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RELIABILITY

Modeling of the Human Operator Reliability with the Aid of the Sugeno Fuzzy Knowledge Base

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Abstract—Whenever a problem to predict and ensure reliability of human-machine systems is posed, regression models are usually applied to evaluate the influence of different factors on faultlessness, exactitude, operating speed, and other characteristics of the operator performance. The Sugeno fuzzy knowledge bases are proposed to model multi-factor relations of reliability. It is shown that this approach allows to combine expert knowledge and analytical relations of the parametric reliability theory in operator activity models. The expert component of a model provides with a comprehensive interpretation, while analytical input-output relations make a model compact. Appropriate examples are presented to demonstrate advantages of the Sugeno knowledge base application to describe multi-factor reliability relations of human operator.

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1. INTRODUCTION

When the reliability of human-machine systems is modeled, we need to take into account the influence of different factors on various characteristics of operator performance, such as probability of right execution, operating speed, exactitude, etc. The study of those milti-factor relations is carried out in the frame of the theory of reliability and operating quality for human-machine systems and that of ergonomics and engineering psychology [1–9]. In these papers (and in others) dependences of the operator reliability on qualification, intensity of work, tiredness level, instrument quality, workplace convenience, and other factors are represented by regression models.

Restrictions of regression models result from a very high complexity to incorporate expert knowledge about dependences of reliability characteristics on various factors. Expert knowledge is usually formulated as linguistic rules of the type “If the operator qualification is high and the intensity of work is medium, then the faultlessness is high,” or “If the operator is tired, then the number of faults doubles.” It is convenient to transform such expert rules into mathematical models by using theory of fuzzy sets [10]. The totality of expert rules constitutes the fuzzy knowledge base. This can be associated with the step of the multi-factor dependence structure identification. The parametric identification is carried out basing on experimental data: membership functions for fuzzy sets are found such that the deviation between the desired and the real behavior of a model is minimum [11, 12].

We propose in this paper to describe multi-factor dependences of functional reliability in terms of a new model class based on the Sugeno fuzzy knowledge base [12]. This knowledge base consists of rules with fuzzy sets as premises and linear functions of inputs as conclusions. The knowledge base can be treated as a partitioning of the factor space by domains with fuzzy boundaries, each domain having its own input-output law. Since the boundaries are fuzzy, several linear laws are acting simultaneously (however, with different grades) in any point of the factor space. The Sugeno fuzzy knowledge base is convenient to describe the reliability of dynamical systems which get old, degrade, or are subject to other changes. Each system development phase is associated with a rule in the Sugeno knowledge base.

The paper is organized as follows: at first, we present the mathematical problem statement for the multi-factor reliability model design, then we describe modeling theory based on the Sugeno fuzzy knowledge base and state the problem of teaching the knowledge base by experimental data, and, finally, we present some examples of fuzzy model design for the human operator faultlessness.

2. PROBLEM STATEMENT

By $X = (x_1, x_2, \ldots, x_n)$ denote the vector of factors which influence the human operator reliability characteristic $y \in [\underline{y},\ \overline{y}]$. Then, from the cybernetics point of view, to design a reliability model means to find a mapping $X \to y$. Let's describe this mapping in terms of the Sugeno fuzzy knowledge base.

3. SUGENO FUZZY KNOWLEDGE BASE

The Sugeno fuzzy knowledge base consists of a set of rules [12]:

$$\text{if} \quad (x_1 = \widetilde{a}_{1j} \ \text{ and } \ x_2 = \widetilde{a}_{2j} \ \text{ and } \ \ldots \ \text{ and } \ x_n = \widetilde{a}_{nj}), \quad \text{then} \quad y = d_j, \quad j = \overline{1, m}, \tag{1}$$

when $\widetilde{a}_{ij}$ is a fuzzy term such as "Low," "Medium," "High," etc., that estimates the value of the factor x_i in the jth rule ($i = \overline{1, n}$, $j = \overline{1, m}$);

m is the number of rules in the knowledge base;

$d_j = b_{j0} + b_{j1}x_1 + b_{j2}x_2 + \ldots + b_{jn}x_n$ is the conclusion of the jth rule in the form of linear function with real coefficients.

Terms are usually described in fuzzy knowledge bases by parametric membership functions. We will use the Gauss membership function:

$$\mu(x) = \exp\left(-(x - b)^2/2c^2\right), \tag{2}$$

where $\mu(x) \in [0,\ 1]$ is the grade of membership of x;

b and c are parameters of the membership function: the maximum coordinate and the concentration coefficient.

4. FUZZY LOGICAL CONCLUSION

The grades of membership of the current input vector $X^* = (x_1^*, x_2^*, \ldots, x_n^*)$ with respect to the rules $d_1, d_2, \ldots, d_m$ is calculated according to the formula from [12]:

$$\mu_{d_j}(X^*) = \mu_j(x_1^*) \wedge \mu_j(x_2^*) \wedge \ldots \wedge \mu_j(x_n^*), \quad j = \overline{1, m}, \tag{3}$$

where $\mu_j(x_i^*)$ is the grade of membership of x_i^* with respect to the fuzzy term $\widetilde{a}_{ij}$, calculated according to (2); $\wedge$ is the t-norm that corresponds to the logical conjunction. The t-norm is usually realized by the product in the Sugeno algorithm.

On implementing (3) to all rules of knowledge base (1), we get the following fuzzy value of the output variable: $\widetilde{y}^* = \left(\frac{\mu_{d_1}(X^*)}{d_1}, \frac{\mu_{d_2}(X^*)}{d_2}, \ldots, \frac{\mu_{d_m}(X^*)}{d_m}\right)$. The appropriate non-fuzzy value is determined by the defuzzification according to the center of gravity rule: $y^* = \frac{\sum_{j=1}^{m} d_j \times \mu_{d_j}(X^*)}{\sum_{j=1}^{m} \mu_{d_j}(X^*)}$.

5. FUZZY MODEL TEACHING BY EXPERIMENTAL DATA

Suppose that the experimental data are available for a dependence of y on X:

$$(X_r,\ y_r)\,, \quad r=\overline{1,M}, \tag{4}$$

where $X_r=(x_{r1},x_{r2},\ldots,x_{rn})$ is the output vector in the rth couple of the teaching sample, and $y_r\in[\underline{y},\ \overline{y}]$ is the appropriate output.

To teach the Sugeno fuzzy model by sample (4) means to find a vector (P,B) such that [12, 13]:

$$\mathrm{RMSE}=\sqrt{\frac{1}{M}\sum_{r=\overline{1,M}}\left(y_r-F\left(P,\ B,\ X_r\right)\right)^2}\to\min, \tag{5}$$

where P is the vector of parameters of the fuzzy term membership functions;

B is the vector of coefficients in the rule conclusions;

$F\left(P,B,X_r\right)$ is the logical conclusion result for the input vector X_r according to the fuzzy models with parameters (P,B).

When a model is taught according to the RMSE criterion, large deviations of experimental data from theory may occur in some domains of the factor space. For problems where it is important to ensure both a good behavior of a system on average and a guaranteed accuracy in the worst case, we propose to teach the fuzzy knowledge base according to

$$\begin{cases} \mathrm{RMSE}=\sqrt{\dfrac{1}{M}\displaystyle\sum_{r=\overline{1,\ M}}\left(y_r-F\left(P,B,X_r\right)\right)^2}\to\min \\ \mathrm{MaxErr}=\max\left|y_r-F\left(P,B,X_r\right)\right|\le\Delta_{\max}, \end{cases} \tag{6}$$

where $\Delta_{\max}$ is the maximum admissible absolute residual.

Problems (5) and (6) are those of optimization. They can be solved using typical methods of mathematical programming.

6. FUZZY MODEL OF COMPUTER OPERATOR FAULTLESS TYPEWRITING

[1, 2] contain regression models for the probability p_1 of the correct keyboard text input depending on the two factors: the maximum time to enter one character x_1 and the duration of work x_2. The regression model for a medium-qualified operator is

$$p_1=\left(0.9975-0.495e^{-0.35x_1}\right)e^{-0.0009(x_2-2.11)^2}. \tag{7}$$

Considering (7) as a standard dependence, let's create on its base an analogous Sugeno fuzzy model. The model below sticks together three linear laws $p_1=b_0+b_1x_1+b_2x_2$ with three sets of coefficients. The values of coefficients depend on the duration of work x_2. The first rule of the knowledge base models the operator faultlessness during the training stage, the second during the normal work, and the third during the stage of tiredness. Let's form a teaching sample of 20 couples "input-output" and a testing one of 1000 couples (Fig. 1). The input values in these samples are taken at random from the intervals $[0,3]$ s for x_1 and $[0,8]$ h for x_2, the probability p_1 is calculated according to (7).

After teaching according to criterion (5), the following fuzzy knowledge base is constructed:

if $x_2=$ "Beginning," then $p_1=0.9452+0.0106x_1+0,0052x_2$;

if $x_2=$ "Middle," then $p_1=0.953+0.0096x_1+0.001x_2$;

if $x_2=$ "End," then $p_1=0.9718+0.085x_1-0.0062x_2$.

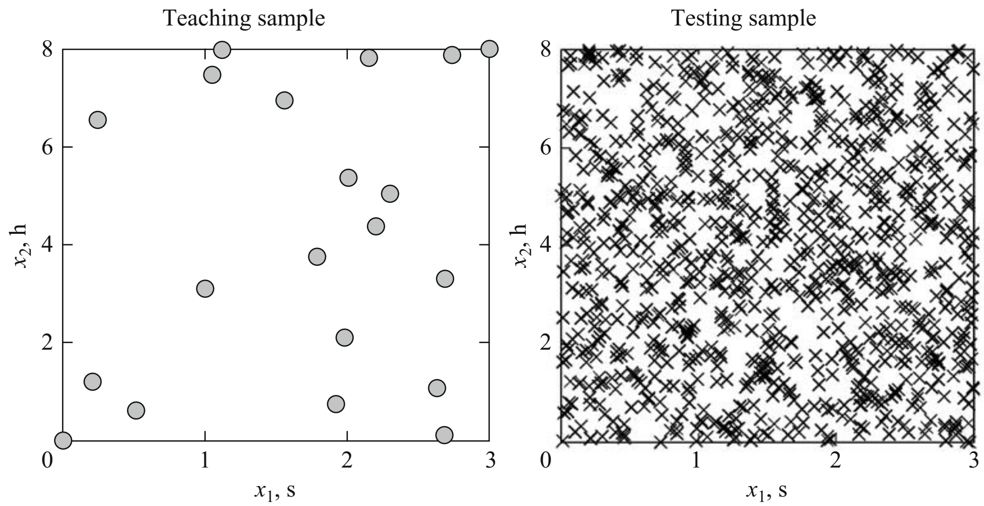

Fig. 1. Data distributions in samples.

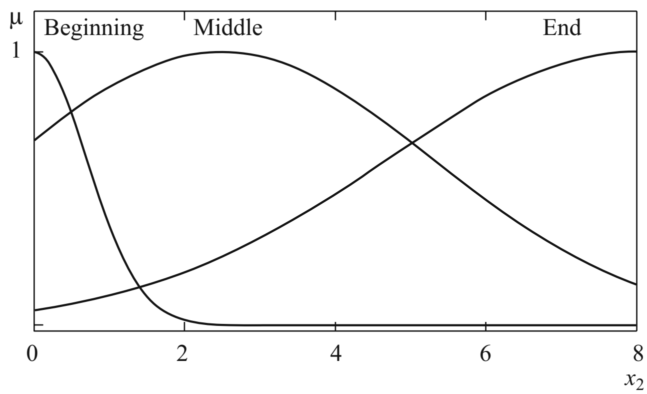

Fig. 2. Membership functions after fuzzy model teaching according to (5).

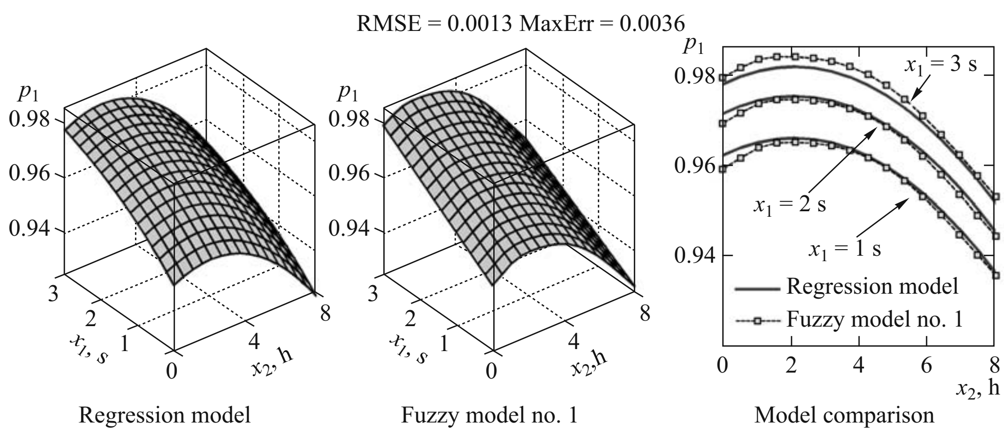

Fig. 3. Comparison of standard (regression) and fuzzy models.

The positive coefficient x_2 in the first rule indicates that the number of errors dwindles as the operator gets used to working, and the negative x_2 in the third rule means that the errors increase as the operator gets tired. The small value of x_2 in the second rule means that the faultlessness does not depend on time at the stage of normal work. Optimized membership functions are represented

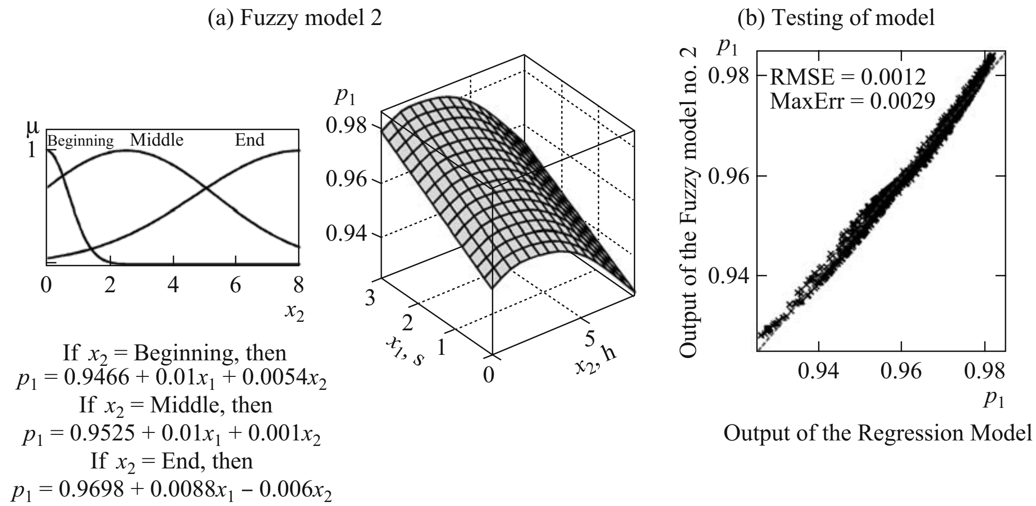

Fig. 4. Fuzzy model after teaching according to (6).

in Fig. 2. The comparison of the standard and fuzzy models reveals that the results are the same (Fig. 3).

By teaching according to (6) with the threshold $\Delta_{\max} = 0.002$, we obtain the fuzzy model represented in Fig. 4. The fuzzy models are quasi identical with respect to the RMSE criterion. But the second model is better with respect to the MaxErr criterion. Note that the optimization according to (6) is usually more time consuming due to the additional restriction.

7. FUZZY MODEL OF VISUAL SIGNAL DETECTION

Develop a model for the probability p_1 of the correct visual signal detection depending on the following workplace parameters: indication type x_1; signal lamp diameter x_2; number of lamps in the group x_3. Experimental data for these dependences are given in Table 1. Basing on these data, let's construct a Sugeno fuzzy model of order 0, i.e., a model with knowledge base (1) with all coefficients in rule conclusions being zero except for free terms $b_{ji} = 0$, $i = \overline{1, n}$, $j = \overline{1, m}$.

Table 1. Experimental data [14]

no.	x_1	x_2	x_3	p_1	no.	x_1	x_2	x_3	p_1
1	Continuous	< 6	1–2	0.9993	13	Blinking	< 6	1–2	0.9991
2	The same	< 6	3–4	0.998	14	The same	< 6	3–4	0.9978
3	"–"	< 6	5–7	0.9957	15	"–"	< 6	5–7	0.9945
4	"–"	< 6	8–10	0.9951	16	"–"	< 6	8–10	0.9939
5	"–"	6–12	1–2	0.9994	17	"–"	6–12	1–2	0.9992
6	"–"	6–12	3–4	0.9981	18	"–"	6–12	3–4	0.9979
7	"–"	6–12	5–7	0.9958	19	"–"	6–12	5–7	0.9946
8	"–"	6–12	8–10	0.9952	20	"–"	6–12	8–10	0.9940
9	"–"	12–25	1–2	0.9995	21	"–"	12–25	1–2	0.9993
10	"–"	12–25	3–4	0.9982	22	"–"	12–25	3–4	0.9980
11	"–"	12–25	5–7	0.9959	23	"–"	12–25	5–7	0.9947
12	"–"	12–25	8–10	0.9953	24	"–"	12–25	8–10	0.9941

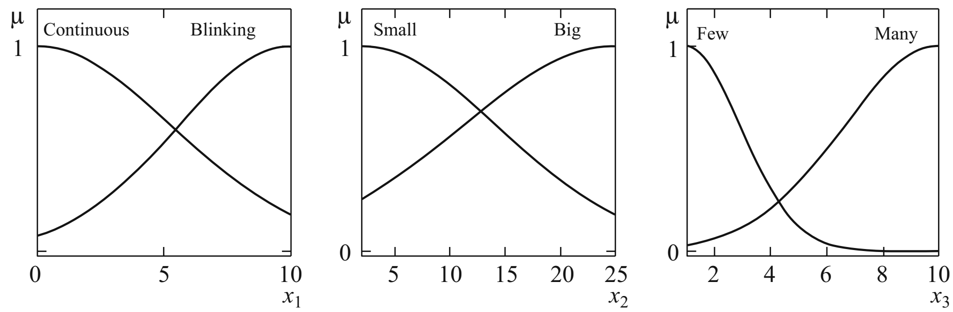

Fig. 5. Membership function after training.

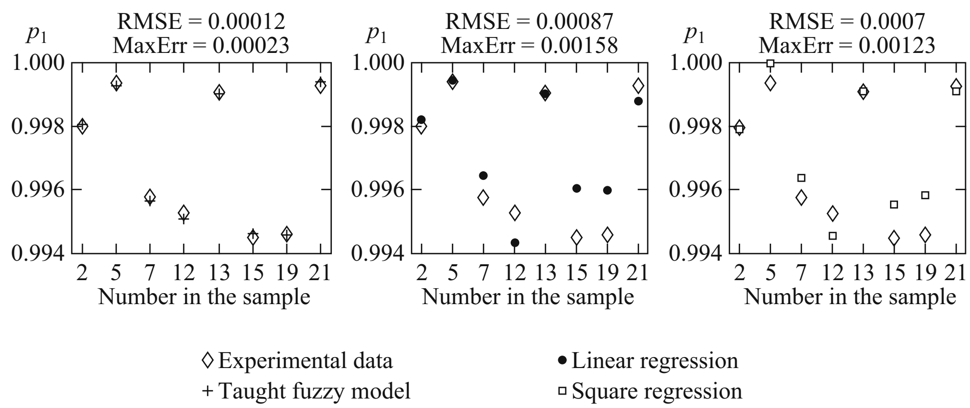

Fig. 6. Model testing by the test sample.

To develop the model we use the average data of Table 1. In addition, assign numerical values to the linguistic estimates: "continuous"= 0, "blinking"= 10. Include data with the numbers 2, 5, 7, 12, 13, 15, 19, and 21 into the teaching sample, and the others into the test sample.

Develop the fuzzy knowledge base (Table 2) from the rows 4, 9, 16, and 21 of Table 1. The rule conclusion values are given in the last column of Table 2. Optimal membership functions plots are presented in Fig. 5. Test results are shown in Fig. 6. To compare, we use the linear regression model

$$p_1 = 1.00059 - 0.00005x_1 - 0.00002x_2 - 0.00066x_3$$

and the square regression model

$$p_1 = 1.00079 + 0.00013x_2 - 0.00108x_3 - 0.00001(x_1^2 + x_2^2) + 0.00004x_3^2,$$

which are developed using the same data. It is clear that the designed fuzzy model is more accurate than the regression ones both with respect to RMSE and MaxErr. Note that the obtained fuzzy model is clear and accurate.

Table 2. Fuzzy knowledge base

IF			THEN	
x_1	x_2	x_3	p_1 (before tuning)	p_1 (after tuning)
Continuous	Small	Many	0.9951	0.9954
The same	Big	Few	0.9995	1
Blinking	Small	Many	0.9939	0.9936
The same	Big	Few	0.9993	0.9997

8. CONCLUSION

The Sugeno fuzzy knowledge bases are proposed to model multi-factor dependences of the human operator reliability. The two examples are given to confirm that it is possible to design reliability models with such knowledge bases. The first example demonstrates that the Sugeno fuzzy knowledge base can accurately approximate two-factor regression models of the text typewriting faultlessness. The second example demonstrates that, by tuning a fuzzy model, we can reconstruct a three-factor dependence from experimental data for the visual signal detection faultlessness. The identification accuracy is substantionally higher than that in regression data analysis.

The proposed approach allows to combine expert knowledge and analytical relations of the parametric reliability theory in operator action models. The expert component of a model provides with a comprehensive interpretation, while analytical input-output relations make a model compact.

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