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IMPROVEMENT OF THE METHOD FOR OPTIMIZATION OF PREDICTING THE EFFICIENCY OF A ROBOTIC PLATFORM

Purpose. Improving the optimization method for predicting the efficiency of a robotic platform (using the gradient boosting method as an example).

Methodology. The process of refining the optimization method for predicting efficiency has been investigated using robotic platforms as complex systems comprising hardware components, data exchange technology, security systems, and navigation, along with user interaction methods. The optimization method relies on a linear equation, whose mathematical model, through the triple interaction of factors, consolidates assessments of subsystem elements into an efficiency index for the robotic platform. The outcomes of the proposed optimization algorithm result in regression models from machine learning. These acquired models are employed for predicting the efficiency of a specific configuration of a robotic platform designed to perform particular practical tasks.

Findings. The optimization method for predicting the efficiency of a robotic platform has been enhanced by utilizing evaluations of the robotic platform efficiency index as input data. In comparison to existing methods, the proposed index demonstrates minimal values of root mean square deviation at 0.1794, 0.14 and 0.1245, respectively. This particular characteristic has enabled the development of a more accurate optimization method for predicting the efficiency of robotic platforms. This assertion is supported both theoretically and empirically through criteria such as Root Mean Square Error, Mean Absolute Error, and Maximum Absolute Error on experimental datasets.

Originality. The optimization method for predicting the efficiency of a robotic platform differs from existing approaches through its model-building process, which consists of two iterations and incorporates different sets of input evaluations. The first iteration involves primary and index-based evaluations of the robotic platform's efficiency, while the second iteration incorporates primary, index-based evaluations, and predicted index-based evaluations.

Practical value. Selection of the optimal configuration of a robotic platform for addressing tasks in the energy sector. Cost reduction through a finely tuned combination of robotic platforms. The proposed solutions will contribute to the Development Concept of Artificial Intelligence in Ukraine.

Keywords: *robotic platform, linear equation, dual interaction, triple interaction, efficiency index, optimization method*

Introduction. Existing highly advanced robotic systems operating on the basis of artificial intelligence, according to the prerequisites of the industrial revolution, envisage a human-centered approach [1]. Furthermore, classical directions in robotics, where the research object encompasses elements of robotic platforms or auxiliary equipment, are gaining further development [2]. The results of the literature analysis for 2021–2023 using VOSViewer, SciVal tools, allowed the identification of the most discussed criteria for predicting the efficiency of robotic platforms. Various criteria are used to monitor the efficiency of robotic platforms, including minimization of time costs, maximization of profit, reduction in failures, and enhancement of safety. Limitations of existing approaches lie in the subjective elements in selecting the structure of machine learning models, neural networks, and so forth.

The optimal selection of components for robotic platforms is a key factor in efficiently accomplishing tasks, affecting both the cost of construction and the correlated functional capabilities. For instance, powerful equipment might be employed for elementary tasks, while simpler equipment is used for more complex tasks. Finding a balance between the level of equipment in robotic platforms and the tasks they perform requires understanding and defining the platform's efficiency level.

The problem is partially addressed, which is associated with the peculiarities of the input assessments, whether primary or index-based, that do not fully consider the optimization process. Hence, it is pertinent to resolve the issue of creating a methodology for optimizing the predict of robotic platform efficiency, which would enable cost reduction.

Literature review. Existing research on the development of tools for optimizing robotic manufacturing processes includes both new optimization ideas and improvements to existing methods. For instance, in the work [3], a process of iterative optimization of robotic assembly productivity is proposed, enhancing the well-known Bayesian optimization algorithm. The reliability of the obtained results is confirmed experimentally within an enterprise, demonstrating a reduction in production costs per unit.

An approach to optimizing path planning for robots is developed and studied in work [4]. The proposed solution is based on a heuristic multi-directional rapidly exploring tree, allowing the robot to effectively navigate and avoid obstacles during movement. Experimental verification was conducted using a created general obstacle environment, as well as maze and cluttered environments. Consequently, the robot selects an optimal route while moving.

Authors in [5] have proposed the Chaotic Bat Algorithm for predicting the complex motion of floating platforms. To decompose the data concerning the motion of a floating platform, an algorithm for decomposing the empirical mode ensemble is suggested.

The approach proposed in [6] relies on a predictive model of human movement compared to the planned trajectory of the robot and online monitoring with the enforcement of safety requirements using formal methods.

A deep model enabling a robot to predict the consequences of its manipulative actions based on its own experience interacting with objects of various shapes was studied in the work [7]. It involved an iterative process where the robot learned from data collected from sensors. The development of such robots relies on the necessity of predicting and compensating for the deformation of industrial robots' rigidity [8], as well as exploring robotic platforms for complex setups capable of operating on vertical, curved, and uneven surfaces [9]. However, these scientific works did not delve into the process of aggregating assessments into indices, using only primary assessments or signals obtained from sensors.

It is also important to distinguish the optimization approaches of the authors, such as those in [10], which involve developing control system diagrams, justifying control principles, and implementing software on the respective elementary basis of the robot. In other words, optimization is achieved by selecting specific components of the robotic platform.

In this field, there are classical optimization methods that are differentiated into various categories, including one-dimensional, multi-dimensional, or universal optimization methods aimed at solving different types of optimization problems [11] and identifying errors [12].

The scientific work by Oleksandr Laktionov [13] involved studying the process of constructing index methods used to describe human-machine systems but did not address the development of optimization algorithms for predicting the effectiveness of robotic platforms.

Unsolved aspects of the problem. The existing approaches to optimizing the predicting efficiency of robotic platforms [3–13] address various tasks. However, in the structure of these developments and model constructions, the complete utilization of index assessments (first iteration) and the integration of index and predicted index assessments of robotic platform efficiency (second iteration) are not fully anticipated. Therefore, the research focus should be directed toward finding a path to improve predicts of robotic platform efficiency and developing a corresponding method to achieve this goal.

Formulation of the article's goal and setting tasks. The goal of the study is to refine the method for optimizing the prediction efficiency of robotic platforms, using the principles of gradient boosting as an example. This enhancement aims to enable the optimal selection of robotic platforms for specific tasks.

To achieve the set goal, the following tasks were outlined:

- to select an optimal linear equation whose mathematical model will combine the assessments of subsystem elements into an efficiency index of the robotic platform;

- to propose an enhanced method for optimizing the prediction of the efficiency of a robotics platform (using an example) that takes into account the Development Concept of Artificial Intelligence in Ukraine (Cabinet of Ministers of Ukraine order dated 02.12.2020 No. 1556-r);

- to implement software realization and experimental verification of the optimization method for predicting the efficiency of a robotics platform.

Description of the methodology for conducting research on optimizing the prediction of the effectiveness of a robotic platform. Let us create a formal task statement regarding the enhancement of the optimization method for predicting the efficiency of robotics platforms.

Given RP – a set of robotics platforms. $S = \{x_1, x_2, x_3, x_4\}$ – set of component platforms. $L = \{l_1, l_2, l_3, l_4, l_5\}$ – the set of assessment levels for each component. The formal task is as follows:

1. To create a survey to determine the levels of components of the robotics platform for collecting primary assessments, where x_i belongs to set L, and RP belongs to the set of robotics platforms.

2. To select the optimal linear equation $f(x_1, x_2, x_3, x_4)$, a mathematical model that consolidates the ratings of subsystem elements into an index of robotics platform efficiency. The linear equation should characterize the interaction of factors. The criteria for selecting the optimal model include the root mean square deviation (minimum value) and a method for determining the normality of the distribution – the Anderson-Darling test at $p > 0.05$.

3. To enhance the existing method for optimizing the predicting efficiency of robotic platforms (using gradient boosting, for instance) by employing a two-iteration approach.

First iteration. Input assessments: initial evaluations x_i and the efficiency index assessments (rp). Building machine learning models.

The result obtained from the first iteration – predicted new values of the efficiency index. $EI_{RP\,pred}\,(rp)$. Investigating the predicted values of $EI_{RP\,pred}\,(rp)$ using metrics like RMSE, MAE, MAX, R^2.

Second iteration involves using previous arrays of input assessments along with an additional set of evaluations. Input assessments include initial ratings x_i, efficiency index ratings EI_{RP} (rp), and predicted new values of the efficiency index $EI_{RP\,pred}\,(rp)$. Building machine learning models.

The result obtained from the second iteration involves additional predicting of efficiency based on updated input assessments. The predicted values were studied using metrics such as RMSE, MAE, MAX, R^2.

The research structure aimed at refining the method for optimizing the efficiency predict of robotic platforms involved two stages. The first stage comprised a comparative analysis of indexing methods integrated into the optimization algorithm and considering the Development Concept of Artificial Intelligence in Ukraine (Cabinet of Ministers of Ukraine order dated 02.12.2020 No. 1556-r). The second stage involved constructing the optimization algorithm and conducting experimental verification.

Based on the results of the first stage, two existing and seven proposed linear equations were considered. The mathematical model of these equations combined the assessments of subsystem elements into an efficiency index of the robotic platform. Identifying the optimal linear equation involved forming theoretical and experimental samples representative of the population model. The theoretical samples were determined using combinatorial methods, finding all possible combinations of primary assessments. Experimental sample sizes were determined based on a 99.7 % confidence level, with a confidence interval of ±5 % from a population of 501 robotic complexes within Ukrainian industrial enterprises. Surveys containing lists of assessment levels for robotic platforms were used to collect primary assessments. The proposed survey format was implemented programmatically using PHP, HTML, and CSS. The consolidation of primary assessments into indices was executed through PHP and MySQL tools.

The diagnostics of the distribution law were performed using SciPy at a significance level of $p > 0.05$. Comparative analysis of the investigated methods was conducted based on the criterion of root mean square error (RMSE). Consequently, the diagnosed values of the index assessments were used as input estimations for the respective optimization algorithm.

During the second stage of the research, the toolkit of the Sklearn library was utilized, particularly machine learning models without hyperparameter tuning for regression tasks. Models included Gradient Boosting, Random Forest, KN, Bagging, and Bagging (base_estimator = KN). Comparative analysis of the models was conducted using metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Maximum Absolute Error (MAX), and coefficients of determination for the training and testing datasets.

Since multiple machine learning models were examined during the research, lists were employed to expedite the program text creation. The creation of training and testing datasets utilized the train_test_split method, where test_size = 0.35 was used.

The ultimate outcome of the research is a dashboard constructed using Streamlit, programmatically implementing machine learning models for user interaction.

Results. The text discusses robotics platforms in industrial enterprises, highlighting four components: hardware, technological subsystems, safety subsystems, and interaction subsystems. The description of the elements of the robotics platform involves the existence of initial assessments, as demonstrated in Table 1.

Ratings of combinations of elements within the robotics platform are used to select the optimal linear equation based on specific criteria. To select the optimal linear equation, a mathematical model, which combines the ratings of subsystem elements into an index of robotics platform efficiency, considered nine models as demonstrated in Table 2.

The proposed methods M_3, M_4, M_5 and M_6, M_7, M_8, M_9 are built on the principle of double and triple interaction of factors based on four levels of primary assessments. The total number of all combinations, $n = 4$ elements with $m = 2$ and $m = 3$, is determined by a known combinatorial method. Let us examine each method in detail and assess their adequacy using a theoretically formed set of assessments (N1 = 256 assessments). The adequacy of the methods is determined by the Anderson-Darling criterion at $p > 0.05$. The accuracy level of the methods is determined using the root mean square deviation. The summarized research results are presented in Table 3.

Table 1

A proposed experimentally formed list of assessment levels for elements of the robotics platform

The studied components of the robotic platform	Levels of assessment	Assessment
Hardware component by data processing level (hardware subsystem) x_1	Without data processing	1
	Microcontroller for data processing	2
	Minicomputer for data processing	3
	Cloud processing	4
	Distributed systems	5
Data exchange technologies (technological subsystem) x_2	Optical channels	1
	Radio frequency systems	2
	Cable connections	3
	Ultrasonic communication	4
	Geolocation systems	5
Security and navigation systems (security subsystem) x_3	Without security and navigation systems	1
	Inertial systems	2
	Cameras and computer vision	3
	Ground-based positioning systems	4
	Lidar	5
User interaction method (interaction subsystem) x_4	Touchscreens	1
	Gestures and motion	2
	Monitors	3
	Wireless interfaces	4
	Artificial intelligence systems	5

Based on the criterion of supporting the normal distribution condition and minimal root mean square deviation values, M_5 and M_9 stand out, while other methods do not support the normal distribution condition. We will choose M_9 as the basis for the linear equation, where $M_9 = EI_{RP}$, merging the assessments of subsystem elements into the index of robotics platform efficiency. In contrast to existing methods [13, 14], the proposed index is constructed based on triple interaction ideas among factor combinations. This particular concept ensures the minimization of the root mean square deviation values.

The efficiency index of robotics platforms (EI_{RP}) is utilized as a component of the algorithm for optimizing the predicting of robotics platform efficiency, which includes the following blocks.

Block 1. Inputting the initial features of robotics platform elements *xi* and the target variable (efficiency index of robotics platforms) EI_{RP}.

Block 2. Preparing assessments for building machine learning regression models.

Block 3. Creating a list of machine learning regression models – Model 1, Model 2, Model n.

Block 4. Establishing a for loop to iterate through the list of machine learning regression models.

Subblock 4.1. Training regression models.

Subblock 4.2. Predicting the efficiency of robotics platforms (*EIRP*).

Subblock 4.3. Determining quality metrics of the obtained machine learning models. Investigating the quality of the results based on R^2 criteria (for training and testing sets), RMSE, MAX, MAE. The research results are documented in Table 4.

Block 5. Displaying the results of model construction to the user for intermediate decision-making.

Block 6. Preparing initial ratings x_i, efficiency index ratings EI_{RP} from Block 1, and predicted new efficiency index ratings $EI_{RP\,pred}$ for the second iteration (second cycle of building machine learning models with updated input assessments).

Block 7 – Block 9. Execution of instructions similar to Blocks 2–4.

Table 2

The existing (M_1, M_2) [13] and proposed by the authors of the study (M_3, M_4, M_5, M_6, M_7, M_8, M_9) methods for combining assessments of four elements of robotics platform subsystems into an efficiency index

No.	The investigated method
1	$M_1 = x_1x_2 + x_2x_3 + x_3x_4 + x_4x_1$, where x_i is assessments of subsystems of the robotic platform [14]
2	$M_2 = x_1\alpha_1 + x_2\alpha_2 + x_3\alpha_3 + x_4\alpha_4$, where x_i is assessments of subsystems of the robotic platform; α_i – weight coefficients [14]
3	$M_3 = (x_1x_2 + x_1x_3 + x_1x_4 + x_2x_3 + x_2x_4 + x_3x_4)$, where x_i is assessments of subsystems of the robotic platform
4	$M_4 = x_1x_2 + x_1x_3 + x_1x_4 + x_2x_3 + x_2x_4 + x_3x_4$, where x_i is assessments of subsystems of the robotic platform
5	$M_5 = (x_1x_2 + x_1x_3 + x_1x_4 + x_2x_3 + x_2x_4 + x_3x_4)^{1/2}$, where x_i is assessments of subsystems of the robotic platform
6	$M_6 = x_1x_2x_3 + x_1x_2x_4 + x_1x_3x_4 + x_2x_3x_4$, where x_i is assessments of subsystems of the robotic platform
7	$M_7 = ((x_1x_2x_3) + (x_1x_2x_4) + (x_1x_3x_4) + (x_2x_3x_4))/4$, where x_i is assessments of subsystems of the robotic platform
8	$M_8 = (x_1x_2x_3 + x_1x_2x_4 + x_1x_3x_4 + x_2x_3x_4)^{1/2}$, where x_i is assessments of subsystems of the robotic platform
9	$M_9 = (x_1x_2x_3 + x_1x_2x_4 + x_1x_3x_4 + x_2x_3x_4)^{1/4}$, where x_i is assessments of subsystems of the robotic platform

Table 3

The research results on the adequacy and accuracy of methods (M_1, M_2 – existing [13]; M_2, M_3, M_4, M_5 and M_6, M_7, M_8, M_9 – proposed) with a theoretically formed sample of assessments (N1 = 256 assessments)

Criterion name	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9
p	$p < 0.05$	$p < 0.05$	$p < 0.05$	$p < 0.05$	$p > 0.05$	$p < 0.01$	p < 0.01	$p < 0.01$	$p > 0.05$
RMSE	0.1794	0.14	0.1779	0.1779	0.143	0.175	0.175	0.169	0.1245

Table 4

The results of the research on the quality of the proposed method for optimizing the prediction of the efficiency of robotic platforms

	Model 1	Model 2	Model *n*
R^2train/R^2test	R^2train/R^2test(Model 1)	R^2train/R^2test(Model 2)	R^2train/R^2test(Model *n*)
RMSE	RMSE(Model 1)	RMSE (Model 2)	RMSE (Model *n*)
MAX	MAX (Model 1)	MAX (Model 2)	MAX (Model *n*)
MAE	MAE(Model 1)	MAE (Model 2)	MAE (Model *n*)

Block 10. Displaying the final results of modeling and decision-making. Optimal models are selected based on criteria such as RMSE, MAX, MAE, R^2 (for both training and testing datasets).

Let us conduct an experimental verification of the proposed algorithm based on the theoretical (N_2 = 625 rows of assessments of robotics complexes) and experimental samples of index assessments. Initial assessments for establishing the research base were gathered using previously provided questionnaires. The experimental sample was formed from a model of the population consisting of 501 robotics complexes in industrial enterprises. With a confidence probability of 99.7 % and a confidence interval of ±5 %, the studied sample size amounted to N_3 = 322 robotics platforms, representing the population model. The initial assessments of robotics platforms are presented in Table 5.

The mentioned assessments are used for constructing the proposed optimization algorithm. Machine learning models were used according to the research methodology. The results of studying regression models based on assessments of the existing and proposed indices (first, second iterations, theoretical, experimental samples) indicate the superiority of models built using the proposed approach. This is evidenced by the comparative analysis of models using criteria such as RMSE, MAX, MAE, where the values are lower in models constructed based on assessments of the proposed index.

The results of investigating the quality of the optimization method for predicting the efficiency of robotics platforms based on index assessments (first iteration) and the theoretical sample are presented in Table 6.

The Gradient Boosting model is favored based on the determinacy criterion for both cases, as there is a balance observed in the determination coefficients around 0.99 for both the training and testing datasets (a balance between bias and variance). Other models show signs of overfitting because there is a discrepancy observed in the determination coefficients. The results of investigating the quality of the optimization method for predicting the efficiency of robotics platforms based on index assessments (second iteration) and the theoretical sample are presented in Table 7.

Based on the results of the second iteration, the Gradient Boosting model appears to be overfitted for both investigated cases, as indicated by the determination coefficients for the training and testing datasets, which are 1.0/0.95 and 1.0/0.98, respectively. Models like KN and Bagging (base_estimator = KN) exhibit low determination coefficients of 0.4/0.24; 0.37/0.22 and 0.37/0.21; 0.36/0.2, respectively. The models with the best quality metrics are Random Forest and Bagging, showing slight signs of overfitting with determination coefficients of 0.99/0.96; 0.99/0.98 and 0.99/0.96; 0.99/0.98, respectively. The reason behind these quality metrics of the models is attributed to the limitations posed by the theoretical sample, restricting the extent of the research but allowing for theoretical confirmation of the research hypotheses. For practical validation of the proposed ideas and experimental confirmation, an experimental sample was utilized. During the experiment, achieving an ideal balance between determination coefficients for the training and testing datasets was not possible.

The results of investigating the quality of the optimization method for predicting the efficiency of robotics platforms based on index assessments (first iteration) and the experimental sample are presented in Table 8.

The results of the first iteration showed the advantage of models built based on assessments of the proposed index, as their metric indicators are lower. According to the MAE metric, the Gradient Boosting model prevails with 0.012723, while the Random Forest, KN, Bagging, Bagging (base_estimator = KN) models demonstrate 0.021989; 0.025401; 0.020376; 0.023401 respectively.

Similarly, according to the MAX metric, the Gradient Boosting model also has an advantage with a value of 0.043743, compared to Random Forest, KN, Bagging, Bagging (base_estimator = KN) with values of 0.080916; 0.099443; 0.079732; 0.103964 respectively.

A similar situation is observed with the RMSE metric. Gradient Boosting shows 0.016786, while Random Forest, KN, Bagging, Bagging (base_estimator = KN) demonstrate 0.029383; 0.032921; 0.028086; 0.031178 respectively, which correlates with the level of overfitting.

The results of investigating the quality of the optimization method for predicting the efficiency of robotics platforms based on index assessments (second iteration) and the experimental sample are presented in Table 9.

The obtained determination coefficient values for the KN and Bagging (base_estimator = KN) models are negative (–0.36; –0.17), indicating issues with these models, so they are

Table 5

The experimental sample of assessments of robotic platforms (N_3 = 322 robotic platforms)

No.	The name of the robotics platform	x_1	x_2	x_3	x_4	EI_{RP}
1	Robotics platform 1	1	5	5	5	0.828
…	…	…	…	…	…	…
322	Robotics platform 322	2	2	5	4	0.723
The sum		965	991	943	962	215.84

Table 6

The results of the study on the quality of the method for optimizing the prediction of robotic platform efficiency based on index assessments (first iteration), theoretical sample

The models constructed based on assessments of the existing index, first iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	0.99/0.99	0.99/0.68	0.98/0.97	0.99/0.96	0.98/0.96
RMSE	0.00963	0.0224	0,01971	0.02413	0.02084
MAX	0.0119	0.0269	0.0257	0.029	0.0261
MAE	0.0334	0.0615	0.08	0.075	0.089
The models constructed based on assessments of the proposed index, first iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	0.99/0.99	0.99/0.97	0.97/0.96	0.99/0.96	0.97/0.96
RMSE	0.00834	0.01684	0.01947	0.0188	0.02033
MAX	0.0105	0.0208	0.0247	0.0235	0.0254
MAE	0.0266	0.0534	0.0747	0.064	0.0855

Table 7

The results of the study on the quality of the method for optimizing the prediction of robotic platform efficiency based on index assessments (second iteration), theoretical sample

The models constructed based on assessments of the existing index, second iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	1.0/0.95	0.99/0.96	0.4/0.24	0.99/0.96	0.37/0.21
RMSE	0.0139	0.0121	0.0575	0.0126	0.058
MAX	0.05	0.05	0.15	0.05	0.16
MAE	0.00385	0.0036	0.043	0.00375	0.044
The models constructed based on assessments of the proposed index, second iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	1.0/0.98	0.99/0.98	0.37/0.22	0.99/0.98	0.36/0.2
RMSE	0.0063	0.0067	0.0512	0.0071	0.051
MAX	0.0224	0.0179	0.1605	0.0201	0.1506
MAE	0.00292	0.00409	0.04003	0.00451	0.0407

Table 8

The results of the study on the quality of the method for optimizing the prediction of robotic platform efficiency based on index assessments (first iteration), experimental sample

The models built based on assessments of the existing index, first iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	0.99/0.98	0.99/0.95	0.96/0.94	0.98/0.93	0.96/0.94
RMSE	0.0191	0.0325	0.0359	0.0369	0.0348
MAX	0.0495	0.105	0.11	0.1	0.109
MAE	0.01475	0.02334	0.02664	0.0285	0.02542
The models constructed based on assessments of the proposed index, first iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	0.99/0.98	0.99/0.95	0.95/0.94	0.98/0.96	0.96/0.95
RMSE	0.016786	0.029383	0.032921	0.028086	0.031178
MAX	0.043743	0.080916	0.099443	0.079732	0.103964
MAE	0.012723	0.021989	0.025401	0.020376	0.023401

Table 9

The results of the study on the quality of the method for optimizing the prediction of robotic platform efficiency based on index assessments (second iteration), experimental sample

The models built based on assessments of the existing index, second iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	1.0/0.82	0.98/0.8	0.3/-0.63	0.97/0.78	0.33/-0.6
RMSE	0.0283	0.0299	0.0856	0.031	0.0847
MAX	0.095	0.0765	0.18	0.065	0.183
MAE	0.01856	0.02313	0.06783	0.0238	0.06891
The models constructed based on assessments of the proposed index, second iteration					
The investigated criterion	Gradient Boosting	Random Forest	KN	Bagging	Bagging (base_estimator = KN)
R^2train/R^2test	1.0/0.97	0.99/0.98	0.38/-0.36	0.99/0.98	0.37/-0.17
RMSE	0.0077	0.0056	0.062	0.0061	0.0575
MAX	0.0395	0.0206	0.1394	0.0254	0.1281
MAE	0.00343	0.00329	0.05001	0.00357	0.04816

excluded from consideration. The Gradient Boosting model, which was dominant after the first iteration, seems to be overfitted. Therefore, the final decision regarding predicting the efficiency of robotic platforms should be based on the metrics of the Random Forest and Bagging models.

Let us consider a specific example of practical application of the proposed approach to predicting the efficiency of a robotic platform. The researched model is Random Forest. With hardware subsystem level at 1, technological subsystem at 5, security subsystem at 4, and interaction subsystem at 4, the efficiency index stands at 0.559.

The obtained results regarding the predict of the effectiveness of the robotic platform using the enhanced proposed approach are more promising than those using the existing one. Evidence of this is the obtained results of the comparative analysis between the proposed and existing approaches on samples of varying sizes.

The proposed approach consists of two iterations. According to the modeling results of the first iteration, certain machine learning models dominate, while others take precedence after the second iteration. This is attributed to the peculiarities of the sample used in the second iteration. On the one hand, a new variable is added to the sample – the predicted values of effectiveness indices. This allows for a more precise predict of the efficiency of the robotic platform. On the other hand, this process limits the sample size, where not all machine learning models work adequately. Consequently, the effectiveness level of selecting components for the robotic platform is increased by employing the proposed approach. From a practical standpoint, it enables the selection of components of the robotic platform to fulfill specific client tasks.

Conclusions. During the research, the task of improving the optimization method for predicting the efficiency of robotic platforms was addressed. The objective of selecting the optimal linear equation, a mathematical model uniting the subsystem elements' assessments into an efficiency index, is achieved by choosing an equation based on the triple interaction of factors. This equation minimizes the root mean square deviation compared to existing methods, resulting in values of 0.1245 and 0.143 or higher, respectively, while demonstrating more robust adherence to the conditions of normal distribution. The obtained result indicates a scientific novelty in further development.

The task of developing an enhanced method for predicting the efficiency of robotic platforms, considering the Development Concepts of Artificial Intelligence in Ukraine, is accomplished by building predicting models. Unlike existing models, the proposed ones consist of two iterations, with the second iteration considering primary, index, and predicted index evaluations as input estimations.

The superiority of the proposed approach over the existing one has been confirmed on an experimental sample, particularly with the Random Forest model. Following the second iteration, the Random Forest model constructed using evaluations from the proposed approach demonstrated the following metric values: RMSE, MAX, MAE as 0.0056, 0.0206, 0.00329, respectively. In contrast, a similar model constructed using evaluations from known indices showed RMSE, MAX, MAE as 0.0299, 0.0765, 0.02313, respectively, with a tendency towards overfitting ($R^2train/R^2test = 0.98/0.8$).

The practical application of this approach lies in the energy sector and industrial machinery enterprises, where existing robotic equipment can be optimally selected for specific equipment installation tasks.

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Удосконалення методу оптимізації прогнозування ефективності робототехнічної платформи

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Мета. Удосконалення методу оптимізації прогнозування ефективності робототехнічної платформи (на прикладі ідей методу градієнтного бустингу).

Методика. Досліджено процес удосконалення методу оптимізації прогнозування ефективності на прикладі робототехнічних платформ як складних систем, що складаються з апаратної складової, технології обміну даними, системи безпеки й навігації, способу взаємодії з користувачем. Основою методу оптимізації є лінійне рівняння, математична модель якого, за рахунок потрійної взаємодії факторів, об'єднує оцінки елементів підсистем у індекс ефективності робототехнічної платформи. Результатами роботи запропонованого алгоритму оптимізації є регресійні моделі машинного навчання. Отримані моделі використовуються для прогнозування ефективності робототехнічної платформи певної конфігурації, що виконуватиме конкретні практичні завдання.

Результати. Удосконалено метод оптимізації прогнозування ефективності робототехнічної платформи за рахунок використання оцінок індексу ефективності робототехнічної платформи в якості вхідних даних. Порівняно з існуючими запропонований індекс характеризується мінімальним значенням середньоквадратичного відхилення 0,1794; 0,14; 0,1245 відповідно. Саме ця особливість дозволила отримати точніший метод оптимізації прогнозування ефективності робототехнічних платформ. Це підтверджено як на теоретичній, так і на експериментальній вибірках за критеріями Root Mean Square Error, Mean Absolute Error, Maximum Absolute Error.

Наукова новизна. Метод оптимізації прогнозування ефективності робототехнічної платформи відрізняється від існуючих процесом побудови моделей прогнозування, що складається із двох ітерацій і враховує різні набори вхідних оцінок. Перша ітерація включає первинні та індексні оцінки ефективності робототехнічної платформи, а друга – первинні, індексні оцінки та прогнозовані індексні оцінки.

Практична значимість. Підбір оптимальної конфігурації робототехнічної платформи для вирішення завдань у сфері енергетики. Зниження витрат за рахунок оптимально підібраної комбінації робототехнічної платформи. Запропоновані рішення сприятимуть Концепції розвитку штучного інтелекту в Україні.

Ключові слова: *робототехнічна платформа, лінійне рівняння, подвійна взаємодія, потрійна взаємодія, індекс ефективності, метод оптимізації*

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