Int j simul model 21 (2022) 3, 537-547
Original scientific paper

MANAGEMENT DECISIONS IN MULTI-VARIETY SMALL-BATCH PRODUCT MANUFACTURING PROCESS

Li, Z. P.
School of Economics, The University of Queensland, Brisbane 4072, Australia
E-Mail: zepeili828@163.com

Abstract
The existing mathematical analysis approaches for the management of product manufacturing process cannot satisfy the global optimization and high feasibility required for product manufacturing. Neither do they reflect the actual production situation accurately and comprehensively. Therefore, this paper explores the simulation and modelling of management decisions in multi-variety small-batch product manufacturing process in discrete production environment. Firstly, the management knowledge in product manufacturing process was expressed mathematically, and the product manufacturing system was modelled in discrete production environment. Then, the flow of the interactive simulation model was explained, along with the realization steps of the model. Taking a real multi-variety small-batch production unit as the engineering background, an empirical analysis was carried out to detail the interactive simulation of the line change management for the production lines in the management system of the product manufacturing process, and to build a simulation model for the product manufacturing system. The simulation model was proved effective through simulations.
(Received in April 2022, accepted in July 2022. This paper was with the authors 1 month for 2 revisions.)

Key Words: Discrete Production Environment, Multi-Variety Small-Batch, Product Manufacturing Process, Management Decisions, Simulation

1. INTRODUCTION

Efficient and reliable product manufacturing process is the development trend of the management technology for product manufacturing process [1-4]. Through effective optimization of the management of product manufacturing process, it is possible to fully utilize the production resources in the workshop, and maintain an orderly production state [4-11]. However, the real-world discrete production environment is highly complex. Thus, the existing mathematical analysis approaches for the management of product manufacturing process cannot satisfy the global optimization and high feasibility required for the product manufacturing process. Neither do they reflect the actual production situation accurately and comprehensively [12-18]. In addition, they have difficulty in quantifying the factors affecting the management of product manufacturing process.

Focusing on the production quality management of filter rods in the production and execution process of cigarette enterprises, Gang et al. [19] analysed the necessity of implementing the manufacturing execution system (MES) in the production of filter rods, fully examined the MES-based filter rod quality system of cigarette enterprises, and carried out the demand analysis for building an information management system. Besides, they provided the cigarette quality control process, the design of system function modules, and explained how to realize the design. In addition, the effect of these modules was tested. Finally, the optimal cigarette processing system was found through fuzzy analytic hierarchy process (FAHP).

Manufacturing process management (MPM) defines how products are manufactured. Fandáková et al. [20] outlined several aspects of the three-dimensional (3D) models for manufacturing process management, which are applicable to the design of product manufacturing system. Vitliemov [21] briefly overviewed the conditions, methods, and prospects of optimizing manufacturing production control and monitoring by implementing information systems, and answered the specific questions of successfully managing machinery manufacturers through integrated software solutions. In addition, they considered the relevance of integrating cyber-physical system with the strategic management system of the manufacturing system, based on decision support technology.

Protalinskiy et al. [22] described the functional flow, information, and algorithm provision of a strategic decision support system based on balanced scorecard and simulation modelling. The optimal allocation of limited resources is crucial to the results of corporate investment tasks. In the context of limited resources, Demidenko et al. [23] mathematically expressed the indicative task of corporate investment optimization, and demonstrated with the following example: a three-factor integral model with a multiplicative objective function.

At present, the product manufacturing process in many workshops is mainly managed manually. Experienced management experts are capable of managing dynamic, multi-objective product manufacturing processes for different production tasks. This management idea gives birth to the management strategy for product manufacturing process based on expert knowledge. Some problems remain unresolvable in the domestic and foreign research into the expert system-based management of product manufacturing process: the current measures cannot effectively extract expert knowledge, the knowledge rules for the management of product manufacturing process are not extracted ideally, and the expert system could not adapt to the complex discrete production environment.

Therefore, this paper explores the simulation and modelling of management decisions in multi-variety small-batch product manufacturing process in discrete production environment. The main contents are as follows: (1) The management knowledge in product manufacturing process was expressed mathematically, and the product manufacturing system was modelled in discrete production environment. (2) The flow of the interactive simulation model was explained, along with the realization steps of the model. (3) Taking a real multi-variety small-batch production unit as the engineering background, an empirical analysis was carried out to detail the interactive simulation of the line change management for the production lines in the management system of the product manufacturing process, and to build a simulation model for the product manufacturing system. Finally, the simulation model was proved effective through simulations.

2. KNOWLEDGE EXPRESSION

As the basis for interactive simulation, the simulation model for the management of product manufacturing process supports the management decisions of complex production systems. Fig. 1 shows the structure of this model. It can be seen that the model plays two major roles: acquiring the data of expert decisions, and screening expert decisions. The architecture of the model mainly consists of three parts: simulation model of product manufacturing process, model management and control module, and databases.

To acquire the management knowledge of product manufacturing process, this paper explores interactive simulation, the premise for building the management knowledge library of product manufacturing process. Before constructing the interactive simulation model, this paper firstly mathematically expresses the management knowledge of product manufacturing process, and then builds up the architecture of the multi-variety small-batch product manufacturing system in the discrete production environment. On this basis, simulation experiments were carried out to generate the management decisions for product manufacturing process, and save the decisions properly.

This paper represents the knowledge in management expert decisions of product manufacturing process, based on the external manifestations of product manufacturing process. In the product manufacturing system, the external manifestations of expert decisions in the product manufacturing system were illustrated based on state space graph and the decision knowledge of generalized operator method:

Let *Ar* denote the state vector of the product manufacturing system; A_h denote the vector of production objective; G_v denote the realization of production objective. This paper characterizes the expert decision knowledge in the management of product manufacturing process as a triple: <*Ar*,*Gv*,*Ah*>. The experts derive the control strategy vector of the product manufacturing system at the next moment from the state vector of the system at the current moment. The state space graph can be expressed as:

$$(Ar)v \xrightarrow{\{Gv\}} (Ah) \tag{1}$$

The above formula contains all the knowledge in the management decisions of product manufacturing process.

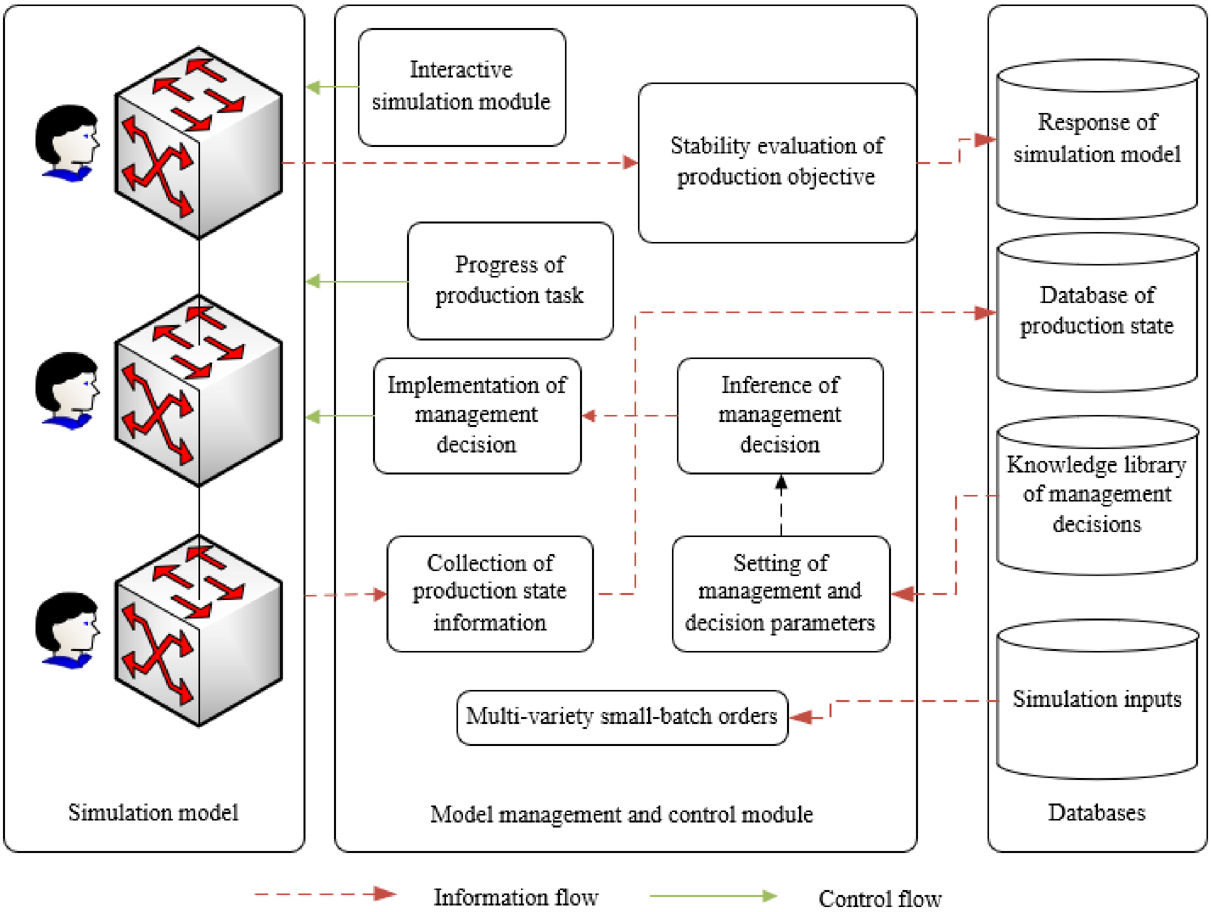

Figure 1: Structure of the simulation model for the management of product manufacturing process.

Let *l*(.) denote the generalized operator. Then, the decision knowledge of generalized operator method can be expressed as:

$$Gv \leftarrow l(\cdot)Ar \tag{2}$$

Combining the state space graph and the decision knowledge of generalized operator method, it is possible to mathematically express the knowledge in management decisions of product manufacturing process. The effective mathematical expressions underpin the further construction of the management knowledge library and inference engine of product manufacturing process. Through interactive simulation, the data on the three external manifestations, namely, A_h, A_r, and G_v, of the management decisions of product manufacturing process were collected. Among them, A_r and G_v are used to train the neural network, while A_h is used to optimize the management decisions of product manufacturing process.

3. REALIZATION OF INTERACTIVE SIMULATION

To acquire the management expert knowledge in product manufacturing process, it is necessary to collect the production state data at the site of production, as well as the data on the management decisions of product manufacturing process, and focus on the update and adjustment of system management parameters under the influence of the expert management decisions of product manufacturing process. Fig. 2 explains the execution flow of interactive simulation model.

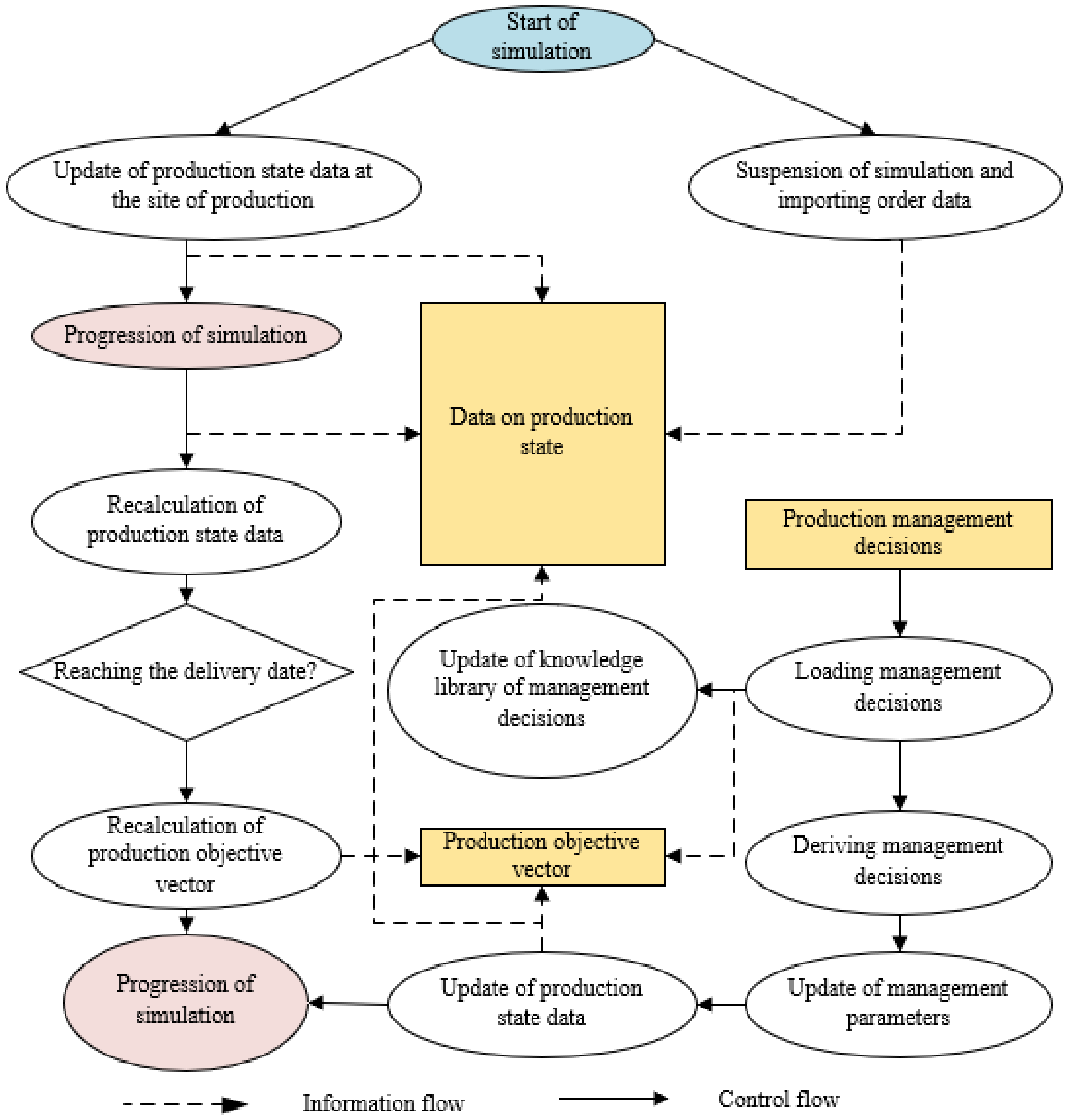

Figure 2: Execution flow of interactive simulation model.

To stabilize the production objective state, the management expert system of product manufacturing process needs a good stability evaluation algorithm. Due to the stochasticity of the objective generation process of interactive simulation, the stationarity of the product manufacturing process could be approximately assessed based on the mean variance of the production objective:

$$E\left(\overline{A}\right)=E\left(\frac{1}{m}\sum_{i=1}^{m}a_i\right)=\frac{1}{m^2}\left[E\left(a_1\right)+E\left(a_2\right)+...+E\left(a_m\right)\right] \tag{3}$$

In actual product manufacturing process, the product manufacturing system progressively stabilizes with the elapse of time. Therefore, only the residuals of the last few measurements need to be considered comprehensively. It is necessary to solve and normalize the residual of the measured state of the product manufacturing system in each cycle. Let u_{max} and u_{min} denote the maximum and minimum residuals, respectively. Then, we have:

$$u_i=\frac{\left(\left|a_i-\overline{A}\right|-u_{min}\right)}{u_{max}-u_{min}} \tag{4}$$

The distance between the residuals of the measured system states in different cycles can be calculated by:

$$\delta_{ij}=\sqrt{u_i^2-u_j^2} \tag{5}$$

Suppose class P_s has m samples, and class P_3 has n samples. Then, the minimum distance between measured states can be calculated by:

$$\delta_{min}=\min\left(\delta_{ij}\right) \tag{6}$$

The two samples with the minimum distance of measured system states are allocated to the same class. The minimum inter-class distance can be calculated by:

$$\delta_{min}=\sqrt{\left(\frac{1}{m}\sum_{u\in P_s}^{m}u_i\right)^2-\left(\frac{1}{n}\sum_{u\in P_r}^{n}u_i\right)^2} \tag{7}$$

The two classes with the minimum δ_{min} are merged and recalculated until the objective vector is divided into two classes. If one class contains measured states of the production objective and has a large variance, then the sample size of the class will be counted. Before the simulation, a ratio has been pre-set for the sample size in the class with a relatively small variance. If the statistics on the sample size in a class with a small variance is smaller than that pre-set ratio, then the interactive simulation is stable, and suitable for subsequent expert decision screening.

In the management expert system of product manufacturing process, the expert decisions are screened based on factorial design. Let s denote the number of experts participating in the decision-making process, r denote the types of production tasks, o denote the number of interactive simulations for each production task carried out by each expert, and A_{ijl} denote the l^{th} interactive simulation of the i^{th} expert on the j^{th} production task. Then, the sum of squares IE_{FO} for the observed interactive effect can be calculated by:

$$IE_{FO}=o\sum_{i=1}^{s}\sum_{j=1}^{r}\left(\frac{1}{o}\sum_{l=1}^{o}A_{ijl}-\frac{1}{ro}\sum_{j=1}^{r}\sum_{l=1}^{o}A_{ijl}-\frac{1}{so}\sum_{i=1}^{s}\sum_{l=1}^{o}A_{ijl}+\frac{1}{sro}\sum_{i=1}^{s}\sum_{j=1}^{r}\sum_{l=1}^{o}A_{ijl}\right) \tag{8}$$

The sum of squares for the error effect can be calculated by:

$$IE_T=\sum_{i=1}^{s}\sum_{j=1}^{r}\sum_{l=1}^{o}\left(A_{ijl}-\frac{1}{o}\sum_{l=1}^{o}A_{ijl}\right) \tag{9}$$

Let fg denote the degrees of freedom corresponding to a sum of squares. Then, the testing statistic of the interactive effect can be calculated by:

$$G_{FO}=\left(IE_{FO}/g_{FO}\right)/\left(IE_T/g_T\right) \tag{10}$$

If the simulation yields an obvious interactive effect, then G_{FO} obeys the G-distribution with the degree of freedom of (g_{FO}, g_T).

Let S_{ij}^* denote the mean result of the interactive simulations of the i^{th} expert for the j^{th} production task. If the interactive effect is significant, then find S_{ij}^*. Based on the value of the j^{th} task, the management decision scheme for product manufacturing process with the maximum $S.j^*$ is selected, and saved to the management knowledge library of product manufacturing process. If the interactive effect is not significant, but the expert effect is significant, the mean result C_i of all experts on the management decisions of product manufacturing process for all production tasks can be calculated by:

$$C_i = \frac{1}{ro}\sum_{j=1}^{r}\sum_{l=1}^{o} A_{jl} \tag{11}$$

The management decision scheme for product manufacturing process with the maximum C_i is selected and saved. If the interactive effect and expert effect are not obvious, the decision data of each expert can be calculated by:

$$IND_i = \frac{\sqrt{\sum_{j=1}^{r}\sum_{l=1}^{o}\left(A_{ijl} - \frac{1}{jl}\sum_{j=1}^{r}\sum_{l=1}^{o} A_{ijl}\right)^2}}{\frac{1}{jl}\sum_{j=1}^{r}\sum_{l=1}^{o} A_{ijl}} \tag{12}$$

The management decision scheme for product manufacturing process with the minimum IND_i is selected and saved.

4. CONSTRUCTION OF SIMULATION MODEL

To verify the feasibility of the proposed theory on the management expert system for product manufacturing process, this paper carries out an empirical analysis with a real multi-variety small-batch production unit as the engineering background, and details the interactive simulation of the line change management for the production lines in the management system of the product manufacturing process.

The management simulation model of product manufacturing process includes such functions as importing expert decisions, generating product state vector, and monitoring the demand for expert management decisions. Fig. 3 illustrates the program flow of the management simulation model for product manufacturing process.

According to the preceding section, the first step of the construction of the management expert system for product manufacturing process is to express the management knowledge in product manufacturing process. In the management system of product manufacturing process, the knowledge in the line change for the production lines involves production objective vector, production state vector, and production management strategy vector.

Let $Gv = (NQO, RKR, DR)$ denote the production management strategy vector, NQO denote the time in need of line change, RKR denote the mode of line change, and DR denote the strategy of line change.

Let N_{IN} denote the inventory quantity of semi-finished products on the production line; TI_{FN} denote the remaining time of semi-finished products to completion; N_{IN} denote the number of semi-finished products; TI_{FA} denote the system failure duration; HO denote the packaging state of online finished products; $EQST$ denote the state of processing equipment (if $EQST = 0$, then the equipment is not working currently); TP_{NO} denote the type of new order; N_{NO} denote the quantity required for delivery of the new order; FA_{NO} denote the urgency of the new order; TI_{NO} denote the delivery time of the new order. Then, the production state vector can be expressed as $A_f = (N_{IN}, TI_{FN}, N_{IN}, TI_{FA}, HO\text{-}N_{IN}, HO\text{-}TI_{FN}, HO\text{-}N_{IN}, HO\text{-}TI_{FA}, EQST, TP_{NO}, N_{NO}, FA_{NO}, TI_{NO})$.

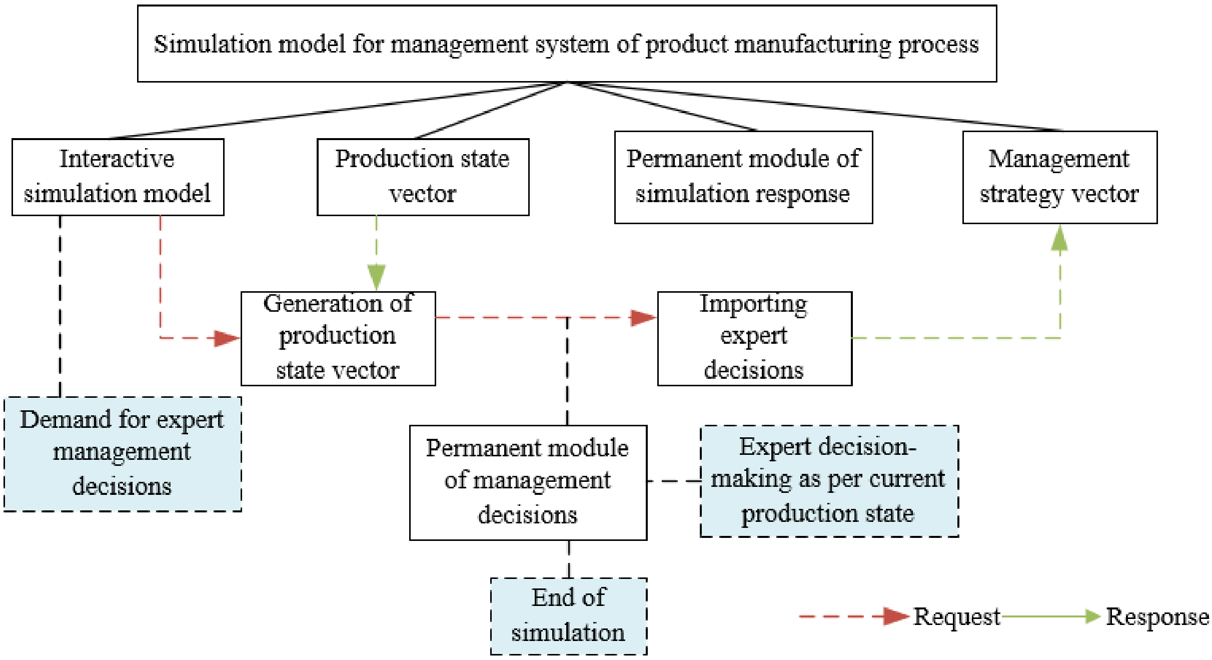

Figure 3: Program flow of the management simulation model for product manufacturing process.

Let *OFR* denote the cumulative historical order completion rate; *IR* denote the cumulative historical inventory rate; *EU* denote the global utilization rate of all equipment. Then, the production objective vector can be expressed as: $Ah = (OFR, IR, EU)$.

To maximize the adaptability of the expert management decisions of product manufacturing process generated by the simulation, and to simulate the unexpected events that may occur in the product manufacturing system, this paper attributes the uncertain emergencies like the shortage of production resources and the failure of processing equipment to the failure of the product manufacturing system. The stochasticity of the simulation system mainly arises from the maintenance degree and reliability of the computing system, which are subject to log-normal distribution and normal distribution, respectively. The distribution ($S(o)$) of the maintenance degree, and the distribution ($N(o)$) of the reliability of the computing system can be respectively calculated by:

$$S(o) = \int_0^o \frac{1}{1.2o\sqrt{2\pi}} exp\left[-\frac{(\ln o - 1.6)^2}{2.86}\right] \tag{13}$$

$$N(o) = \int_0^o \frac{1}{1.17o\sqrt{2\pi}} exp\left[-\frac{(o - 1.32)^2}{2.74}\right] \tag{14}$$

In the simulation model, the objective vector algorithm evaluates the product manufacturing system at the moments of interaction. Let N_{FP} denote the total number of finished products in the current simulation; N_{OP} denote the total number of products required by the order. Then, the inventory rate *IR* of the production objective vector $Ah = (OFR, IR, EU)$ can be calculated by:

$$FR = (N_{FP} - N_{OP}) / N_{OP} \tag{15}$$

Let N_{UF} be the number of uncompleted orders. Then, the *OFR* can be calculated by:

$$OFR = N_{UF} / N_{OF} \tag{16}$$

Let T_{EP} be the effective processing time of processing equipment; T_{SS} be the system simulation time. Then, *EU* can be calculated by:

$$EU = T_{EP} / T_{SS} \tag{17}$$

5. SIMULATIONS AND RESULTS ANALYSIS

Drawing on the theories in Sections 2-3, this paper randomly chooses three experienced experts on actual production tasks for interactive simulation. Table I provides the interactive simulation results on production objective vector.

Table I: Interactive simulation data of different experts.

	Expert 1			Expert 2			Expert 3		
Serial number	**Task 1**	**Task 2**	**Task 3**	**Task 1**	**Task 2**	**Task 3**	**Task 1**	**Task 2**	**Task 3**
1	0.02	0.05	0.01	0.06	1.52	0.06	0.06	1.62	0.07
2	0.04	0.52	0.16	263.41	1.27	0.39	315	1.47	0.06
3	227.36	0.68	0.35	485.62	0.63	0.37	458	1.69	0.35
4	364.85	0.56	0.39	415.79	0.73	0.35	739	1.27	0.26
5	315.62	0.67	0.26	958.42	0.85	0.33	743	1.15	0.49
6	342.29	0.74	0.23	869.51	0.87	0.39	1302	1.59	0.41
7	0.04	0.71	0.39	415.83	0.69	0.35	1625	1.95	0.38
8	462.84	0.69	0.37	462.58	0.85	0.37	1029	0.83	0.42
9	439.21	0.62	0.34	958.42	0.81	0.32	1745	0.95	0.46
10	519.48	0.75	0.32	834.15	0.86	0.38	1526	0.97	0.49
11	937.35	0.79	0.35	562.17	0.83	0.34	1836	0.84	0.25
12	942.63	0.74	0.31	385.52	0.88	0.36	1169	0.81	0.37

To obtain stable production objective states, this paper verifies the effectiveness of the stability verification algorithm for the management expert system of product manufacturing process. Table II presents the cluster analysis results on different experts in different production tasks under the random conditions obtained by algorithm solving.

Table II: Clustering results.

Expert 1 Task 1	**Quantity**	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Class	2	1	2	1	2	2	2	2	1	2	2	1	1	2
Expert 2 Task 2	**Quantity**	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Class	1	1	1	1	1	2	2	1	2	1	1	2	2	2
Expert 3 Task 3	**Quantity**	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Class	2	2	2	1	1	1	1	2	2	2	2	1	1	1

According to the clustering results in Table II, all 14 production task samples satisfied the stability of interactive simulation. Based on the annual production tasks of the real multi-variety small-batch production unit, the regular production tasks can be determined. Tables III to V present the interactive simulation responses, including reducing inventory, ensuring timely completion, and improving production efficiency.

On the interactive simulation responses, the interactive effect significantly affected the response to the management decisions of product manufacturing process in the simulation aimed at reducing inventory. To lower the inventory, when executing tasks 1 and 3, the mean inventory level can be minimized by expert 2's decision strategy for the management of product manufacturing process; when executing task 2, the mean inventory level can be minimized by expert 3's decision strategy for the management of product manufacturing process.

The interactive effect significantly affected the response to the management decisions of product manufacturing process in the simulation aimed at ensuring timely completion. To ensure the completion of orders, when executing tasks 1 and 2, the mean timely completion rate of the orders can be maximized by expert 1's decision strategy for the management of product manufacturing process; when executing task 3, the mean timely completion rate of the orders can be maximized by expert 2's decision strategy for the management of product manufacturing process.

The interactive effect did not significantly affect the response to the management decisions of product manufacturing process in the simulation aimed at increasing production efficiency, but experts significantly affected that response. Thus, the interactive effect between production tasks and experts is negligible, yet the experts' management decisions of product manufacturing process help to improve the production efficiency of the system. To enhance the system production efficiency, expert 2's strategy should be adopted for all three tasks.

Table III: Responses in the interactive simulation aimed at reducing inventory.

Reducing inventory	Expert 1			Expert 2			Expert 3		
Task 1	847	741	562	218	362	185	1273	41	562
Task 2	1574	2561	1847	926	1052	274	195	237	128
Task 3	1847	2635	1958	128	136	227	1412	1625	3625

Table IV: Responses in the interactive simulation aimed at ensuring timely completion.

Ensuring timely completion	Expert 1			Expert 2			Expert 3		
Task 1	1	1	1	0.948	0.872	0.73	0.84	0.865	0.514
Task 2	0.988	1	0.958	0.74	1	0.947	0.632	1	0.928
Task 3	0.654	1	0.741	0.83	0.865	1	0.952	1	0.941

Table V: Responses in the interactive simulation aimed at increasing production efficiency.

Increasing production efficiency	Expert 1			Expert 2			Expert 3		
Task 1	0.326	0.365	0.311	0.452	0.441	0.471	0.359	0.351	0.259
Task 2	0.472	0.493	0.541	0.439	0.524	0.423	0.748	0.463	0.452
Task 3	0.471	0.353	0.475	0.419	0.461	0.442	0.362	0.484	0.622

Table VI: Testing results.

Probability	Expert	Task	Interaction
Simulation aimed at reducing inventory	0.4153625187	0.032625341	0.569862279
Simulation aimed at ensuring timely completion	0.021514254	0.463257	0.632514241
Simulation aimed at increasing production efficiency	0.847712239	6.325124128	0.032512486

The experimental scheme of the specific production case was determined through the stability testing on reducing inventory, ensuring timely completion, and increasing production efficiency, in the light of the production tasks of a multi-variety small-batch production unit in the real scenario. Table VI presents the testing results. Based on the above simulation results, the authors determined the optimal management strategy for product manufacturing process under the specific production objective and task of the multi-variety small-batch production unit. Table VII presents the simulation results of the specific production case, which further confirm the effectiveness of the optimal management strategy for product manufacturing process.

Table VII: Simulation results.

Simulation number	1	2	3	4	5
Realization rate of decisions	11/13	11/12	14/15	16/17	9/10
Task completion time	2105	2635	2847	2612	2301
Mean utilization rate of processing equipment	3.1524	3.2658	3.6259	3.1425	3.4715
Mean waiting queue	98.4512	96.5235	97.4812	92.5148	96.8532
Mean waiting time	45.1265	42.3512	40.6259	47.5182	44.1263

6. CONCLUSIONS

This paper studies the simulation and modelling of management decisions in multi-variety small-batch product manufacturing process in discrete production environment. Firstly, the management knowledge in product manufacturing process was expressed mathematically, and the product manufacturing system was modelled in discrete production environment. Then, the authors explained the flow of the interactive simulation model, and the realization steps of the model. With a real multi-variety small-batch production unit as the engineering background, an empirical analysis was carried out to detail the interactive simulation of the line change management for the production lines in the management system of the product manufacturing process, and to build a simulation model for the product manufacturing system.

Through simulations, the authors obtained the interactive simulation results for the production objective vector, and the cluster analysis results on different experts in different production tasks under the random conditions obtained by algorithm solving, producing relatively stable production objective state. In addition, the responses to interactive simulations aimed at reducing inventory, ensuring timely completion, and increasing production efficiency were obtained, and used to optimize the management strategy for product manufacturing process. Finally, the proposed simulation model was verified through a stability test, and the simulation results were obtained for the specific production case. The results further confirm the effectiveness of the optimal management strategy for product manufacturing process.

REFERENCES

[1] Liu, M.; Wang, Q.; Ling, L.; Zhang, M. (2015). RFID-enabled real-time manufacturing operation management system for the assembly process of mechanical products, *International Journal of RF Technologies*, Vol. 6, No. 4, 185-205, doi:10.3233/RFT-150066

[2] Shamsuzzoha, A.; Helo, P. T. (2014). Virtual business process management within collaborative manufacturing network: an implementation case, *International Journal of Networking and Virtual Organisations*, Vol. 14, No. 4, 319-339, doi:10.1504/IJNVO.2014.067879

[3] Dong, S. Y.; Xu, J. X.; Wang, K. Q.; Qin, X. S. (2013). Management model and key technologies in aircraft manufacturing process, *Computer Integrated Manufacturing Systems*, Vol. 19, No. 4, 704-713

[4] Solomentsev, Y. M.; Frolov, E. B.; Feofanov, A. N. (2017). MES-based management of manufacturing processes, *Russian Engineering Research*, Vol. 37, No. 11, 950-953, doi:10.3103/S1068798X17110168

[5] Chambers, A. A. (2018). Management of TEOS-CVD process tool exhausts in 3D-NAND manufacturing, *2018 China Semiconductor Technology International Conference (CSTIC)*, 3 pages, doi:10.1109/CSTIC.2018.8369246

[6] Corallo, A.; Espostito, M.; Massafra, A.; Totaro, S. (2018). A relational database management system approach for data integration in manufacturing process, *2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, 7 pages, doi:10.1109/ICE.2018.8436290

[7] Cheng, C.-Y.; Ou, T.-Y.; Chen, T.-L.; Chen, Y.-Y. (2014). Transferring cognitive apprenticeship to manufacturing process knowledge management system: a case study of small-and medium-sized coating industry, *Vine*, Vol. 44, No. 3, 420-444, doi:10.1108/VINE-03-2013-0011

[8] Ngai, E. W. T.; Chau, D. C. K.; Poon, J. K. L.; To, C. K. M. (2013). Energy and utility management maturity model for sustainable manufacturing process, *International Journal of Production Economics*, Vol. 146, No. 2, 453-464, doi:10.1016/j.ijpe.2012.12.018

[9] Bracewell, D. G.; Francis, R.; Smales, C. M. (2015). The future of host cell protein (HCP) identification during process development and manufacturing linked to a risk-based management for their control, *Biotechnology and Bioengineering*, Vol. 112, No. 9, 1727-1737, doi:10.1002/bit.25628

[10] Walsh, B. P.; Bruton, K.; O'Sullivan, D. T. J. (2017). The true value of water: a case-study in manufacturing process water-management, *Journal of Cleaner Production*, Vol. 141, 551-567, doi:10.1016/j.jclepro.2016.09.106

[11] Koch, J.; Gritsch, A.; Reinhart, G. (2016). Process design for the management of changes in manufacturing: toward a Manufacturing Change Management process, *CIRP Journal of Manufacturing Science and Technology*, Vol. 14, 10-19, doi:10.1016/j.cirpj.2016.04.010

[12] Wang, M. (2021). Manufacturing capacity evaluation of smart job-shop based on neural network, *International Journal of Simulation Modelling*, Vol. 20, No. 4, 778-789, doi:10.2507/IJSIMM20-4-CO19

[13] He, S.; Wang, Y.; Li, X.; Liu, H. (2018). Research on recycling of waste leather produced in leather manufacturing process based on supply chain management, *Revista de Pielarie Incaltaminte – Leather and Footwear Journal*, Vol. 18, No. 2, 75-82, doi:10.24264/lfj.18.2.1

[14] Kilic, R.; Erkayman, B. (2021). A simulation approach for transition to JIT production system, *International Journal of Simulation Modelling*, Vol. 20, No. 3, 489-500, doi:10.2507/IJSIMM20-3-566

[15] Han, J.; Lee, S.-H.; Kim, J. K. (2017). A process integrated engineering knowledge acquisition and management model for a project based manufacturing, *International Journal of Precision Engineering and Manufacturing*, Vol. 18, No. 2, 175-185, doi:10.1007/s12541-017-0023-6

[16] Li, J.; Gao, Z.; Li, T.; Yang, J.; Xu, A.; Wang, B. (2017). Information integration management system for spiral bevel gear networked manufacturing process, *Transactions of the Chinese Society of Agricultural Engineering*, Vol. 33, No. 15, 227-236

[17] Buń, P.; Grajewski, D.; Górski, F. (2021). Using augmented reality devices for remote support in manufacturing: A case study and analysis, *Advances in Production Engineering & Management*, Vol. 16, No. 4, 418-430, doi:10.14743/apem2021.4.410

[18] Febriana, T. H.; Hasbullah, H. (2021). Analysis and defect improvement using FTA, FMEA, and MLR through DMAIC phase: case study in mixing process tire manufacturing industry, *Journal Européen des Systèmes Automatisés*, Vol. 54, No. 5, 721-731, doi:10.18280/jesa.540507

[19] Song, G.; Wang, X.; Wu, J.; Li, S.; Liu, Z.; Wang, X. (2021). Analysis of the information management system in the manufacturing process of cigarette enterprises using fuzzy AHP, *Journal of Intelligent & Fuzzy Systems*, Vol. 40, No. 4, 8257-8267, doi:10.3233/JIFS-189648

[20] Fandáková, M.; Bučko, B.; Zábovská, K. (2019). Parametric versus direct modeling in manufacturing process management, *2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 1543-1547, doi:10.23919/MIPRO.2019.8757006

[21] Vitliemov, P. (2019). Features in management and monitoring of production process in manufacturing industry using integrated information technologies solutions, *IOP Conference Series: Materials Science and Engineering*, Vol. 618, Paper 012076, 7 pages, doi:10.1088/1757-899X/618/1/012076

[22] Protalinskiy, O.; Andryushin, A.; Shcherbatov, I.; Khanova, A.; Urazaliev, N. (2018). Strategic decision support in the process of manufacturing systems management, *2018 Eleventh International Conference "Management of large-scale system development" (MLSD)*, 4 pages, doi:10.1109/MLSD.2018.8551760

[23] Demidenko, D.; Malevskaia-Malevich, E.; Dubolazova, Y. (2018). Optimization of the innovation process management at a manufacturing enterprise, *Advanced Science Letters*, Vol. 24, No. 9, 6308-6310, doi:10.1166/asl.2018.13038