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The Risk Assessment Method in Prognostic Models of Production Systems Management with Account of the Time Factor

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Abstract:
The possibility of planning risks assessment and the setting of the planning horizon are analysed with account of the time factor basing. A risk metrics approach is used, with risks estimated as a time function given in tabular form for the purposes of master production.

Dependence of the integrated planning risks on the accuracy of forecasts used is proved and a time point is identified after which the risk assessment value increases sharply.

The study enables to obtain the values of planning risks integral assessment in management problems using forecast data for groups of indicators and parameters involved in decision-making.

Keywords: *risk assessment method; risk assessment; production system; production system management; time factor; planning risks assessment; forecast models; constraint optimisation problems; risk metrics approach; production scheduling; historical data; production volume; integrated planning risks; risk assessment value; planning risks integral assessment.*

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1. Introduction

The implementation of projects in production systems (PS) raises new needs and requests for products manufacture, as well as production facilities meeting the special requirements of the PS. At the same time, implementation of any changes takes place in a strictly limited time and budget. One can often observe a phenomenon when for the introduction of new projects and developments necessitates the creation of subsidiaries or the projects being implemented are considered as independent ones with the same resources or goals as for other works.

In each project like this it is necessary to solve management and planning problems, taking into account available resources, environmental factors, and a strategic plan for the PS development (Markina and Diachkov, 2014).

At the same time, individual numerical estimates and decisions start to play a lesser role in management and taking managerial decisions, whereas the importance of qualitative and integrated assessments is increasing. The increasing volumes of accumulated information led to the emergence of certain tasks of parameters: monitoring and forecasting, creating systems for monitoring the dynamics of changes in parameters and matching their values with the planned ones (Kaiser *et al.,* 2011).

According to the international rating of production competitiveness for 2016, the use of predictive models in management has the greatest impact on the competitiveness of industrial production. This has allowed the USA and China to take the leading positions in industrial competitiveness over the last 5 years. However, this problem has not been fully solved by now.

The methods of objective decision-making under conditions of limited time are required for solving planning problems when implementing PS projects have not been fully developed. Dealing with these problems, one faces the challenge of NP-completeness and can solve them using approximate methods only. This increases the importance of risk assessment with regard for the time factor when using the forecast values in planning tasks, the time variation factor with account of the ranges of permissible values and their fuzzy PS nature as well as the specifics of production in joint pricing, master production scheduling, procurement management, etc (Golovina and Uvarova, 2014).

The development of the concepts of Industry 4.0 and IIoTenables to gather data on each unit of equipment and to timely manage production processes in the PS (Arnold et al., 2016), thus facilitating the development of industrial engineering methods.

In this regard, one should keep in mind that reaching target values is not a one-step process, but rather a trajectory of interdependent states. Moreover, target values themselves change over time and can be represented by a set of values dealing with different types of relationships (Mia and Winata, 2014; Kosinova *et al.,* 2016). Management problems should be considered with account of the time factor, while using statistical data for this purpose enables to build forecasts and assess planning risks, accounting for the specifics of the PS as a whole, the equipment used and the organization of processes in a time-limited environment.

Thus, the study aims to develop a method of accounting for planning and production risks associated with the implementation of commodity projects in the PS and which takes into account the time factor in planning and non-deterministic risks. The specific research task involves using the risk assessment apparatus when working with several model parameters on the basis of forecasting data to obtain risk estimates as a time function on the example of a mathematically formalisable management problem (Lado González and Calvo Dopico, 2017).

2. Literature Overview

Initially, the issue of product management was considered by Albert Kalmes (Voigt, 2008) as a problem of accounting and statistics in manufacture and commodity production. The problem has further necessitated the development of planning methods (see the works by Frederick Taylor and Henry Gantt (Gantt and Forrer, 2006)). The further development in this field deals with the improvement of mathematical formalisation methods (carried out by some researchers (Kantorovich, 1939; Von Neumann and Morgenstern, 2007) which involved consideration of the highest number of methods possible, and then elaborating managerial decisions for the whole branch of production (e.g., the works by J. Tirole on management in the industry markets (Joskow and Tirole, 2007; Theriou, 2015; Theriou *et al.,* 2014).

Due to the fact that over a long time only general data on the analysed PS were collected, the methods applied dealt with decision-making in the conditions of limited data and using expert estimates. These methods included the utility theory (taking into account users' preferences to maximize the expected utility, probabilistic models (Von Neumann and Morgenstern, 2007). Savage's (Savage, L.J., 1954) axiomatic theory which allows to simultaneously measure utility and subjective probability, a decision tree approach which implies dividing a task into a range of subtasks (Raiffa, 2002), a multicriteria utility theory developed on the basis of Keeney's works (Keeney and Raiffa, 1976), the prospect theory methods, ELECTRE methods developed by the French school of decision theory headed by Roy (Roy & Bouyssou, 1993), the analytic hierarchy process proposed Saaty and Forman, (1996), heuristic methods for example, the weighted sum method of estimating criteria, compensation method, etc., Rubinstein's (Rubinstein, 1998) bounded rationality models, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Walczak and Rutkowska, 2017).

A significant increase in the amount of statistical data has given a new impetus to the development of mathematical formalisation methods of management of materials, parts (components), operations, the selection of suppliers (Aissaoui *et al.*, 2007), the inclusion of stochastic factors, the use of probabilistic approaches to assess risks taking into account the varying nature of the events examined (joint, interdependent, incompatible and interdependent) aimed to solve planning problems regarding the dynamics of the processes studied (Angelakis *et al.*, 2015).

Consideration of random factors and probabilistic approaches make it possible to assess risks by means of models. Researchers identify planning risks, i.e. risks associated with making decisions on models (Olson, 2015) that depend on the current situation (changes in prices, sales volumes, etc.), and production activity risks: risks associated with equipment failure, non-delivery of necessary materials or components, etc., (Salimova and Makolov, 2016).

Probabilistic models involve using risk assessment (Abdullaev *et al.*, 2012), the Bayes theorem (Tajbakhsh *et al.*, 2015) or the Monte Carlo method (Moghaddam, 2015). Such approaches allow moving from risk assessment of individual cases and tasks to the consideration of projects, processes and the PS as a whole. Management of the project implementation is connected with the management of the project life cycle, which, as a rule, is viewed regarding its individual parameters.

Typically, enterprises implement not individual projects, but groups of them within the established schedules, financial constraints, workload of personnel, equipment, other restrictions and rules. As a result, project management turns into a process characterized by prompt decision making, revision and updating of the list of projects implemented, their priorities (resources allocated for their implementation) (Buchmann, 2015). Thus, project management in the PS implies managing the PS performance and efficiency.

Efficiency is directly connected with the organization of processes and their interconnections in the PS. The process approach is characterized by understandable actions, clear initial conditions and outcomes. However, there are long-term processes that do not have a rigidly defined description and end result (Kuster *et al.*, 2011) (training and management are examples of such processes). In practice, there is a difference between well-formalized and automated production processes and ongoing management and business processes (Gadatsch, 2012).

Thus, we can conclude that the processes consist of a set of specific tasks and transitions between them that take place both within the studied PS or are connected to processes and tasks external to it. It is important to note that processes can only be changed by the systems that manage them and are their holders (Damij and Damij, 2014), which means managerial decisions should be taken at the appropriate level. Such a need arises if the results set for the PS are not achieved. The project, unlike the process, is usually a one-time initiative that involves many PS subsystems and focuses on specific objectives (urgent, interdisciplinary, important or critical) that cannot be achieved in the existing management structure and require special monitoring (Kuster *et al.*, 2011); this makes each project unique. In addition, projects can have shifting end goals, especially innovative projects implemented in a competitive market environment and are crucial for the PS since they are a prerequisite for their existence and affect the speed of their development. According to some authors (Kaschny *et al.*, 2015), these include new projects that will be relevant for social, economic and environmental development and have previously been unavailable in the proposed form. Implementation of innovative projects in various systems will be directly connected with the organization of the general process for managing them. Talking about commodity innovation projects and the PS, this will mainly imply strategic and operational management based on planning objectives, forecasting, selecting the best projects, and assessing intermediate results. However, such projects will be more open than traditional ones and "longer-playing" as the implementation period will exceed the traditional planning period.

The projects implementation is managed by means of certain existing methods (Hoffmann *et al.*, 2016). However, if we talk about commodity projects implemented in the PS, we should keep in mind that they are based on the operational management of a group of projects in the context of the already existing performance evaluation processes in the PS (Foster *et al.*, 1985) which is based on the traditional hierarchy of indicators (e.g., the DuPont model). They have only one target indicator – profit, which is not sufficient for the implementation of commodity innovation projects since their management is based on several sometimes contradictory indicators; implementation and control of new projects (Kerssens-van Drongelen and Cooke, 1997) which enables to take into account the multidimensional nature of the innovative project, but does not aim to develop and increase the profitability of the PS or efficiency of decisions taken; collection and analysis of input data, production process data, output data and output (Brown and Svenson, 1998) (collecting general system data, as a rule, does not allow singling out the data that describe an individual project); information infrastructure (Kütz, 2014).

3. Methods

The commodity project is a controlled object in the state space. The coordinates of this - dimensional space represent the control parameters that are crucial for achieving goals, and their values describe the current state and distance from selected targets.

If we represent the target indicators with the vector P_p, and the current state with the vector P_a, then we will obtain a mathematically measurable metric (P_p, P_a)describing the deviation of the current position from the target one, which denotes the successful implementation of the project (the end of the implementation, $P_p = P_a$). However, for management, it is not enough to know the metric (P_p, P_a), one needs the vector of parameters Y that has a significant effect on the project state and includes values describing the project states, the PS and the environment in which the project is implemented, the dynamics of the change as well as the forecast values of all these parameters. It is worth noting that the achievement of target values $P_p = P_a$does not always mean achieving the vector Y values expected for this state. In this case, the management tasks are the following: to define parameters that will become state indicators for the project, the PS and the external environment; to determine the values of these parameters, which will show the desired target state; to monitor changes in the values of the selected parameters and to determine the permissible range of their deviations; to interpret the obtained values and to develop well-founded managerial decisions leading to the desired change in the parameters.

Given the above, it is possible to establish indicators according to the following project types: 1) simple projects, 2) projects consisting of several stages, 3) project groups; processes occurring in the PS: 4) ordinary processes, 5) alternating processes, 6) invariant processes; management tasks: A) master production, B) inventory and procurement management, C) service and utilization management, D) organization of the production (sequence of operations), E) production scheduling, F) sales management, G) production reliability management (accidents and failures at the production site), H) customers satisfaction, product characteristics; I) change management (modernisation), J) modification management, K) risk management, L) product quality management, M) usability (size, user-friendliness, design); and N) other indicators (providing a complex description of the system). In the end, we obtain groups of indicators forming the basis for the management to implement commodity innovation projects.

Within the management problem, the values and the parameters themselves can be classified into four groups: parameters and values describing the current state $P_p^{(i)}$, values and parameters describing the impact (external factors and control action $Y = A \cup \Theta$, where A is the set of control actions, Θ is the set of the environment values), the values and parameters describing the following state P_a, the value and parameters describing the system performance result of a transition from state $P_p^{(i)}$ to $P_a^{(i+1)}$ - $R^{(i)}$ (performance results) and time $T^{(i)}$.

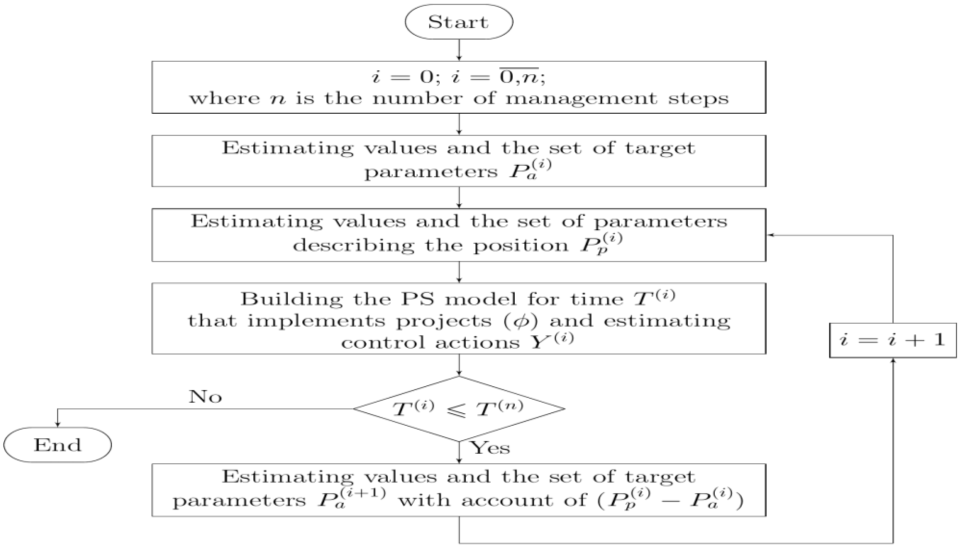
Next, the management problem enables to use an automat the next state of which is determined by experts on the basis of the current state and the state that was planned to be achieved at the previous stage and the time when it should occur – $(P_p^{(0)}, P_a^{(0)}, T^{(0)}), (P_p^{(1)}, P_a^{(1)}, T^{(1)}), \ \ldots \ , (P_p^{(n)}, P_a^{(n)}, T^{(n)})$. This allows us to consider targets as variable values, depending on the current state of the PS, the projects implemented in it and the external environment (to implement flexible management methods). In order to move to a new state, it is necessary to determine the impact $A^{(i)}$. This impact can be estimated using the PS model that implements innovation projects $\phi_j = \{U, S\}$, where U is the vector of control parameters, S is the set of project resource requirement, j– the project number. Such an approach enables to develop hierarchically coordinated managerial decisions by taking into account the system-interconnected and interacting external and internal factors of the PS. The management of the PS is considered as an integral, non-deterministic process. Schematically, this model can be represented as:

$$\Psi = \{Y, P_p, P_a, T, \phi, q_0\} \quad (1)$$

where $\phi = (\phi_1, \phi_2, \dots, \phi_n)$ is the project vector, Y is the control function ($Y(\phi, q)$, with q as the state), P_p is the finite set of system states, P_a is the vector of the target states of the system ($P_a \in P_p$), T is a vector of decision points, q_0 is the initial or current state of the system from P_p. We can estimate decision points if a set of controlled parameters is known (according to the stages and specifics of the characteristics change), and the additional information on the PS properties that we control (equipment maintenance periods, internal production cycles, etc.) (Faizrakhmanov and Mylnikov, 2016).

Thus, at decision points this model can be divided into a number of models of the form $\Psi = \{Y, P_p, P_a, \phi, q_0\}$. A special case of this problem is the combined task of market choice and master production planning (Van den Heuvel et al., 2012) which is NP-complete. It has been proven (Hopcroft et al., 2007) that if the problem P_1 is NP-complete, and there is a polynomial reduction of P_1 to P_2, then the problem P_2 is also NP-complete. Hence, the problem of managing production systems that is formalised in standard form is NP-complete and is not solvable algorithmically. In this case, the use of the model (1) is described by a nondeterministic algorithm, see Figure 1.

Figure 1. *Algorithm for managing the PS used in projects implementation*



This leads to the management task becoming more specific. However, new components, its subtasks, arise and they are: to define decision points, to determine a set of indicators and their values for each stage of the project, to build a PS model when implementing projects (ϕ) to estimate the vector of control actions Y.

Formulating the management problem with reference to time $T^{(i)}$ reduces to the formalisation of the models $Y^{(i)} \rightarrow M^{(i)}\{A, \Theta, \overline{T^{(i-1)}, T^{(i)}}\}$. The structure of the model involves the establishment of formal relationships between its parameters, and its type at each stage will depend on the management task considered (forecasting the properties and behavior of the controlled object; managing the object, selecting the best effects by testing them on the model; studying the object; improving the controlled object).

The model itself can use both non-causal (component-oriented) and causal (block-oriented) modelling, whereas the model components determine certain requirements for the model creation tool (for example, the ability to work with large volumes of data with given time series, the ability to apply methods used for incomplete data, the ability to solve problems presented in the form of mathematical programming problems, the implementation of methods for working with probabilistic models, etc.).

Concretization of models $Y^{(i)}$ generates, on the one hand, the problem of choosing formalisation approaches and methods based on various known approaches, methods, and models (Vanini, 2012) that will be collected as a composition (with corresponding departure and arrival domains), and on the other hand, their application for obtaining the modeling results as a time function.

When setting criteria, the problem will be formalised depending on the selected indicators and data that will be used to make decisions and the relationship between them. For example, all PSs work with data such as resource requirements, a list of resources used, the time and cost of operations, a list of possible operations, the price of production, etc.

Taking various parameters as unknown values with account of their invariance and using them as parameters for calculating other indicators, we will obtain a range of PS management tasks when setting the criteria:

- The task of selecting a market and sales planning, taking into account the features of production (determining the value of the marginal returns, output elasticity, etc.).
- The task of master production scheduling.
- The task of inventory management and procurement planning $V = AX$, where A is an incidence matrix the values of which show resource requirement and X is the vector of the resource column.
- The tasks of selecting equipment, recruiting staff, locating the production and the project, taking into account the cost of ownership.
- The task of time management and production performance $W = BY$, where B is the incidence matrix the values of which indicate the time required for performing necessary operations, Y is the vector of possible operations. In this case, each operation can be described through the intermediate products obtained. So, we can establish the relationship between production time, resources and operations if we assume that the production of a commodity unit A requires X resources: $W = VAX$.
- The task of managing the production cost, when instead of the time required for performing an operation the cost of the operation is used $S = CAX$, where S is the price of production.
- The tasks of managing the production directly.
- The task of recycling.
- Formalisation in the form of the operational management task allows us to narrow the set of the system states and management functions, and also formulate the problem as:

  $$F(x, s) \rightarrow opt$$

  where x is the input value, s is the parameter value at which the function value is optimal.

At the operational level such an approach is called a production functions approach since the PS or the project are considered as a “black box” (see the work by an

American economist J.B. Clark), and the formulation is reduced to such functions as the Cobb-Douglas and the Leontief-Harrod-Domar function, etc. It allows accomplishing various tasks, for instance, to construct a set of solutions, to determine the volume of marginal return and the output elasticity in the PS. However, classical production functions that establish functional dependencies between the PS parameters and the indicators of their effectiveness do not take into account the time factor and the constraints imposed on the problem by decision makers and system constraints.

Therefore, describing a problem like this, one should add constraints and consider it in dynamics; for this purpose the parameters of the production function (in this case a criterial one) and the parameters found in the constraints should be considered as functions of time given in tabular form (for the periods with available statistical data) and functionally for the periods in the past and the future for which we use the forecast values.

The constraints that arise can be of all kinds, namely parameters or indicator values estimated on the basis of parameters can be larger, smaller than some specified values or take values within a given range. In practice, this is of real significance and manifests itself, for example, in procurement: there are restrictions on the minimum batch after the payment or weight, the minimum and maximum terms, the period from order to delivery that is discrete by weight or the amount (determined from the package parameters) of the batch as well as the parameters dealing with weight loss from packaging, shelf life, etc.

Let us consider the problem of master production scheduling (Józefowska and Węglarz, 2006). The problem accounts for various factors and features of production (Chen, 2006). As an example, let us take one of the formulations (which do not consider each piece of equipment separately) and view individual parameters (obtained as a result of forecasting or calculated in dynamics) as a function of time (t):

$$\sum_i \sum_l K_{il} \sum_t (C_l(t)x_l(t) + C_i(t)x_i(t)) \to max$$

$$\sum_i \sum_t R_{ij}x_i(t) \le P_j, \qquad j = \overline{1 \dots M}$$

$$\sum_i \sum_t S_{ki}x_i(t) \le T_k, \qquad k = \overline{1 \dots K}$$

$$\sum_i \sum_t \alpha_i^q x_i(t) \le G^q(t), \qquad q = \overline{1 \dots Q}$$

$$\sum_l \sum_t R_{lj} x_l(t) \le P_j, \qquad j = \overline{1 \dots M}$$

$$\sum_l \sum_t S_{ki} x_l(t) \le T_k, \qquad k = \overline{1 \dots K}$$

$$\sum_l \sum_t \alpha_l^q x_l(t) \le G^q(t), \qquad q = \overline{1 \dots Q}$$

$$x_l(t), x_i(t) \ge 0, \qquad \forall l, i, t$$

where K_{il} is the coefficient of conformity of goods i and h; x_i, $i = \overline{1 \dots N}$ is a vector of unknowns, each component of which determines the quantity of products output of type i; C_i, $i = \overline{1 \dots N}$ the net profit from the production of this product; R_{ij},$j = \overline{1 \dots M}$, $i = \overline{1 \dots N}$ the need for the capacity of each equipment type per unit of finished product, given in accordance with technological production routes; P_j, $j = \overline{1 \dots M}$ is total resource in capacities for each type of equipment, found by calculating average productivity for all equipment of this type; S_{ki}, $k = \overline{1 \dots K}$, $i = \overline{1 \dots N}$ – the need for key materials per unit of finished product, given on the basis of the product specification; T_k, $k = \overline{1 \dots K}$ is the amount of available key materials, according to the data on stock and the procurement plan:

$$\alpha_i^q = \begin{cases} 1 - \text{if i} - \text{th product belongs to the q} \\ 0 - \text{if i} - \text{th product does not belong to set q} \end{cases}; G^q, q = \overline{1 \dots Q}$$

is the market constraint (sales volume in the market considered). The calculations will be done using the data on sales volumes and price changes in the US Ford market, published on the official website in quarterly reports and the forecasts derived from them. Results will differ when different forecasting methods and methods parameters are applied. The choice of the method and its parameters is based on expert assessments, verification of the accuracy of the results obtained, etc. Retrospective data are used for this purpose. The statistical sample is divided into: the practice one (used to build the forecasting model) and the test one (the last in time section of the historical data and used to test the model, see Table 1) of the sample.

Table 1. *Sales and price changes in the Ford US market*

No	Date dd.mm.yy	Ford Mustang		Ford F-Series		Ford Expedition	
		Sales, units	Avg. price, $	Sales, units	Avg. price, $	Sales, units	Avg. price, $
1	01.11.13	5376	36654	65501	40004	14268	35528
2	01.12.13	5727	36652	74592	40330	16907	35558
3	01.01.14	3881	36650	46536	37782	12810	35672

4	01.02.14	6410	36365	55882	38108	13924	35703
5	01.03.14	9305	36080	70940	38434	19334	35734
6	01.04.14	7243	35795	63387	38760	18479	35764
7	01.05.14	9761	35510	68520	39085	22623	35795
8	01.06.14	7631	35225	60560	39411	17290	35826
9	01.07.14	6564	34940	63240	39737	19006	35857
10	01.08.14	5878	34655	68109	40063	19391	35887
11	01.09.14	3158	34370	59863	40389	15795	35918
12	01.10.14	4565	34085	63410	40715	16496	35949
13	01.11.14	8728	33800	59049	41040	16382	35980
14	01.12.14	9511	33515	74355	41366	18464	36010
15	01.01.15	8694	33230	54370	38386	17036	36129
16	01.02.15	8454	33252	55236	38712	18613	36160
17	01.03.15	12663	33274	67706	39038	23058	36191
18	01.04.15	13144	33296	62827	39364	18844	36221
19	01.05.15	13616	33318	61870	39689	22304	36252
20	01.06.15	11719	33340	55171	40015	22549	36283
21	01.07.15	8482	33363	66288	40341	23381	36314
22	01.08.15	9997	33385	71332	40667	23671	36344
23	01.09.15	9456	33407	69651	40993	20715	36375
24	01.10.15	10096	33429	65500	41319	20723	36406
25	01.11.15	7286	33451	65192	41644	16690	36437
26	01.12.15	8742	33473	85211	41970	21667	36467
27	01.01.16	7580	33495	51540	40764	16614	39439
28	01.02.16	9993	33517	60697	40962	22389	39715
29	01.03.16	12563	33539	73884	41160	24412	39991
30	01.04.16	12726	33561	70774	41359	23546	40267
31	01.05.16	10327	33583	67412	41557	21790	40542
32	01.06.16	9776	33605	70937	41755	20356	40818
33	01.07.16	9565	33628	65657	41953	19192	41094
34	01.08.16	8299	33650	66946	42151	20980	41370
35	01.09.16	6429	33672	67809	42349	19146	41646
36	01.10.16	5414	33694	65542	42548	18597	41922
37	01.11.16	6196	33716	72089	42746	19628	42197

38	01.12.16	7064	33738	87512	42944	21857	42473
39	01.01.17	5046	36284	57995	46033	17650	44010

Upon taking a decision to use the model, the test data will be added to the practice data and refine the model parameters for the use in real conditions. The sales forecast itself already presents valuable information that enables to identify seasonality and factors that indirectly indicate misuse or theft (e.g., increased consumption with stable demand), etc. When working with the forecasting data (to assess their reliability), we will use the risk assessment value (Mylnikov, 2016). The risk assessment is calculated on the basis of a certain number of factors that affect the risk:

$$r = |1 - \frac{a}{a^*}|,$$

Where a is the predicted value of the evaluated factor; a^* is the exact value of the evaluated factor from the test sample.

4. Findings

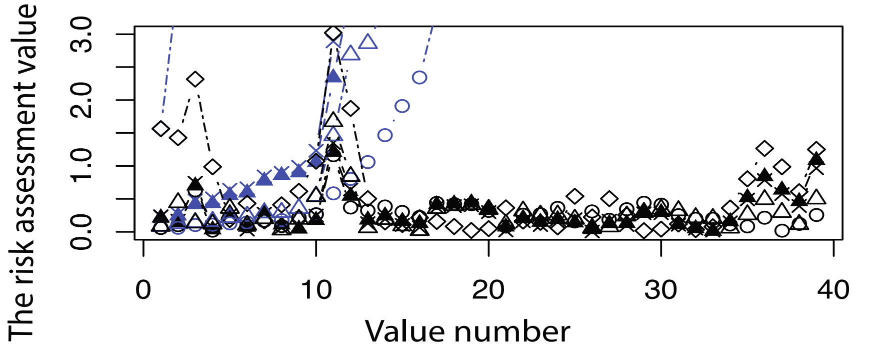
To determine the horizon for each of the forecasts, we will use the progressive total of the risk assessment value (see Figure 2). To estimate the overall risk, we will use the expression $P = 1 - r$ (according to the definition of the risk assessment) and the value of the risk assessment given in tabular form considered as a chain of interrelated events. Given that the probability that events c_1 and c_2 are dependent, provided that c_2 occurs when $c_1 P(c_1 + c_2) = P(c_1) + P(c_2) - P(c_1)P(c_2)$, we obtain

$$r(c_1 + c_2) = 1 - P(c_1 + c_2) = 1 - 1 + r(c_1) - 1 + r(c_2) + 1 - r(c_1) - r(c_2) + r(c_1)r(c_2) = r(c_1)r(c_2)$$

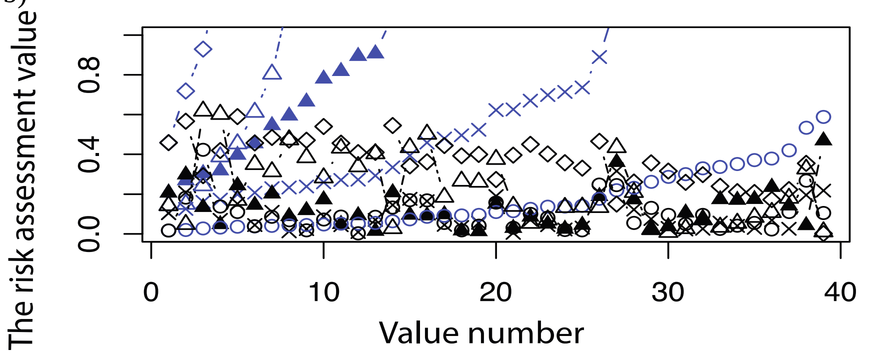
The values obtained show that, from a certain moment, the risk assessment value begins to increase sharply, which allows us to choose the planning horizon.
The values received demonstrate that after a certain moment there is a sharp increase in the value of the risk assessment, which allows us to determine the forecast horizon for each method and the preferable forecasting method (the method with the longest planning horizon, see Figure 2).

Figure 2. *Instantaneous value of the risk assessment using forecasts and cumulative values, where the cross is the support vector machine, the black triangle is the regression, the white circle is the autoregression, the rhombus is the wavelet analysis, the white triangle is the fractal method: a) Ford Mustang, b) Ford F-Series, c) Ford Explorer.*

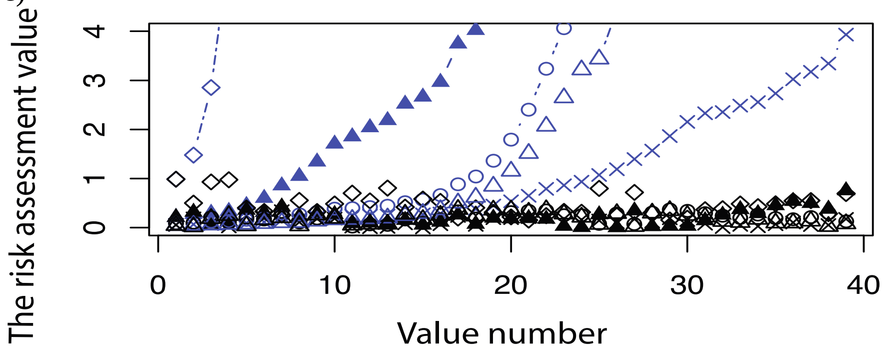
a)



b)



c)



The use of a risk-assessment approach is justified since the results obtained fully correlate with other methods of accuracy assessment: the root-mean-square error $\delta_{rel} = \sqrt{\frac{\sum_{t=i}^{n}(y_t-\widehat{y_t})^2}{n}}$, where− n is the length of the time series, y_t and $\widehat{y_t}$ predictive and exact (retrospective statistical) values and the average approximation error $\bar{\Delta}F = \frac{\sum_{t=i}^{n}\Delta p}{n} = \frac{\sum_{t=i}^{n}|y_t-\widehat{y_t}|}{n}$. As we can see from Table 2, the proposed method gives a match for the first and second optimal methods (in terms of the accuracy of prediction).

Table 2. *Results of the accuracy estimation of the obtained forecasts for the Mustang car*

	Regression method	Support vector machine	Autoregression method	Wavelet analysis	Fractal analysis
Ford Mustang					
Mean square error	2792.051	**2586.582**	2780.096	4444.728	2902.137
Mean error of approximation, %	30.05322	28.54587	**26.8457**	59.44638	28.5975
The number of iterations before the sharp increase in the value of the risk assessment	5	5	**10**	8	9
Ford F-Series					
Mean square error	10543.86	**7769.33**	8167.399	9522.45	12945.55
Mean error of approximation, %	13.04173	**9.30563**	9.527343	12.13911	15.67242
The number of iterations before the sharp increase in the value of the risk assessment	1	10	**28**	1	2
Ford Explorer					
Mean square error	5355.316	**2371.569**	4883.227	17161.69	3131.141
Mean error of approximation, %	22.35523	**10.77976**	20.56545	90.50585	13.18923
The number of iterations before the sharp increase in the value of the risk assessment	7	**25**	18	1	19

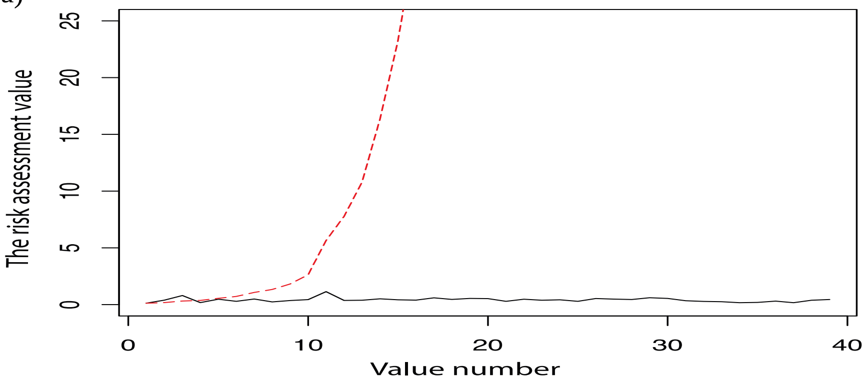
As we noted above, when using forecasts in decision support models, it is necessary to estimate the risk assessment values for the values obtained. We will consider the forecasts used as independent parameters. Since independent parameters c_1 and c_2 are $P(c_1 c_2) = P(c_1)P(c_2)$, then the risk assessment value will be determined as

$$r(c_1 c_2) = 1 - P(c_1 c_2) = 1 - P(c_1)P(c_2) = 1 - \left(1 - r(c_1)\right)\left(1 - r(c_2)\right) = 1 - 1 + r(c_1) + r(c_2) - r(c_1)r(c_2) = r(c_1) + r(c_2) - r(c_1)r(c_2)$$

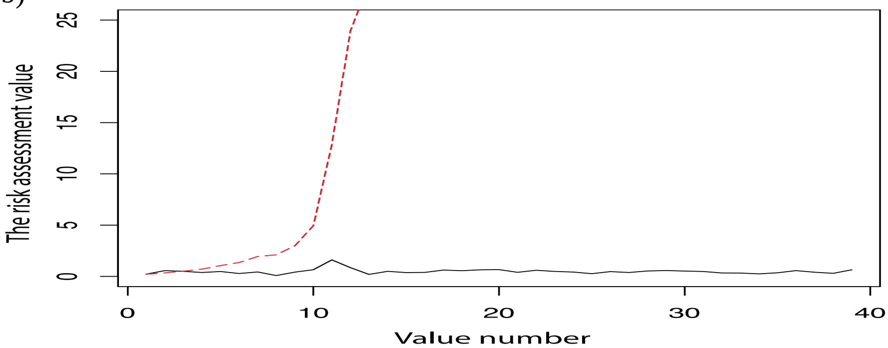
The values obtained for master production scheduling for the three Ford models considered are shown in Figure 3.

Figure 3. *Risk assessment values (solid line) and the progressive total of the risk assessment (dotted line) for solving the problem of master production scheduling on the basis of forecast values for two goods: a) using the best forecasting results; b) using second-best forecasts.*

a)



b)



The graphs demonstrate that, like in case of the risk assessment of individual parameters, from a certain point there is a sharp increase in the risk assessment value. This allows us to set the planning horizon for the method used, which, as we can see from Figures 2 and 3, is shorter than the confidence planning horizon for individual parameters. It should be noted that the increase in the risk value is sharper compared to the assessment of individual parameters, which indicates that going beyond the horizon examined will almost certainly lead to management errors and the need for regular adjustment of plans (Fang and DeLaurentis, 2014).

5. Discussion

The study considers mathematically formalisable planning and management problems. Such problems, as a rule, are NP-complete and solved with approximate algorithms (Cormen, 2009). The solutions obtained are approximate and this requires the assessment of management (planning) risks. In addition, these problems are solved using forecast data. Thus, the problem is formulated in terms of statistics, but the model itself can combine different types of formalisations, the result of which being the combination of different types of modeling (criterial and variable-counter). Concretization of models necessitates choosing approaches and methods of formalisation among various already known approaches, methods, and models that are assembled as a composition (correspondence of departure and arrival domains) (the Post correspondence problem). The application of forecast data and risk assessments in optimal management problems 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. Risk management in the models obtained enables to take into account the probabilistic nature of the processes that take place outside the examined PS, but directly affect its operation.

The approach proposed in the article involves the use of forecasts in planning and management problems through the application of risk assessments and allows one to take into account the time factor. This makes it possible to set a planning horizon based on risk assessments and to carry out risk assessment within the selected solutions. In this case, the method does not put forward requirements for model formalisation, but solely relies on the selected parameters, the forecast data and the statistical data used to build the forecast models.

The paper considers only some examples of obtaining values in the model when implementing projects. It may happen that the actual values will differ from those obtained as a result of the prediction within the confidence interval. To take this factor into account, one should carry out multiple modeling of deviations in forecast values in confidence intervals regarding their probability density. Thus, we will receive not single values of risk assessment for each time point, but possible ranges of values. Such estimates will develop the propositions of the following study, allowing us to obtain not only risk assessments related to the use of forecasts in decision-making, but also the accuracy and sensitivity of the models used.

The method examined in the study can be extended to obtain assessments of production risks when performing multiple calculations and accounting for the risks associated with the wear and tear of equipment (Pan et al., 2012). For this purpose, one can use the probability values dealing with production which are obtained from statistical data. This will enable to take into account the time factor in planning and production activities dealing with the implementation of commodity projects in the PS as well as consider non-deterministic risks.

6. Conclusion

The article demonstrates that the management of commodity innovation projects relies on a group of indicators depending on the type of project, processes occurring in the PS, management tasks and product characteristics. We considered the task of justifying the choice of managerial decisions by means of numerical methods using optimisation models taking into account time factors and risk assessments. In case of risk assessments, one can consider the probabilistic nature of the solutions obtained, and the results of these assessments are presented as a tabular time function with the time step chosen for the solution of the problem.

This approach is particularly important regarding the growing number of management problems formulated as optimisation problems. At the same time, such problems are, as a rule, NP-complete problems with approximate algorithms used to solve them. This makes it possible to form a set of solutions close to the Pareto-optimal solution (the range of their distribution can also vary with time depending on the constraints imposed). Within their original method, the authors used R language and RStudio development environment. These results are consistent with data obtained by other methods of assessing the reliability of forecasts and allow, in contrast to these, making integrated risk assessment of the results depending on the chosen parameters introducing the factor of uncertainty, and what is more, to determine the numerical value of the planning horizon.

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