
11	1.54755e-4	0.999930	2.32812e-5	0.999976	9.99734e-3	0.995764
12	1.17251e-4	0.999697	7.73285e-6	0.999972	1.254823-2	0.995194
13	1.53007e-4	0.999793	1.27526e-5	0.999982	2.27819e-2	0.986049
14	1.04919e-3	0.998664	2.31026e-5	0.999977	4.48133e-4	0.998582
15	5.761154e-4	0.998698	1.36876e-5	0.999979	6.83172e-3	0.988135

Table 4.10. Results in the study of FFNN models for predictive analysis of input variables x_2 and x_3 and different training algorithms

Input variables x_2 и x_3						
Hidden neurons	**Levenberg-Marquardt**		**Bayesian Regularization**		**Scaled Conjugate Gradient**	
	MSE при тестване	**R при тестване**	**MSE при тестване**	**R при тестване**	**MSE при тестване**	**R при тестване**

5	5.73373e-5	0.999882	1.19938e-5	0.999987	6.09723e-3	0.993193
6	1.44124e-4	0.999923	1.65318e-5	0.999974	7.84788e-2	0.862890
7	1.67926e-5	0.999973	1.99778-e-5	0.999971	9.70160e-3	0.998716
8	1.75572e-5	0.999964	2.68760e-5	0.999966	4.46214e-4	0.999649
9	5.71159e-5	0.999927	1.45921e-5	0.999981	4.12709e-3	0.994168
10	1.32510e-4	0.999911	1.39287e-5	0.999967	1.06766e-3	0.999101
11	1.12462e-4	0.999871	1.45404e-5	0.999976	3.63054e-3	0.996383
12	6.16591e-5	0.999860	**8.52469e-6**	**0.999976**	5.19627e-3	0.993164
13	2.86715e-5	0.999954	1.17933e-5	0.999979	7.51613e-3	0.994223
14	2.63716e-4	0.999828	1.43185e-5	0.999985	3.04749e-3	0.994463
15	8.37373e-4	0.999076	2.66765e-5	0.999978	1.81558e-3	0.997741

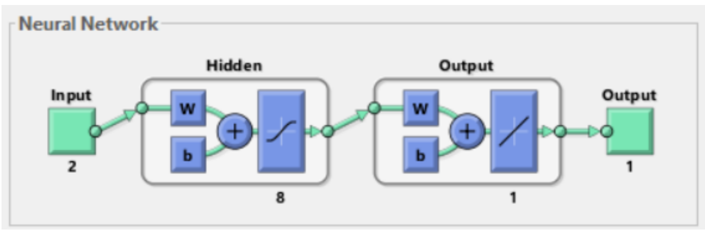
According to the presented results for factor combinations:

- “x_1 and x_2” the lowest values were obtained MSE = 1.184425e-4, MSE = 7.87707e-6 and MSE = 2.00065e-4, respectively for 12, 8 and 5 hidden neurons in LM, BR and SCG training algorithms;
- “x_1 and x_3” minimal RMS errors were recorded in LM “1.62596e-5”, BR “4.38308e-6” and SCG “4.48133e-4” in structures with 6, 10 and 14 intermediate neurons;
- “x_2 and x_3” the lowest error rates were reported, respectively "1.67926e-5" for 7 hidden neurons for LM algorithm, "8.52469e-6" for architecture with 12 intermediate units for BR training and "4.46214e-4" in connection with FFNN model in 8 intermediate neurons and using the SCG approach;
- “x_1, x_2 and x_3” minimal indications were found MSE = 1.92693e-5, MSE = 8.88908e-6 and MSE = 1.67612e-4, respectively in 6, 13 and 9 structural hidden neurons with sequential application of LM, BR and SCG algorithms.

Таблица 4.11. Резултати при изследване на FFNN модели за прогнозен анализ при входни променливи x_1,x_2 и x_3 различни алгоритми за обучение

Input variables x_1, x_2 and x_3						
Hidden neurons	Levenberg-Marquardt		Bayesian Regularization		Scaled Conjugate Gradient	
	MSE in testing	R in testing	MSE in testing	R in testing	MSE in testing	R in testing
5	4.45379e-5	0.999953	1.84230e-5	0.999949	4.25524e-4	0.999586
6	1.92693e-5	0.999974	3.52834e-5	0.999977	2.09231e-3	0.998037
7	2.03792e-4	0.999765	2.75634e-5	0.999975	1.79957e-3	0.997545
8	5.36125e-5	0.999932	1.19765e-5	0.999982	4.03832e-3	0.999654
9	2.52754e-5	0.999972	2.78891e-5	0.999986	1.67612e-4	0.999211
10	2.96257e-5	0.999971	2.05384e-5	0.999990	1.19369e-3	0.998780
11	2.17546e-5	0.999946	2.27914e-5	0.999955	3.40757e-3	0.991529
12	5.18882e-5	0.999932	1.43303e-5	0.999972	1.46945e-2	0.990674
13	3.82764e-5	0.999971	**8.88908e-6**	**0.999975**	7.13208e-3	0.990926
14	9.36914e-5	0.999794	3.22447e-5	0.999974	1.94604e-2	0.976522
15	4.31546e-5	0.999974	2.24857e-5	0.999975	5.76271e-3	0.975872

Given the registered "..e^{-2}" and "..e^{-3}" orders of magnitude of the root mean square errors, the Scaled Conjugate Gradient approach used can be defined as the least effective. Comparing the presented results, the highest degree of adequacy to the task of predictive analysis was reported in Bayesian Regularization training for the considered cases of input impacts.



a)

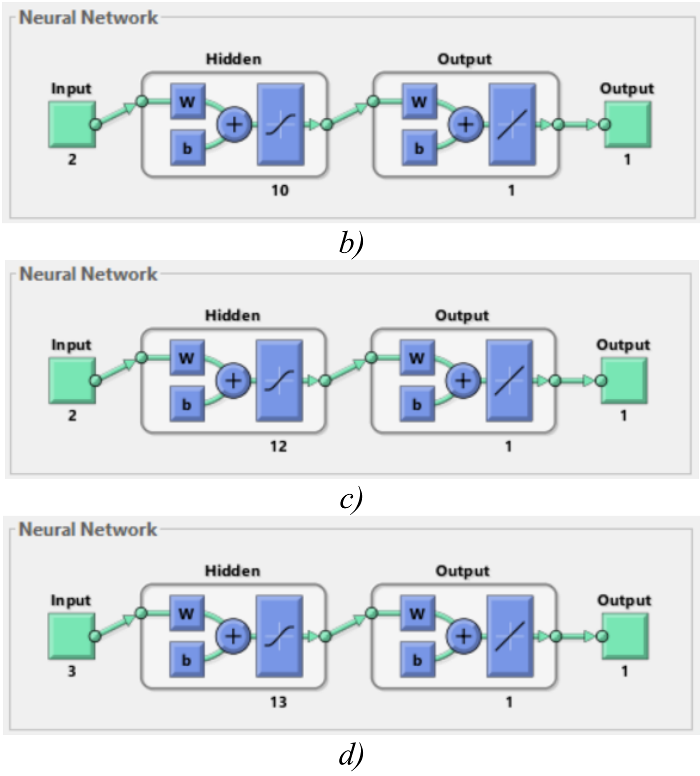


Fig. 4.20. *Synthesized feed-forward neural models for predictive analysis of traffic load based on BR training in a) x_1 and x_2, b) x_1 and x_3, c) x_2 and x_3 u d) x_1, x_2 and x_3*

With regard to this fig. 4.20 shows the final synthesized FFNN models for 8, 10, 12 and 13 neurons in the intermediate layers for the specified algorithm. Almost the same correlation levels achieved from the test neural processes are as follows R = 0.999978 for input combination “x_1 and x_2”, R = 0.999976 for controllable factors “x_1 and x_3” and “x_2 and x_3” and R = 0.999975 for model with three input variables. The registered MSEs in the minimum range of "..e^{-6}" give grounds to define FFNNs as a regression modeling tool with confirmed better efficiency compared to the GRNNs apparatus.

4.7. CFNN architectures for predictive analysis of served user requests on server stations in the M/M/c/k chain for different input variables LM training.

4.7.1. Training and selection of CFNN architectures for predictive analysis of the processed traffic from server stations in the M/M/c/k chain.

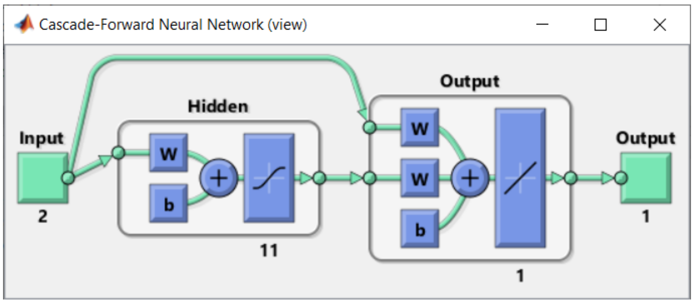
The last stage of the research concerns the application of a variant of FFNN architectures in which there is a structural connection between the input and output layer or the so-called Cascade-forward Neural Networks to approximate the response of the object y_1. With respect to the initial linear layer, the addition of a functional bond is reflected in the inclusion of a second weight matrix. In connection with CFNN training, the Levenberg-Marquardt algorithm was again used in test models containing 5 to 15 latent neurons with tangential-sigmoidal activation. This type of neural network, like FFNNs, has the ability to add new intermediate layers depending on the specific purpose.

Table 4.12. Results in the study of CFNN architectures for predictive analysis of different combinations of input variables and LM training

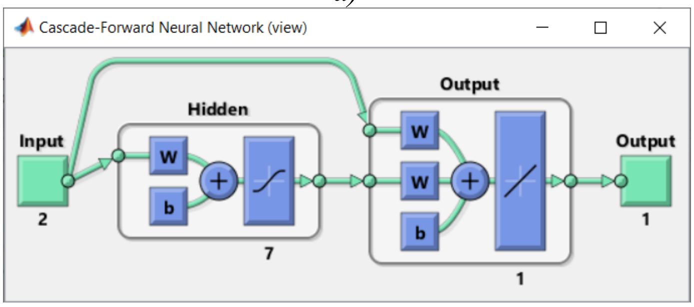
Hidden neurons	MSE at x_1 and x_2	MSE at x_1 and x_3	MSE at x_2 and x_3	MSE at x_1, x_2 and x_3
5	2.8061e-05	1.3164e-05	4.8955e-05	1.0164e-05
6	1.1751e-05	1.1977e-05	**7.6726e-06**	1.6125e-05
7	2.0405e-05	**9.4212e-06**	2.0250e-05	2.2224e-05
8	9.8043e-06	1.3144e-05	1.2254e-05	1.0584e-05

9	1.8516e-05	1.4764e-05	1.0857e-05	6.1230e-05
10	1.7005e-05	2.9226e-05	1.9434e-05	1.0617e-05
11	**8.1190e-06**	1.2741e-05	1.5408e-05	3.4340e-05
12	8.3677e-06	1.4098e-05	1.9071e-05	2.1702e-05
13	2.6177e-05	2.9015e-05	3.4903e-05	**9.2107e-06**
14	1.0827e-05	9.8218e-06	2.0853e-05	2.2893e-05
15	1.0253e-05	1.8246e-05	3.7645e-05	1.3529e-05

Table 4.12 summarizes the root mean square error data for CFNNs in pairs and a set of three controllable factors. A common feature of the test models is the registered changes of MSE of the order "e-05".



a)



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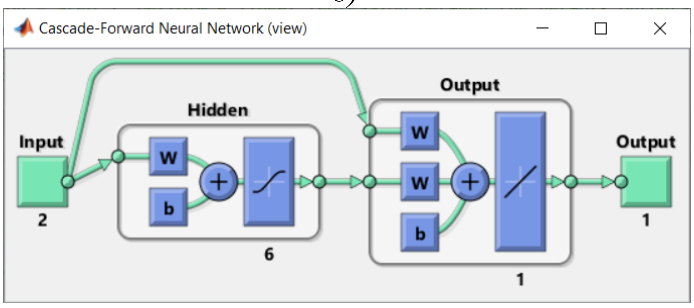

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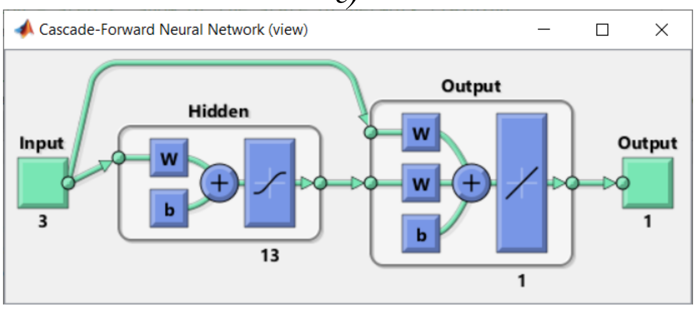

d)

Fig. 4.27. *Selected cascade-forward neural architectures for predictive analysis of users served at a) x_1 and x_2, b) x_1 and x_3, c) x_2 and x_3 and d) x_1, x_2 and x_3*

For each analyzed combination of input variables - “x_1 and x_2”, “x_1 and x_3”, “x_2 and x_3” and “x_1, x_2 and x_3”, CFNN architecture was selected with the most acceptable levels according to the requirements for minimizing the MSE criterion , respectively MSE = 8.1190e-06, MSE = 9.4212e-

06, MSE = 7.6726e-06 and MSE = 9.2107e-06. The error values were reported for models with 11, 7, 6 and 13 intermediate neurons shown in fig. 4.27.

Conclusions to the fourth chapter

- ❖ An approach for regression modeling and diagnostics of analytical and software objects for forecast analysis of the traffic load of service stations in simulated information and communication channels for connection and data transfer based on regression analysis, Generalized Regression, Feed-Forward and Cascade-Forward types of Artificial Intelligence;
- ❖ Insufficient degree of adequacy of regression architectures for multivariate choice of solutions based on Decision tree method for forecast analysis of traffic was found due to the established need to increase the amount of manageable factors;
- ❖ Polynomial mathematical regression models for forecasting the variations of the potential quantity of served traffic and the times for processing user requests in simulation information-communication systems for data transmission are derived;
- ❖ Generalized Regression Neural Networks architectures have been synthesized for predictive traffic load analysis in solving a functional approximation problem for different combinations of two controllable factors and a set of three factors;
- ❖ Feed-Forward Neural Models have been selected for predictive analysis of the range of system users served based on training and network selection using Levenberg-Marquartd, Bayesian Regularization and Scaled Conjugate Gradient algorithms;
- ❖ Cascade-Forward neural architectures have been developed for predictive traffic analysis in simulated information and communication channels using the Levenberg-Marquartd training algorithm;
- ❖ Verification of the synthesized models based on artificial intelligence has been made, confirming their effectiveness in simulation and potentially successful applicability in real environment conditions in the processing and analysis of real information traffic.

III. CONCLUSION

The dissertation proposes a concept for testing and measuring the impact of applied forces on metal parts and objects based on strain gauges. Attention is paid to basic aspects concerning the procedural provision of technical possibilities for:

- ❖ type identification and prediction of the amplitude levels of simulated potential interferences in communication channels when transmitting measurement and specific information in communication channels for communication in a simulation environment;
- ❖ qualitative analysis with regard to the combinations of working transducers used in the monitoring of loads on test parts, as well as forecasting of the quantitative measurements of the applied forces of influence;
- ❖ estimated analysis of the potential amount of processed user requests regarding transmitted measuring sensor information in simulated traffic transmission environment in connection with the planning of the capacity of served system traffic.

With regard to the realized series of researches, the following directions can be identified, upgrading the functionality of the presented system solutions and defining the following stages of development of the affected issues in the dissertation:

- ❖ introduction of new sensor types for monitoring and registration of the applied load forces on tested metal objects;
- ❖ expanding the range of analyzed mechanical quantities, which are obtained as a result of applied sets of forces on the tested parts;

- selection of methods in software design, evaluation of the characteristics and overall efficiency of IIR and FIR units for digital filtering of measuring electrical signals from functional converters;
- integration of machine learning methods and algorithms in the course of synthesis and evaluation of models for identification and forecast analysis on various parametric indicators;
- design and implementation of wireless transmission environment based on modern communication standards in the field of wireless communications for transmission of sensor information.

IV. CONTRIBUTIONS OF THE DISSERTATION

Scientific-applied contributions:

- A methodology for identification of interference effects, analysis of strain gauge measurement data "and forecasting the capacity of the served traffic when applying forces on metals with compensation of the influence of noise and optimization of processed user requests was developed;
- Structures of artificial neural networks with inverse error propagation based on Levenberg-Marquardt and Scaled Conjugate Gradient algorithms with different activation functions with accepted quality indicators for identification of Gaussian constant noise and Periodic constant noise, as well as digital signals with the presence of the indicated impacts, in communication channels;
- Neural models have been created for the right propagation of signals and back propagation of the error in various training algorithms for quantitative identification of applied working strain gauge transducers in monitoring and registration of forces on metals;
- Neural structures with backpropagation of the error and generalized regression neural networks for forecasting the potential applied force loads on test metal samples in mechanical test procedures are derived;
- Artificial intelligence models have been synthesized for predictive analysis of the served traffic in simulated information and communication units with the help of Generalized Regression Neural Networks, Feed-Forward Neural Networks and Cascade-forward Neural Networks at LM, SCG and BR training algorithms with confirmed advantages over classical regression analysis.

Applied contributions:

- A conceptual system has been proposed for studying the characteristics of strain gauge sensor elements in measuring forces on metals with introduced modules for digital filtration in connection with noise reduction and descriptive analysis of the processed data;
- Linear regression models are derived when switching on one and two working strain gauge transducers for predictive analysis of the change of applied force loads when testing metal samples;
- Analytical polynomial models based on regression analysis for forecasting the potential served traffic with packet measuring and specified data with consideration and assessment of the influence of controllable factors in simulated telecommunication systems are obtained.

V. LIST OF PUBLICATIONS ON THE DISSERTATION

1. Kogias P., Angelov K., **Daskalaki D.**, Sadinov S., Malamatoudis M., "Performance Analysis of High-Speed Single Channel Transmission in Optical Communication Line". Journal of Engineering Science and Technology Review (JESTR), Special Issue on Conference in Telecommunications, Informatics, Energy and Management, Kavala Institute of Technology, pp. 94-97, ISSN: 1791-9320, E-ISSN:1791-2377, 2019. (Scopus, SJR 0.190, Q3).
2. Malamatoudis M., Kogias P., **Daskalaki D.**, Sadinov S., "Communication System for Strain Analysis Over Metals on the Base of Tensoresistor Transducers". Advances in Intelligent Systems and Computing, 1226 AISC, pp. 321-328, 2020. ISSN: 2194-5357, (Scopus, SJR 0.184, Q4).
3. **Daskalaki D.**, "Recognition of Noise in Communication Channels by Means of Artificial Neural Networks". International Scientific Conference Unitech 2020 November 20-21, Gabrovo, p. I-229 – I-235, ISSN: 2603-378X, 2020.
4. Balabanova I., Sadinov S., **Daskalaki D.**, Georgiev G., "Prediction of forces on metal objects by applying artificial intelligence". 5th National Scientific Conference with International Participation TechCo'21, 2-3 July, Lovech, ISSN:2535-079X, 66-70 p., 2021.
5. Balabanova I., Sadinov S., **Daskalaki D.**, Georgiev G., „Forecasting of communication traffic load by means of artificial neural networks". International Scientific Conference United, 19-20 November, Gabrovo, Bulgaria, volume. 1, p. I-183-188, ISSN: 2603-378X, 2021.
6. Balabanova I., Sadinov S., **Daskalaki D.**, Georgiev G., „Synthesis of Classification and Predictive FFNN Models on the Basis of Tenzoresistive Transducer Data". AIP Publishing (Scopus), International Scientific Conference on Communications, Information, Electronic and Energy Systems – CIEES, 25 – 27 November, Ruse, pp. 1-7, 2021. In print! (IEEE Xplore, Scopus).

ABSTRACT

The dissertation deals with aspects related to the measurement of forces when testing the loads of parts, structures, modules and complete equipment, which are made of metal in various fields of business and industry. The concept of artificial intelligence in approaches for qualitative and quantitative analysis of acquired measurement data from the inclusion of strain gages functional converters in classical bridge circuits for monitoring and control of power loads has been introduced. One of the most important aspects in modern communications is related to the identification and assessment of superimposed unwanted random noises in the communication channels for communication in the transmission of specialized data again on the basis of artificial neural networks. An essential aspect, which is also the subject of analysis in the dissertation with integration of artificial intelligence, concerns the ability to predict the quantitative measurability of the volume of packet data served. This will ensure quality control and optimization of the served traffic regarding the normal functioning of a specific information and communication measuring system for monitoring of power impacts, without deviations in the processes of customer service.