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INVESTIGATION OF COMBINED ENSEMBLE METHODS FOR DIAGNOSTICS OF THE QUALITY OF INTERACTION OF HUMAN-MACHINE SYSTEMS

Purpose. Study on the process of combining several methods for determining the quality indices of human-machine interaction, containing various configurations for determining the weight coefficients in an ensemble.

Methodology. The process of diagnosing the quality of the interaction of a human-machine system with four elements of subsystems is studied using the example of the system "Operator–Machining Center – Control Program – Safe Environment". The main hypothesis of the study is the combination of several methods for determining the quality indices of human-machine interaction, containing different configurations for determining the weight coefficients in the ensemble. A combined method for diagnosing the quality of interaction between human-machine systems based on ensemble models, which include non-ensemble ones, has been proposed. The ensemble index has been determined by averaging the non-ensemble indices. The defined ensemble indices and element scores of the four subsystems are used as input scores to a multiple regression model to generate prediction.

Findings. Four combinations of ensemble indices have been developed and implemented in software, which are characterized by a minimum value of the standard deviation compared to the existing ones. According to the results of experimental verification, the proposed models demonstrate the value of the standard deviation of 0.1404; 0.1401; 0.1411; 0.1397, and the existing ones are 0.1532; 0.1535; 0.1532; 0.1532.

Originality. The combined ensemble method for diagnosing the quality of interaction between elements of subsystems takes into account linear models with non-linear variables and different ways of determining weight coefficients.

Practical value. The scenario for the practical use of the results obtained is a possible option for optimizing production, where, depending on the final result, specialists can adjust the value of a particular subsystem to achieve the desired result.

Keywords: *ensemble index, averaging model, nonlinear relationship, linear equation, nonlinear transformation, IT-technologies*

Introduction. The quality of the interaction of human-machine systems in terms of practical value plays an important role in the industry when adjusting the results of the systems. But the limitations of existing models are not the display of the behavior of nonlinear systems; in the absence of at least one primary assessment, the model inaccurately describes the human-machine system [1]. In [2], the diagnostics of the subsystem elements interaction has been carried out by ensemble methods, which are programmatically implemented. This is useful for dynamic changes in the states of a man-machine production system with three or more subsystem elements. The effectiveness of ensemble methods depends on their variety, where systematic biases are observed, which affects the decrease in the accuracy of system diagnostics [3].

The bias problem is resolved through the use of complex indicators of human-machine systems [4]. Solving displacement problems is a well-known practice, and there are unsolved problems in diagnosing the quality of interaction between elements of subsystems [5]. The problems are related to the improvement of the existing mathematical tools or the development of new ones for diagnosing the quality of interaction between human-machine systems in production. Existing models do not show the desired level of efficiency. In this regard, the study on ensemble methods of the quality of interaction between human-machine systems has been being updated.

Literature review. Existing research studies are focused on the development and improvement of complex models describing complex human-machine (ergatic) systems. Diagnostics of complex systems is carried out according to a typical procedure [6]: data collection, model building, function study and decision making. In [6], a general overview of convolutional neural networks for machine diagnostics is provided, and a description of the conditions and processes for collecting primary assessments from subsystem elements is given. By monitoring information from sensors, various operating conditions of machines are monitored, but the issue of diagnostics of human-machine systems, taking into account the social and safety subsystems, is not studied.

Data collection in complex systems, using the example of a numerical control machine, is possible through various sensors that are part of the system structure [7]. This allows for the detection of equipment malfunction anomalies. Linear regression, nearest neighbors, random forest, and support vector machines were used as tools. The selected research methods, under the studied conditions, achieved a prediction accuracy of 97.6 %, compared to other approaches with 95.5 and 95 % respectively. However, in [7], there is no comparison of the obtained results with other technologies, including ensemble methods and neural networks. Researchers focus on Industry 4.0 and do not consider other features of production.

The description of complex systems of simulation models requires a lot of resources, in particular, computation time [8]. Therefore, the urgent problem is the construction of metamodels or their application to solve specific practical problems at industrial enterprises. The study proposes a new modeling method based on evolutionary learning embedded in ordinal optimization [8]. The advantage of the considering approach is the features of the developed metamodel using genetic programming. However, the study has been conducted within a specific area, in particular, for planning the activities of workplaces, and the issues of solving other problems using the proposed tools have not been studied. Perhaps, in this regard, the features of building other metamodels have not been considered and a comparative analysis with existing ones has not been carried out.

One of the ways to overcome the existing difficulties is the life cycle of the metamodel, which considers the tools for maintaining the model. The RAI4.0 metamodel from the study [9] defines the modeling elements needed to describe systems designed according to the RAI4.0 reference architecture. The proposed approach is certainly valuable, since in addition to the developed model, a tool has been proposed that is compatible with the metamodel, automating the process of the model use. At the same time, the automation of production processes is a complex process that needs human resources, funding, compliance with international standards, and security. In addition, the presence of a large amount of data requires careful protection and consideration of the conditions of this planned storage of data on external media. But the study does not consider the development of ensemble models based on indices that consider both the synergistic effect and the social component.

Another way to overcome existing contradictions is to improve the structure of models or develop new metamodels. In [10], a four-level structure is proposed for modeling information about the production process based on a meta-model. However, the proposed metamodel does not fully describe a system with four elements of subsystems, where each element of the subsystem has five possible states. The considered approach is complex and requires appropriate knowledge in terms of mathematics and the relationship of the considered models with UML. Since the object of study can be a system with a large number of subsystem elements, where for their description it is necessary to consider the process of building both models and metamodels. At the same time, an approach to a specific object of study is proposed. The use of these ideas on other objects of study requires qualified experts in this area.

The metamodeling methodology of simulation models based on an artificial neural network is studied in [11]. Unlike the existing ones, the proposed model accepts as input not only numerical parameters but also control strategies. The proposed approach [11] is of practical importance and is used as an order-picking system. The disadvantages include the existence of both relative error outliers and an accompanying statistical assessment of performance prediction accuracy.

Data assimilation based on an ensemble with extended deep learning for high-dimensional nonlinear dynamic systems was studied in [12]. The authors used a hybrid Kalman filter ensemble for diagnosing nonlinear dynamic systems. Despite the significant advantages of the proposed approach, among the disadvantages, the need to use a large amount of data was highlighted, the quality of which needs to be checked. Thus, the system has limited universality, and spends significant resources for complex calculations of a large number of states.

The work [13] studies artificial intelligence in predicting and managing the performance of engineering systems, where the relationship between artificial intelligence and various types of activities of human-machine systems is considered. However, artificial intelligence can have a great impact on society, in particular machine operators, by fully automating machine tools. Collecting data to predict the performance of engineering systems is a cumbersome process that requires high-quality data, simplicity, and training on representative samples. However, in [13], complex systems with 5 or more subsystems were studied, and systems with four elements of both subsystems and methods for constructing metamodels were not considered.

The behavior of complex systems can be determined by a nonlinear risk assessment [14]. This approach aims to overcome the subjectivity associated with qualitative analysis based on expert judgments. The complexity of the approach is explained by the use of a sophisticated research toolkit. As a result, the formation of input data is conditioned by high accuracy, reliability, and validity.

The paper [15] proposes an ensemble method of hybrid-extreme learning machine for online dynamic security assessment of power systems. The constructed ensemble of models takes into account additional information, which in turn enhances the model's generalization capability. Incorporating external parameters and control strategies, on the one hand, improves the accuracy of the models, but on the other hand, it complicates the model and goes beyond the scope of the study.

The detection of productive meta-models is performed by solving classification tasks through the adaptation of deep learning techniques, which have gained significant popularity in other domains [16]. The approach proposed in [16] for model classification is quite complex for a system with four subsystem elements and requires a large amount of computation. Additionally, the considered approach may be sensitive to changes in input assessments.

The paper [17] explored the issue of developing a refinement of student performance assessment using fuzzy logic. The proposed fuzzy model diagnoses the accuracy of student assessments, taking into account various external factors, including exercise complexity and effort, where the reliability of the obtained data is confirmed by the t-test. However, the proposed approach [17] is oriented towards the activities of another system outside the production boundaries and requires the development of a corresponding methodological framework, which entails additional resources both in terms of material and human resources.

Formulation of the purpose of the article and setting the tasks. The purpose of the work is to use non-ensemble models to develop an ensemble method for assessing the quality of interaction between human-machine systems. It enables to obtain more accurate estimates of the quality of interaction between subsystem elements and use them to diagnose complex systems with four subsystem elements at industrial enterprises.

To achieve the goals set, the following tasks were set:

- to use a linear equation (non-ensemble model) to create a mathematical model that links the four subsystems X_1, X_2, X_3, X_4 and the weighting coefficients λ_i to the initial variable I_{QI};
- to develop a combined ensemble method for diagnosing the quality of interaction between human-machine systems;
- to investigate the adequacy of ensemble models;
- to carry out experimental verification of models;
- to conduct a comparative analysis of both proposed and existing indices.

Description of the methodology for conducting the study of ensemble indices. The structure of the study provided for both development and use of a combined method for diagnosing production systems "Operator – Machining Center – Control Program – Safe Environment". A prerequisite for developing a method for diagnosing the quality of human-machine systems interaction is the linear equation use to create a mathematical model that links four subsystems and weights to the original variable index.

The sequence of the model study involved the formation of a representative sample, the study on abnormal values, the proof of adequacy, reliability, convergence, and a comparative analysis of existing approaches.

Determination of the sample size of theoretical estimates was carried out by the rearrangement method. The general population model was formed by questioning systems at industrial enterprises of Ukraine in 2017–2021. The formation of the experimental sample was carried out on the basis of the general population model of complex human-machine systems with a confidence level of 95 %, a confidence interval of 5 % using the enumeration method.

The existing samples were subjected to a study to identify abnormal values by the interquartile spread method. After that, a graphical interpretation of the results was made using the functionality of both matplotlib and seaborn libraries.

Proving the model validity was carried out by using the Kolmohorov-Smyrnov test at the significance level at $p > 0.2$ and generalizing new estimates. To summarize the scores, the cross_val_score function of the Sklearn library from n_splits = 10, shuffle = True and scoring = 'r2' was used. Linear regression, gradient boosting and random forest were used as models. The independent variables were always the primary estimates of X, and the dependent variables were the ensemble indices proposed I_{QI}^{i} and the existing $I1$, $I2$, $I3$, $I4$ [17]. The statistical significance of the cross-validation scores is tested by a correlative t-test between the cross-validation scores and the baseline scores. The null hypothesis is that there is no difference between the mean cross-validation score and the baseline score. If the p-value of the correlative t-test is less than the selected significance level of 0.05, then the null hypothesis is rejected. The cross-validation results are statistically significant. The implementation of a correlative t-test between cross-validation scores and baseline scores is implemented by the scipy.stats functionality, including ttest_rel.

The reliability and convergence of models based on the proposed and existing input estimates was studied using the multiple regression method in the statsmodels package. To conduct it, multiple regression and analysis of the multiple determination coefficient, model coefficients, p-values, t-statistics and residuals were built. In the study on p-values, the null hypothesis of the statistical significance of the coefficients was tested at a significance level of 0.05. In the study on t-statistics, the hypothesis that the coefficients differ from zero was tested to confirm their significance.

The constructed model of multiple regression was also used to diagnose the systems "Operator – Machining Center – Control Program – Safe Environment". It enables to effectively select operators and study their interaction with the machining center, control program and safe environment.

Hence, there are several practical ways to use the method for diagnosing the quality of the interaction of subsystem elements, in particular, to improve production efficiency. The enterprise can select operators with different skill levels and study their interaction with the machining center, the control program, and the safe environment. Further examples are the ability of the enterprise to control complexity level of the control program, the type of machining center performance, and the environmental conditions in which the production process is carried out.

Results. The combined method for diagnosing the quality of interaction between human-machine systems based on ensemble models of machine learning consists of six stages.

Stage 1. The formation of input estimates for the elements of subsystems $X1$, $X2$, $X3$, $X4$ is carried out according to four criteria. Each criterion has five answer options, one of which be must chosen. For example, the questionnaire form is given in Table 1.

Stage 2. Determination of indicators $W1$, $W2$, $W3$, $W4$, $W5$, $W6$, $W7$ according to formula

$$W_j = 4 \cdot (X_i X_j - 1/24) + 1, \quad (1)$$

where i, j are different indices of primary evaluations of subsystem elements between 1 and 4, and $i < j$.

Stage 3. Identification of the weight coefficients of the combined method for diagnosing the quality of interaction between human-machine systems. Depending on the research objectives, a method for determining the weight coefficients is chosen. *Method 1.* Weight coefficients are the same. *Method 2.* Weight coefficients are determined based on the error rate of a number of estimates $X1$, $X2$, $X3$, $X4$ and indicators $W1$, $W2$, $W3$, $W4$, $W5$, $W6$, $W7$. *Method 3.* Weight coefficients are determined based on the percentage. *Method 4.* Weight coefficients are determined by the three methods described above simultaneously (in parallel).

Stage 4. Diagnostics of the quality of human-machine interaction based on averaging models. The choice of the method for evaluating human-machine interaction is carried out. The basic studied model of the quality index of interaction with the four elements of the I_{QI} subsystems is defined in the formula [18]

$$I_{QI} = \lambda_1 X_1 + \lambda_2 X_2 + \lambda_3 X_3 + \lambda_4 X_4 + \sum_{i=1}^{7} \lambda_i W_i, \quad (2)$$

where λ_i is the value of the specific weight of the weighting coefficients; X_i is evaluation of subsystem elements, determined using a questionnaire; W_i evaluation of subsystem elements [1, 5], determined using a questionnaire (1).

Method 1. I_{QI}^{1} index construction using the same weighting coefficients according to the formula (2).

Method 2. Construction of index I_{QI}^{2} based on weight coefficients considering the errors in the series of estimates $X1$, $X2$, $X3$, $X4$ and indicators $W1$, $W2$, $W3$, $W4$, $W5$, $W6$, $W7$ according to the formula (2).

Method 3. Construction of index I_{QI}^{3} based on weight coefficients indices, which are indicated on the basis of the percentage according to the formula (2).

The initial values of the models are converted into a dimensionless scale from 0 to 1 according to the known formula

$$I_{QIij} = I_{QIij}/I_{QI\,\max j},$$

where I_{QIij} is the actual index value; $I_{QI\,\max j}$ is the maximum index value.

The obtained dimensionless values of the assessments are used to determine the indices by method 4.

Method 4. Building an index based on the averaging ensemble model. It separately includes several models. Models are defined by methods 1, 2, 3 – I_{QI}^{4}, formula

$$I_{QI}^{4} = (I_{QI}^{1} + I_{QI}^{2} + I_{QI}^{3})/3,$$

where I_{QI}^{1} is the interaction quality index, considering the synergistic effect with the same weighting coefficients $\lambda_з^1$; I_{QI}^{2} is the interaction quality index, considering the synergistic effect, determined on the basis of the absolute errors of the series of estimates; I_{QI}^{3} is the interaction quality index, considering the synergistic effect, where the weighting coefficients $\lambda_з^3$ are determined based on the percentage.

To obtain special cases, the definition of ensemble indices is necessary from the set of non-ensemble indices $NA = \{I_{QI}^{1}, I_{QI}^{2}, I_{QI}^{3}\}$ to find the number of all combinations with I_{QI}^{1}, I_{QI}^{3} each twice using the known formula

$$C_{NA}^{2} = NA!/(2!(NA-2)!),$$

where 2 is the total number of elements in the set.

For the specified case $C_{NA}^{2} = 3!/(2!(3-2)!) = 3$. Thus, from set $\{I_{QI}^{1}, I_{QI}^{2}, I_{QI}^{3}\}$ three possible pairs of elements have been formed (I_{QI}^{1}, I_{QI}^{2}), and (I_{QI}^{2}, I_{QI}^{3}). The resulting pairs of indices form a new representation of formula I_{QI}^{4} for a particular case.

If there is a set from n elements $\{I_{QI}^{1}, I_{QI}^{2}, \ldots, I_{QI}^{n}\}$, and it is necessary to calculate the ensemble indices $I_{QI}^{4.k}$ for $k = 1$ for $n - 1$, the following formula is used

$$I_{QI}^{4.k} = (I_{QI}^{k} + I_{QI}^{(k+1)})/2, \quad (3)$$

Table 1

Form for collecting primary estimates of four subsystems of the production system

Evaluation criterion	Answer options	Assessment
Subsystem 1	Answers 1, 2, 3, 4, 5	1, 2, 3, 4, 5
Subsystem 2	Answers 1, 2, 3, 4, 5	1, 2, 3, 4, 5
Subsystem 3	Answers 1, 2, 3, 4, 5	1, 2, 3, 4, 5
Subsystem 4	Answers 1, 2, 3, 4, 5	1, 2, 3, 4, 5

where k is the k^{th} element in the set of ensemble indices; $k + 1$ introduces $(k + 1)$ in the set of ensemble indices.

Formula (3) calculates average k and $(k + 1)^{th}$ elements to achieve ensemble index $I_{QI}^{4,k}$. It is used only for calculating the ensemble index $I_{QI}^{4,k}$ for $k = 1$ to $n - 1$, thus, for $k = n$ there is no $(n+1)$ element.

Stage 5. Formation of reporting tables. The results of the ensemble determination are shown in Table 2.

Stage 6. Outputting the results to the interface. The proposed approach can be programmatically implemented and used to diagnose the systems "Operator – Machining Center – Control Program – Safe Environment". It enables to effectively select operators and study their interaction with the machining center, the control program and the safe environment.

Based on this, there are several practical ways to use the method of diagnosing the quality of the interaction of subsystem elements, in particular, to improve production efficiency. The enterprise can select operators with different skill levels, and study their interaction with the machining center, the control program and the safe environment. Further examples are the ability of the enterprise to control the level of control program complexity, the type of machining center performance, and the environmental conditions in which the production process is carried out.

Experimental verification of the proposed approach involved the use of a model of the general set of $N = 541$ production systems. With a confidence level of 95 %, a confidence interval of 5 %, a representative sample was formed in the number of $n = 225$ production systems, a diagnostic test of 2021. In order to correct or delete the questionnaires of respondents who did not express a desire to take part in the study, the optimal size of the study sample was increased by 10 % to $n_2 = 250$ production systems.

The collection of primary assessments was carried out at industrial enterprises using questionnaires, where the research objects were the production systems "Operator – Machining Center – Control Program – Safe Environment". Fixed in the software environment, the primary estimates collected by the questionnaire are used to conduct the study. The results of certain ensemble indices on a five-point scale, converted into a dimensionless scale, are shown in Table 3.

The obtained experimental estimates of the ensemble indices were subjected to a study in order to identify anomalous values. Indexes I_{QI}^{4}, $I_{QI}^{4.1}$, $I_{QI}^{4.2}$, $I_{QI}^{4.3}$ have upper limits 0.959; 0.955; 0.968; 0.95 and lower limits 0.122; 0.122; 0.127; 0.121. In all series of estimates of ensemble indices, two anomalous values were found (system 197 and system 224, which have primary estimates 4; 5; 5; 5 and 5; 5; 5; 4; 5), what in turn affected the size of the updated experimental sample (n_{21} = = 248 selection systems).

The ensemble indices, in a certain experimental way, are characterized by the support of the condition of normal distribution. This is evidenced by the calculation results of the Kolmohorov-Smyrnov criterion for the indices I_{QI}^{4}, $I_{QI}^{4.1}$, $I_{QI}^{4.2}$, $I_{QI}^{4.3}$ and are 0.0635; 0.0621; 0.0645; 0.0624 at $p > 0.2$.

In Table 4, the study results of the proposed and existing approach are shown by generalizing ability based on models of estimates built using an experimental sample.

The results obtained indicate a high consistency of models with marks, which was statistically confirmed by the correlative t-test. This means that the models are accurate in predicting scores. Generalizing ability on estimates of existing indices, in particular, the multiple regression model has signs of overfitting, since the multiple coefficient of determination is 1.0. The results obtained indicate the convergence of the models built on the basis of both proposed and existing estimates according to the criterion of the multiple coefficient of determination.

The study on the model reliability was carried out by constructing a multiple regression model, which was used to predict the level of quality of interaction between the elements of subsystems. Received Models: $I_{QI}^{4} = 0.0505X_1 + 0.0511X_2 + 0.0504X_3 + 0.0503X_4$; $I_{QI}^{4.1} = 0.0501X_1 + 0.0510X_2 + 0.05X_3 + 0.05X_3 + 0.05X_4$; $I_{QI}^{4.2} = 0.0506X_1 + 0.0517X_2 + 0.0507X_3 + 0.0507X_4$; $I_{QI}^{4.3} = 0.0509X_1 + 0.0507X_2 + 0.0495X_3 + 0.0501X_4$. The results of studies on the coefficients of four multiple linear regression models indicate the presence of a relationship between the ensemble index $I_{QI}^{4.1}$ and the primary X estimates. The obtained study results of p-values of the constructed models indicate the statistical significance of the relationship between each independent and dependent variable. According to the results of the study on t-statistics, each of the coefficients is statistically significant at 0.05. Thus, the constructed multiple regressions prove the reliability of ensemble and primary estimates, since their coefficients are statistically significant.

The practical interpretation of the results obtained is explained by the existence of a relationship between the estimates of subsystem elements, the complexity level, the type of processing center productivity, the operator's qualification level, working conditions and the interaction quality index. Thus, by adjusting the estimates of the subsystem elements $X1$, $X2$, $X3$, $X4$, it is possible to change the level of the interaction quality index I_{QI}^{i}, which affects the production efficiency and productivity made by the system.

For example, an enterprise can increase the level of the information subsystem (control program for manufacturing a part) by selecting the appropriate values and monitor the level of interaction quality. Thus, the practitioner can use the proposed equations of the model.

Table 2

The results of determining the ensemble indices of the quality of the interaction of the elements of the subsystems of the system

No.	System name	Ensemble index models			
		I_{QI}^{4}	$I_{QI}^{4.1}$	$I_{QI}^{4.2}$	$I_{QI}^{4.3}$
1	System 1	I_{QI1}^{4}	$I_{QI1}^{4.1}$	$I_{QI1}^{4.2}$	$I_{QI1}^{4.3}$
2	System 2	I_{QI2}^{4}	$I_{QI2}^{4.1}$	$I_{QI2}^{4.2}$	$I_{QI2}^{4.3}$
…	…	…	…	…	…
n	System n	I_{QIn}^{4}	$I_{QIn}^{4.1}$	$I_{QIn}^{4.2}$	$I_{QIn}^{4.3}$

Table 3

Results of human-machine system quality indices on experimental sample ($n_2 = 250$ production systems)

No.	System name	I_{QI}^{4}		$I_{QI}^{4.1}$		$I_{QI}^{4.2}$		$I_{QI}^{4.3}$	
1	System 1	1.146	0.247	1.144	0.247	1.152	0.248	1.145	0.247
…	…	…	…	…	…	…	…	…	…
250	System 250	4.633	1.0	4.632	1.0	4.645	1.0	4.626	0.998
Total amount		625.28	134.9	623.43	134.5	633.55	136.3	618.87	133.7

Table 4

The results of the study of the proposed and existing approach by generalizing ability based on models of estimates built using an experimental sample (n_{21} = 248 production systems)

Dependent variable proposed/existing	Multiple regression	Gradient boosting	Random forest
$I_{QI}^{4}/I1$	0.99/1.0	0.98/0.98	0.94/0.94
$I_{QI}^{4.1}/I2$	0.99/1.0	0.98/0.98	0.94/0.94
$I_{QI}^{4.2}/I3$	0.99/1.0	0.98/0.98	0.94/0.94
$I_{QI}^{4.3}/I4$	0.99/1.0	0.98/0.98	0.94/0.94

The comparative analysis of the proposed and existing indices of the quality of interaction between human-machine systems was carried out according to the standard deviation criterion. The existing method for determining the index is based on a linear convolution model with four variables. The weight coefficients of the existing linear convolution model are determined in the same way as the proposed approach, followed by the formation of ensemble models. The comparative analysis of both proposed and existing ensemble indices was carried out on the basis of the standard deviation for estimates of the experimental sample (n_{21} = 248 production systems).

On the basis of the standard deviation, the proposed ensemble indices have an advantage over the existing ones. Thus, the standard deviation of the proposed ensemble indices I_{QI}^{4}, $I_{QI}^{4.1}$, $I_{QI}^{4.2}$, $I_{QI}^{4.3}$ on the experimental sample is 0.1404; 0.1401; 0.1411; 0.1397 and existing 0.1532; 0.1535; 0.1532; 0.1532 respectively. The best value of the standard deviation was demonstrated by the model of ensemble indices, which is 0.1397. Certain values of the standard deviation based on the theoretical sample confirm the validity and reliability of the results obtained.

Conclusions. The task of developing a mathematical model connecting the subsystem elements and weight coefficients has been solved by using a linear equation with non-linear transformations of input variables.

The task of developing a combined method for determining the interaction property of human-machine systems has been solved by using the averaging ensemble model, which includes different methods for determining weight coefficients and indices.

The problem of proving the adequacy of the proposed models of ensemble indices has been solved by using a number of actions. The following steps were used: outlier analysis by interquartile spread method; support determination for the condition of normal distribution by the Kolmohorov-Smyrnov criterion; convergence testing by examining the generalizing ability of estimates by machine learning models; the reliability of the approach has been confirmed by building multiple regression models, where their statistical significance has been confirmed.

Experimental verification of the proposed indices has confirmed the reliability and convergence of the reflection of the model behavior based on a representative experimental sample.

The comparative analysis of the proposed and existing indices was carried out by using the standard deviation criterion. Based on the experimental sample, the proposed models demonstrate the value of the standard deviation of 0.1404; 0.1401; 0.1411; 0.1397, and existing 0.1532; 0.1535; 0.1532; 0.1532 respectively.

From a practical perspective, the proposed indices demonstrate an assessment of the interaction quality, which more accurately reflects the adjustment of subsystem element elements to obtain the desired level of interaction between subsystem elements.

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Дослідження комбінованих ансамблевих методів діагностики якості взаємодії людино-машинних систем

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Мета. Дослідження процесу об'єднання декількох методів визначення індексів якості людино-машинної взаємодії, що містять різні конфігурації визначення вагових коефіцієнтів у ансамблі.

Методика. Досліджено процес діагностики якості взаємодії людино-машинної системи з чотирма елементами підсистем на прикладі системи «Оператор – Оброблювальний центр – Керуюча програма – Безпечне середовище». Основною гіпотезою дослідження є об'єднання декількох методів визначення індексів якості людино-машинної взаємодії, що містять різні конфігурації визначення вагових коефіцієнтів у ансамблі. Запропоновано комбінований метод діагностики якості взаємодії людино-машинних систем на основі ансамблевих моделей, що включають у своїй основі неансамблеві. Ансамблевий індекс визначається шляхом усереднення неансамблевих індексів. Визначені ансамблеві індекси та оцінки елементів чотирьох підсистем використовуються як вхідні оцінки моделі множинної регресії для створення прогнозів.

Результати. Розроблені та програмно реалізовані чотири комбінації ансамблевих індексів, для яких характерне мінімальне, порівняно з існуючими, значення середньоквадратичного відхилення. За результатами експериментальної верифікації запропоновані моделі демонструють значення середньоквадратичного відхилення 0,1404; 0,1401; 0,1411; 0,1397, а існуючі 0,1532; 0,1535; 0,1532; 0,1532.

Наукова новизна. Комбінований ансамблевий метод діагностики якості взаємодії елементів підсистем ураховує лінійні моделі з нелінійними змінними й різними способами визначення вагових коефіцієнтів.

Практична значимість. Сценарієм практичного використання отриманих результатів є можливий варіант оптимізації виробництва, де залежно від кінцевого результату фахівці можуть регулювати значення конкретної підсистеми для досягнення необхідного результату.

Ключові слова: *ансамблевий індекс, модель усереднення, нелінійний зв'язок, лінійне рівняння, нелінійне перетворення, IT-технології*

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