Prediction-Based Planning in Production System Management through Subsystem Interaction

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Abstract: The research concerns the investigation of predictive models based on optimal control task. It allows increasing the management efficiency due to joint consideration and synchronization of internal and external processes towards the system. In this paper, the predictive model for solving multicriterion product management task was developed. To develop a model, automotive industry data was processed. The paper follows the reflexive approach and provides an application of simulation modelling to solve jointly the optimization problem taking into account the mutual influence of the production subsystems. The feasible solutions were received as functions of time. The solutions obtained were compared with the practical ones that based on historical data. The practical significance of the research lies in using market data to estimate company capabilities preliminarily whether they meet the market needs. At the same time, the objectivity of strategic decisions is increasing due to the formalization of process description, objective data preparation, and the company synchronization with the external environment.

1 INTRODUCTION

The market situation changes dynamically and the competition increases. The potential effect of the better management quality in production systems is concerned with company's susceptibility to the market changes and customer preferences. Companies have to implement new developments following fashion and customer preferences, create new markets, take into account the reduction of the product lifetime, the increase of modification number, product structural complexity, energy and resource intensity of production processes, a number of production systems involved in the production cycle. Furthermore, transferring from flow production to small-batch and even job (one-off) production for customer needs is an upward trend. The project developers start regarding production as a service. Thereby, there is an opportunity to order the service from different manufacturers in different countries, change the lot sizes, and make modifications. The production systems aspire to improve their universality and production processes flexibility, follow the path of progressive transformation of computer-aided manufacturing into automatic one and the virtual fabric. Therefore, the process of manufacturing tasks solving requires the better quality and the higher efficiency of the management decisions, especially for the small companies.

The factors that are not considered together previously, begin to influence the efficiency of the production system operation significantly. Thus, for example, it becomes impossible to consider management tasks only as industrial engineering and selling. The joint consideration of production and power-supply systems, warehouse operation, logistical organization, recycling and resource reusing tasks is required.

The subsystem interaction is considered with the time factor and traditionally based on using differential calculus. However, when developing the predictive model to manage production and technological processes it becomes complicated to formulate it because of the processes complexity. And when it is done the model obtained is usually insoluble. Therefore, the approaches based on the optimal control [1] and game theory [2] principles get widespread. When several subsystems are considered jointly, these approaches are confronted with the multicriteria problem. It causes an appearance of such methods as folding technique, criteria ranking, and reflexive control. The approaches increase task dimension, and solution finding faces NP-completeness and necessity of using metaheuristic methods.

The introduction of the time factor makes the task more complicated and necessitates simulation modelling of Δt or special condition principles. In this case, the solution will be found in the form of tabulated function. This formulation permits turning to the proactive management due to using the predictive models and solving the problem of lagging between decision and external situations regarding the system under consideration (internal processes synchronization and market condition). On the other hand, it requires better forecast quality.

2 THE PROBLEM STATEMENT

The predictive model development is based on forecasts [5].

The initial data of industry-oriented predictive model is generally represented in time series. The example is in Table 1.

Table 1: The initial data example described price changing.

Date	Price of Ford Mustang
01.11.2013	36654
01.12.2013	36652
…	…
01.01.2017	36284

Up-to-date models in the industrial engineering field are directed to the external and internal processes synchronization in order to reduce

- financial, time, and energy costs
- warehouse capacity
- path length travelled by components within a company
- negative impact on the environment, etc.

The models, therefore, are directed not only at process optimization but also at risk minimization [6], [7].

These tasks need to be considered according to the process proceeded dynamics. The description with using differentials prove to be too complex though, so simulation modelling is necessary.

In this case, each of the tasks is possible to describe with a separate criterion using reflexive approach. Moreover, we could find their solutions as a set of optimization problems, that have common parameters and use forecast-based data. Figure 1 shows the scheme of the models interaction. The received solution will be a tabulated time function with a fixed time step (the Δt principle).

Let us examine the tasks for the model described in Figure 1.

The economic lot-scheduling problem is mathematically described in the following way:

$$\sum_{ww^*} K_{ww^*}(C_w(t) * x_w(t) + C_{w^*}(t) * x_{w^*}(t)) \to \max,$$

$$\sum_{zw} R_{zwj} * S_{wk} * x_w(t) \le P_j, \forall j,$$

$$\sum_{w} S_{wz} * x_w(t) \le L_z, \forall z,$$

$$x_w(t) \le G_w(t), \forall w,$$

$$x_w(t) \ge 0, \forall w,$$

where K_{ih} — product w and w^*compliance coefficient;

w — product index;

x_w — production volume of product w;

C_w — net profit from product w manufacturing;

R_{zwj} — requirement in facility capacity for treatment material/ item/ component z of product w by facility j;

P_j — total capacity of facility j;

S_{wz} — requirement of material/ item/ component z per product unit w;

L_z — available material/ item/ component z;

z — index of material/ item/ component;

G_w — market/ demand/ order restriction for product w.

The purchase management task could be formulated as:

$$\sum_{zw} A_{zw}(t) * u_{zw}(t) + V_z(t) * L_z(t) + N_z(t) * y_z(t) \to \min,$$

$$L_z(t-1) + y_z(t) - B_z(t) = L_{zw}(t), \forall z,$$

$$\sum_{zw} R_{zwj} * S_{wk} * x_w(t) \le P_j, \forall j,$$

$$u_{zw}(t) \in [0,1], \forall z, w,$$

$$y_{zw}(t), L_{zw}(t) \ge 0, \forall z, w,$$

where u — Boolean flag representing if re-equipment/ revision/ reboot needed;

y — purchase volume;

A_{zw} — re-equipment/ revision/ reboot cost;

B_z — requirement/consumption of material/ item/ component z for manufacturing product w;

V_z — storage cost of material/ item/ component z;

N_z — cost of material/ item/ component z.

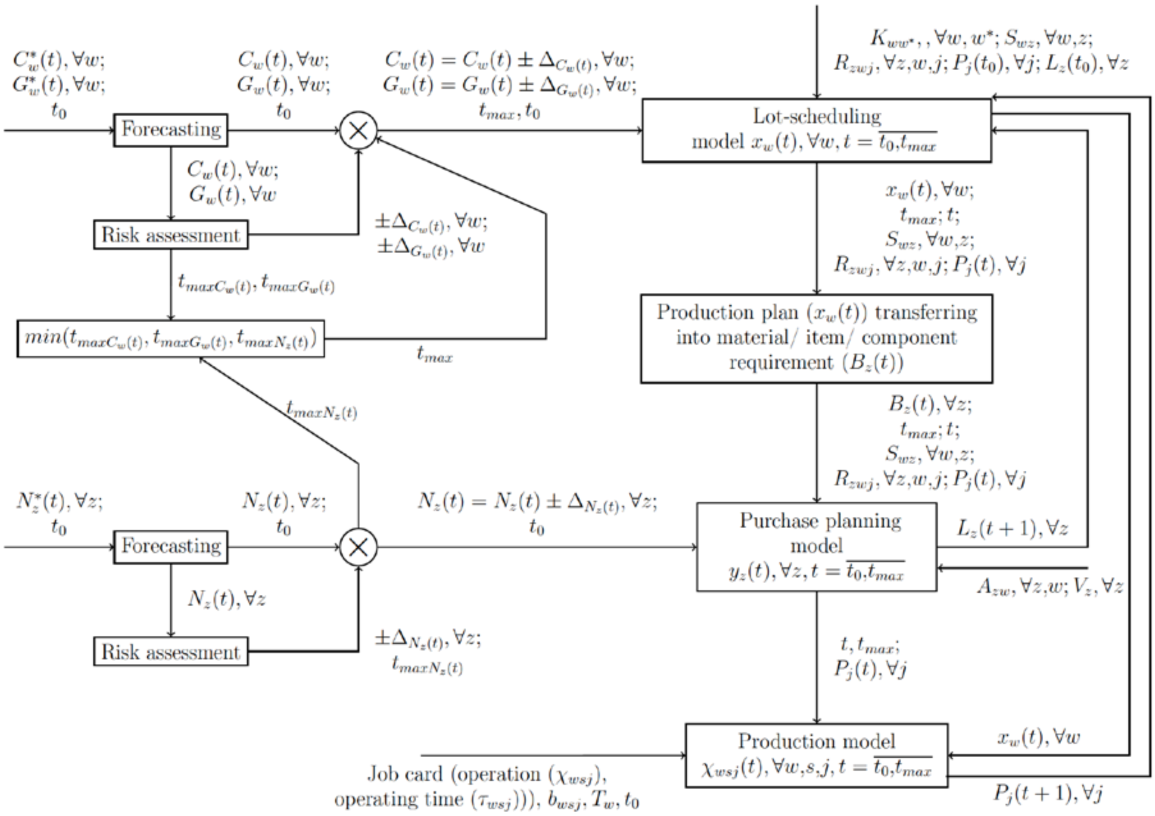

Figure 1: Structural scheme of predictive model interaction when their joint solution finding.

Below is a sequence of work planning task when assembling a product from a multitude of parts:

$$\sum_{wsj} k_{wsj} * \chi_{wsj}(t) * \tau_{wsj} \to \min,$$

$$\sum_{ws} \tau_{wsj} \le P_j(t), \forall j,$$

$$\sum_{js} \tau_{wsj} \le T_w * x_w(t), \forall j,$$

$$\sum_{j} k_{wsj} * \chi_{wsj}(t) * b_{wsj} = \sum_{j} \chi_{w(s+1)}(t) * \tau_{w(s+1)},$$

$$\forall w, s = \overline{1,(s^* - 1)},$$

where s – assembly step $s = 1, s^*$, s^* – last operation;

k_{wsj} – variable production costs

χ_{wsj} – number of operation at the point in time t

τ_{wsj} – time costs at step s on the facility j when manufacturing product w

b_{wsj} – coefficient of spoilage ($0 \ge b_{wsj} \ge 1$)

T_w – total time of manufacturing product w

Some parameters are computable. We could find their values using a job card. The general form of the job card is shown in Table 2.

For example, within the purchase management problem, B_z is the very parameter, which value depends on the production value of each product and total requirement of material/ item/ component z.

When considering the range of optimization problems as time problems, we are able to take into account a number of parameters as time functions. The set of item and storage costs time functions are represented in Table 3.

Table 2: Job card structure.

ID	Number/code of product (w)	Operation (χ)	Operation time(τ)	Previous operation (χ)	Facility (j)	Number of facilities (R)	Material/ component (z)	Consumption rate of material/ component (S)
1	1	$\chi_{1,s,j}$	τ_{1s1}	$\chi_{1,s-1,j}$	1,2	1,2	1	1
2	1	$\chi_{1,s,j}$	τ_{1s2}	$\chi_{1,s-1,j}$	2	1	2	1
3	1	$\chi_{1,s,j}$	τ_{1s3}	$\chi_{1,s-1,j}$	3	1	2,3	2,4
4	2	$\chi_{2,s,j}$	τ_{2s4}	$\chi_{2,s-1,j}$	3,4	1,1	2	1
5	2	$\chi_{2,s,j}$	τ_{2s5}	$\chi_{2,s-1,j}$	5	1	1,3	2,1
6	2	$\chi_{2,s,j}$	τ_{2s6}	$\chi_{2,s-1,j}$	6	1	1	1
…	…	…	…	…	…	…	…	…
	w	$\chi_{w,s,j}$	τ_{wsj}	$\chi_{w,s-1,j}$	j	R_{zwj}	z	S_{wz}
…	…	…	…	…	…	…	…	…

Table 3: Item and storage costs changing.

Date	Item	Item cost (RUB)	Storage cost (RUB)
Jan	1	100	10
	2	150	10
	3	220	12
Feb	1	100	10
	2	150	10
	3	220	12
Mar	1	110	10
	2	160	10
	3	230	12
Apr	1	110	10
	2	160	10
	3	240	12
…	…	…	…

A large number of parameters is defined with the time series and used them for forecast describing. Consequently, the result depends on forecast accuracy increases. In this case, the system behaviour investigation by modelling of predicted values deviation becomes actual. The use of forecasts leads to probabilistic models appearing based on risk assessment [8], Bayes theorem [9], and Monte-Carlo method [10].

3 PROBABILISTIC CHARACTER OF PARAMETER FORECASTING DEFINED WITH TIME SERIES

The use of forecasted values brings up the question of error estimate what computing risk assessment can be used for [11]. The risk assessment is calculated subject to the factors influence on the risk value: $r = \left|1 - \frac{a}{a^*}\right|$, where a – forecasted value of the estimated factor; a^*– exact value of the estimated factor.

In order to determine the planning horizon, we used the test sample. The continuous independent variables should be selected for considering management task, that uses forecasts of several factors. Consequently, the values of the variables are also independent events.

For independent parameters c_1 and c_2 the following dependence is correct:

$P(c_1c_2) = P(c_1)P(c_2)$, where $P(c)$ – probability of occurrence c.

Based on $P = 1 - r$, where P – probability, we could determine risk assessment values:

$$r(c_1c_2) = 1 - P(c_1c_2) = 1 - P(c_1)P(c_2) =$$

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

The forecasted values are time series. Therefore, the values could be considered jointly according to their simultaneous calculation.

Hence, risk assessment could be carried out with the cumulative sum. Parameter c_1 in the probability of occurrence formula takes values c_{1_1} and c_{1_2}:
$P\left(c_{1_1} + c_{1_2}\right) = P\left(c_{1_1}\right) + P\left(c_{1_2}\right) - P\left(c_{1_1}\right)P\left(c_{1_2}\right).$
$r\left(c_{1_1} + c_{1_2}\right) = 1 - P\left(c_{1_1} + c_{1_2}\right) = 1 - 1 +.$
$+r\left(c_{1_1}\right) - 1 + r\left(c_{1_2}\right) + 1 - r\left(c_{1_1}\right) - r\left(c_{1_2}\right) +$
$+r\left(c_{1_1}\right)r\left(c_{1_2}\right) = r\left(c_{1_1}\right)r\left(c_{1_2}\right).$

In order to calculate the following risk assessment values we used formula
$r(c_{1_{i-2}} + c_{1_{i-1}} + c_{1_i}) = r\left(c_{1_{i-2}} + c_{1_{i-1}}\right) +$
$+r\left(c_{1_{i-1}}\right)r\left(c_{1_i}\right)$

4 JOINT SOLUTION OF MANAGEMENT AND PURCHASE PROBLEMS

Each of optimization tasks received can be classified as a multiparameter task with non-linear restriction, some parameters of which are defined as time functions. The solutions of the tasks will be also time functions.

The gradient methods were the first to appear. They need the function to be twice differentiable and convex. The disadvantage of the methods is sensitivity towards the initial value, and also freezing in local extrema in the case of multiextremality, nonconvex restrictions, multiply connected feasible region etc.

Modern methods divided conditionally into three groups [12]: clustering, constraint propagation, and metaheuristic methods. When choosing the solving method, it should be taken into account that completeness is the most important feature of combinatorial optimization methods. The comprehensive method guarantees solution finding in the case of its existence. However, the large dimension of search space complicates the application of the method. In addition, solution search time might be unacceptable, e.g. because of decision time restriction. In case heuristic methods are used or combinatorial methods are supplemented with heuristic elements, the proof of the method completeness becomes more complicated. Heuristic search methods are for the most part incomplete.

In practice, hybrid methods are widespread. Moreover, any algorithm results would be improved due to joint solver constructing. In view of specialized solving method absence, it is reasonable to apply the evolutionary approach namely stochastic search method. The disadvantage of evolutionary methods is result and optimization time dependence on initial approximation.

For calculating tasks mentioned above, we used the genetic algorithm and its implementation in the programming language R – rgenoud package. The package combines evolutionary search algorithm with the methods based on derivatives (Newton or quasi-Newton) [13].

The example of product management problem solving, with the economic lot-scheduling subsystem considered, is described in Listing 1.

Listing 1. Function calculating production value

```
opt_GA_volume_time_plan <- function(C,
G, P, R, L, q1, q2, t){
    var <- length(C[1,])
    x <- matrix(NA, nrow = length(C[,1]
), ncol = var, byrow = TRUE)
    y<- NA
    for (i in 1:t) {
        x[i,] <- genoud(function(y) K[1
,2]*(C[i,1]*y[1] + C[i,2]*y[2]), nvars
= var, max = TRUE, starting.values = NU
LL, Domains = matrix(c(0, G[i,1], 0,G[i
,2]), ncol = 2, byrow = TRUE),data.type
.int = TRUE)$par
    }
    return(x)
}
```

The joint solution problems under discussion are represented algorithmically in Figure 2.

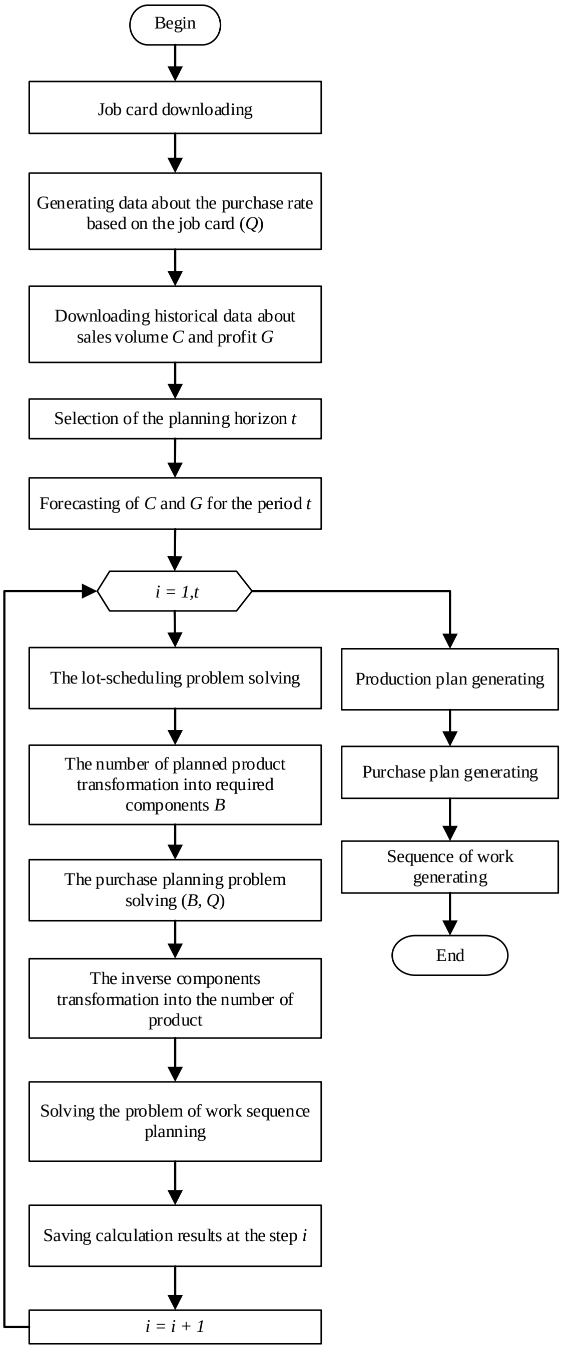

Figure 2: Flow chart of predictive model for joint optimization.

6 THE FINDINGS ANALYSIS

As a result, we received the set of findings:

- The planning horizon estimation for the methods used (Figure 3);
- The optimum production plan (Figure 4);
- The estimation of criterion function variation (Figure 5);
- The estimation of parameters sensitive to criterion function variation (Figure 6).

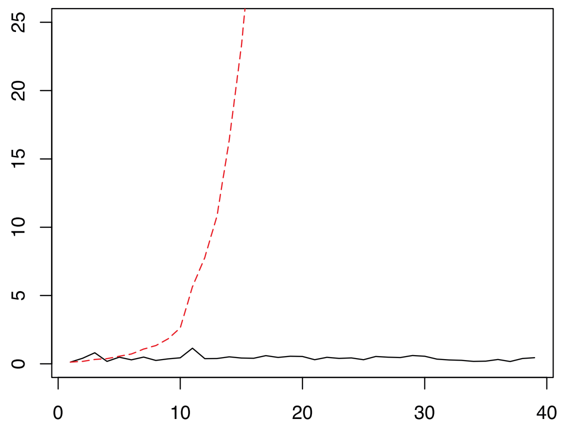

Figure 3: The magnitude of risk assessment obtained using the fractal forecast method.

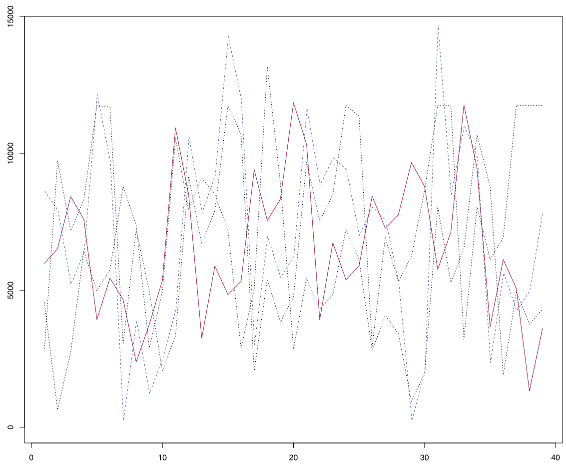

Figure 4: The lot-scheduling plan (plan and fact matching for two products).

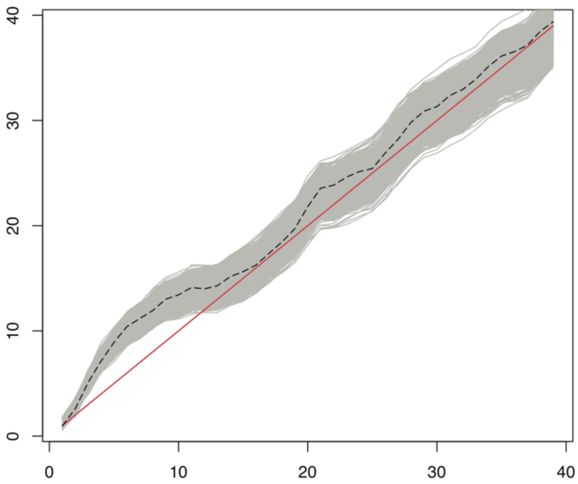

Figure 5: The reduced criterion variation obtained using the fractal forecast method.

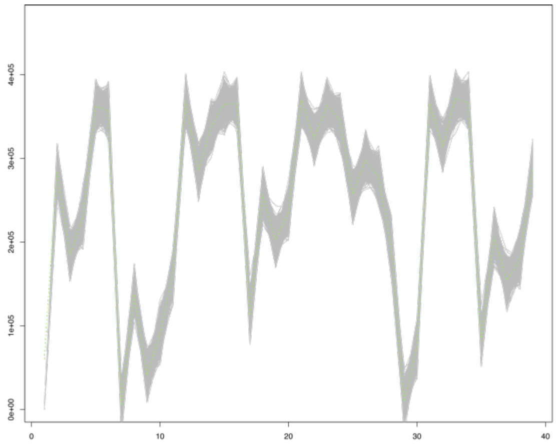

Figure 6: The requirement for one kind of item according to possible variation in the production plan.

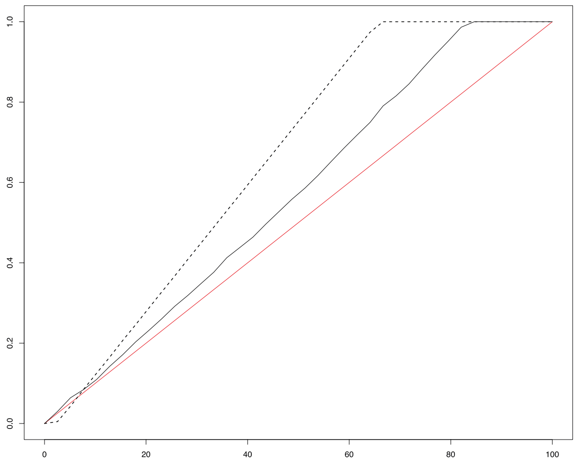

Figure 7: The comparison of loading (lot-scheduling) when implementing various production plans by ROC analysis.

The variation in production plan and management affects the production system. It is necessary to take into account during a process of management decision making. For example, in some cases, we can expect the system profitability increase with a decline in production value and facility/ warehouse/ staff loading. Thereby, the comparative analysis is needed. It would be made using the ROC curve (Figure 7).

6 CONCLUSION

The findings show, that the result depends on the forecast accuracy. It is worth noting that results do not consider delay and inertia factors, which take place in real production systems, load them more, and can cause an organizational change in production.

Despite it, the created models could be implemented. Expected that they improve the efficiency of the production system work during the transition to the virtual production and Industry 4.0 concepts. The described in this paper models take into account several factors such as energy and resource intensity of the production processes tending to increase.

The development of the model should be solving the tasks associated with:

- inertia factor
- costs of the production volume changing
- transport subsystem risks
- delivery of defective parts
- product returns.

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