OPTIMIZATION OF LABOR INPUTS IN IMPORT SUBSTITUTION PROJECTS USING NEURAL NETWORK ALGORITHMS

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Vladimir S. Makarov,
Nizhny Novgorod State Technical University named after R.E. Alekseev, Nizhny Novgorod, Russia, ***makvl2010@gmail.com***

Alexey V. Terentyev,
State University of Management, Moscow, Russia, ***av_terentev@guu.ru***

Nikita S. Akinshin,
State University of Management, Moscow, Russia, ***ns_akinshin@guu.ru***

Denis A. Yudin,
State University of Management, Moscow, Russia, ***da_yudin.@guu.ru***

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Predictive assessment of the complexity of design and technological training is the basis for cost formation, determining the timing of the project and making informed management decisions about the feasibility of its launch. This article examines modern methods for automating and optimizing production processes in the import substitution of machine parts for agricultural machinery. An artificial intelligence-based algorithm has been developed to estimate labor inputs across various industries, such as general machinery, automotive, and tractor manufacturing. The analysis of factors influencing task complexity and labor intensity is conducted. Particular attention is paid to the optimization of labor inputs to reduce the lead time for manufacturing machine-building products. This approach enhances the quality and efficiency of producing domestic equivalents of machine parts and improves the accuracy of resource and timeline planning during the development and design stages.

Information about authors:

Vladimir S. Makarov, *Doctor of Technical Sciences, Professor, Nizhny Novgorod State Technical University named after R.E. Alekseev, Nizhny Novgorod, Russia*

Alexey V. Terentyev, *Doctor of Technical Sciences, Professor, Professor of the Department of Management of Transport Complexes, State University of Management, Moscow, Russia*

Nikita S. Akinshin, *PhD Student, Specialist, Center for Engineering Project Management, State University of Management, Moscow, Russia*

Denis A. Yudin, *PhD Student, Specialist, Reverse Engineering Laboratory, State University of Management, Moscow, Russia*

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Introduction

The strategic course towards achieving technological sovereignty and the need for rapid response to disruptions in production chains pose complex challenges for the modern machine-building industry related to the accelerated development and production of a new product range. In this context, reverse engineering is becoming not just one of the technical tools, but a key element of the import substitution strategy. The success of such projects is largely determined by the quality of planning at the earliest stages, when the economic foundation for future production is being laid. The central task of this stage is a predictive assessment of the complexity of design and technological training, since this assessment is the basis for cost formation, determining the timing of the project and making informed management decisions about the feasibility of its launch.

Historically, a paradigm based on the use of integrated calculation methods, such as the method of specific normalization, the method of mass accounting, multifactorial and regression analysis, has developed in engineering practice to solve this problem. These approaches are based on the hypothesis that it is possible to approximate labor intensity based on statistical data on previously manufactured analog products and their key physical or operational parameters. The effectiveness of these methods has been repeatedly confirmed in conditions of stable large-scale and mass production, characterized by a limited range and a high level of repeatability of technological processes.

However, with the transition to the conditions of modern small-scale production and, in particular, in relation to the tasks of reverse engineering, the fundamental assumptions underlying traditional approaches cease to be fulfilled. This leads to a number of system limitations that critically reduce the reliability of the estimates obtained. Firstly, the basic requirement of having a statistically significant and relevant database of analog products is violated, since reverse engineering facilities are often unique to the enterprise. Secondly, these methods demonstrate a high sensitivity to the subjective factor: the completeness of the set of parameters and the values of correction coefficients are determined by the qualifications and experience of a particular expert technologist, which introduces a systematic error into the calculations and makes the result irreproducible.

The most significant disadvantage is the inability of traditional methods to work with the primary carrier of information about the complexity of a product – its geometric and topological representation. Models that operate solely on a set of scalar parameters (mass, dimensions) completely ignore the unstructured information contained in engineering graphics (drawings, CAD models, polygonal grids after 3D scanning). This leads to the fact that two products with the same weight, but with radically different geometry complexity, will receive a similar assessment of labor intensity, which is fundamentally wrong [1].

The identified methodological gap necessitates the formation of a new scientific approach capable of overcoming these limitations. It requires a transition to a class of models capable of automatically extracting features from heterogeneous, including unstructured, data sources and approximating complex nonlinear dependencies without a priori assumptions about their form. The purpose of this paper is to present the methodological foundations and mathematical apparatus for building such a system, which makes it possible to move from subjective expert assessment to objective, data-based predictive labor management in projects of design and technological preparation of production [2].

Materials and methods

At the initial stages of production preparation, various methods of integrated calculation are used to assess labor intensity, which allow us to obtain initial but fairly accurate estimates of the time and resources spent.

<u>A. The method of mass accounting</u>

This methodological approach (1) is based on the hypothesis that there is a correlation between the labor intensity of the production process and the dynamics of changes in the mass of the final product.

$$T_a + K_m = T, \quad (1)$$

where T_a – the labor intensity of a product that is an analog of the one being designed or obtained statistically for products that have common design and technological features with the analyzed product; K_m – a coefficient that takes into account differences in the size or weight of the compared structures.

<u>B. The method of specific rationing</u>

The method of specific rationing is a more universal methodology in comparison with the method of mass accounting. The calculation of labor costs (2) for the production of a product using the method of specific rationing involves the preliminary determination, rationing and establishment of standard labor indicators for similar product designs. It is assumed that the specific rate is the same for the analogue and the product in question.

$$(T_a/P_a) \times P = T_a^{ud} \times P = T\# \quad (2)$$

where T_a – the labor intensity of a product that is an analog of the one being designed or obtained statistically for products that have common design and technological features with the analyzed product; T_a^{ud} – the specific labor intensity of an analog product; P – the value of the main technical parameter of the product, or the beneficial effect realized by the product when used for its intended purpose; P_a – the value of the main technical parameter of the analog product.

If the mass of the product is selected as such a parameter (P), the method of specific rationing is transformed into the method of mass accounting.

<u>C. The method of multifactorial analysis</u>

A more accurate assessment of labor intensity is provided by the method of multifactorial analysis, which allows taking into account the impact of several key product parameters on labor intensity at once [3]. In this context, labor intensity (3) is defined as a complex function depending on the combination of these parameters.

$$T_u - K_0 = T \quad (3)$$

where T_u – the initial indicator of the labor intensity of a product of a basic (characteristic) design under certain conditions of work; K_o – a correction factor that takes into account the impact of specific work conditions (4).

$$(K_c/K_T) \times K_{go} \times K_N = K_o \# \quad (4)$$

where K_N – a coefficient that takes into account the change in T depending on the product release program;

K_{go} – a coefficient that takes into account the change in T depending on the duration of product release in production.

K_c – a coefficient that takes into account the change in T depending on the serial production of products.

K_T – a coefficient that takes into account the technological equipment of the work.

The calculations do not include the cost of performing a scan or adapting the results of polygonal models into a full-fledged 3D model. The absence of these variables makes it impossible to accurately estimate the labor costs and deadlines for reverse engineering projects.

For a preliminary assessment of the complexity of products in the early stages of reverse engineering, when the working drawings have not yet been developed, the method of element coefficients is used. This method takes into account the complexity of the reverse engineering process and allows us to obtain reasonable data on the required resources and time for the implementation of the project [4].

The number of elements and their complexity are taken as a measure of complexity in the method of element coefficients.

$$\frac{T_e}{T_e^{isx}} = K_e \qquad (5)$$

where T_e – the complexity of the element; T_e^{isx} – ore intensity of the element taken as the source; K_e – the element coefficient.

Knowing the element coefficients $K_{эi}$ and the parameters (employee's qualifications, the complexity of the part, the dimensions of the part), you can calculate the complexity and estimated labor intensity of the product in manufacturing.

$$\sum_{i=1}^{I} K_i N_i = K_{sl} \# \qquad (6)$$

$$K_{ei} T_e^{isx} = K_e \qquad (7)$$

where $N_{эi}$ – the number of identical elements in the ith group; I – the number of groups of elements.

The regression analysis method is used to plan the time and resources needed to produce a part or product. This method uses statistical data to estimate the labor intensity of production, taking into account factors such as shape, material, and purpose of the product. The use of regression analysis helps to more accurately predict production costs and make reasonable use of resources, which makes production more efficient [5].

In the process of reverse engineering, this method allows you to create mathematical models that relate design features to the time and resources required for its production [6]. This helps not only to estimate in advance how long it will take to produce, but also to identify important factors that affect labor intensity.

The use of regression analysis also helps to optimize production processes, for example, to make decisions about which technologies and materials to use, in the process of reverse engineering, production systems are more competitive and cost-effective [7]. The correlation relationship is expressed using a multiple regression equation in two ways.

$$A \times P_1^{a1} \times \ldots \times P_n^{n1} = T \qquad (8)$$

$$A + a_1 P_1 + a_2 P_2 + \cdots + a_n P_n = T \qquad (9)$$

where A – a certain constant that varies depending on which category the analyzed part belongs to.; $P_n \ldots$ – parameters taken into account in the model; a_n – indicators (coefficients) indicating the degree of influence of the parameters P_n by the amount of labor intensity.

Further detailing of the factors is carried out by highlighting the values of the complexity of the main and auxiliary work [8]. When analyzing and evaluating labor costs using reverse engineering, it is necessary to take into account factors related to the methodology and specifics of this approach.

The calculations of this method use coefficients reflecting the degree of influence of the engineer's qualifications on the amount of labor intensity, as well as a parameter characterizing the engineer's qualifications [9].

In the calculations of this method, it is proposed to use:

• a coefficient reflecting the degree of influence of an engineer's qualifications on the amount of labor intensity;

• the p rameter characterizing the engineer's qualification;

• t e complexity factor of the part, which affects the complexity of the process;

• the duration factor of the 3D scan, reflecting the time required to obtain a digital model of the part;

• the drawing's occupancy rate, which takes into account the density of information in the drawing and affects the speed of its analysis;

• the format of the drawing, which can affect the convenience and accuracy of working with it, and therefore the complexity of the process.

In this case, each of the coefficients and parameters can have its own weight in the equation.

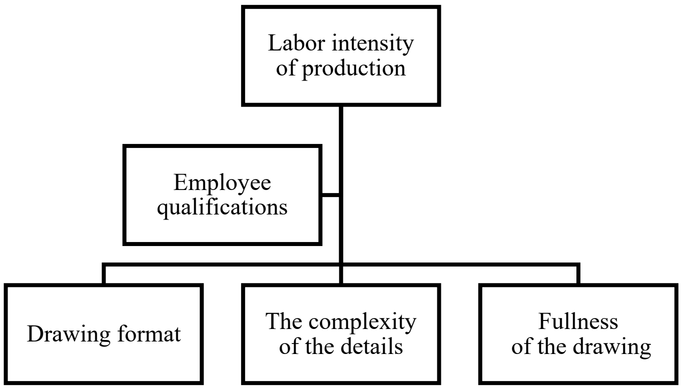

Fig. 1. Factors influencing the calculation of labor costs for reverse engineering projects

Results and discussion

The analysis of existing approaches to assessing labor intensity, including the correlation and regression method, shows their focus on establishing a formalized dependence of the type

$$T = f(P_1, P_2, \ldots P_n), \qquad (10)$$

where T – the total labor intensity, and P is the set of product parameters. This approach makes it possible to obtain a quantitative assessment, but its application is associated with a number of fundamental limitations that reduce accuracy and adaptability in modern small-scale and medium-scale production.

The main limitations are the a priori defined structure of functional dependence and subjectivity at the stage of feature selection. Models based on linear or polynomial regression are not able to accurately approximate the nonlinear relationships of complex topology that exist between design parameters and technological complexity. In addition, the completeness and representativeness of the set of parameters P entirely depend on the expert's qualifications, which introduces an unavoidable systematic error into the model. These methods do not provide for direct analysis of unstructured and semi-structured data formats, such as engineering graphics (drawings) or CAD system data, which leads to the loss of a significant amount of information [11-12].

These limitations, systematized in Table 1, necessitate the transition to a class of models capable of automatically extracting features from heterogeneous data and approximating functions of arbitrary complexity [13].

Table 1

System limitations of traditional labor intensity assessment methods

Disadvantage	Description	A consequence for assessing labor intensity
The fixed shape of the model	The need for an a priori choice of the type of function (linear, polynomial), linking the parameters and complexity.	Low accuracy in the presence of complex, nonlinear dependencies; risk of overfitting or underfitting the model.
Manual selection of features	The subjective choice of a set of parameters is made by an expert technologist based on his experience.	Loss of information due to an incomplete set of features; dependence of the accuracy of the model on the expert's qualifications.
Working with structured data	Inability to directly analyze raw data such as drawings, 3D models, or textual specifications.	Ignoring a significant amount of information contained in the initial design documentation; the need for time-consuming preliminary data preparation.

To overcome these limitations, an architecture based on the principle of functional decomposition is proposed. This approach involves dividing the overall task of optimizing labor costs into two consecutive subtasks:

1) accurate prediction of the complexity of atomic technological operations;

2) formation of an optimal sequence of these operations and resource allocation.

The proposed concept is based on the interaction of two key modules: predictive and optimization. The predictive module, implemented on the basis of a multimodal neural network, solves the regression problem by approximating the labor intensity function based on heterogeneous input data (structural, visual). The optimization module, which uses the mathematical apparatus of Reinforcement Learning, solves the management problem by developing an optimal stochastic task allocation policy among performers, taking into account their individual competencies [14].

The main task of the predictive module is to construct a function approximating the dependence of the complexity of a technological operation on the heterogeneous characteristics of the input data. Unlike classical regression models that operate exclusively with structured features, the proposed architecture implements a multimodal approach that allows for comprehensive data analysis of various types: structured tabular data and unstructured visual data (engineering graphics).

The architecture of the module is a pipeline processing of data by several parallel processing branches, each of which is specialized in a specific type of data. The output representations of the data from each branch are combined (concatenated) and fed into a common block to form a final forecast. This multimodal approach marks a conceptual transition from the paradigm of manual feature engineering to the paradigm of automatic representation learning. In traditional methods of analysis, there is a semantic gap between a set of formal, easily measurable product parameters (weight, dimensions) and an abstract, difficult-to-formalize concept of its "technological complexity".

An expert technologist tries to bridge this gap intuitively, based on his experience. The proposed architecture, in particular its convolutional branch, solves this problem systematically. During the learning process, a convolutional neural network independently forms a hierarchical system of features, moving from low-level graphical primitives (lines, arcs) to complex structural elements (holes, edges, chamfers) and their spatial combinations (Fig. 2).

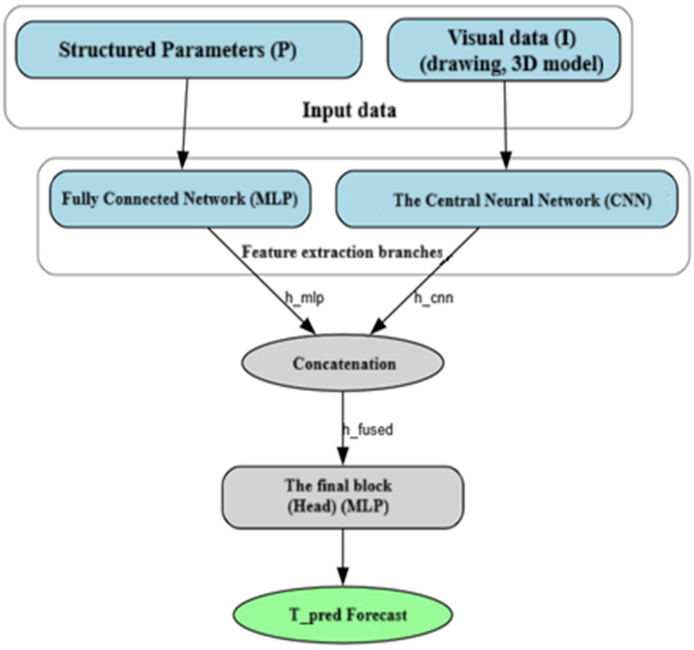

Fig. 2. Data processing pipeline

Mathematically, if the traditional model can be represented as a function described in formula (10), whose argument is a vector of structured parameters, then the proposed model is a function Φ of a data set that includes both a vector P and a tensor I representing visual data (for example, a raster image of a drawing):

$$T_{pred} = \Phi(P, I) \tag{11}$$

This function Φ is implemented by a composition of functions corresponding to the elements of the architecture. The feature vectors extracted by each branch are defined as:

$$\begin{cases} h_{mlp} = \varphi_{mlp}(P;\Theta_{mlp}) \\ h_{mlp} = \varphi_{mlp}(P;\Theta_{mlp}) \end{cases} \quad (12)$$

where φ_{mlp} и φ_{cnn}– nonlinear functions implemented by MLP and CNN networks with sets of trainable parameters Θ_{mlp} и Θ_{cnn} accordingly. The final forecast is formed based on a concatenated feature vector. h_{fused}, obtained by combining vectors from each branch:

$$h_{fused} = h_{mlp} \oplus h_{cnn} \quad (13)$$

where ⊕ denotes a concatenation operation. This vector is fed to the input of the final block. φ_{head}:

$$T_{pred} = \varphi_{head}\left(h_{fused};\Theta_{head}\right) \quad (14)$$

The training of the predictive module is carried out within the framework of the Supervised Learning paradigm. A training sample is being formed D, consisting of N object-response pairs:

$$D = \{(X_i, y_i)\}_{i=1}^{N}\# \quad (15)$$

where $X_i = (P_i, I_i)$ – a multimodal description of the i-th technological operation, and $y_i = T_i$ is the corresponding actual labor intensity value from historical data.

Optimization of model parameters

$$\Theta = \left\{\Theta_{mlp,}\, \Theta_{cnn}, \Theta_{head}\right\}\# \quad (16)$$

It is produced by minimizing the loss function L(Θ), which uses the root-mean-square error (Mean Squared Error, MSE):

$$L(\Theta) = \frac{1}{N}\sum_{i=1}^{N}(\Phi(P_i, I_i) - T_i)^2 \quad (17)$$

Minimization is carried out iteratively using stochastic gradient descent methods, for example, the Adam algorithm.

The optimization module solves the management problem, the purpose of which is to form an optimal work plan to minimize the final labor costs of the project. The task of forming such a plan is formalized in the form of the Markov Decision Process (MDP), which uses Reinforcement Learning (RL) to solve it. In this formulation, the "virtual agent" is trained to make consistent decisions on assigning performers to tasks [14, 15].

Markov's decision-making process (MDP) defined by a tuple (S, A, P, R, γ) where, respectively: S is the state space, A is the action space, P is the state transition function, R is the reward function, γ is the discount factor.

For each engineer e_j, a competence vector C_j is introduced, characterizing his level of mastery of K key skills:

$$C_j = \left[c_{j1}, c_{j2}, \dots, c_{jK}\right]\# \quad (18)$$

This vector is used to parameterize the reward function. The reward function is defined as the negative value of the predicted labor intensity obtained from the predictive module, which takes into account both the parameters of the task and the competence of the performer:

$$R(s_t, a_t) = -\Phi\left(P_k, I_k, C_j\right)\# \quad (19)$$

where (P_k, I_k) – multimodal task description j_k; Φ – neural network function from the predictive module.

The agent receives a higher reward for appointing a more competent employee, since the predicted labor intensity (negative remuneration) will be lower (Fig. 3) [16].

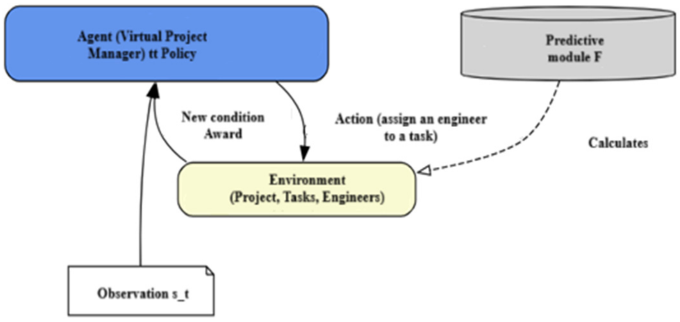

Fig. 3. Interaction of the RL agent with the environment

The purpose of the RL agent is to find the optimal policy. $\pi^*(a \mid s)$, which assigns to each states an action a that maximizes the expected discounted amount of future rewards (return) G_t:

$$G_t = \sum_{i=0}^{\infty}\gamma^i R_{t+i+1} \quad (20)$$

Optimal policy π^* is in the process of iterative interaction of the agent with the environment using algorithms such as Q-learning or its neural network analogues (Deep Q-Networks, DQN). As a result of the work of a trained agent, for a given initial state (the full pool of project tasks), a sequence of actions is generated that represents the optimal work allocation plan that minimizes the total projected labor costs.

Conclusion

In this paper, a study was conducted and a solution was proposed to one of the most pressing tasks of modern mechanical engineering – increasing the reliability of labor intensity estimates at the early stages of design and technological preparation of production. The analysis showed that traditional approaches based on generalized calculations based on analogues demonstrate their inconsistency in conditions of high uncertainty typical for reverse engineering and small-scale production projects. Their fundamental limitations, which consist in the a priori defined structure of the mathematical model, dependence on the subjective experience of an expert and inability to analyze primary design information, lead to significant errors in planning and, as a result, to economic costs.

As an alternative, a neural network architecture is proposed, the methodological apparatus of which forms the core of this article. The presented model is not just an improved forecasting tool, but represents a conceptual shift in the approach to labor management itself. The key scientific result is the development and formalization of a multimodal predictive module. For the first time, a mechanism has been proposed that allows for joint, synchronous analysis of heterogeneous data – structured tabular parameters and unstructured visual data (engineering graphics). This approach allows us to move from indirect and often incomplete features (weight, dimensions) to a direct, objective analysis of the main labor–intensive factor – the complexity of the geometry of the product, extracting the relevant features automatically, without human intervention.

The second significant element of the novelty is the integration of the predictive module with the optimization module, which operates on the basis of Reinforcement Learning. This combination provides a transition from solving the passive regression problem (answering the question "how long will it take?") to solving the active management problem (answering the question "how to organize work to minimize time?"). The developed model does not just provide a forecast, but generates an optimal policy for distributing project tasks among performers, taking into account their individual competencies. This marks the transition from static rationing to dynamic, adaptive resource management in real time.

The proposed architecture lays the theoretical foundation for the creation of intelligent decision support systems of a new generation. The practical significance of this approach lies in the potential to significantly reduce the risks and costs of implementing import substitution projects, improve budgeting accuracy, and ensure more efficient use of human resources in design and technology services. In a broader perspective, such systems are a necessary step towards realizing the concept of a "Digital Twin" not only for the product, but also for the entire process of its development and technological preparation.

It should be noted that this work is primarily theoretical and methodological in nature. Further research should be aimed at practical verification and development of the proposed ideas. The primary task is the industrial testing of architecture on real datasets of machine-building enterprises in order to quantify the accuracy of forecasting and optimization efficiency. Subsequent scientific research can focus on expanding the functionality of the model, in particular, on detailing the forecast to the level of individual technological operations, as well as on exploring methods for integrating this system into the existing IT landscape of an enterprise (ERP, PDM, PLM systems).

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ОПТИМИЗАЦИЯ ТРУДОЗАТРАТ ПРИ РЕАЛИЗАЦИИ ПРОЕКТОВ ИМПОРТОЗАМЕЩЕНИЯ НА ОСНОВЕ НЕЙРОСЕТЕВЫХ АЛГОРИТМОВ

Макаров Владимир Сергеевич, *Нижегородский государственный технический университет им. Р.Е. Алексеева, Нижний Новгород, Россия,* **makvl2010@gmail.com**
Терентьев Алексей Вячеславович, *Государственный университет управления, Москва, Россия,* **av_terentev@guu.ru**
Акиньшин Никита Сергеевич, *Государственный университет управления, Москва, Россия,* **ns_akinshin@guu.ru**
Юдин Денис Александрович, *Государственный университет управления, Россия, Москва,* **da_yudin.@guu.ru**

Аннотация
В данной статье рассмотрены современные методы автоматизации и оптимизации производственных процессов при импортозамещении деталей машин сельскохозяйственной техники. Разработан алгоритм на основе искусственного интеллекта, позволяющий оценить трудозатраты в различных отраслях промышленности, таких как машиностроение, автомобилестроение и тракторостроение. Проведен анализ факторов, влияющих на сложность и трудоемкость работы. Особое внимание уделяется оптимизации трудозатрат для сокращения времени выпуска машиностроительных изделий, позволяющих повысить качество и эффективность производства отечественных аналогов деталей машин, улучшает точность планирования ресурсов и сроков на этапах разработки и проектирования.

Ключевые слова: *ИИ, machine parts, data processing methods, оптиматизация производственных процессов*

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Информация об авторах:
Макаров Владимир Сергеевич, *д.т.н., профессор, Нижегородский государственный технический университет им. Р.Е. Алексеева, Нижний Новгород, Россия*
Терентьев Алексей Вячеславович, *д.т.н., профессор, профессор кафедры управления транспортными комплексами, Государственный университет управления, Москва, Россия*
Акиньшин Никита Сергеевич, *аспирант, специалист Центра управления инжиниринговыми проектами, Государственный университет управления, Москва, Россия*
Юдин Денис Александрович, *аспирант, специалист Лаборатории реверсивного инжиниринга, Государственный университет управления, Россия, Москва*