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DEMAND PREDICTION OF PRODUCTION MATERIALS AND SIMULATION OF PRODUCTION MANAGEMENT

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Abstract
In modern times, production management must quickly respond to the fluctuations in the demand for production materials by production equipment oriented to different orders. This calls for a reasonable plan for production management. Based on Markov model, this paper explores the demand prediction of production materials, and investigates the simulation of production management. Firstly, the grey system model and the Markov chain model were combined into a hybrid prediction model for the dynamic and time-varying demand for production materials in the production process. Through dynamic scenario analysis, the authors explored the formulation of production management and control strategies under multiple uncertain demands for production materials, and gave the specific analysis process. Multiple performance indices were considered synthetically, the optimization objectives of production control simulation were given under the multiple uncertain demands for production materials, and a solution was put forward for the production control problem. The simulation results verify the effectiveness of the proposed model.
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Key Words: Markov Model, Demand Prediction of Production Materials, Simulation of Production Management

1. INTRODUCTION

With the progress of the manufacturing industry and the improvement of consumer demand for consumption quality and individualization, enterprises must pursue the diversification and intellectualization of product demand and production process, and production management must quickly respond to the fluctuations in the demand for production materials by production equipment oriented to different orders [1-9]. Facing different orders, the production material guarantees for production equipment involves the purchase, deployment, transportation and storage of materials. Hence, the management of production materials is crucial to the smooth completion of production tasks [10-16]. As various intelligent manufacturing technologies and intelligent production equipment enter the production workshop, there is a growth in the types and consumption of different production materials, in the pursuit of a short time interval between production processes [17-21]. The fluctuations in the demand for production materials by production equipment arise from the uncertainty of the demand by consumer orders. Therefore, it is extremely important to arrange and implement a reasonable plan for production management.

The design of the industrial product service system involves many difficulties, such as uncertain customer demand, strong subjectivity of experience design, and long debugging time. It is crucial to find a suitable way to solve these difficulties. Zhang et al. [22] presented a design model that integrates an improved affinity propagation (AP) clustering algorithm, quality function development (QFD) and axiomatic design (AD), determined and standardized the uncertain consumer demand, and examined the function of the product service system. The results demonstrate that the upper-level processes and methods can effectively guide the design process in production applications. To utilize material requirements planning (MRP) software for efficient production planning and raw material inventory management, Yimsri et al. [23] collected the data related to the production planning process, analysed inventory, raw material

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and warehouse management issues with the Ishikawa diagram, and obtained a solution by a software implementing the MRP principle. Their solution can fully calculate and manage spare parts required for production. Mezentsev et al. [24] raised the issue of controlling the input and output logistics of industrial enterprises, supplemented the condition of setting the selling price, and adjusted the condition according to the number of sold products. Concerning the model constraints, they systematically considered production factors, resource constraints, and the logic of input and output logistics. The considered model and the given control problem were investigated by a unified approach, which can handle any complex logical conditions and set the corresponding formal optimization problem. The algorithm was tested on the data close to industrial (real) size. Huang et al. [25] established a production material management system based on polymorphic wireless technology. The system can capture real-time data of various measuring instruments and electronic balances installed in industrial sites, laying a scientific basis for production management.

Unlike the literature, this paper explores the demand prediction of production materials based on Markov model, and investigates the simulation of production management. Firstly, Section 2 combines the grey system model and the Markov chain model into a hybrid prediction model for the dynamic and time-varying demand for production materials in the production process. Next, Section 3 carries out dynamic scenario analysis, explores the formulation of production management and control strategies under multiple uncertain demands for production materials, and illustrates the specific analysis process. Two or more performance indices, including the type, quantity, equipment, and time of material demand, were considered synthetically, the optimization objectives of production control simulation were given under the multiple uncertain demands for production materials, and a solution was put forward for the production control problem. Finally, the effectiveness of the proposed model was demonstrated by the simulation results.

2. CONSTRUCTION OF GREY MARKOV PREDICTION MODEL

The Markov chain is a stochastic process about the random transfer between states. The grey system model and the Markov chain model, both of which can be used for series prediction, can compensate for each other's shortcomings. The combination of these two methods is suitable for long-term, data-volatile prediction problems, and forecast the overall trend of the prediction system according to the current state of the variable and the law of state transfer. Because the demand for production materials in the manufacturing process is dynamic and time-varying, the long-standing historical data of the manufacturing process for real-time predictions have a low reference value. Therefore, this paper combines the grey system model and the Markov chain model into a composite prediction model, trying to achieve more ideal prediction effect.

In the grey Markov prediction model, the raw data of the demand variables for different kinds of production materials in the production process can be expressed as:

$$A^{(0)} = \left(A^{(0)}(1), A^{(0)}(2), A^{(0)}(3), \ldots A^{(0)}(m)\right) \tag{1}$$

Suppose $A^{(1)}(l) = \sum^{m}_{i=1}A^{(0)}(i)$, i = 1, 2, 3, ..., m. Through accumulated generating operation (AGO) of Eq. (1), the following first-order AGO series of the demand variables for production materials can be obtained as:

$$A^{(1)} = \left(A^{(1)}(1), A^{(1)}(2), A^{(1)}(3), \ldots A^{(1)}(m)\right) \tag{2}$$

Based on Eq. (2), the first-order linear differential equation can be derived for the GM (1, 1) model for the demand prediction of production materials:

$$\frac{dA^{(1)}}{dA} + \tau A^{(1)} = \kappa \tag{3}$$

Let τ and κ denote the grey parameters to be identified. The former represents the development coefficient that characterizes the trend of the estimated series of production behaviour for different orders. The latter is the grey action quantity that characterizes the relationship between the changes in the demand data of production materials. This quantity is mined from the series of production behaviour from different orders. The grey parameters can be solved by the least squares method:

$$\hat{\beta} = \begin{pmatrix} \tau \\ \kappa \end{pmatrix} = \left(Y^T Y\right)^{-1} Y^T B_{(m)} \tag{4}$$

where,

$$Y = \begin{bmatrix} -0.5\left[A^{(1)}(1) + A^{(1)}(2)\right] & 1 \\ -0.5\left[A^{(1)}(2) + A^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -0.5\left[A^{(1)}(m-1) + A^{(1)}(m-2)\right] & 1 \end{bmatrix}, B_{(m)} = \begin{bmatrix} A^{(0)}(2) \\ A^{(0)}(3) \\ \vdots \\ A^{(0)}(m) \end{bmatrix} \tag{5}$$

Substituting the solved τ and κ into the demand prediction model of production materials, the corresponding time response function can be obtained as:

$$\hat{A}^{(0)}(l) = \hat{A}^{(1)}(l) - \hat{A}^{(1)}(l-1) = \left(\hat{A}^{(0)} - \frac{\kappa}{\tau}\right) * o^{-\tau l} + \frac{\kappa}{\tau} \tag{6}$$

To improve the accuracy of the real-time demand prediction of production materials, this paper corrects the prediction of the grey prediction model based on the grey Markov principle. The direct relative error between the prediction outputted by the grey prediction model and the actual demand for production materials can be calculated by:

$$W = \frac{\hat{A}^{(0)}(l)}{A^{(0)}(l)} * 100\% \tag{7}$$

The residual series of grey prediction can be expressed as:

$$o(i) = A^{(0)}(i) - \hat{A}(i), \text{ where } i = 1, 2, ..., m \tag{8}$$

The Markov state interval can be divided based on the W value:

$$R_{ij} = \left[K_{ij}, V_{ij}\right] \tag{9}$$

The Markov state transfer probability matrix can be given by:

$$T_l = \begin{bmatrix} T_{11l} & T_{12l} & \vdots & T_{1nl} \\ T_{21l} & T_{22l} & \vdots & T_{2nl} \\ \cdots & \cdots & \vdots & \cdots \\ T_{n1l} & T_{n2l} & \vdots & T_{nml} \end{bmatrix}, \text{ where } T_{ij} = \frac{m_{ij}(l)}{m_i} \tag{10}$$

Selecting the intermedia value of $[K_{ij}, V_{ij}]$, the prediction outputted by the grey prediction model was corrected by T_l. Then, the demand prediction of production materials can be optimized by:

$$b = \frac{\hat{A}^{(0)}(l)}{1 \pm 0.5 * \left(K_{ij} + V_{ij}\right)} \tag{11}$$

3. DESIGN OF PRODUCTION CONTROL STRATEGY

Since the demand for production materials with multiple uncertainties may occur at any time, this paper explores the formulation of production control strategies under the demand for production materials with multiple uncertainties through dynamic scenario analysis. The specific analysis process is detailed as follows.

Let OT denote the set of the classes of diversified orders, which include batch orders, personalized orders, urgent orders, additional orders and deleted orders. Let UD denote the set of production material demands with multiple uncertainties, which include the type, quantity, equipment, and time of material demand: $UD_f = (CV_f, CW_f, CQ_f, CP_f)$, ($f$ = 1, 2, ..., F). Let ES denote the set of working states of equipment. Let STR denote the set of production control strategies. Then, the scenario state space ST can be expressed as:

$$ST=\{OT, UD, ES\ , STR\} \tag{12}$$

The causal relationship between the factors affecting the uncertain demand for production materials leads to the evolution of the production control scenarios. This causal relationship is generally direct or indirect (Fig. 1).

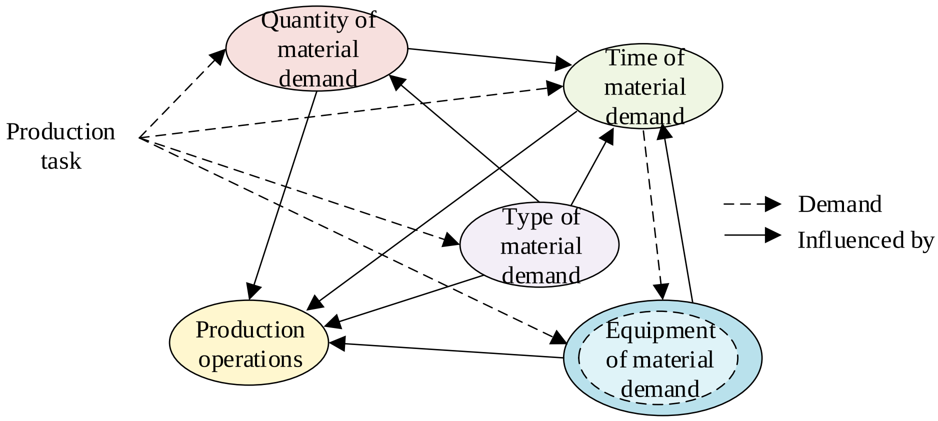

Figure 1: Causal relationship between the factors affecting the uncertain demand for production materials.

Let S^1_{ab}, S^2_{ab}, and S^3_{ab} denote the set of influencing relationships between UD_a and UD_b, UD_a and OT, and UD_a and STR, respectively. Then, the set $SS_{ab} = \{S^1_{ab}, S^1_{ab}, S^1_{ab}\}$of influencing relationships between UD_a and UD_b can be expressed as:

$$UD_a = SS_{ab}(UD_b) \tag{13}$$

To sum up, the formulation strategy of production control strategy R under multiple uncertain production material demands can be expressed as:

$$R = \{p, ST, UD, SS\} \tag{14}$$

where, p is the time of the scenario; UD is the uncertain demand; $SS=\{SS_{ab}\}\subset UD\times UD$; $a,b\in M^*$ is the set of influencing relationships between scenario elements at time p.

Based on the relationship between the influencing factors of uncertain production material demands, it can be found that the formulation of production control strategy will occur in various scenarios, when diversified production tasks face multiple uncertain production material demands. Let x_1 and x_2 be the certain and uncertain types of material demand, respectively; y_1 and y_2 be the certain and uncertain quantities of material demand, respectively; f_1 and f_2 be the certain and uncertain equipment of material demand, respectively; g_1 and g_2 be the certain and uncertain time of material demand, respectively. Then, the specific scenario of production material demand with multiple uncertainties in the actual production process includes:

(1) $x_1\rightarrow y_1\rightarrow f_1\rightarrow g_1$; (2) $x_1\rightarrow y_1\rightarrow f_1\rightarrow g_2$; (3) $x_1\rightarrow y_1\rightarrow f_2\rightarrow g_1$; (4) $x_1\rightarrow y_1\rightarrow f_2\rightarrow g_2$; (5) $x_1\rightarrow y_2\rightarrow f_1\rightarrow g_1$; (6) $x_1\rightarrow y_2\rightarrow f_1\rightarrow g_2$; (7) $x_1\rightarrow y_2\rightarrow f_2\rightarrow g_1$; (8) $x_1\rightarrow y_2\rightarrow f_2\rightarrow g_2$; (9) $x_2\rightarrow y_2\rightarrow f_2\rightarrow g_2$

For the demand prediction of production materials with multiple uncertainties, the strategies are generally to establish a multi-objective model or to perform full random or full fuzzy processing. In order to formulate the production control strategy under uncertain types, quantities, equipment, and time of materials, it is feasible to construct a production control model for the demand similarities of production materials with multiple uncertainties, based on the non-equilibrium strategy that meets the demand.

4. DESIGN OF SIMULATION SCHEME

Our formulation of production control strategy gives comprehensive consideration to two or more performance indices, such as material demand type, material demand quantity, material demand equipment, and material demand time, making the production control affected by uncertain production material demands more realistic. This paper takes the mean process time of the production material workshop as the optimization objective:

$$\frac{1}{m}\sum_{i=1}^{m}\left(d_i - s_i\right) \tag{15}$$

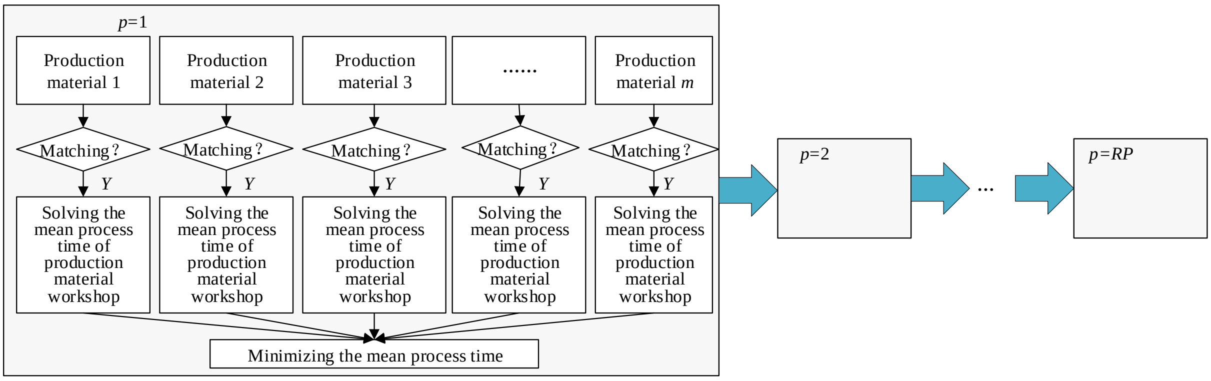

Figure 2: Production control flow under the multiple uncertain demands for production materials.

To complete the production task timely, it is necessary to minimize the mean process time of the production material workshop. The production material must match the equipment with the earliest start time of the production process. When consumers raise a new demand for producing a product, it is necessary to arrange the production process and production materials for the ordered product, following the control process in Fig. 2.

This paper uses the NSGA-II algorithm to simulate and solve the production control problem under multiple uncertain demands for production materials. The first thing is to the production materials, production equipment and production operations in the production control problem into natural numbers. Here, $m\times n$ genes are generated based on the serial number of production materials and production operations. The m materials are represented by natural numbers 1, 2..., m, and the n operations are represented by natural numbers 1, 2, ... Then, there are 1_1, 1_2, 1_3, ……, 1_n, ……, m_1, m_2,……, m_n initial codes. Gene m_1 stands for that operation 1 needs to complete the processing of material m; gene 1_n stands for that operation n needs to complete the processing of material 1.

Before solving the production control problem, it is necessary to convert the chromosomes in a form that can be quickly identified and solved, that is, complete the decoding process. Based on the serial number of production materials and production operations in the genes of each chromosome, an $n\times m$ matrix of the sequence of production material demands can be established. Referring to the coding principle, the authors overlooked the selection of equipment for materials, but only considered the matching of materials and equipment. Let t be an individual in the chromosome population T_p. Then, the decoding process involves the following steps:

Step 1. To facilitate the query and recording of the sequence and serial number of production operations, build up an all-zero matrix $W1$ with n rows and m columns, and set $i = 1$;

Step 2. Judge whether i is smaller than $m\times n$. If yes, return to *Step 3*; otherwise, output $W1$.

Step 3. Let X and Y denote the serial number of materials and operations, respectively. Divide the elements of $t(i)$ into X and Y.

Step 4. Modify the first zero element of row Y in $W1$ to a, add 1 to i, and return to *Step 2*.

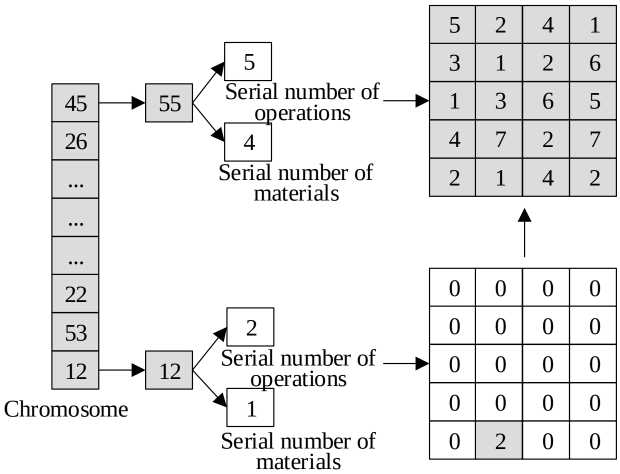

Figure 3: Decoding process.

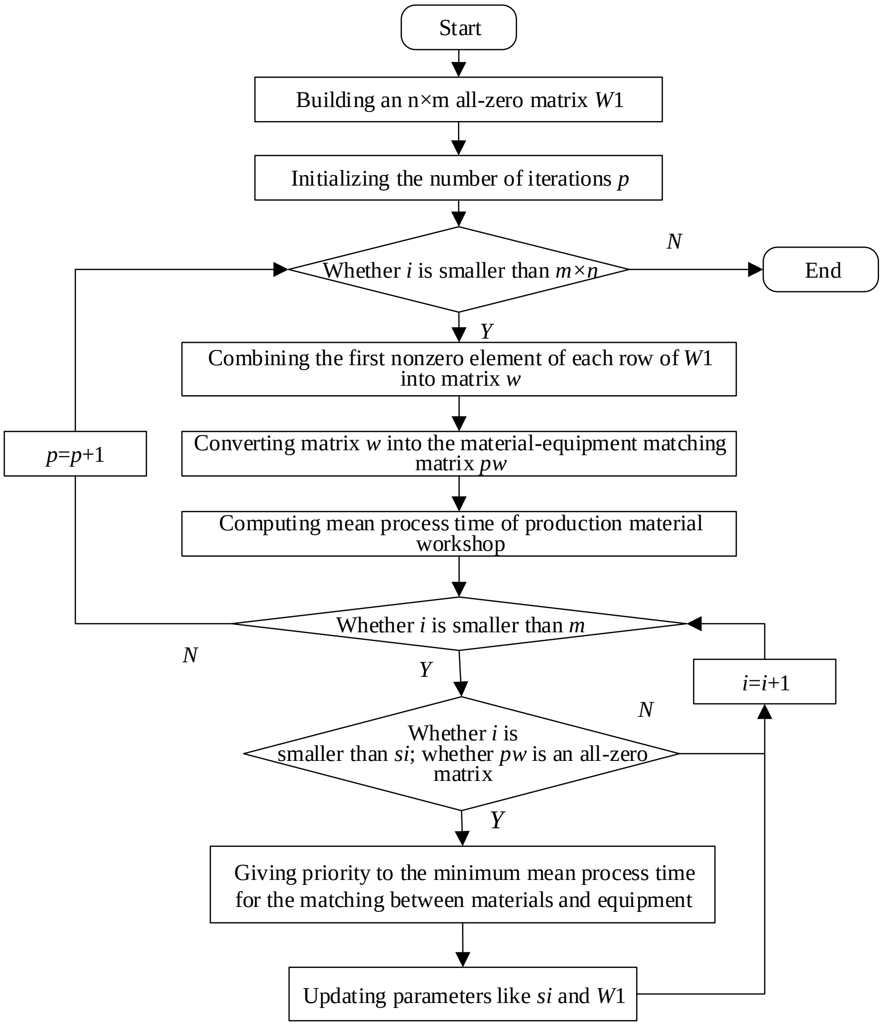

Figure 4: Calculation flow of optimization objective.

Fig. 3 gives an example of the chromosome decoding for the production control under the multiple uncertain demands for production materials. The decoded matrix represents the processing sequence of materials on each operation. The calculation rule for the matching between materials and equipment is that the priority is given to the operation with the shortest mean process time of production material workshop in future.

Fig. 4 shows the calculation flow of the optimization target. There is often more than one non-dominated solutions in the process of solving the production control problem under multiple uncertain demands for production materials. If the optimization aims to minimize g_1 and g_2, then compare solution X with solution Z. If X is better than Z on both g_1 and g_2, then X dominates over Z, and the optimal solution set is $\{X, Y\}$. X and Y formulate the Pareto front of the production control problem.

To obtain the result of the problem, this paper stratifies the chromosome population based on the definition of non-dominated solution. Let i denote any individual solution in the chromosome population. Then, the set numerical variables and set variables of i correspond to the number m_i of remaining solutions that can dominate i, and the number R_i of remaining solution individuals set dominated by i, respectively.

Firstly, the dominance among the individuals of each solution in the chromosome population is judged in turn, and the m_i and R_i of each individual are recorded in real time. Let C denote the empty set, and record the chromosome with $m_i = 0$ as the first layer in C. Let $m_i = m_i–1$ for each solution i in C, and record the chromosome with $m_i = 0$ as the second layer in C_1. The above steps are repeated until all chromosomes are assigned to each layer.

The simulation steps are detailed as follows:

Step 1. Let T_p be the chromosome population. Set i and FR to 1. Define M as the number of chromosomes in T_p.

Step 2. If i is greater than M, a_i belongs to T_p. Let all individual layers in C be $RA = FR$. Classify all chromosomes in C as the first layer, and go to *Step 7*. If i is smaller than M, let R_i be an empty set, $m_i = 0$, $j = 1$, C be an empty set, and go to *Step 3*.

Step 3. If j is greater than M, a_j belongs to T_p, and go to *Step 6*. If j is smaller than M, let the smaller than term $DL = 0$, the equal to term $DE = 0$, the greater than term $DM = 0$, and $l = 0$, and go to *Step 4*.

Step 4. If l is greater than 2, define the objective function of the chromosome in T_p as g_l, and go to *Step 5*; if l is smaller than 2, go to *Step 4.1*.

Step 4.1. If $g_l(a_i)$ is smaller than $g_i(a_j)$, set $DL = DL_1$, $l = l+1$, and go to *Step 4*. If $g_l(a_i)$ is greater than $g_i(a_j)$, go to *Step 4.2*.

Step 4.2. If $g_l(a_i)$ equals $g_i(a_j)$, let $DE = DE+1$, $l = l+1$, and go to *Step 4*. Otherwise, let $DM = DM+1$, $l = l+1$, and go to *Step 4*.

Step 5. If DL equals 0 and DE equals 2, let $m_i = m_i+1$, $j = j+1$, and go to *Step 3*. Otherwise, let $R_i = R_i \cup j$, let $j = j+1$, go to *Step 3*.

Step 6. If m_i equals 0, let $C=C\cup i$, $i = i+1$, and go to *Step 2*. Otherwise, set $i = i+1$, and go to *Step 7*.

Step 7. If C is an empty set, terminate the algorithm. Otherwise, then $i_1=1$, C_1 is an empty set, and go to *Step 8*.

Step 8. If i_1 is greater than the number of elements X in C, go to *Step 12*. If i_1 is smaller than x, go to *Step 9*.

Step 9. If $R_{C(i1)}$ is an empty set, then $i_1 = i_1+1$, and go to *Step 8*. If $R_{C(i1)}$ is an empty set, let $j_1 = 1$, and go to *Step 10*.

Step 10. If j_1 is greater than the number of elements Y in $R_{C(i1)}$, set $i_1 = i_1+1$, and go to *Step 8*. If j_1 is smaller than y, then set $d=R_{c(i1)}(j_1)$, $m_d = m_d–1$, and go to *Step 11*.

Step 11: If m_d equals 0, let $C_1 = C_1 \cup d$, $j_1 = j_1+1$, and go to *Step 10*. Otherwise, set $j_1 = j_1+1$, and go to *Step 10*.

Step 12: $FR = FR+1$, $C = C_1$, let all chromosomes in C $RA = FR$, and go to *Step 7*.

5. SIMULATION AND RESULTS ANALYSIS

The residual test method of the grey prediction model was used to judge the accuracy of the proposed grey Markov prediction model. The calculation results are displayed in Table I.

Table I: Prediction errors of material demand types in the production process.

Operation number	Number of correct predictions	Number of tests	Residual	Prediction error (%)	Absolute prediction error (%)
0	56	59	3	0.051	0.014
1	57	60	3	0.050	0.046
2	52	56	4	0.071	0.125
3	50	53	3	0.057	0.046
4	61	62	1	0.016	0.086
5	63	70	7	0.100	0.012
6	64	65	1	0.015	0.043
7	60	61	1	0.016	0.024
8	63	69	6	0.086	0.081
9	61	64	3	0.046	0.028
Mean relative prediction error					0.051

Table II: Prediction of the quantity of material demand in the production process.

Equipment number	Operation number	Predicted value	Actual value	State transfer probability matrix				Demand state
				1	2	3	4	
A	1	3324	3457	0.1582	0.1362	0.5269	0.2965	Satisfied
	2	5647	5632	0.1695	0.1847	0.5327	0.2741	Satisfied
	3	12471	12345	0.1084	0.1692	0.5182	0.2815	Satisfied
	4	6885	6853	0.1692	0.1528	0.5382	0.2637	Satisfied
	Cumulative state transfer probability			0.4158	0.4271	2.6014	0.9584	Satisfied
B	1	11247	11296	0.15	0.16	0.52	0.28	Satisfied
	2	6345	6317	0.11	0.12	0.59	0.29	Satisfied
	3	3894	3811	0.12	0.14	0.51	0.23	Satisfied
	4	7034	7016	0.14	0.11	0.53	0.28	Satisfied
	Cumulative state transfer probability			0.528	0.595	2.147	1.241	Satisfied

According to the prediction idea of grey Markov prediction model, four production operations of two main equipment were selected for predicting the quantity of material demand. Table II displays the predicted types of material demand in the production process, including the predicted and actual quantities of material demand, and the state transfer probability matrix. It can be seen that, under the optimization objective of production control, the production material demands of different operations on different equipment can be basically satisfied.

Based on the forecast of the type and quantity of material demand in the production process, the cumulative transfer probability can be further derived from the execution time of each operation and the information on material demand (Table III). Here, the possible value of material demand time in the future production process is defined as the maximum of the cumulative state transfer probability. Thus, the grey prediction model underestimates the material demand time, while the corrected prediction by the grey Markov model is closer to the actual value. This is consistent with the results given in Table III, which verifies the superiority of the proposed grey Markov prediction model.

Table III: Predicted material demand time for the production process.

Equipment number	Operation number	Cumulative state transfer probability	Actual value (s)	Predicted value (s)	Corrected prediction (s)
A	1	1.58, 0.21, 0.45, 1.69	541	514	536
	2	1.69, 1.15, 0.02, 0.96	1866	1626	1857
	3	0.81, 0.91, 1.05, 0.85	1246	1213	1235
	4	0.42, 0.47, 2.36, 0.95	793	625	781
B	1	1.62, 0.27, 0.49, 1.47	336	328	319
	2	1.62, 1.94, 0.02, 0.85	2267	2174	2216
	3	0.81, 0.96, 1.24, 0.85	1389	1259	1328
	4	0.51, 0.58, 2.62, 1.37	782	715	796

According to the actual situation that the production materials match the production equipment, the grey Markov model was used to predict the material demand and equipment in the production process, and the residual error testing and the posterior error testing were carried out to check the prediction accuracy of the proposed model. Three evaluation indices were selected: relative error, mean squared error, and small error probability. The test results are shown in Table IV.

Table IV: Prediction accuracy test of the matching between material demand and equipment in the production process.

Prediction object	Relative error	Mean squared error	Small probability error
Equipment A	1.25	0.19	1
Equipment B	0.72	0.35	1
Equipment C	1.85	0.31	1
Equipment D	1.69	0.34	1

Table V: Test results on solving production control problem.

Independent solution density	Best objective function value	Worst objective function value	Mean objective function value	Number of iterations
0.40	23.6	21.7	22.8	25
0.46	21.5	20.3	21.1	31.7
0.58	23	21.6	25.8	36.9
0.51	23	24.1	23.4	42.1
0.62	20	20.4	20.2	114

Four main production equipment were selected for predicting the matching between material demand and equipment. As shown in Table IV, the relative errors of our model for the prediction of the matching between material demand and equipment in the production process were all smaller than 1.9, the small probability errors were all greater than 0.98, and the mean squared errors were below 0.36. Therefore, the three prediction metrics of the grey prediction model after Markov correction are all ideal. The corrected model is much more accurate than the original model in prediction accuracy, and makes reliable prediction of the matching between material demand and equipment in the production process. This provides a reference for the design of production control strategy under different material demands.

Table V presents the test results on solving production control problem. It can be seen that when the independent solution density fell in the range of (0.4, 0.65), the objective function value (mean process time of production material workshop) solved by the five tests gradually approached the optimal solution, as the density grew, while the mean number of maximum iterations of the model increased. The best solution was achieved at the density of 0.5.

Table VI shows the simulation results on the production control strategies under different material demands. Eight working conditions were simulated, in which the type, quantity, equipment and time of material demand are all uncertain. The simulation data show that, it is not scientific to consider the completion rate of production operations and production cost, given the difference between production line products in the production quantity and delivery period. This paper chooses to measure the effectiveness of the production control strategies under different material demands by three indices: planned production sequence, planned production cycle, and delivery delay.

Table VI: Production control strategies under different material demands.

Order number		1	2	3	4	5	6	7	8
Machine A	Planned production sequence	2	5	8	1	4	3	8	2
	Planned production cycle	1	3	0	4	1	5	2	4
	Delivery delay	23.28	14.08	19.62	25.38	25.16	19.62	18.37	12.58
Machine B	Planned production sequence	1	6	2	5	2	4	1	7
	Planned production cycle	2	8	1	5	3	6	0	2
	Delivery delay	29.41	25.38	25.62	15.49	15.37	25.68	25.71	15.24
Machine C	Planned production sequence	3	5	8	1	4	6	2	0
	Planned production cycle	5	1	3	6	2	4	1	5
	Delivery delay	16.59	15.65	14.72	25.62	17.98	18.52	16.31	14.75
Machine D	Planned production sequence	8	5	2	4	6	1	8	2
	Planned production cycle	3	1	6	2	4	7	5	0
	Delivery delay	12.69	21.7	29.612	15.27	25.65	14.27	12.62	15.71

The production situation of production equipment for different orders is uncertain and changes randomly. To ensure the operational efficiency under our production control strategy, the mean time to implement a control is 0.0454 s. Overall, the production control strategy is fully in line with the actual production demand for production materials. It can not only ensure minimize the mean process time of the production material workshop in future, but also control the delivery delay of all products within 30 s.

6. CONCLUSIONS

Based on Markov model, this paper explores the demand prediction of production materials, and investigates the simulation of production management. Specifically, the grey system model and the Markov chain model were combined into a hybrid prediction model for the dynamic and time-varying demand for production materials in the production process. Through dynamic scenario analysis, the authors explored the formulation of production management and control strategies under multiple uncertain demands for production materials, and gave the specific analysis process. Two or more performance indices, including the type, quantity, equipment, and time of material demand, were considered synthetically, the optimization objectives of production control simulation were given under the multiple uncertain demands for production materials, and a solution was put forward for the production control problem. Through experiments, the type, quantity, equipment, and time of material demand, were predicted for the production process. The results show that the three prediction metrics of the grey prediction model after Markov correction are all ideal. The corrected model makes reliable prediction of the matching between material demand and equipment in the production process. In addition, the solving of the production control problem was simulated, and the production control strategies under different material demands were emulated. Overall, the production control strategy is fully in line with the actual production demand for production materials, and thus effective.

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