SOI: 1.1/TAS DOI: 10.15863/TAS
International Scientific Journal
Theoretical & Applied Science

p-ISSN: 2308-4944 (print) e-ISSN: 2409-0085 (online)

Year: 2021 Issue: 04 Volume: 96

Published: 18.04.2021 http://T-Science.org

QR – Issue QR – Article

Olimjon Israilovich Djumanov
Samarkand State University
Candidate of Technical Sciences, assistant professor,
Information Technologies department

Sunatillo Makhmudovich Kholmonov
Samarkand State University
PhD in Technical, assistant professor,
Information Technologies department

J.M. Ganiev
Samarkand State University
Master

OPTIMIZATION OF DATA PROCESSING BASED ON NEURAL NETWORKS AND PROPERTIES OF NON-STATIONARY OBJECTS

Abstract: *Methodological foundations have been developed for the creation of methods for optimizing the analysis of data of non-stationary objects based on neural networks (NN) and genetic algorithms (GA) with mechanisms of simplified search, adjusting the weights of neurons, coefficients of synaptic connections, activation functions, the number of neurons in the layers of NN. Improvement and development of methods for optimizing learning of neural networks based on the synthesis of GA s, the use of operators of crossworing, mutation, inversion, selection of the best individuals, generation of the initial and subsequent populations has been carried out. Mechanisms for generating a bank of individuals for the formation of rational sets of parameters and training samples based on a knowledge base with fuzzy inference rules are proposed.*

Key words: *data processing, neural network, genetic algorithm, tuning, optimization, bank of individuals, database, knowledge base.*

Language: *English*

Citation: Djumanov, O. I., Kholmonov, S. M., & Ganiev, J. M. (2021). Optimization of data processing based on neural networks and properties of non-stationary objects. *ISJ Theoretical & Applied Science, 04 (96),* 165-168.

Soi: http://s-o-i.org/1.1/TAS-04-96-35 ***Doi***: crossref https://dx.doi.org/10.15863/TAS.2021.04.96.35

Scopus ASCC: *1700.*

Introduction

Relevance of the topic. An effective toolkit for the construction of modern data mining systems (DMS) of non-stationary objects is represented by the components of the mathematical apparatus of soft computing based on neural networks (NN), evolutionary modeling, genetic algorithms (GA) for solving key problems of optimization of learning NN, identification and approximation of non-stationary objects [1].

This paper proposes methods and algorithms for optimizing data processing based on learning algorithms for neural networks using GA, simplified search procedures and mechanisms for setting parameters [2].

II.Literature review

The principles of designing methods for searching and adjusting the parameters of structural components of a multilayer neural network to optimize training involve the development of methods for synthesizing GAs with algorithms for stochastic modeling, search with annealing, prohibitions, and self-organizing learning [3]. A feature of the hybrid model of optimization of training in the NN is the use of GA as a regulator of parameters to provide a simplified adjustment of the weights of neurons, the coefficients of synaptic connections, the rational structure of the network, the number of neurons in the layers of the NN [4].

The improvement and development of optimization methods is carried out through the execution of genetic operators to generate a bank of individuals, which serve as additional information support in determining and adjusting the parameters of synaptic connections, neuron weights, activation functions [5]. The determination and adjustment of the parameters of the NN components is based on the use of the chromosome length (individuals), chromosome filling (loci and alleles) and particular parameters determined using the operators of crossover, mutation, inversion, selection of the best individuals, generation of the initial and subsequent populations [6].

III.Analysis

The DMS system algorithms include synthesis mechanisms for a random search with annealing and with stochastic modeling, which are used to select informative parameters about successful previous searches [7]. Other key tasks of optimizing the training of neural networks based on the hybrid model are the formation of knowledge bases, the creation of a generation unit and the receipt of new individuals. The NS training unit receives data on the common chromosome, the parameters of the designed NS, the training process, the method, speed and schedule of training. At the output of each layer of the network, matrices of weights of synaptic connections are given [8].

It is believed that an individual consists of several chromosomes, and the NN has a large number of variations in the number of inputs, outputs, layers, and the number of neurons in the layers [9]. The principles of operation of mutation, crossover and inversion operators for a modified chromosome are as follows: the crossover operator works only with the main chromosome; the inversion operator works with the main chromosome and the daughter, which are responsible for inputs and outputs; the mutation operator works with the main chromosome and the daughter, which are responsible for the number of neurons; the generator of new individuals and knowledge base is responsible only for the inputs and outputs of the NS [10].

The implemented multilayer neural network with the backpropagation algorithm is synthesized with the zero-order Sugeno fuzzy inference algorithm, has two input variables and, EZ and EF the network output is determined by a linguistic variable VK [11].

For the linguistic assessment of the input variable, seven terms are used, for a variable EF one term with direct and inverse output, which are used when reducing the number of terms [12].

As a term-set of a linguistic variable, a set is used: T_{EZ} = {"acceptable", "positive small", "negative small", "positive average", "negative average", "positive large", "negative large"}, which is written in symbolically

$$T_{EZ} = \{EZD, EZP4, EZN4, EZP3, EZN3, EZP2, EZN2\}.$$

As a term-set of a linguistic variable EF the term "small" is used.

Mechanisms for adjusting the accessory functions (AF) of linguistic terms, which are performed in accordance with the information for one NN learning cycle, have been implemented. Dimension of the term-set of the output variable T_{VK} is equal to the number of rules. A five-layer neural fuzzy network (NFN) has been implemented, which has the following purposes.

Layer 1. Defines fuzzy terms of input parameters. The outputs of the nodes of this layer represent the values of the FP at specific values of the inputs. Each node of the layer is adaptive with FP $\mu_{A_i}(x)$, where x – entrance i - th node, $i = 1,...,n$; A_i – linguistic fuzzy variable associated with this node.

For the terms of the input variables, triangular, trapezoidal, S -shaped and Z - shaped FP.

Layer 2. This layer is non-adaptive and forms the premise of fuzzy rules. Each node is connected to those nodes of the first layer that form the prerequisites of the corresponding rule.

Layer 3. Performs the normalization of the degree of rule fulfillment. Non-adaptive nodes of this layer calculate the relative degree (weight) of the fuzzy rule fulfillment

$$\overline{w_j} = w_j \sum_{j=1}^{8} w_j$$

Layer 4. A crisp number v_{kj}, specifying the conclusion of each j -th rule is considered as a fuzzy set with a singleton FP. The adaptive nodes of this layer calculate the contribution of each fuzzy rule to the network output

$$y_j = \overline{w_j v_{kj}}, \quad j = 1,...,8.$$

Layer 5. The non-adaptive node of this layer sums up the contributions of all rules:

$$y = \sum_{j=1}^{8} y_j .$$

IV.Discussion

The discrepancy error between the experimentally measured parameter and v_L the calculated network output VK is determined by the condition

$$\delta = \sqrt{\frac{1}{N}\sum_{t=1}^{N}[v_L(t) - VK(t)]^2} \to \min ,$$

Where N is the number of measurements in the training data sample v_L .

The hybrid learning algorithm is a combination of least squares and backpropagation of error. Modeling of control processes was carried out in MATLAB with the Fuzzy Logic Toolbox extension package. Before and after training, training samples of the conditional parameters of the tested object and are fed to the network input EF and EZ . The training set contains $N = 947$ observations. The initial step value is set 10^{-4} towards criterion δ when changing the FP parameters. Allowable change in step size per iteration – 20%. Before network training, the value of the training criterion $\delta = 0{,}0972$, and after 200 iterations $\delta = 0{,}0859$. The reduction of the parameter is achieved due to the mechanisms of synthesis of heuristic search algorithms with annealing and stochastic modeling based on the Markov chain.

V.Conclusion

Analysis of the research results of the considered example of identifying a conditional technological parameter shows that the combination of NN with GA and NFN with GA makes it possible to achieve a decrease in the variation of statistical parameters of the initial non-stationary process at the output of the system. At the same time, the relative sample variance of the calculated data does not exceed 5%, which confirms the achievement of the required accuracy of analysis and data processing at significantly lower computational costs.

References:

1. Bozhich, V.I., Lebedev, O.B., & Shnicer, Jy.L. (2001). Razrabotka geneticheskogo algoritma obuchenija nejronnyh setej. *Izvestija TRTU. Tematicheskij vypusk*. T. 22. №4, pp.170-174.
2. Chipiga, A.F., & Voronkin, R.A. (n.d.). Obuchenie iskusstvennyh nejronnyh setej putem sovmestnogo ispol`zovanija metodov lokal`noj optimizacii i geneticheskih algoritmov. *Izvestija TRTU*. T. 33. №4, pp.172-174.
3. Zhumanov, I.I., & Holmonov, S.M. (2011). Optimizacija obuchenija nejrosetevoj sistemy obrabotki dannyh na osnove statisticheskih svojstv informacii. *Uzbekskij zhurnal «Problemy informatiki i jenergetiki»*, №3., Izd. «Fan» AN RUz, Tashkent, pp.50-56.
4. Rutkovskaja, D. (2004). *Nejronnye seti, geneticheskie algoritmy i nechetkie sistemy* / D. Rutkovskaja, M. Pilin`skij, L. Rutkovskij, (p.452). Moscow: Gorjachaja linija-Telekom.
5. Zhumanov, I.I., & Holmonov, S.M. (2011). Optimizacija obuchenija nejrosetevoj sistemy obrabotki dannyh na osnove statisticheskih svojstv informacii. *«Problemy informatiki i jenergetiki»*, №3., Izd. «Fan» AN RUz, Tashkent, pp.50-56.
6. Zhumanov, I.I. (2017). Optimizacija obrabotki dannyh nestacionarnyh ob#ektov na osnove nechetkih modelej identifikacii s nastrojkoj parametrov. *Zhurnal «Vestnik TUIT», Tashkentskij universitet informacionnyh tehnologij*, Tashkent, №1(41), pp. 34-47.
7. Zhumanov, I.I., & Holmonov, S.M. (2017). Issledovanie jeffektivnosti programmnogo kompleksa identifikacii sluchajnyh vremennyh rjadov na osnove geneticheskoj nastrojki parametrov. *Nauchno-metodicheskij zhurnal «Problemy sovremennoj nauki i obrazovanija»,* Ivanovo. № 19 (101), pp.22-25.
8. Holmonov, S.M., & Hamroeva, B. (2016). Metody i algoritmy komp`uternogo zrenija izobrazhenij nepreryvnyh ob#ektov na osnove sinteza metodov statisticheskogo i nechetkogo modelirovanija. *Sbornik statej po materialam XLV mezhdunarodnoj nauchno-prakticheskoj konferencii «Nauchnaja diskussija: voprosy tehnicheskih nauk»*, aprel` 2016g , Moskva, №4 (34), pp.65-70.
9. Holmonov, S.M., & Israilov, N.O. (2015). *Reguljator parametrov nestacionarnyh ob#ektov na osnove geneticheskih algoritmov dlja*

optimizacii obuchenija nejronnoj seti. Trudy HI Mezhdunarodnoj Aziatskoj shkoly-seminara «Problemy optimizacii slozhnyh sistem», 27 iulja - 7 avgusta 2015g., Kyrgyzskaja Respublika, Issyk-Kul`skaja oblast`. (pp.663-668). Bulan-Sogotu - Almaty.

10. Jumanov, I.I., & Kholmonov, S.M. (2020). Optimization of identification under the conditions of low reliability of information and parametric uncertainty of non-stationary objects. *Chemical Technology, Control and Management*: Vol. 2020: Iss. 5, Article 19. DOI: https://doi.org/10.34920/2020.5-6.104-111
11. Jumanov, I.I., & Xolmonov, S.M. (2018). Optimization of data processing based on accounting for factors of external expenses, regulation and correction of variables .," *Chemical Technology, Control and Management:* Vol. 2018: Iss.4, Article 10. DOI: https://doi.org/10.34920/2018.6.54-61
12. Djumanov, O.I., & Kholmonov, S.M. (2016). The modified model of training of neural networks in computer industrial systems with modules for nonstationary objects images processing. *Journal of Korea Multimedia Society, Chemical Technology. Control and Management.* South Korea, Seoul – Uzbekistan, Tashkent – 2016, № 5, pp.54-58.