УДК 621.372:538.56

M.Kopytchuk, V.Perederii

Odesa national polytechnic university
department of computer intelligence systems and networks
Mykolaiv Sykhomlynskyi national university
department of computer systems and networks

DEFINING OF ENVIRONMENTAL EFFECT FUZZY SITUATIONS ON THE COGNITIVE STATE OF INDIVIDUAL WHO MAKES DECISIONS IN THE ERGATIC SYSTEMS

Fuzzy classifiers which allow to accurately describe the factors for which there are no strict regularities and one must associate quantitative and qualitative assessments of factors which influence the individual while decision-making.

Key words: individual making a decision, environmental factors, fuzzy sets, fuzzy classifiers.

Introduction

The peculiarities of man-machine control systems lie in the fact that they include both engineering systems and humans which cooperate with them as their elements. For effective operation of these systems one must choose effective means of communication of the users' cognitive characteristics with the equipment by virtue of man-machine study conclusions and environmental influence. If the ergatic system operation is involved under fuzzy conditions, control quality is provided by the work quality of individual making a decision (IMD).

Upon that the main difficulties are connected not only with the technical and software tools improvement but also with the insufficient development of human factor accounting methods and the failure to predict the influence on the environmental change system in the process of complex systems forming and exploitation apparently. As a result the task of the defining the environmental effect fuzzy situations on the cognitive state of individual who makes decisions is of high applicability.

Problem definition

In the works [4-5] the authors have analyzed the main reasons which impinge the work quality and the incapacitation of an individual who makes a decision in the man-machine control system of complex elements where human factor is one of the main reasons. The problem of comfortable working environment defining in the process of system operating is viewed fundamentally in the references. The considerations of arithmetic models and algorithms forming which allow to evaluate the relevance of the decisions made with account of the external and personal factors influence on the security of man-machine systems operation are described in [5,6]. In [6] the authors have developed the formalization algorithms of the users' external factors and psycho-functional characteristics on the basis of the fuzzy sets theory and the algorithm of the decision-making optimization. But all these do not allow to accurately describe the factors for which there are no strict regularities and one must associate quantitative and qualitative assessments of factors which influence the individual while decision-making.

Work objective

To develop a method of defining of environmental effect fuzzy situations on the cognitive state of an individual making a decision on the basis of fuzzy classifiers.

Base material exposition

Uncontrolled factors hold a special place in the activity of an individual who makes a decision in the ergatic systems. They can be subdivided into two groups [6]:

1. Ergonomic and external environment factors Sc (table 1):
- noise intensity IN;
- vibration intensity IV;
- workplace illumination E;
- temperature T;
- humidity f;
- atmosphere pressure P.
2. Factors conditioned by the cognitive state Sp (table 2):
- level of information handling effectiveness Io;
- fatigue level of a user F;
- time limitation of decision making Tp;
- voltage level nonconformance TS;
- attention focusing A.

The peculiarity of these factors lies in their non-numeric nature, failure to introduce them in the form of a real number, and interdependence between two groups of factors.

The solving of the task set comes down to the defining the target function maximum:

$$R_p = F\left(Sc^+, Sp^+\right) \to \max \qquad (1)$$

where the state of the first group of factors is

$$S_c = f_1\left(I_N^-, I_V^-, E^+, T^{+-}, f^+, \left(\frac{\Delta P}{\Delta t}\right)^- \right) \qquad (2)$$

the state of the second group of factors is

$$S_p = f_2\left(I_0^+, F^-, T_p^-, TS^-, A^+\right) \qquad (3)$$

Having inserted (2) and (3) into (1) we receive the target function of factors which influence the individual making a decision in the ergotic systems:

$$R_p = F\left[f_1\left(I_N^-, I_V^-, E^+, T^{+-}, f^+, \left(\frac{\Delta P}{\Delta t}\right)^- \right)^+, f_2\left(I_0^+, F^-, T_p^-, TS^-, A^+\right)^+ \right] \to \max \qquad (4)$$

Let's apply while factor describing the fuzzy sets theory. For defining fuzzy sets a set U which includes element u and mapping of this set onto an interval [0,1] is viewed – $\mu : U \to [0,1]$

Defining: A fuzzy set A fixed on the basic set U is a variety of pairs $A = \{\mu_A(u)/u : u \in U\}$ where $\mu_A(u)$ is called a fuzzy set membership function A [1].

In such a way to fix a fuzzy set A one need set its membership function $\mu_A(u)$ on a basic set U. The example of a fuzzy set "average noise intensity" is introduced on the figure 1 where U is a range of noise intensity.

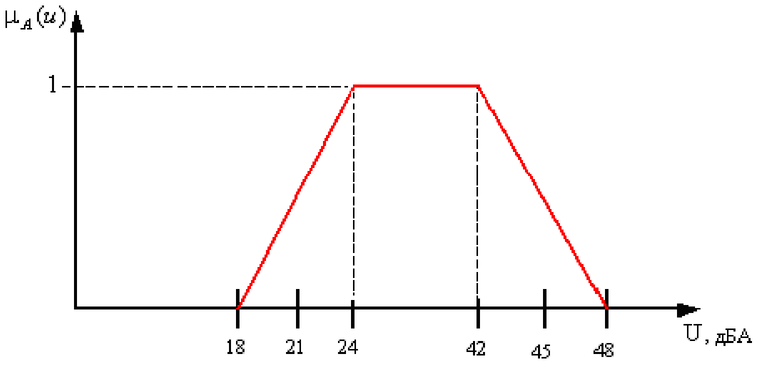

Figure 1 fuzzy set “average noise intensity”.

Using the notion of a fuzzy set we can come over while describing the factors from numeral variables to linguistic ones (LV) the value of which is a certain bag of words in natural of formal language. LVs allow to approximately describe phenomena which cannot be described by means of quantity characteristics because of any given reason.

Defining: A linguistic variable is a five element tuple (X, T(X), U, G, M) where X is a name of a LV that is a set of linguistic values each of which is a fuzzy set on a basic set U, G – is a set of syntax rules created by the names of LV values, M – is a set of semantic rules which place each LV term in correspondence with a relevant fuzzy set [1].

The example of a LV which describes the factor noise intensity is introduced on the figure 2. In such a way, a set of linguistic variables a_i which describes a given topical area is determined by a set of fuzzy values $A_i = \{U_i^k\}_{k=1..K_i}$ where K_i ... is a quantity of fuzzy values adopted by i-parameter in the form of fuzzy figures with trapezium membership function μ_i^k which is positively determined on a certain interval (u_{ib}^k, u_{ie}^k) where $u_{ib}^k, u_{ie}^k \in U_i$ is a value of the beginning and the end of interval correspondingly, and U_i is a basic set of parameter a_i fuzzy values.

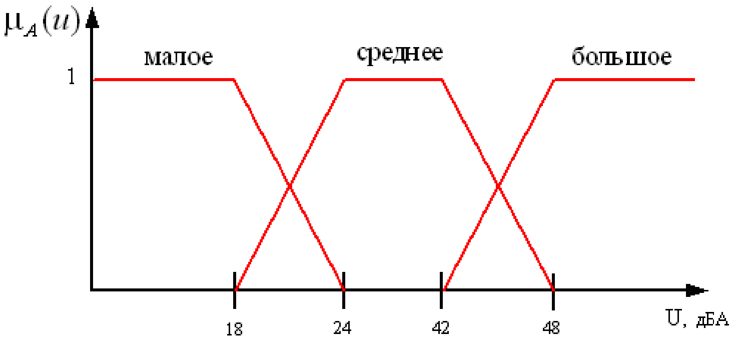

Fig. 2 – Linguistic variable “noise intensity”.

Every fussy figure $U_i^k \in A_i$ is defined through the membership function of the form:

$$U_k^i \Rightarrow \mu_k^i(u_i) = \begin{cases} 0, & u_i \le u_{kb}^i, u_i \ge u_{ke}^i \\ \frac{u_i - u_{kb}^i}{u_{kb_1}^i - u_{kb}^i}, & u_{kb}^i < u_i < u_{kb_1}^i \\ 1, & u_{kb_1}^i \le u_i \le u_{ke_1}^i \\ \frac{u_i - u_{ke}^i}{u_{ke_1}^i - u_{ke}^i}, & u_{ke_1}^i < u_i < u_{ke}^i \end{cases}, \quad i = 1..\tilde{N}_u, k = 1...3. \tag{5}$$

where u_{kb}^i, u_{ke}^i is an initial and final values of the basic set U_i value interval on which the membership function of the k-ro fuzzy value and i-parameter is positively defined; $u_{kb_1}^i, u_{ke_1}^i$ is an initial and final value of the basic set U_i value interval correspondingly on which the membership function of the k-ro fuzzy value and i-parameter is equal to one.

The membership functions of LV terms “noise intensity” in view of their trapezium form can be described through a four-value tuple $(u_{kb}^i, u_{kb_1}^i, u_{ke_1}^i, u_{ke}^i)$ which define the initial and final zero and one level α abscissa. For membership functions introduced on the figure 2 one can give a description in the form of four-value tuple

$$\mu_H = (0, 0, 18, 24);$$
$$\mu_C = (18, 24, 42, 48);$$
$$\mu_B = (42, 48, 75, 75).$$

Table 1

Formalization of the environment state factors in a linguistic variable

Initial factor	Limits of iation (U_i)	Linguistic evaluation terms		
		«H»(low) μ_H ,	З»(middle) μ_C ,	«B»(high) μ_B ,
IN (дБА)	0–75	(0,0,18,24)	(18,24,42,48)	(42,48,75,75)
IV (мм/с)	0–15	(0,0,3,5)	(3,5,9,11)	(9,11,15,15)
E (Лк)	0–600	(0,0,160,240)	(160,240, 360,440)	(360,440, 600, 600)
T (°З)	10–40	(10,10,15,19)	(15,19,23,27)	(23,27,40,40)
f (%)	0–90	(0,0,26,34)	(26,34,56,64)	(56,64,90,90)
$\Delta P / \Delta t$ (мм.рт.ст/сут)	0–15	(0,0,2.5,3.5)	(2.5,3.5,6,8)	(6,8,15,15)

Table 2

Formalization of the user flow state in a linguistic variable

Initial factor	Limits of variation	Linguistic evaluation terms:		
		«H»(low) μ_H ,	3»(middle) μ_C ,	«B»(high) μ_B ,
I_o (ранг)	0–15	(0,0,4,6)	(4,6,9,11)	(9,11,15,15)
F (ранг)	0–15	(0,0,4,6)	(4,6,9,11)	(9,11,15,15)
Tp (хв)	0–60	(26,34,60,60)	(4,6,26,34)	(0,0,4,6)
TS (ранг)	0–15	(0,0,4,6)	(4,6,9,11)	(9,11,15,15)
A (ранг)	0–15	(0,0,4,6)	(4,6,9,11)	(9,11,15,15)

Fuzzy classifiers.

Let's fix a linguistic variable (LV) $B^{(5)}$ with the name "index level" and the term-set of values B_1 **"**Very Low (VL), B_2 Low (L), B_3 Middle (M), B_4 High (H), B_5 Very High (VH)**"** which are introduced on the Fig.3. The basic set of a given variable is an interval [0,1], and every term LV B_i, $i = 1,...,5$ is described by the trapezium membership function which complies with the formula (1). In equivalent to [3] let's view a set of double points $\alpha = \{0.1, 0.3, 0.5, 0.7, 0.9\}$ which are the abscissas of membership function maxima of the LV terms $B^{(5)}$ and lie equidistant on the interval [0,1] and symmetrically to the abscissa 0.5. The combination of LV $B^{(5)}$ and a set of double points α is called a standard fuzzy five-level 01-classifier [3].

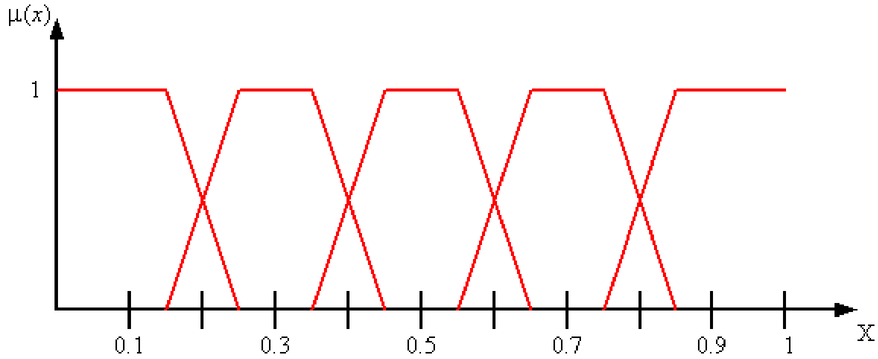

Fig. 3 A diagram of a term-set of standard fuzzy five-level 01-classifier membership functions.

The membership functions of the terms B_i, $i = 1,...,5$ in view of their trapezium form can be described through a tuple of four values which define the initial and final abscissa of a zero and one α levels. Taking this into consideration the term-set of a standard fuzzy five-level 01-classifier can de defined in the following way:

$$
\begin{aligned}
\mu_{OH} &= (0,0,0.15,0.25);\\
\mu_{H} &= (0.15,0.25,0.35,0.45);\\
\mu_{C} &= (0.35,0.45,0.55,0.65);\\
\mu_{B} &= (0.55,0.65,0.75,0.85);\\
\mu_{OB} &= (0.75,0.85,1,1).
\end{aligned} \tag{6}
$$

All above-mentioned facts are applicable to a more general case – the construction of an n-level fuzzy classifier if $n > 1$, $n \in Z$ where Z – is a set of counting numbers. The number of n-levels is chosen according to the demands made on the model. Two-level classifier is of no concern because it doesn't contain middle fuzzy value around which group real objects states.

That is why it makes sense to view a classifier with n=3. A standard three-level fuzzy 01-classifier is introduced through a linguistic variable $B^{(3)}$ with a term-set of values B_1 "Low (L), B_2 Middle (M), B_3 High (H)". The membership functions of the corresponding terms are described by the following formulas:

$$
\begin{aligned}
\mu_{H} &= (0,0,0.2,0.4);\\
\mu_{C} &= (0.2,0.4,0.6,0.8);\\
\mu_{B} &= (0.6,0.8,1,1);
\end{aligned} \tag{7}
$$

The diagram of membership functions described by the formulas (7), is introduced on the figure 4. A set of double points takes a value of $\alpha = \{0.1, 0.5, 0.9\}$

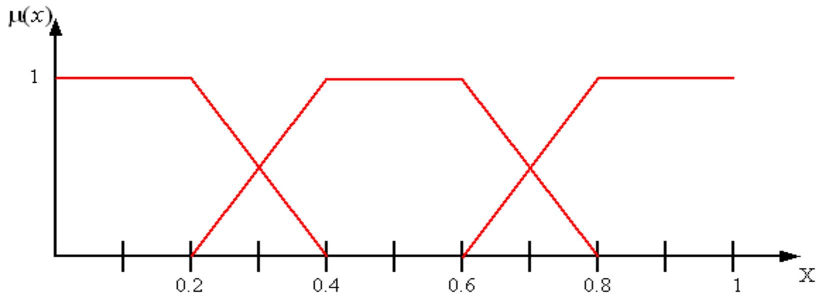

Fig.4 A diagram of a term-set of standard fuzzy three-level 01-classifier membership functions.

Please note that the value area of some factors introduced in the tables 1, 2 can be led to the fuzzy classifier bearer with the help of linear transformations, and the terms which describe fuzzy values – to the terms of a standard fuzzy three-lever classifier.

Fuzzy classifiers are essential because they allow to accurately describe the factors for which there are no strict regularities and one must associate quantitative and qualitative assessments of factors. If there is some additional information about the factor nature while classifier construction, in general case the classifier isn't standard because double points are not symmetrical to the middle of corresponding factor bearer.

Let's view the next hierarchy level of the analyzed model the target function of which is determined (4). Let's introduce vectors:

$$
x_1 = \{x_{1i}\}_{i=1}^{N_1} = [I_N^-, I_V^-, E^+, T^{+-}, f^+, \left(\frac{\Delta P}{\Delta t}\right)^-], N_1 = 6, ,
$$

$$x_2 = \{x_{2i}\}_{i=1}^{N_2} = [I_0^+, F^-, T_p^-, TS^-, A^+], N_2 = 5, \quad (8)$$

$$r = [r_1, r_2] = [S_c, S_p] .$$

In vector version the dependences (2) and (3) can be rewritten in the form:

$$r_i = f_i(x_i), \quad i = 1, 2. \quad (9)$$

For each of certain factors x_{mi}, $m = \overline{1,2}$, $i = \overline{1, N_m}$ certain three-level classifiers which do not depend on the parameter type are constructed. To describe the dependences (9) one can use a formula:

$$r_m = \sum_{i=1}^{N_m} z_{m,i} v_{m,i} \sum_{k=1}^{3} \alpha_k^m \mu_{ki}^m (x_{mi})$$
$$\sum_{i=1}^{N_m} v_{m,i} = 1. \quad (10)$$

Where α_k are double points of a standard classifier;

$v_{m,i}$ - weight of m-factor for i-parameter;

$\mu_{ki}^m (x_{mi})$ - value of membership function of k-term and i-factor, m-dependence;

$z_{m,i} \in \{1, -1\}$ - coefficient which defines positive or negative influence direction of i-parameter.

To evaluate the dependence one must in its turn to form a fuzzy knowledge data base which allows to evaluate the membership function value of k-term and i-factor.

The parameters of the environment and the system state can describe a certain fuzzy situation or be of no concern taking into account fuzzy situations description. That is why on the basis of facts collected on a certain investigation interval one can define fuzzy situations which occur more often and introduce a set of standard situations.

Conclusions

The parameters of the environment and the system state can describe a certain fuzzy situation or be of no concern taking into account fuzzy situations description. That is why on the basis of facts collected on a certain investigation interval one can define fuzzy situations which occur more often and introduce a set of standard situations.

Fuzzy classifiers are essential because they allow to accurately describe the factors for which there are no strict regularities and one must associate quantitative and qualitative assessments of factors. If there is some additional information about the factor nature while classifier construction, in general case the classifier isn't standard because double points are not symmetrical to the middle of corresponding factor bearer.

1.Борисов В. В. Нечеткие модели и сети / В. В. Борисов, В. В. Круглов, В. В. Федулом – М. : Горячая линия – Телеком, 2007. – С. 284. 2. Рыжов А. П. Элементы теории нечетких множеств и ее приложений. / А. П. Рыжов – Москва, 2003. – С. 81. 3. Недосекин А. О. Методологические основы моделирования финансовой деятельности с испльзованием нечетко-множественных описаний : дисертационная работа на соискание ученой степени доктора экономических наук // СПб., Санкт-Петербургский государственнiй университет єкономики и финансов, 2003. – С. 280. 4.Шеридан Т. Б. Системы человек-машина: Модели обработки информации, управления и *принятия решений человеком-оператором / Т. Б. Шеридан, У. Р. Феррел; пер. с англ.; под ред. К. В. Фролова. – М.: Машиностроение, 1980. – 400 с. 5.Человеческий фактор. В 6-ти тт. Т. 2. Эргономические основы проектирования производственной среды: Пер. с англ. / Д. Джоунз, Д. Бродбент, Д. Е. Вассерман и др. – М.: Мир, 1991. – 500 с. 6.Передерий В.И., Еременко А.П. Математические модели и алгоритмы определения релевантности принимаемых решений с учетом психофункциональных характеристик пользователей при управлении автоматизированными системами. [Текст] / В.И. Передерий, А.П. Еременко // Автоматика. Автоматизація. Електротехнічні комплекси та системи. – Херсон: – 2007, №2. – С. 34–40. 7.Кофман А. Введение в теорию нечетких множеств / Кофман А. – М.: Радио и связь, 1982. – 432 с. 8.Ricardo J.G.B. Campello, Wagner Caradori do Amaral. Hierarchical Fuzzy Ralational Models: Linguistic Interpretation and Universal Approximation (2006), IEEE Transactions on Fuzzy Systems, vol. 14, No. 3, pp. 446–453, doi: 10.1109/TFUZZ.2006.876365. государственный технический университет. 30.06.2006. – Обнинск: 2006. – 159 с. 9.Справочник по инженерной психологии / Под ред. Б. Ф. Ломова. – М.: Машиностроение, 1982. – 368 с.10.Koji Shimojima, Toshio Fukuda, Yasuhisa Hasegawa. Self-tuning fuzzy modeling with adaptive membership function, rules, and hierarchical structure based on genetic algorithm (1995), Fuzzy Sets and Systems, vol. 71, pp. 295-309.*