SYSTEMATIZATION OF RADIO-ELECTRONIC CONTROL COMPLEXES ON RESISTANCE TO DESTABILIZING FACTORS ON THE BASIS OF A NEURAL NETWORK MODEL

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Alexey N. Shevtsov,
Southwestern State University, Kursk, Russia,
aleksey_shevtsov95@mail.ru

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The expansion of the sphere of influence of commercial activities and the prospects for the development of "transatlantic" alliances, in such key market segments as the business of extracted hydrocarbons, objectively determines the growing role of electronic means complexes for solving a huge range of tele-communication tasks. An example is the tasks associated with the need for remote control of oil and gas industry equipment both domestically and abroad. These tasks are aimed at solving the problem of reliable operation of the equipment used: radio communications, control and measuring and control and diagnostic equipment, individual signaling devices (electronic rescue beacon), security and operational damage detection, etc. The entire arsenal of operated electronic means must be ready to solve problems for their intended purpose in any region of the Russian Federation (RF) or abroad. This article discusses the issue of increasing the resistance to external destabilizing factors of electronic control systems for technical means by targeted delivery to the climatic regions of the Russian Federation.

Information about author:
Alexey N. Shevtsov, *postgraduate student of the Department of Software Engineering, Southwestern State University, Kursk, Russia*

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Introduction

One of the areas in the protection of commercial interests is the complexes of remote radio electronic control (CREC) by technical means: geopositioning and geolocation, video surveillance and detection, marking and signaling, etc. The most important requirement for CREC is resistance to external influencing factors (EIF) in various climatic regions, especially when electronics, including its batteries, are widely used in "extreme" or critical macroclimatic regions.

The existing set of design documentation, or rather, directly in the technical specifications (TS) for the created and (or) already used products of the CREC TS, does not provide for and does not provide for the targeted delivery of radio electronic products (REP) to specific climatic areas of operation. There are no criteria for such a possible configuration and delivery. The specifications indicate only the operation group (and often with restrictions), which includes a large area, both in terms of temperatures and the rest of the EIF.

In this regard, it is important and relevant to take into account the climatic conditions for the operation of CREC TS products and a new look at solving the problem of differentiated configuration and targeted delivery of CREC TS to the climatic regions of the Russian Federation or the globe. To this end, a study was made of the possibility of building climate models for products of the CREC TS based on the results of climatic tests in order to develop a methodology for differentiating products of the CREC TS for targeted delivery and further operation in the climatic regions of the Russian Federation [1].The climatic zoning of the territory of the USSR was established by the standard and is a detail of the macroclimatic zoning of the globe according to [2]. According to the specified standard, the territory of the former USSR is located in macroclimatic regions with a temperate and cold climate.

The purpose of this article is to build neural network cluster models for the development on their basis of a new method for differentiating and completing products of the CREC TS, which increases the resistance of complexes to EIF during their operation by targeted delivery to the climatic regions of the Russian Federation.

Materials and methods of research

The experience of conducting various types of climatic-mechanical tests (CMT) of REP, components and products of the CREC TS as a whole, measuring their characteristics in a testing laboratory shows that in a single batch of serial products that fully meet the requirements of TS, each product has its own electrical (electrical engineering) characteristics are unique. This allows you to build an "individual image" of the product according to its key parameters.

The scatter in the values of the key parameters of individual images allows us to put forward a hypothesis about the presence in the batch of products under study, groups (clusters) with similar values of the measured characteristics. The proposed new approach to product differentiation is based on the analysis of statistical data on the results of CMI in a neural network logical basis using the apparatus of artificial neural networks (ANN). Neural network clustering makes it possible to build climatic cluster models of products and further classification of this batch of products on the basis of the obtained models allows for a more targeted final assembly of CREC TS products and differentiated delivery of products to various climatic regions of the Russian Federation.

The only condition for the readiness of products for acceptance and further shipment to the consumer is the result of a positive passage of all types of tests, i.e. compliance of the individual parameters of the product (electrical, electro technical, etc.) with the requirements of technical specifications.

It should be noted that the technical requirements for KMI are mainly qualitative. At the same time, requirements can be set for specific numerical values of the parameters, or their numerical ranges, in the form of formulations: “not less than” or “not more than”.

The existing approach to the supply of finished products assumes that from the entire batch of finished products that have passed all types of tests, their delivery to the consumer in the areas of further operation in accordance with contracts is centralized. But this does not take into account the conditions for the further operation of products in a certain macroclimatic region of the Russian Federation.

The experience of carrying out KMI of a product of CREC TS in a testing laboratory confirms the fact that the tested products, even those belonging to the same batch of serial products, are unique in their individual electrical, electrical and other measured parameters. This trend also manifests itself under normal test conditions (NTI) [3] and is all the more pronounced during and after exposure to EIF, provided for by the KMI.

Results and discussion

The results of the study of the possibility of neural network clustering of the product of the CREC TS according to their individual image at the KMI stage made it possible to obtain the climatic characteristics of the cluster and determine the potential resistance of the tested products to a specific type of VVF, which ultimately made it possible to increase the efficiency of operating a batch of products.

The experiment was carried out within the framework of KMI products CREC TS according to the methods according to TS. The investigated batch of serial products CREC TS amounted to 61 sets. A total of 7076 measurements were carried out.

As a result of the experiment, statistical samples were obtained corresponding to the proposed individual images of the constituent blocks of the product of the CREC TS. Then, a neural network analysis of the statistical data was performed in order to identify the topology and patterns in the data, and a neural network clustering of the statistical data of the KMI of the components of the CREC TS was performed.

The software package "Statistical Neural Networks" [4] was used as a neural network analysis tool.

Artificial Neural Networks (ANNs) are an effective tool for multivariate statistical data mining and pattern recognition. Neural network analysis, study of the topology of data in the space of variables under study, clustering and classification of data make it possible to increase the level of knowledge about the object under study and build a cluster climate model. Theoretical foundations of artificial neural networks, examples of solving practical problems and computer modeling experiments are fully described in the scientific literature [5-7].

To cluster the obtained data, Kohonen's self-organizing neural network [7] was used as part of the ANN package, which implements the competitive learning algorithm as a learning method. As a result of competitive learning, Kohonen's self-organizing network (map) maps a continuous n-dimensional space of neuron activation patterns into a discrete 2-dimensional output space. There is a clustering of data, pattern recognition.

To solve the clustering problem, we used the classical deterministic mathematical model of the neuron, which implements the scalar function of the vector argument S with a non-linear neuron activation function:

$$S = \sum_{i=1}^{n} \omega_i + x_i + b; \quad (1)$$

$$y = f(s), \quad (2)$$

where n – the number of synaptic weights (inputs) of the neuron (the number of neuron inputs) corresponding to the dimension of the input vector-image of the analyzed product;

ω_i – weight of the synapse (input) of the neuron, $ii = \overline{1,n}$;

b – value of the neuron displacement;

x_i – component (one of the key parameters) of the input vector-image of the analyzed product;

S – result of "weighted summation" of neuron inputs;

y – output signal of the neuron;

f – neuron activation function (nonlinear function of transformation of summation result).

The logistic function with saturation (S-shaped function, sigmoid) was used as the neuron activation function:

$$f(s) = \frac{1}{1+e^{-as}}, \quad (3)$$

where is the sigmoid parameter, which has a range of values (0, 1) and determines the output value of the neuron also in the range (0, 1).

Competitive determination of the winning neuron in the Kohonen network is based on the determination of the minimum Euclidean distance between the input image vector and the neuron synaptic weight vectors. The Euclidean distance between the neuron vector of the Kohonen network and the input image vector is determined by the formula:

$$D_j = \sum_{i=1}^{n} (\omega_{ij} - x_i)^2, \quad (4)$$

where x_i – is a component of the input image vector;

n – dimension of the image vector (the number of key parameters of the analyzed product);

$i = \overline{1,n}$ – ordinal number of the input vector component;

ω_{ij} – weight of the synapse (input) of neuron;

m – number of neurons in the Kohonen lattice;

$j = \overline{1,m}$ – serial number of the neuron in the grid.

Adaptation of the synaptic weights of the j-th winning neuron at the learning step (epoch) is carried out by recalculating their previous value at the step according to the formula:

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \eta(t)[x_i - \omega_{ij}], \quad (5)$$

where $\eta(t)$ – network learning rate.

Based on the existing experience in solving such problems, the recommendations of literary and Internet sources [8], the recommendations of the Intelligent Problem Solver, the built-in Advise for creating a network, several dozen trial preliminary solutions to the network learning problem were performed and data clustering. As a result of the iterations of training networks with different topologies and training parameters, taking into account the main criterion – "Training Error", to solve the problem for each statistical sample, their own individual topology and network training parameters were chosen: "Number of network inputs" (Inputs); "Number of network outputs" (Outputs); “Number of network layers” (No Layers); "Number of neurons in the output layer" (Layer 2).

The network training process was carried out in two stages: a rough fast approximation and a slower refinement. During training, the Shuffle Cases option was enabled and the Cross-verification option was disabled. Cross-validation during network training in this case is not carried out due to the lack of a control subset (since there are objectively no pre-marked observations in the problem of clustering the analyzed sample), which is typical for our case when studying the topology of statistical data, in contrast to classification and forecasting problems.

In the Kohonen Training window, at each stage of training, individual parameters were selected for each network: Number of training epochs (Epochs); "Initial learning rate" (Learning Rate, Start); "Final learning rate" (Learning Rate, End); "The size of the topological neighborhood of the winning neuron" (Neighborhood).

The duration of the training stages was chosen taking into account the recommendation [9]. At the first stage, it is recommended to perform approximately 20% of the total number of Epochs training steps and allocate 80% of the total training time for the second stage to fine-tune the network. The criterion for the quality of training and the end of the learning process of the Kohonen network is considered to be the achievement of a stable state by the neural network in the learning process, which means that this network has exhausted its resources in generalizing the analyzed data. If, at the same time, the numerical characteristics of the results of its training suit the researcher, then training stops and the next step of the clustering algorithm is performed: formal selection (conditional labeling) of the resulting clusters.

To identify the centers of clusters and formally label the resulting clusters, the Topological Map was used with simultaneous analysis of the results of neuron gains and the degree of activation of neurons of the Kohonen map during the run (testing) of the next observation [10-13]. Activation is the distance from the observation vector to the vector of neuron weights, the lower the activation level, the greater the similarity of these vectors. The numerical value of the activation level of the winning element is displayed in the field of the topological map window.

The visualization of the results of testing observations on the topological map was also taken into account: complete black coloring of the square symbolically depicting a neuron means the complete coincidence of the vectors of the tested observation and the neuron of the Kohonen map [14-15].

An important and responsible step in solving the problem of clustering is the interpretation of learning outcomes: the transition from formally identified clusters with symbolic names to their physical meaning. The purpose of interpretation is to determine what the identified clusters.

Figure 1. Cluster neural network data model

To do this, we again turn to the original applied problem and study the initial data. The analyzed observations are tested again to determine whether they belong to the selected clusters. For further interpretation of the clustering results, the leading observations were combined for each of the selected symbolic clusters and the average values of the measured parameters for these clusters were obtained. Then, based on the knowledge of the essence of the constituent blocks of the CREC TS product, the features of their operation and intended use.

Thus, clustering of all statistical data for the studied serial batch of products was performed and climatic cluster neural network models were built (trained Kohonen neural networks visualizing topological maps of clustering results) of all constituent blocks of the CREC TM complex.

As part of the study, the following tasks of neural network analysis of the topology of statistical data of test results and their neural network clustering were solved:

1. lustering of data sets of parameter measurements products in NIE after exposure to sinusoidal vibration.

2. Clustering multiple test results data products obtained under the influence of a working low temperature of the environment equal to minus 20ºC.

3. Clustering multiple test results data products obtained when exposed to a working elevated temperature of the environment equal to plus 55ºC.

4. Clustering multiple test results data products obtained when exposed to high humidity (95% ± 3%, at +40ºC).

An example of one of the built climate cluster neural network models is shown in Figure 1.

The final labels of clusters (according to the results of interpretation) have the following semantic meanings for a specific task: P1 – cluster of the 1st (higher) configuration priority; P2 – cluster of the 2nd (lower) picking priority for targeted delivery of the product. Cluster P1 contains semantic subclusters: P1O – "excellent", P1H – "good", P1U – "satisfactory".

In total, 12 climate models were obtained for the tested serial product of the CREC TS: 4 models for each of the three objects under study – product blocks.

Thus, in order to increase the resistance to EIF of products of the CREC TS, a new look at the problem under study is proposed, which consists in neural network clustering of products according to their individual image, and further determining the resistance to EIF of each cluster. The proposed approach will increase the durability and reliability of products supplied to the VVF in specific climatic regions of operation. Ultimately, when applying a differentiated supply of finished products to various climatic regions of the Russian Federation, the efficiency of operation of products of the CREC TS increases.

Conclusion

Based on the presented material, the following conclusions can be drawn:

1. he put forward hypotheses about the presence of compact clusters in the statistical data are confirmed. Results of measurements of parameters in the NIE and statistical data of climatic tests of the studied batches of products.

2. Climate clusters were built neural network models of the objects under study – product blocks. A total of 12 climate models were obtained: 4 models for each of the three studied objects. The models are presented as trained Kohonen neural networks with visualization of the results in the form of topological clustering maps with symbolic cluster names.

3. I erpretation of the physical meaning of the topology of statistical data and the results of solving clustering problems with the symbolic names of clusters made it possible to gain new knowledge and identify the presence of semantic priority clusters for future differentiation of products for their purposeful delivery to climatic regions of the Russian Federation or the globe. The results of semantic interpretation are presented in the form of

trained Kohonen neural networks with visualization of the results in the form of topological maps with semantic cluster names.

4. hus obtained climatic neural network cluster models of radio electronic products can be used to develop a methodology and build on their basis a system for classifying products in order to differentiate them according to the results of KMI, targeted packaging and delivery of products to various climatic regions of the Russian Federation.

References

1. GOST 30630.2.1-2013. Test methods for resistance to climatic external factors of machines, instruments and other technical products. Tests for resistance to temperature. Moscow: Standartinform, 2020.
2. GOST 30630.0.0-99. Test methods for resistance to external influencing factors of machines, devices and other technical products. General requirements. Minsk: Interstate Council for Standardization, Metrology and Certification, 2000.
3. V. I. Syryamkin, S. V. Suntsov (2013). Adaptive neural network algorithms for diagnosing materials, equipment and electronic equipment. Saarbrucken: LAMBERT Academic Publishing, 2013. 269 p.
4. V. P. Borovikov (2008). Neural networks. Statistica Neural Networks: Methodology and technologies of modern data analysis. Moscow. Hotline-Telecom. 392 p.
5. S. Khaikin (2008). Neural networks: a complete course, 2nd edition. Moscow: Williams Publishing House. 96 p.
6. Callan Robert (2011). Basic concepts of neural networks. Moscow: Williams Publishing House. 287 p.
7. Artificial neural networks. URL: https://ru.wikipedia.org/wiki (date of access: 01/01/2022).
8. V.I. Anikin, A.A. Karmanova (2015). Modeling and research of Kohonen's cellular neural network in spreadsheets. XVII All-Russian scientific and technical conference "Neuroinformatics-2015": Collection of scientific papers. In 3 parts. Part 2. Moscow: NRNU MEPhI. P. 118-127.
9. V.I. Anikin, A.A. Karmanova (2014). Training of an artificial neural network of Kohonen by a cellular automaton. *Information Technology*. No. 11. P. 73-80.
10. T. Kohonen (2013). Self-organizing maps. Moscow: BINOM. Knowledge Laboratory. 655 p.
11. A.V. Melnikov, V.V. Soldatov, I.N. Georgian (2014). Using the Kohonen Neural Network for Clustering Information Security Incidents. *Security, safety, communications.* No. 3 (3). P. 192-198.
12. V.I. Anikin, A.A. Karmanova (2015). Clustering and classification of multidimensional data by Kohonen's cellular neural network. *Information Technology*. No. 6. P. 470-477.
13. A.V. Akhterov, A.A. Kirilchenko (2009). Fundamentals of theoretical robotics. examples of the use of artificial neural networks. IPM IM preprints. M.V. Keldysh. No. 46. P. 1-21.
14. A.S. Zainulin (2017). An improved clustering method based on self-organizing Kohonen maps. *Scientific thought*. No. 4(26). P. 95-99.
15. J. Nagi (2007). Design of an Efficient High-speed Face Recognition System. Department of Electrical and Electronics Engineering, College of Engineering, Universiti Tenaga Nasional, March 2007.

СИСТЕМАТИЗАЦИЯ КОМПЛЕКСОВ РАДИОЭЛЕКТРОННОГО УПРАВЛЕНИЯ ПО УСТОЙЧИВОСТИ К ДЕСТАБИЛИЗИРУЮЩИМ ФАКТОРАМ НА ОСНОВЕ НЕЙРОСЕТЕВОЙ МОДЕЛИ

Шевцов Алексей Николаевич, *Юго-Западный государственный университет, г. Курск,* ***aleksey_shevtsov95@mail.ru***

Аннотация

Расширение сферы влияния коммерческой деятельности и перспективы развития "трансатлантических" союзов, в таких ключевых сегментах рынка, как бизнес добываемых углеводородов, объективно обуславливает возрастание роли комплексов электронных средств для решения ог-ромного спектра телекоммуникационных задач. В качестве примера можно привести задачи, связанные с необходимостью дистанционного управления оборудованием нефтегазовой отрасли как внутри страны, так и за рубежом. Эти задачи направлены на решение проблемы надежной эксплуатации используемого оборудования: средств радиосвязи, контрольно-измерительной и контрольно-диагностической аппаратуры, устройств индивидуальной сигнализации (электронный маяк спасателя), средств охраны и оперативного обнаружения повреждений и др. Весь арсенал эксплуатируемых электронных средств должен быть готов к решению задач по предназначению в любом районе Российской Федерации (РФ) или за рубежом. В данной статье обсуждается вопрос повышения стойкости к внешним дестабилизующим факторам комплексов радиоэлектронного управления техническими средствами путем целенаправленной поставки по климатическим районам Российской Федерации.

Ключевые слова: *воздействующий фактор, комплекс управления радиоэлектронными средствами, электромагнитная совместимость, шумовая адаптация, нейросеть, алгоритм кластеризации, сегментирование.*

Литература

1. ГОСТ 30630.2.1-2013. Методы испытаний на стойкость к климатическим внешним воздействующим факторам машин, приборов и других технических изделий. Испытания на устойчивость к воздействию температуры [Текст]. - Москва: Стандартинформ, 2020.
2. ГОСТ 30630.0.0-99. Методы испытаний на стойкость к внешним воздействующим факторам машин, приборов и других технических изделий. Общие требования [Текст]. - Минск: Межгосударственный совет по стандартизации, метрологии и сертификации, 2000.
3. *Сырямкин В. И, Горбачев С. В., Сунцов С. Б.* Адаптивные нейросетевые алгоритмы диагностики материалов, оборудования и радиоэлектронной аппаратуры // Saarbrucken: LAMBERT Academic Publishing, 2013. С. 269.

4. *Боровиков В.П.* Нейронные сети // STATISTICA Neural Networks: Методология и технологии современного анализа данных. М:. Горячая линия-Телеком, 2008. С. 392.
5. *Хайкин С.* Нейронные сети: полный курс, 2-е изданиею М.: Издательский дом "Вильямс", 2008. 96 с.
6. *Каллан Роберт.* Основные концепции нейронных сетей. М.: Издательский дом "Вильямс", 2011. 287 с.
7. Искусственные нейронные сети. URL: https://ru.wikipedia.org/wiki (дата обращения: 01.01.2022).
8. *Аникин В.И., Карманова А.А.* Моделирование и исследование клеточной нейронной сети Кохонена в электронных таблицах // XVII Всероссийская научно-техническая конференция "Нейроинформатика-2015": Сборник научных трудов. В 3-х частях. Ч.2. .: НИЯУ МИФИ, 2015. С. 118-127.
9. *Аникин В.И., Карманова А.А.* Обучение искусственной нейронной сети Кохонена клеточным автоматом // Информационные технологии. 2014. № 11. С. 73-80.
10. *Кохонен Т.* Самоорганизующиеся карты // М.: БИНОМ. Лаборатория знаний, 2013. С. 655.
11. *Мельников А.В., Солдатов В.В., Грузинский И.Н.* Использование нейронной сети Кохонена для кластеризации инцидентов информационной безопасности // Охрана, безопасность, связь. №3(3). 20148. С. 192-198.
12. *Аникин В.И., Карманова А.А.* Кластеризация и классификация многомерных данных клеточной нейронной сетью Кохонена // Информационные технологии. 2015, № 6. С. 470-477.
13. *Ахтеров А.В., Кирильченко А.А.* Основы теоретической робототехники. примеры использования искусственных нейронных сетей // Препринты ИПМ ИМ. М.В. Келдыша. 2009. № 46. С. 1-21.
14. *Зайнулин А.С.* Усовершенствованный метод кластеризации на основе самоорганизующихся карт Кохонена // Научная мысль. 2017. № 4(26). С. 95-99.
15. *Nagi J.* Design of an Efficient High-speed Face Recognition System // Department of Electrical and Electronics Engineering, College of Engineering, Universiti Tenaga Nasional, March 2007.

Информация об авторе:
Шевцов Алексей Николаевич, *аспирант кафедры программной инженерии Юго-Западного государственного университета, г. Курск, Россия*