# Intellectualization of Data Processing of Non-Stationary Objects in a Complex Problem Environment

***Kholmonov Sunatillo Makhmudovich***
*PhD in Technical Sciences, Department of Information Technologies, Samarkand State University, Samarkand, Uzbekistan*

***Shukurov Vasliddin Sobirjon o'g'li***
*Graduate student, Department of Information Technologies, Samarkand State University, Samarkand, Uzbekistan*

A B S T R A C T

*Scientific and methodological foundations for building an intelligent system for analyzing and processing data in a complex problem environment have been developed based on the use of neural networks, fuzzy set models, fuzzy inference algorithms, knowledge bases and databases. Methods for the formation of fuzzy rules of the knowledge base, modeling of membership functions, determination of the boundaries of membership of the values of input variables, intervals of linguistic terms of input and output of neuro-fuzzy networks are proposed.*

A R T I C L E I N F O

*Article history:*
**Received** 28 January 2022
**Received** in revised form
30 January 2022
**Accepted** 16 February 2022

**Keywords**: data processing, non-stationary object, fuzzy set, fuzzy inference, fuzzy rules, optimization.



**Relevance of the topic**. Thanks to the development of artificial intelligence, new systems of data processing, based on the use of neural networks (NN), models of fuzzy sets, algorithms of fuzzy logical inferences, as well as options for their synthesis, are replacing the classical ones. However, despite significant theoretical and practical advances in the application of neuro-fuzzy networks (NFN), there is practically no development of intelligent data processing systems that successfully complement the functionality of systems based on analytical models. [1,2]. Information of control systems for technological, organizational, economic, biological, metrological processes refers to objects with poorly structured data that have the characteristics of uniqueness, continuity, heterogeneity (variety), nonlinearity, and a multilevel organization of relationships [3].

It is supposed to solve two interrelated tasks:

- analysis of a non-stationary object and construction of a description model;
- Synthesis of structural components of a data processing system based on NN, NFN, and hybrid, combined with dynamic models.

Models reflect the behavior of an object, data processing tasks are considered in a discrete representation of information [4-7], which is specified by a mapping of the form

$$\text{PFP: } U_k \times Wo_k \times X_k \to X_{k+1},\ U_k \times X_k \to Y_k\,. \ (1)$$

And the synthesis task is to form the mapping

$$\text{MS: } G_k \times J_k \times Ws_k \times X_k \times T_k \to U_k\,. \ (2)$$

Where $k$ - quantization step (time unit for issuing a control action).

In the system under study, mappings (1) (2) are represented using fuzzy equations.

The most valuable property of NFN is the ability to successfully solve problems in which it is difficult and impossible to find analytical "input-output" relationships; optimal indicators of the dynamics of time series; optimal prediction strategy; organization of the system operation in multidimensional spaces, including spaces of mixed type, in which some of the variables are continuous, and some are discrete. The advantage of using fuzzy sets in modeling lies in the simplicity and generality of the description and presentation of the logic of the system operation [8, 9].

**Principles and methods of fuzzy data processing.** The key link in the system is the presence of fuzzy controllers operating on the basis of computational schemes of NFN. At the same time, the use of fuzzy models provides a relatively simple way to control complex objects in conditions of a priori insufficiency, parametric uncertainty, nonstationarity, which have a nonlinear behavior of the "input-output" dependence [10].

The fuzzy rules that make up the fuzzy controller represent the knowledge or experience of the operator. In fig. 1 shows a general scheme of a fuzzy controller with a fixed knowledge base to provide adaptive data processing in a fuzzy environment [11].

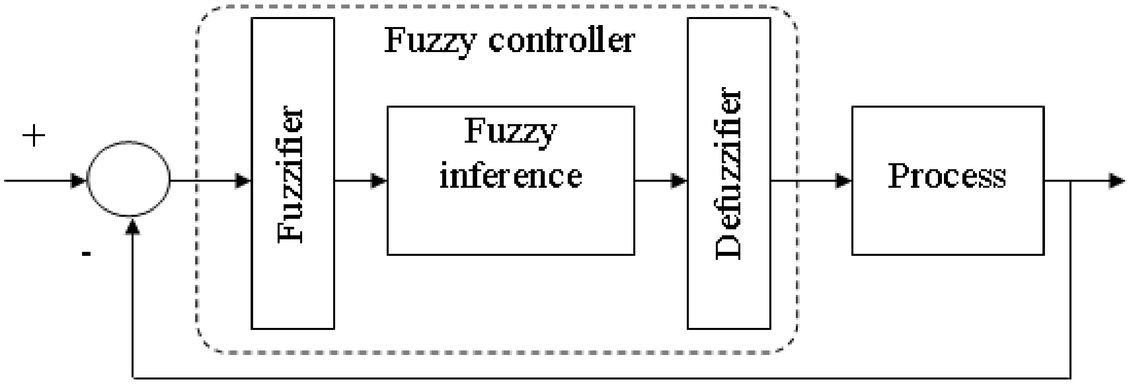


Fig. 1 Fuzzy regulator

A fuzzy controller with a fixed knowledge base (KB) are known as static fuzzy controllers [12,13]. In this case, the knowledge base of the controller (control rules) is formed on the basis of the knowledge of the operator who followed the course of the process. A scheme of a self-organizing regulator with quantifiers has been developed, the main purpose of which is customization the rule base for various situations.

The rule base for different situations may contain not only different rules, but also different values of the characteristics of fuzzy sets and the corresponding linguistic variables.

Conclusions based on the results of information processing are determined by an expert and may include not only deviations of the output coordinate from the required value, but also take into account various restrictions regarding the general nature of the system functioning.

The most complete is the self-learning scheme for constructing the NFN, which includes a heuristic knowledge base in the form of a set of tables, fuzzy controller rules, where each of the tables is determined by its own rules for inclusion in the control loop, the actual database, the main purpose of which is to identify new patterns in the practical process control.

It has been determined that among the known models of logical, production, frame, neural and semantic, production models of knowledge are most suitable for describing the subject area under consideration, with the help of which it seems possible to naturally describe the declarative experience of a person, his intuition and logic of behavior [14,15]. In fig. 2 shows the NFN with self-learning.

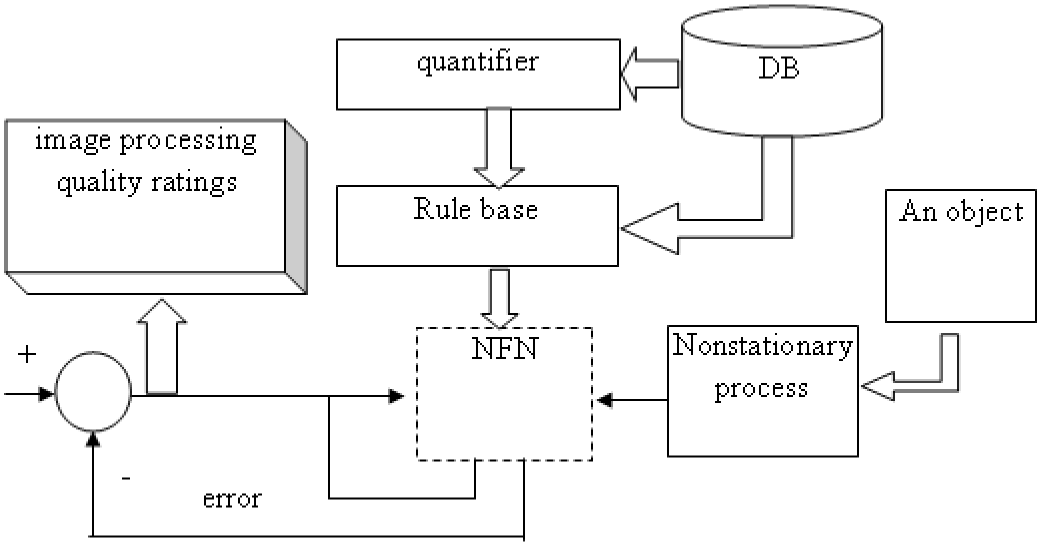


Fig. 2. NFN with self-learning.

**Linguistic description of a fuzzy object with the property of non-stationary.** Specified by a set of rules in the form of

IF Xk=(x1=NB, x2=PM,..., xn=ZE) AND Uk=(u1=PM, u2=NB,..., um=NM) THEN Xk+1=(x1=PB, x2=PS,..., xn=PB),

which reflect the ratio of changes in the output of the network depending on the input actions. For systems with non-stationary objects, the set is written in the form of

Xk+1=Xk*Uk, (3)

where Xk = (x1, x2...,xn) - generalized input state vector of the system;

Uk = (u1, u2..., um) - generalized vector of disturbances impacts, the values of which represent are linguistic variables of the following term-sets:

S={NB,NM,...,ZE,...,PM,PB},

where NB - negative big; NM - negative middle;

ZE – zero; PM - positive middle;

PB - positive big, which are represented by fuzzy sets with given membership functions (MF).

Linguistic rules connecting inputs, control actions U and output are written in the form:

X: Xk+1= R(Xk ,Uk); (4)

or ΔXk= R(Xkk ,Uk), (5)

where X – state of the system;

DX – state change at the next point in time;

R – connection relation.

In table. 1. An example of such a display is given.

Table 1. Table of linguistic rules

| UK\XK | NB | NM | ZE | PM | PB |
|---|---|---|---|---|---|
| NB | NB | NB | NB | NM | ZE |
| NM | NB | NB | NM | ZE | PM |
| ZE | NB | NB | ZE | PB | PB |
| PM | NM | ZE | PM | PB | PB |
| PB | ZE | PM | PB | PB | PB |

To solve problems, we introduce an algebraic system with the help of which model (4) or (5) can be replaced in the form of some algebraic structure.

Let S={NB,NM,ZE,PM,PB} be a set of linguistic variables that for each variable have its own meaning. For example, NB means very low, NM - means low, ZE - means medium, PM - means high, and PB - means very high.

We represent implicative mappings in the form of table. 2.

Table 2 Table of linguistic rules

K(u(k),x2(k)) $\rightarrow$x2(k+1)

| u(k),x2(k) | NB | NM | ZE | PM | PB |
|---|---|---|---|---|---|
| NB | NB | NM | NM | NM | ZE |
| NM | NM | ZE | ZE | ZE | PM |
| ZE | NM | ZE | ZE | ZE | PM |
| PM | NM | ZE | ZE | ZE | PM |
| PB | ZE | PM | PM | PM | PB |

R(x2 (k),x1(k)) $\rightarrow$x1(k+1) at u(k)=NB

| x2(k)\x1(k) | NB | NM | ZE | PM | PB |
|---|---|---|---|---|---|
| NB | ZE | ZE | PM | PB | PB |
| NM | ZE | PM | PB | PB | PB |
| ZE | ZE | PM | PB | PB | PB |
| PM | ZE | PM | PB | PB | PB |
| PB | PM | PB | PB | PB | PB |

Mappings are represented in a similar way.

R(x2 (k),x1(k)) $\rightarrow$x1(k+1) at u(k)=NM; R(x2 (k),x1(k)) ® x1(k+1) at u(k)=ZE;

R(x2 (k),x1(k)) $\rightarrow$x1(k+1) at u(k)=ZE; R(x2 (k),x1(k)) $\rightarrow$x1(k+1) at u(k)=PM;

R(x2 (k),x1(k)) $\rightarrow$x1(k+1) at u(k)=PB, R(x2 (k),x1(k)) $\rightarrow$x1(k+1) at u(k)=PB.

The approximating table of linguistic rules for the output parameter is given in the form of:

$$x_1(k+1) = x_1(k) + 1/2 * x_2(k) - u(k);$$

$$x_2(k+1) = 1/2 * x_2(k) + 1/2 * u(k).$$

**Conclusion**. Thus, the developed methods for synthesizing neural networks, neuro-fuzzy models and fuzzy logic algorithms constitute the scientific and methodological basis for designing effective and promising technologies for intellectualization of data processing, which are focused on using the unique properties of self-adaptation, self-organization, self-learning of neural networks and combined with NFN statistical and dynamic models of non-stationary objects. The stated theoretical provisions, methods and algorithms of data processing are implemented as independent software modules as part of the software of an intelligent system for analyzing and processing data based on the NFN.

## References


1. Simankov V.S., Teploukhov S.V. Intellectualization of the situational center through the selection of methods and algorithms of artificial intelligence, takinginto account the uncertainty of the initial information // Quarterly peer-reviewed, refereed scientific journal “Bulletin of ASU”. Release 4 (271) 2020. pp.60-69.

2. Simankov V.S., Cherkasov A.N. Technique of the analysis and synthesis of intelligent system within the situational center // The Bulletin of the Adyghe State University. Ser.: Natural-Mathematical and Technical Sciences. 2016. Iss. 4 (191). pp. 177–181. URL: http://vestnik.adygnet.ru

3. Bugakova T.Y. Development of a conceptual model and methods for multi-agent state assessment of technogenic systems // Journal of Physics: Conference Series 1661 (2020) 012024, pp.1-6. doi:10.1088/1742-6596/1661/1/012024

4. Dakhnovich A.A. Discrete systems and digital signal processing: textbook // Tambov: Tambov Publishing House. State tech. UN-ta, 2007. - 100 pp.

5. Mirzoev M.S. Fundamentals of Mathematical Information Processing: Textbook // Moscow: "Prometheus", 2016. - 316 pp.

6. Kozlov A.N. Intellectual information systems: textbook // Ministry of agriculture. RF, Perm: Publishing House of FGBOU VPO Perm State Agricultural Academy, 2013. - 278 pp.
7. Ibragimovich, J. I., Isroilovich, D. O., & Maxmudovich, X. S. (2020, November). Effective recognition of pollen grains based on parametric adaptation of the image identification model. In 2020 International Conference on Information Science and Communications Technologies (ICISCT) (pp. 1-5). IEEE.
8. Jumanov, I. I., & Xolmonov, S. M. (2021, February). Optimization of identification of non-stationary objects due to information properties and features of models. In IOP Conference Series: Materials Science and Engineering (Vol. 1047, No. 1, p. 012064). IOP Publishing. DOI:10.1088/1757-899X/1047/1/012064
9. Djumanov, O. I., & Kholmonov, S. M. (2010, October). Optimization of learning the neuronetworking data processing system for non-satinary objects recognition and forecasting. In 2010 4th International Conference on Application of Information and Communication Technologies (pp. 1-4). IEEE. DOI:10.1109/ICAICT.2010.5612037
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, 2020(5), 104-112. doi.org/10.34920/2020.5-6.104-111.
11. Жуманов, И. И., Холмонов, С. М., & Каюмова, Н. (2018). Повышение достоверности обработки данных нестационарных объектов на основе применения мультиконтекстных рекуррентных нейронных сетей. Наука и мир, 1(3), 52-54.
12. Djumanov, O. I., Kholmonov, S. M., & Ganiev, J. M. (2021). Optimization of data processing based on neural networks and properties of non-stationary objects. Theoretical & Applied Science, (4), 165-168.
13. Джуманов, О. И. (2016). Методы адаптивной обработки данных наоснове механизмов гибридной идентификации с настройкой параметров моделей нестационарных объектов. Проблемы информатики, (2 (31)), 13-20.
14. Zhumanov, I. I., & Yusupov, N. R. (2013). Identification optimization of nonstationary objects based on the tools of soft computing. Science and world, 32.
15. Холмонов, С. М., & Абсаломова, Г. Б. (2020). Повышение достоверности текстов на основе логических критериев и базы знаний электронных документов. «Технические науки: проблемы и решения» (pp. 15-19).