Production Planning with Parameters on the Basis of Dynamic Predictive Models: Interconnection and the Inertness of their Interaction

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Abstract:

The research is related to the increasing role of prognostic models in production systems management, which is associated with an increase in the requirements for managerial efficiency, the need to consider external factors affecting the system, the determination of the features of the systems in question, the examination of the processes in progress and the relationship between the chain of managerial decisions and the values of the selected control parameters.

The purpose of the article is to consider and evaluate the consequences of decisions made as a chain of interrelated events in time with regard to the dynamics of the environment in which production systems operate and the variability of control parameters. The leading approach of the research considers the production system as one that is open "in terms of environment" and "in terms of the ultimate goal".

The proprietary results demonstrate that the solutions obtained are of a probabilistic nature, the solutions should be set by ranges of possible values, the decision ranges can be arranged in such a way as to introduce variability into the decisions made, the choice of which will be based on factors not taken into account in the proposed method of analyzing production systems.

The practical and theoretical significance of the research is that the described methodology allows to obtain optimal values of control parameters based on the objectives of the production system under consideration on the basis of its integrated assessment, taking into account the interaction and the mutual influence of the system's parameters, their inertness and probabilistic nature, which makes it possible to increase the validity of managerial decisions and to consider the inertness of the processes taking place in the system during planning.

Keywords: Production system, management, control parameters, decision support, production planning uncertainty.

JEL Classification: L11, C32, C61, O21.

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1. Introduction

The continued increase in the level of automation led to the possibility of increasing the efficiency of production systems by synchronizing the operation of internal subsystems of the production system and shortening the production time, which results in the possibility of achieving greater consistency with the factors that are externally relative to the production system. Such results can also be obtained by decreasing the influence of the human factor in the production process, which leads to an increase in the contribution to the final cost of materials and energy costs. Given the tendency to increase the constructive complexity of the products produced, managerial and planning errors introduce a much greater negative effect.

Orientation of production systems to the open market, where the markets for innovative products are the most promising ones, demand higher standards of the speed and quality of decision-making due to the need to take into account the increasing number of factors and the multiple connections of parameters and indicators of the production system and implemented projects, since innovative products have a shorter life cycle, a larger number of modifications (one can observe the transition even to small-scale or customized single-piece production) and, as a rule, they are more knowledge-intensive, which requires increased flexibility of production systems. At the same time, production systems are inertial control objects that cannot immediately reconstruct the processes occurring in them. It takes additional resources of time, money, staff competencies, and organizational resources to change technological processes.

In conditions of high variability and dynamics of proceeding processes, the use of such approaches as actual data management, reflexive control, and so on, leads to a delay in decision making, which, in case of a large number of subsystems and various products, can result in a large integral control error, manifested in the accumulation of individual parts, components and types of products at different stages of the production cycle, as well as delays with the launch of new products on the market due to its volatility.

To avoid this, it is necessary to minimize the presence of a human person in business processes, which in turn requires the development of new more advanced methods and approaches to the production systems management. The use of dynamic predictive models when considering management tasks and supporting decision-making is a promising approach to solve these difficulties.

In this regard, there is a need to improve the existing methods of management and planning of production systems, enabling to increase the efficiency of their operation by taking into account the characteristics of the dynamics of interaction between the subsystems of the production system and the implemented projects through indicators and parameters.

To achieve this goal, it is necessary to consider the principles of constructing complexes of dynamic predictive models, methods and algorithms to support the process of effective managerial decision-making in production systems with regard to the variability, multifactorial and multi-connected nature of the processes and parameters.

2. Literature Review

Albert Calmes originally considered the concept of management as a problem of bookkeeping and statistics in factory manufacturing and commodity production (Voigt, 2008). After the publication of his book *Die Statistik im Fabrik- und Warenhandelsbetrieb* (The Statistics in the Factory and Commodity Trading Company) in Leipzig in 1911, it became the basis for further development in this research area.

In the context of collecting only general data on the analyzed production systems, methods of decision-making in the conditions of limited data applying expert estimates were developed for a long time; one can refer the following to such methods: the utility theory (Neumann and Morgenstern, 2007); the hierarchy analysis method proposed by Saati and Forman (1996); heuristic methods (for example, the method of weighted sum of criteria estimates, compensation method, etc.), bounded rationality models of Rubinstein (1998); the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) developed by Walczak and Rutkowska (2017).

Currently, most decision support tasks based on formal methods are considered as problems of searching for solutions with discrete time (the moments of time of the control influence on the system are predetermined) (Díaz-Madroñero *et al.,* 2014). In addition, there has been a steady trend towards the penetration of simulation optimization and machine learning techniques into the problems of production and economic system management (Jalali and Nieuwenhuyse, 2015). The number of jointly considered factors (for example, environmental friendliness) and subsystems in solving decision support tasks based on formal methods (Chan *et al.,* 2017) and processes (Cheng *et al.,* 2013) is continuously growing.

The incentive for the development of such approaches was given after the demonstrated possibility of limited-set management. Since the beginning of the 2000s, the idea of creating an intelligent enterprise has been developed, in which automated human-machine support systems are widely used for making managerial decisions at all levels of production management on the basis of the approach employing the construction of multi-agent systems and the development of theoretical bases and models for managing socio- and production and economic systems. In connection with the increasing volumes of accumulated information, the tasks of monitoring and forecasting parameters, creating systems to monitor the dynamics of changes in parameters and their compliance with the planned ones

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(Kaiser *et al.,* 2011) began to appear. The accumulation of a large number of data has given an advantage to the methods of machine learning that allow models to be built on the basis of empirical data and, thus, to take into account the features of the systems under consideration (Basu *et al.,* 2009), including in the absence of a complete characterization of the available data (semi-controlled training techniques) (Chapelle *et al.,* 2006).

At the same time, the significance of the machine learning methods in the tasks of production system management will only increase due to the development of the concept of Industry 4.0 and IIoT (Arnold *et al.,* 2016). The accumulation of data also stimulates the development of the methods of mathematical formalization to solve the tasks of managing materials, components (parts), operations, supplier selection (Aissaoui *et al.,* 2007) and the inclusion of stochastic factors in them, the use of probabilistic approaches to risk assessment, regarding different characters of the considered events (joint, interdependent, incompatible and interdependent) for solving planning problems taking into account the dynamics of the processes under consideration.

The consideration of random factors and the use of probabilistic approaches make it possible to carry out risk assessments on models. Meanwhile, the distinction is made between the risks associated with model-based decision making (Olson, 2015), where models depend on the current market situation and the risks of production activity. The use of probabilistic models is based on the use of risk assessments (Mylnikov and Kuetz, 2017), the Bayes theorem (Tajbakhsh *et al.,* 2015) and the Monte Carlo method (Moghaddam, 2015). In the field of risk assessment, the significant contribution of Markowitz (1952), Mossin (1961), Sharpe (1964) and Lintner (1966) should also be mentioned.

Modern studies show that the process of supporting managerial decision-making is not limited to finding optimal or good solutions, but is an iterative process that requires the formalization of processes using the approaches and methods discussed above as ways to justify the selection of a solution over time in connection with the fact that the movement towards the target indicators is rather a trajectory of interdependent states than a one-step process. Target indicators vary in time and can represent a variety of values associated with different types of relationships (Mia and Winata, 2014), especially for projects that are implemented in a competitive market environment and are priorities (projects that are necessary for their existence and affecting the speed of their development) (Kaschny *et al.,* 2015).

As a result, the project management process is often viewed as a process of reviewing and updating the list of the implemented projects and resources allocated for their implementation (Buchmann, 2015), and the task of project management in production systems becomes associated with the task of managing productivity and efficiency. To manage the implementation of projects in time, there are already methods (Hoffmann *et al.,* 2016). However, as regards to production projects

implemented in production systems, they are based on the operating management of a group of projects in the context of the already existing processes of efficiency assessment (Foster *et al.,* 1985) and have only one target indicator – profit, which is currently not enough, because management is based on a number of contradicting indicators; implementation and monitoring of new projects (Kerssens *et al.,* 1997), collection and analysis of input data, production process data, output data and production results (Brown and Svenson, 1998).

The process approach, according to modern scholars, is characterized by a limited set of actions, a list of possible initial conditions and results. Processes occurring in production systems are considered as: 1) long-lasting and not having a rigidly defined description and final result (Kuster *et al.,* 2011); 2) well-formalized and automated production processes, ongoing management processes and business processes (Gadatsch, 2013).

Unlike processes, the implementation of projects in production systems is usually considered as a non-recurring initiative that affects multiple subsystems of the production system and focuses on specific goals (urgent, interdisciplinary, critical or particularly important) that cannot be achieved in the current management structure and require special control (Kuster *et al.,* 2011), which makes each project unique.

The methodological aspects of the problem of the planned study are reflected in the works devoted to instrumental methods for researching innovative potential, to economic and mathematical modeling of innovative planning by such authors as Khorsheed *et al.* (2014), Khayrullina *et al.* (2015), Golichenko (2016), Tyrole (2000).

Despite a large number of investigations dealing with various aspects of management and analysis of production and project activities, the issues of studying ongoing processes and the impact of managerial decisions on the systems under study, currently planning and management methods do not allow accounting for all factors related to the availability of necessary resources for production systems, as well as technical, economic and financial indicators and project parameters; therefore, the management and planning of production facilities, whose competitiveness is based on innovation and the constant release of new products, causes difficulties, which will be especially acute with an increase in the level of automation due to the reduction in decision-making time and the declining role of the human factor (despite the large number of negative factors, the inclusion of people in the production process enables to carry out additional control of activities and take urgent decisions, if necessary).

3. Methodology

To achieve effective development indicators, production systems need to successfully combine tactical and strategic aspects of their activities. Their

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profitability is ensured by the market share and cost structure, which defines the balanced production of goods.

Production systems consist of production processes (operations) and projects implemented in them (products, innovations). The operational process means solving current problems of production and sales of goods. The planning process is related to the implementation of innovations, the solution of promising tasks for the future production (the transfer of competition from the sphere of production to the sphere of innovation). Processes of operations and innovations have a consistent and parallel logic of interaction and can be formally represented as a set of life cycles. Consequently, the production system has definite proportions between the processes of operations and innovations, which are to be reflected in the production plan.

The company invests in processes, operations and innovations, but the added value is generated by investments in the operations. In innovation-oriented production systems, investment in innovation provides added value with a certain time lag. Taking into account the probabilistic nature of this process, it should be noted that planning the release of new products (innovations) is the most difficult task in the production planning. The implementation of new projects and the cessation of the production of old ones is a factor of the production systems development that allows upgrading technologies and organizing production processes.

In this case, planning is based on the selection of management indicators; the principle of consistency in the objectives of the production system subsystems and the projects implemented in it; the principle of invariance and the joint nature of states at decision points; the principle of complementarity of projects implemented in the system; the principle of irreversibility of managerial decisions taken; the principle of information support for the operation of production systems, as well as prompt and reliable information.

The production system should follow certain functional relationships, interrelationships between subsystems, parameters and implemented projects, such as output and sale, production costs, and so on. To understand the process of interaction of subsystems in projects and to determine the place of parameters and factors, let us construct a structural diagram of the production system management (Figure 1). Based on the above scheme, algorithms and systems are implemented that make it possible to work with data collected and used by the decision maker. This approach provides for formalization of the system under study and obtaining estimates directly on the model, which enables to analyze the processes taking place in the system. The process of supporting the adoption of managerial decision making is not reduced to a singular search for optimal or good decisions, but is an iterative process, which itself requires the formalization of processes to justify the selection of a certain decision in time; such a statement of the problem is explained by the fact that the movement to the target indicators is not a one-step process, but represents a trajectory of interdependent states.

Figure 1. *Production system management scheme.*
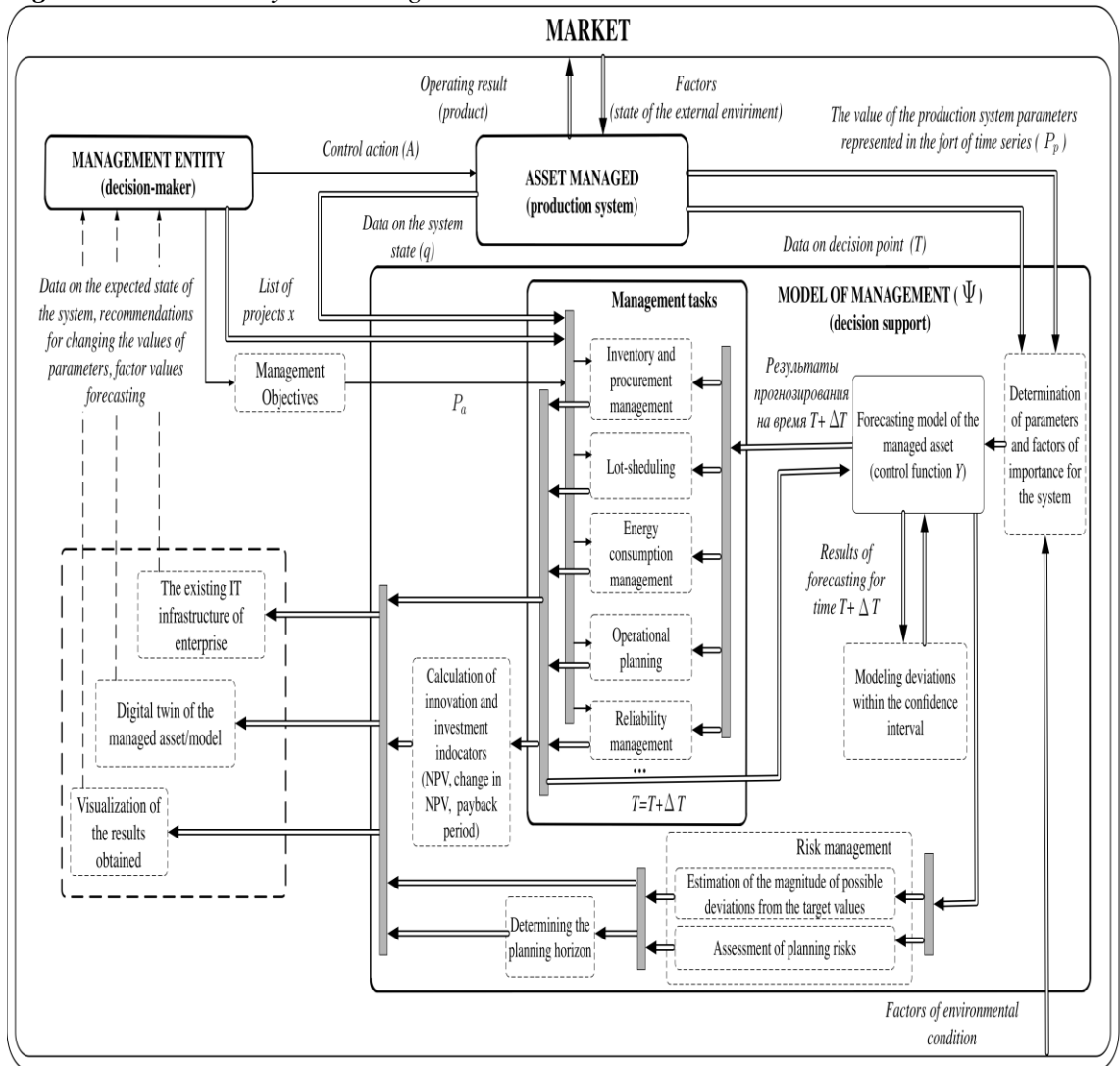
Target indicators vary in time and can represent a set of values associated with different types of relationships. To make managerial decisions, we will analyze the space of the project models states and of the production system. The coordinate axes of this *n*-dimensional space represent parameters and factors whose values give an idea of the current state and the distance from the selected targets. If the target indicators are represented with the vector P_a, and the current state with the vector P_p, then a mathematically measurable metric $\left(P_p, P_a \right)$ will be obtained that characterizes the deviation of the current position from the target one, which is a sign of the success of the project implementation (of the completed implementation, $\left| P_p - P_a \right| \leq \varepsilon$, where ε is the accuracy). However, for management it is insufficient

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to know the metric (P_p, P_a), it is required to know the current values of the parameters and factors that describe the project states, as well as the dynamics of their changes (retrospective and predictive values of the vector elements). It should be noted that achieving the target values $|P_p - P_a| \leq \varepsilon$ does not always mean the achievement of the expected state of the system q.

From the standpoint of the management task, the values and parameters can be classified into four groups: parameters and values describing the current state $\left(P_p^{(i)}\right)$, those describing the control action $A^{(i)}$ for the PS in the state $q^{(i)}$, those describing the next target state $\left(P_a^{(i+1)}\right)$, the and those describing the result of the system transition from the state $P_p^{(i)}$ into $P_p^{(i+1)}$ for the time moments $T^{(i)}$ (decision points).

The management process is reduced to the sequential determination of the new target states $P_a^{(i+1)}$ based on the current state, the state that was planned to be reached at the previous stage, the predictions of the parameter values, and the time when this should happen $- \left(P_p^{(0)}, P_a^{(0)}, T^{(0)}\right), \left(P_p^{(1)}, P_a^{(1)}, T^{(1)}\right), ..., \left(P_p^{(n)}, P_a^{(n)}, T^{(n)}\right)$, as well as the determination of the action $A^{(i)}$.

The control action can be formed on the basis of modeling. For this it is necessary to construct the model Ψ (Faizrakhmanov and Mylnikov, 2016). In general, such a model can be represented as a tuple: $\Psi = \{Y, P_p, P_a, T, x, q\}$, where $x = (x_1, x_2, ..., x_n)$ is the project vector, Y is the system model by group of parameters $\left(Y = Y^{(1)} \cup ... \cup Y^{(j)} \cup ... \cup Y^{(m)}\right)$, where m is the number of model parameters), P_p - the finite set of states of the system, P_a - vector of target states of the system, T - vector of decision points (time), q - state of the system.

The system under consideration is "open in terms of environment" and "open in terms of ultimate goal". Management can be carried out by changing the portfolio of projects implemented in it, the states of the system q are controlled by the influence on the change and dynamics of the change P_p.

The production program determines the list of projects for implementation (x) and the resource endowment; all technical-economic and financial indicators and parameters are calculated. For each project, three functions are formed: sales volumes (based on the forecasted demand), costs and profits. Cost, output and capacity restrictions are formed for the optimization model. The optimization model is formed as a lot-scheduling task:

$$\sum_{ww^*} K_{ww^*}\left(C_w(t)x_w(t) + C_{w^*}(t)x_{w^*}(t)\right) \to \max,$$
$$\sum_{zw} R_{zwj}S_{wz}x_w(t) \leq P_j(t), \forall j,$$

$\sum_w S_{wz} x_w(t) \leq L_z(t), \forall z,$
$x_w(t) \leq G_w(t), \forall w,$
$x_w(t) \geq 0, \forall w,$

where K_{ww^*} is a coefficient of concordance between products w and w^* (is determined by means of the SlopeOne algorithm); w – a product index; x_w – output of product w; C_w – net profit from manufacturing product w; R_{zwj} – capacity requirements to process the material/workpiece/component z for product w at the equipment j; P_j – total resource capacities for equipment of type j; S_{wz} – requirement in material/workpiece/component z per a unit of product w; L_z – available volume of material/workpiece/component z ; z – index of material/workpiece/component; G_w – available market volume/demand/order volume restraints for product w.

It is impossible to consider the task of forming a new project portfolio without taking into account the processes which are already taking place in the production system. In this regard, the task is supplemented by other models of optimal control:

$J(P_p^{(i)}(t), q^{(i)}, \rho) \to \text{opt},$

where $P_p^{(i)} = P_{pparameters}^{(i)} \cup P_{pfactors}^{(i)}$, $P_{pfactors}^{(i)}$ is determined based on the time series forecasting, $P_{pparameters}^{(i)} = Y_l^{(i)}$, l - the number of the parameter under consideration.

The set of models depends on the structure of the production system in question and the tasks to be solved in it. Integration of tasks is carried out through common variables and the production plan, which makes it necessary to determine the calculation sequence that is conditioned by the technological features of the enterprise. The use of forecasts (Figure 1) during planning enables not only to assess the possible development of the production system (when predicting the values of factors affecting the system), but also to avoid the effect of inertia in the transfer of information between the subsystems of the production system (when predicting changes in the values of the system parameters). During joint consideration of three most common tasks (the task of lot-scheduling, the task of warehouse management and procurement planning and the task of planning the sequence of work), the scheme of their interaction will look like that shown in Figure 2. The procurement planning task exemplified by Figure 2 is formulated as follows:

$\sum_{zw} A_{zw} u_{zw} + V_z L_z(t) + N_z(t) y_z(t) \to \text{min},$
$L_z(t-1) + y_z(t) - B_z(t) = L_{zw}(t), \forall z,$
$\sum_{zw} R_{zwj} S_{wz} y_z(t) \leq P_j(t), \forall j,$

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Figure 2. *An example of the structure of a possible model* $Y^{(i)}$ ($C_{w*}(t)$, $G_{w*}(t)$, $N_{z*}(t)$– *statistical data,* t_o – *time of the computation start,* t_{max} – *planning horizon*)
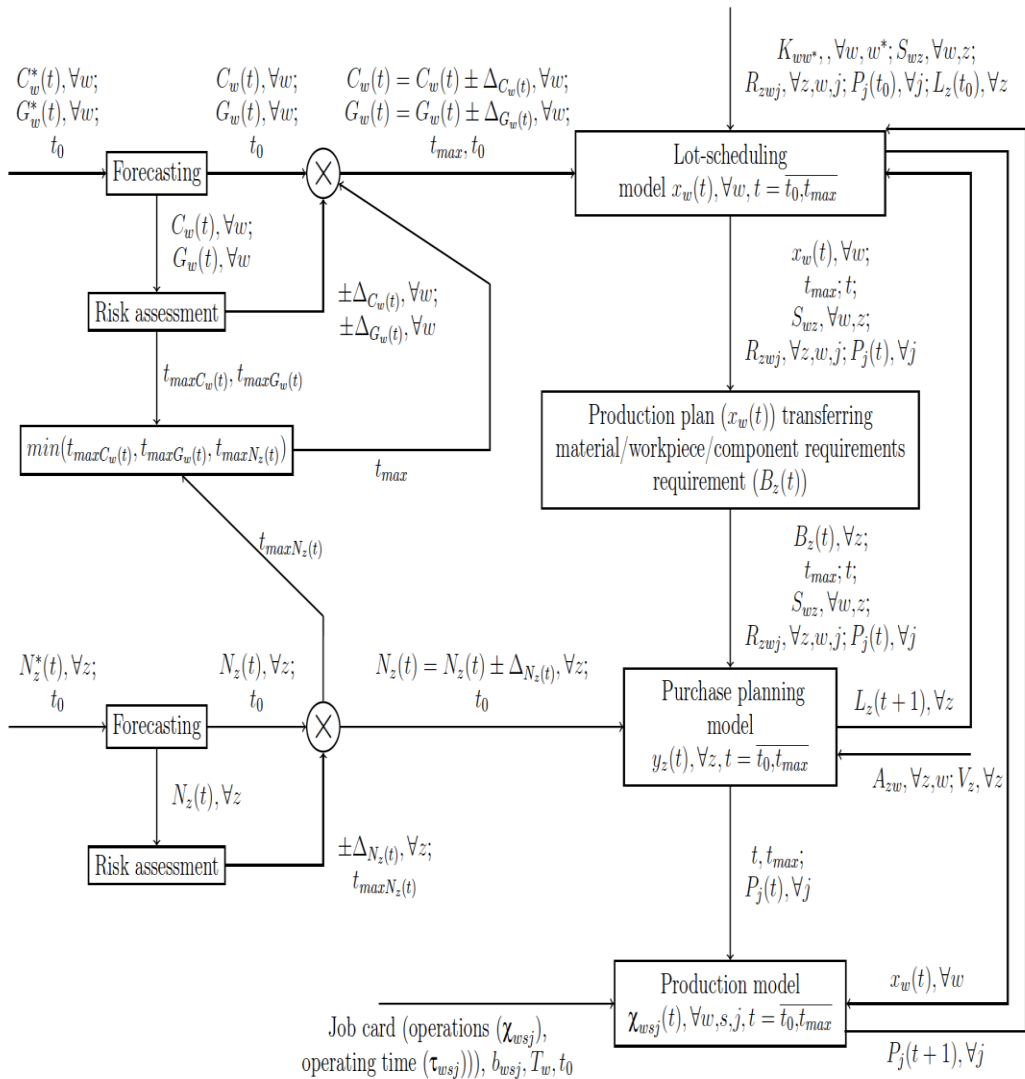
$$u_{zw}(t) \in [0,1], \forall z, w,$$
$$y_{zw}(t), L_{zw}(t) \geq 0, \forall z, w,$$

where u is a variable taking the value of 1 if re-equipment/improvement/transshipment of the acquired material/ workpiece/component is required or, otherwise, it takes the value of 0; y – purchase volume; A_{zw} – cost of re-equipment/improvement/transshipment; B – the requirement in/consumption of the material/ workpiece/component z ; V – the cost

of storing the material/workpiece/component z; N – the cost per unit of material/ workpiece/component z. The task of planning the sequence of production operations when assembling a product from a multitude of parts exemplified by Figure 3 is formulated as:

$$\sum_{wsj} k_{wsj} \chi_{wsj}(t) \tau_{wsj} \to \min,$$
$$\sum_{ws} \tau_{wsj} \leq P_j(t), \forall j,$$
$$\sum_{js} \tau_{wsj} \chi_{wst}(t) \leq T_w x_w(t), \forall w,$$
$$\sum_j \tau_{wsj} \chi_{wst}(t) b_{wsj} = \sum_j \tau_{w(s+1)j} \chi_{w(s+1)j}(t), \forall w, s = \overline{1, (s^* - 1)},$$

where, s is an assembly stage; $s = \overline{1, (s^* - 1)}$, s^* – final operation; k_{wsj} – variable production costs; χ_{wsj} – number of operations in the considered time point t; τ_{wsj} – time consumed at stage s, on equipment j while manufacturing product w; b_{wsj} – rejection coefficient ($0 \leq b_{wsj} \leq 1$), T_w – total time for manufacturing product w.

The time factor is accounted for through the use of forecasts and the available moments of decision-making time $T^{(i)}$. The availability of such time moments indicates the presence of special points in the system, and also that the time step for making the decision $\Delta T^{(i)} = T^{(i+1)} - T^{(i)}$ will not be a constant.

Decision points $T^{(i)}$ are determined based on the set of monitored system parameters (proceeding from the stages and peculiarities of the parameter change) and additional information characterizing its state $q^{(i)}$, for example, equipment maintenance periods, internal technological cycles and so on. As a result, for each time interval $\Delta T^{(i)}$ a quantitative relationship is established between the investment volume $\sum_{j=1}^{n} I_n$ (where n is the number of projects forming the production portfolio) and the criterial function of the lot-scheduling (linked through parameters and restrictions with the production system under in question).

The application of the proposed methods and approaches allows making managerial decisions in production systems that implement innovative projects based on the analysis of quantitative estimates of a multitude of functions with regard to the features of the production system organization, the time factor and the staged character of their implementation. To predict the values of the parameters set up by time series, multiple methods have been developed. Recently, regression techniques based on machine learning methods have become widespread. These methods allow taking into account the peculiarities of the system under consideration and are used to forecast system parameters. When working with external factors, their efficiency is not high, as the data from the external environment may not be enough, they can be unreliable, in addition, such parameters are subject to certain regularities (described by innovative and S-shaped curves) that do not pay due regard to the machine learning methods.

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Figure 3. *Examples of the obtained value of the criterial function in comparison with the real values (red line) when evaluating the effectiveness of the considered approach: a) when solving in a clear statement (black dotted line) and modeling deviations of the values of the parameters predicted to solve the problem with regard to confidence intervals, b) when solving in a fuzzy statement (the dark area is the domain of the most probable values of the criterion).*

a)   *b)*
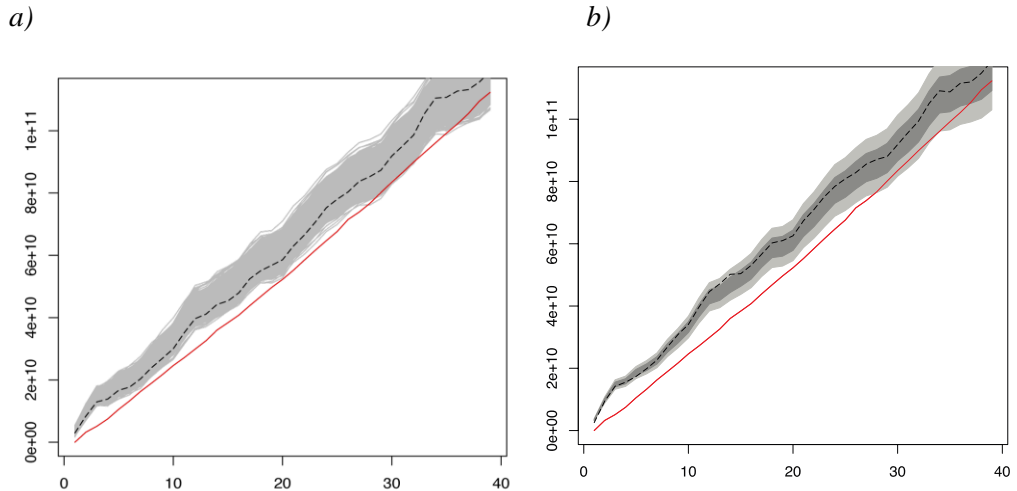
When applying forecasting methods, retrospective data are used to construct a forecast model, presented in the form of time series. To achieve the adequacy of the results obtained, they should be divided into two samples: the training set, which is used to construct the forecast model, and the test set. After checking the model on the test set, in case of its adequacy, the test data is added to the training set and the model is reconstructed.

Thus, the regression models selected to forecast the values of the parameters and factors will be adequate. Given that forecasts are obtained only with certain accuracy, it is possible to set the forecast values in the form of fuzzy numbers or simulate possible deviations of values regarding the probability distribution density of the obtained values and to calculate the magnitude of the planning horizon on the basis of risk assessments (Mylnikov and Kuetz, 2017).

4. Results

When solving optimal control problems taking into account the time factor and some discrete time step $\Delta T^{(i)}$, the solution will be a tabulated function. In this case, the system interacts with the external environment and the solution found may not be achievable due to changes in external or internal factors. According to the Bayes theorem (Russell and Norvig, 2003), the probability of a successful transition to a new state (to a new solution) will depend on the previous state (the state in which we are).

Then, to select the trajectory of project development, it is expedient to consider a set of Pareto optimal solutions, rather than a single solution. In this case, a set of trajectories will be the solution of the problem. If it is assumed that all solutions are unique, the probabilities of achieving each solution will be the same. However, in practice, solutions can be repeated. This is related to the fact that approximate methods are used to solve optimization problems without imposing restrictions on the form of the criterial function. In this case, the probability of transition from the state $X^{(0)}$ to the state $X^{(m)}$ will be determined by the sum of the probabilities of the repeated values and this value will determine the possibility of transition from one decision point to another.

This probability will not be a random variable when performing multiple calculations, since the parameters obtained on the basis of these forecasts will have random walks described by the probability density functions that must be used to generate new forecast values in multiple calculations. $\mu(x_1) = \frac{1}{\sigma_1\sqrt{2\pi}} e^{-\frac{(x-x_1)^2}{2\sigma_1^2}}$, where σ_1 is the standard deviation, x_1 is the value obtained as a result of forecasting. When moving to the next value, the function will change $\mu(x_2) = \frac{1}{(\sigma_1+\sigma_2)\sqrt{2\pi}} e^{-\frac{(x-x_2)^2}{2(\sigma_1^2+\sigma_2^2)}}$, in the new formula the Gaussian perturbation of the constant variance σ_2^2 is added, which is calculated by the formula (Venttsel, 1999):

$$\sigma_2^2 = D[x] = M[x^2] = \sum_{j=1}^{m} x_{1j}^2 \, \mu(x_1)$$

where $D[x]$ is dispersion, $M[x^2]$ mathematical expectation, x_{1j} are possible values for x_1 (falling in the interval σ to test the model for adequacy).

As a result, it will be possible to determine the probabilities of obtaining solutions on the basis of which the most probable ones can be selected. It is possible to estimate the probabilities of achieving a series of successive states s1, s2, $\cdots$, sn by using the probabilities $P_j^{(0)}$ – the probability that we are in the state s_i and this state fully corresponds to the expected state (determined on the basis of previous steps). The probability of achieving each subsequent solution is determined by the chain rule: $P(\mathbb{X}^{(0)}, \dots, \mathbb{X}^{(m)}) = \prod_{j=1}^{m} P(\mathbb{X}^{(j)}|\mathbb{X}^{(j-1)}, \dots, \mathbb{X}^{(1)})$. The vector of values of the variables $\mathbb{X}_i^{(j)}$ corresponds to each state and can be put in correspondence to the value of criterial function $J_i^{(j)}$. The sequences of values $J_{i_0}^{(0)}, \mathbb{X}_{i_0}^{(0)} \xrightarrow{P_{i_0}^{(0)}} J_{i_1}^{(1)}, \mathbb{X}_{i_1}^{(1)} \xrightarrow{P_{i_1}^{(1)}} \dots \xrightarrow{P_{i_{\Delta T-1}}^{(\Delta T-1)}} J_{i_{\Delta T}}^{(\Delta T)}, \mathbb{X}_{i_{\Delta T}}^{(\Delta T)}$ forming the trajectories of a possible development of events will result in the solution. Moreover, each solution on this trajectory will also have a probabilistic nature because it employs the data that are

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set up by the forecasts. The resulting solutions can be illustrated by the graphs shown in Figure 3.

5. Discussion

The research deals with mathematically formalized problems of planning and management. Such tasks encounter the problem of NP-completeness for the solution of which approximate algorithms are applied (Cormen, 2009). The solutions obtained are approximate and the probabilities of achieving target values become necessary even without taking into account the probabilistic nature of the factors influencing the production system. In addition, the task uses the forecast data. Thus, the tasks considered in the article are posed in a statistical statement, but the model itself may combine different types of formalizations (to describe the interrelationships of the production system parameters and to forecast the production system parameters, including with regard to the influence of many factors and parameters on each parameter), which leads to a combination of different empirical methods and approaches.

The use of forecast data and risk assessments in optimal control tasks opens up new opportunities for studying the processes occurring in the PS and caused by the introduction of commodity projects, as well as economic and mathematical models and methods for managing these processes. The use of forecasts makes it possible to consider the reactions for various parameters and, thus, to increase the consistency of the functioning of the system elements and to improve the quality of management. The methodology proposed in the article is related to the use of forecasts in planning tasks, which allows taking into account the time factor. The formulated methodology does not put forward requirements for the method of formalizing the model, but relies only on the parameters used, the forecast data and the statistical data employed to construct the forecast models.

The approach discussed in the research can be extended to obtain assessments of production risks, such as risks associated with equipment wear, shutdowns, repairs, scheduled repairs, replacement, and withdrawal of old projects (Pan *et al.,* 2012). To do this, statistical models can be applied that will complement the set of parameters taken into account and refine the values of the existing assessments.

Thus, the task of accounting for the time factor in the tasks of planning and production activities related to the implementation of commodity projects based on the PS and accounting for non-deterministic risks is being solved.

Transfer of forecasting data into the fuzzy form enables to take into account the uncertainties associated with forecasting the values and exclude the need to study the management model for its dependence on forecasting errors (carrying out numerous calculations). The absence of assumptions and simplifications in the course of the solution makes it possible to define each value as a membership function and,

thereby, to determine individual values and ranges of values, the occurrence of which is most likely based on the forecasting accuracy. Obtaining results in this way is most valuable in production and production-economic systems in which the controlling influence is formed by a human based on the data of analysis of the emerging situation and its dynamics.

6. Conclusion

The proposed methodology for managing project implementation processes on the basis of production systems is premised on the fact that management can be carried out on a group of parameters and indicators that depend on the type of project, processes occurring in the PS, management tasks and product characteristics. The problem of justifying the selection of control solutions obtained by numerical methods on optimization models with regard to the time factor is considered. A group of dynamic-predictive models exemplifies the solution of the problems of managing and planning production systems in the organization of production of commodity projects. The methodology allows formulating additional tasks (for example, the task of managing reprocessing and reusing, controlling the modes of the production electrical system, etc.) that can be considered in conjunction with the above, and formulate their task groups and use other criteria as an assessment of the solution.

The methodology described is of particular importance in connection with the large spread of management tasks formulated in the form of optimization problems. At the same time, such problems can be obtained in the statements requiring to apply approximate algorithms enabling to form a set of solutions close to the Pareto optimal one (whose area of distribution may also vary with time regarding the imposed constraints,), as a result of which it becomes necessary to rank them and make a deeper estimate in terms of the cause-effect relationships.

The findings reported in the article were obtained on the basis of the analysis of retrospective data and algorithmization in the R language in the RStudio development environment.

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