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Investment decision optimization for delayed product differentiation based on queuing theory

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Abstract: To balance inventory cost with diverse demand, an optimal investment decision on necessary process improvement for delayed product differentiation is studied. A two-stage flexible manufacturing system is modeled as a continuous time Markov chain. The first production stage manufactures semi-finished products based on a make-to-stock policy. The second production stage customizes semi-finished products from the first production stage on a make-to-order policy. Various performance measures for this flexible manufacturing system are evaluated by using matrix geometric methods. An optimization model to determine the level of investment on process improvement that minimizes the manufacturer's total cost is established. The results show that, a higher investment level can reduce both the expected customer order fulfillment delay and the expected semi-finished products inventory. When the initial order penetration point is 0.4, the manufacturer's total cost is reduced by 15.89% through process investment. In addition, the optimal investment level increases with the increase in the unit time cost of customer order fulfillment delay, and decreases with the increase in the product value and the initial order penetration point.

Key words: flexible manufacturing system; postponement strategy; order penetration point; investment process; matrix geometric method

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In the era of e-commerce and make-to-order (MTO) manufacturing, customer purchase behavior has a pronounced impact on the manufacturer's production process. Many customers prefer more personalized products that satisfy their specific needs, while others are unwilling to wait long for customized products and prefer standard products on a guaranteed order delivery time. Such diverse customer purchase behaviors require the production process to be flexible while ensuring its productivity[1]. Consequently, the postponement strategy is adopted to match the various behaviors.

In practice, many assembly industries, such as electronics and automobile, have adopted the postponement strategy. Investment on standardization, modular design, and process restructuring are three product/process redesign approaches commonly applied to the postponement[2]. For example, Helmut Schramm, head of BMWi production, claims that it costs BMW around €400 million ($552 million) for the process investment at its plant in Leipzig, Germany[3]. BMW made an investment in parallel assembly of the Life module and the Drive module before the two modules were integrated into the LifeDrive architecture. As a result, the true appearance of the cars emerged only at final assembly rather than in the body shop. Hewlett-Packard (HP) created the so-called design for localization[4]. HP redesigned their products so that the power supply module was the last component to be added. This addition can be easily done at the distribution center. With the above highlighted benefit of delayed product differentiation, it is thus important to have the analytics ability to make an optimal investment decision about necessary process improvement for achieving such delayed product differentiation.

The postponement production system is usually composed of two phases, namely, push and pull. On the one hand, the push phase is forecast-driven. It is located upstream and follows standard production. On the other hand, the pull phase is customer-driven. It is located downstream and follows customized production. The order penetration point (OPP) is the boundary between these two phases, which is also known as the point of differentiation or the customer order decoupling point. Given the importance of the postponement strategy, the OPP decision problem has attracted much attention in the literature.

There are two main lines of literature related to our study, i.e., OPP decision-making with and without consideration of any process improvement. We first review the literature without considering any process improvement. Jewkes et al.[5] found that the optimal OPP moves downstream if customers accept a narrower range of product characteristics. However, the optimal OPP is neither sensitive to the changes in supplier capacity nor customer demand. Pang et al.[6] proposed a cost control model

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with multiple product differentiation points, and analyzed the implementation conditions of process flow reorder. Zhang et al. [7] presented a supply chain postponement strategy model by using the queuing theory to determine the optimal ratio of differentiation and inventory level. Shao et al. [8] modeled various postponement strategies for coping with risk in the thin film transistor liquid crystal display industry. Shan et al. [9] investigated the application of the postponement strategy in apparel supply chain management. They found that it is beneficial to adjust the first production proportion and replenishment ratio to improve competitiveness. Liu et al. [10] proposed an OPP decision model considering time scheduling with capacity and time constraints. Numerical examples showed that OPP moves earlier with the increase in the volume of new orders. Yousself et al. [11] studied the impact of items priority levels on the optimal MTO/MTS decisions. By setting the optimal priority allocation and the base-stock levels, the overall inventory costs are minimized. Nevertheless, the studies discussed above only explored the relationship between the optimal OPP and the postponement strategy. Little investigation has been done on the relationship between OPP and the investment process.

The literature on the impact of process improvement on the OPP decision-making is still in its infancy. Lee[12] was the first to present inventory models for product/process design applications. Those models, however, assume that no buffer stocks are held until the end of the production process. In a further developed model, Lee et al. [2] allowed different process points to hold inventories and incorporated several factors that would normally be affected by delayed product differentiation. However, the average investment cost per period is independent of OPP in their model. Su et al. [13] considered the problem that a firm can make a series of investments to design generic product components with the implementation of postponement structure. However, the one-time investment cost is assumed to be fixed in their model. More recently, Ngniatedema et al. [14] extended the model[2] by incorporating the delivery of product components from an external supplier at the beginning of the production network. However, the investment cost remains independent of OPP.

In our paper, OPP can be pushed downstream through process investment. We model the production process to better understand how the investment level affects the trade-off between customer order fulfillment delay and inventory risks. We use an approach similar to that proposed by Jewkes et al. [5] and propose an alternative model. First, our model is used to investigate the impact of the investment level on the postponement strategy instead of market characteristics[5]. Secondly, the investment level is regarded as a decision variable in our model, not a fixed value. In addition, we assume that the updated OPP through process improvement meets the law of diminishing marginal utility, and thus it is modeled with a continuous, increasing, and concave function with respect to the investment level.

1 Production System Model

For each type of product that the manufacturer offers, the production system consists of two phases. In phase one, the semi-finished parts are made in an MTS fashion, and are stocked at the warehouse. In phase two, when the manufacturer receives customer orders, the semi-finished parts are customized in an MTO fashion and are sent directly to customers. Fig. 1 illustrates the postponement production process.

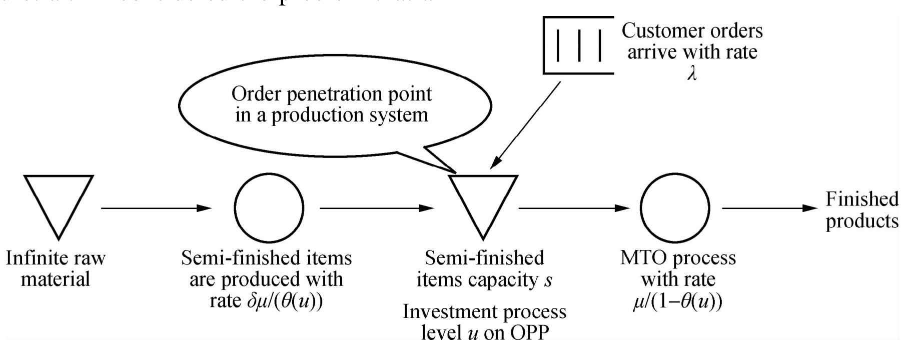

Fig. 1 The postponement production process

As shown in Fig. 1, we assume that the manufacturer can procure an infinite amount of raw materials and never faces shortages. Meanwhile, we assume that it has limited storage capacity for semi-finished products, denoted by s. We quantify the OPP variable, denoted by $\theta(0<\theta<1)$, to be the percentage of product completion after phase one. We set θ_0 to be the initial OPP. Note that we use θ, a continuous variable, to quantify the decision about product differentiation, thus it is more convenient to derive analytical results from our model and conduct sensitivity analyses. While most of the production processes are not continuous with respect to OPP, the optimal value obtained from our model can be used in practice to guide the postponement of product differentiation.

We denote u to be the level of investment on process improvement ($u \geqslant 0$). $\theta(u)$ represents the new OPP that resulted from the process improvement with investment level u. Assume that $\theta(\cdot)$ satisfies $\theta(0)=\theta_0$, $\theta(u) \leqslant \bar{\theta}$,

$\theta'(u)>0$, $\theta''(u)<0$. Additionally, we assume that orders are processed with a mean rate μ. We assume the time taken at phase one to produce one unit of semi-finished product to be exponentially distributed with parameter $\frac{\delta\mu}{\theta(u)}$, where $\delta>0$ is the scaling factor representing the ratio of MTS processing rate to the MTO processing rate. We also assume that the time taken at phase two to process one unit of semi-finished product is exponentially distributed with parameter $\frac{\mu}{1-\theta(u)}$. Next, we assume that customer orders arrive according to a Poisson process with rate λ and they are served on a first-come-first-served (FCFS) basis. Once the products are retrieved and processed, we can fulfill the customer orders.

1.1 Markov model

With the above system specifications, we model the order fulfillment process as a continuous-time Markov chain with infinite states. The state space is $\{(i,j), i\geqslant 0, 0\leqslant j\leqslant s\}$, where i is the number of orders and j is the number of semi-finished products. Fig. 2 presents the transition diagram with row and column indices by i and j. We next explain representative states and state transitions. State $(0,0)$ implies an idle system. When a customer's order is placed, the system state changes from $(0,0)$ to $(1,0)$ with transition rate λ. After completing the first phase of the manufacturing system, the system state changes to $(1,1)$ with transition rate $a=\frac{\delta\mu}{\theta(u)}$. After the order is fulfilled, the system state returns to $(0,0)$ with rate $b=\frac{\mu}{1-\theta(u)}$.

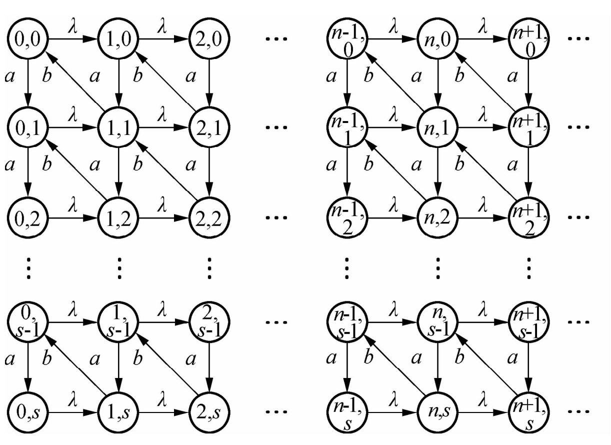

Fig. 2 Transition rate diagram of the Markov chain

Let $\boldsymbol{\pi}=\{\boldsymbol{\pi}_0,\boldsymbol{\pi}_1,\cdots,\boldsymbol{\pi}_n\}$ be the steady-state probability of the Markov chain, where $\boldsymbol{\pi}_n=\{\pi_{(n,0)},\pi_{(n,1)},\cdots,\pi_{(n,s)}\}$ is an $(s+1)$-dimensional row vector. Additionally, $\pi_{(i,j)}$ denotes the steady-state probability associated with the condition that there are i orders and j semi-finished products. Referring to the transition diagram in Fig. 2, we obtain the following balance equations:

$$(a+\lambda)\pi_{(i,j)}=b\pi_{(i+1,j+1)} \qquad i=0, j=0 \tag{1}$$

$$(a+\lambda)\pi_{(i,j)}=a\pi_{(i,j-1)}+b\pi_{(i+1,j+1)} \qquad i=0, 1\leqslant j\leqslant s-1 \tag{2}$$

$$\lambda\pi_{(i,j)}=a\pi_{(i,j-1)} \qquad i=0, j=s \tag{3}$$

$$(a+\lambda)\pi_{(i,j)}=\lambda\pi_{(i-1,j)}+b\pi_{(i+1,j+1)} \qquad 1\leqslant i, j=0 \tag{4}$$

$$(a+\lambda+b)\pi_{(i,j)}=a\pi_{(i,j-1)}+\lambda\pi_{(i-1,j)}+b\pi_{(i+1,j+1)} \qquad 1\leqslant i, 1\leqslant j\leqslant s-1 \tag{5}$$

$$(\lambda+b)\pi_{(i,j)}=a\pi_{(i,j-1)}+\lambda\pi_{(i-1,j)} \qquad 1\leqslant i, j=s \tag{6}$$

The generator matrix of the Markov chain is given by

$$\boldsymbol{Q}=\begin{bmatrix} \boldsymbol{B} & \boldsymbol{A}_0 & & & \\ \boldsymbol{A}_2 & \boldsymbol{A}_1 & \boldsymbol{A}_0 & & \\ & \boldsymbol{A}_2 & \boldsymbol{A}_1 & \boldsymbol{A}_0 & \\ & & \ddots & \ddots & \ddots \end{bmatrix} \tag{7}$$

where

$$\boldsymbol{B}=\begin{bmatrix} -(a+\lambda) & a & & & & \\ & -(a+\lambda) & a & & & \\ & & \ddots & \ddots & \ddots & \\ & & & & -(a+\lambda) & a \\ & & & & & -\lambda \end{bmatrix}$$

$$\boldsymbol{A}_1=\begin{bmatrix} -(a+\lambda) & a & & & & \\ & -(a+\lambda+b) & a & & & \\ & & \ddots & \ddots & \ddots & \\ & & & & -(a+\lambda+b) & a \\ & & & & & -(\lambda+b) \end{bmatrix}$$

$$\boldsymbol{A}_2=\begin{bmatrix} \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{I}b & \boldsymbol{0} \end{bmatrix}, \ \boldsymbol{A}_0=\boldsymbol{I}\lambda$$

1.2 Performance evaluation

Before analyzing the steady states, we check the stability condition inherent to the Markov chain modeled earlier. We introduce matrix $\boldsymbol{A}=\boldsymbol{A}_0+\boldsymbol{A}_1+\boldsymbol{A}_2$, where $\boldsymbol{A}$ is a generator matrix and its associated stationary distribution $\boldsymbol{X}=\{X_0,X_1,X_2,\cdots,X_s\}$ is a solution to $\boldsymbol{XA}=\boldsymbol{0}$ and $\sum_{n=0}^{s}X_n=1$. Considering $\alpha=\frac{a}{b}$, we obtain $\boldsymbol{X}=\frac{1-\alpha}{1-\alpha^{s+1}}\cdot\{\alpha^0,\alpha^1,\alpha^2,\alpha^3,\cdots,\alpha^s\}$.

To ensure the stability of the system, the processing rate for the second phase of the production must be greater than the customer arrival rate and smaller than the processing rate for the first phase. Moreover, the Markov chain is positively recurrent if the following condition is met: $\boldsymbol{XA}_2\boldsymbol{D}>\boldsymbol{XA}_0\boldsymbol{D}$. $\boldsymbol{D}$ is an $(s+1)$-dimentional row vector of which the entries are 1. Thus, we obtain the stability condition as $\lambda<\frac{(1-\alpha^s)\delta\mu}{(1-\alpha^{s+1})\theta(u)}$. Once the Markov chain is shown to be stable, we can derive the steady-state distribution.

To compute the steady-state distribution, we employ the matrix geometric method (MGM), which is effective when dealing with high-dimensional systems[15]. We use the submatrices of $\boldsymbol{Q}$ to compute the steady-state probability vector iteratively, with boundary vector $\boldsymbol{\pi}_0$ determined by $\boldsymbol{\pi}_0(\boldsymbol{B}+\boldsymbol{R}\boldsymbol{A}_2)=\boldsymbol{0}$. The rate matrix $\boldsymbol{R}$ is introduced, which satisfies the matrix geometric equation: $\boldsymbol{\pi}_{i+1}=\boldsymbol{\pi}_i\boldsymbol{R}$, $i\geqslant 0$. Moreover, $\boldsymbol{R}$ is the minimal non-negative solution to the matrix quadratic equation: $\boldsymbol{A}_0+\boldsymbol{R}\boldsymbol{A}_1+\boldsymbol{R}^2\boldsymbol{A}_2=\boldsymbol{0}$. That is, $\boldsymbol{R}$ is determined by the submatrices of the repeating portion in $\boldsymbol{Q}$. One way to compute $\boldsymbol{R}$ numerically follows an iterative approach: $\boldsymbol{R}(n+1)=-(\boldsymbol{A}_0+\boldsymbol{R}(n)^2\cdot\boldsymbol{A}_2)\boldsymbol{A}_1^{-1}$, until $|\boldsymbol{R}(n+1)-\boldsymbol{R}(n)|_{(i,j)}<\varepsilon$, with $\boldsymbol{R}(0)=\boldsymbol{0}$. It is known that the spectral radius of $\boldsymbol{R}$ is less than one if the Markov chain is stable and ergodic.

With the steady-state distribution, we can compute the following queuing performance measures: $E(L)$ is the expected number of customer orders; $E(W)$ is the expected customer order fulfillment delay (i. e., the expected time from customer order arrival to order completion), and $E(O)$ is the expected number of semi-finished products. The measures are then given by

$$E(L)=\boldsymbol{\pi}_1(\boldsymbol{I}-\boldsymbol{R})^{-2}\boldsymbol{D}$$

$$E(W)=E(L)/\lambda$$

$$E(O)=\boldsymbol{\pi}_0(\boldsymbol{I}-\boldsymbol{R})^{-1}\boldsymbol{V},\qquad \boldsymbol{V}=\{0,1,2,\cdots,s\}^{\mathrm{T}}$$

We next present a stylistic numerical example to illustrate how the investment level u and the initial OPP θ_0 affect $E(W)$ and $E(O)$. Set θ_0 to be 0.1, 0.3 and 0.6. Recall that $\theta(0)=\theta_0$, $\theta(u)\leqslant\bar{\theta}$, $\theta'(u)>0$, $\theta''(u)<0$. We consider two functions to represent $\theta(u)$ that satisfy the above conditions. The two functions are $\theta_1(u)=\theta_0+(\bar{\theta}-\theta_0)(1-\mathrm{e}^{-\gamma u})$[16] and $\theta_2(u)=\theta_0+c\sqrt{u}$[17], shown in Fig. 3. Other parameters are as follows: $\lambda=0.55$, $s=3$, $\bar{\theta}=0.9$, $\varepsilon=10^{-100}$, $c=0.07$ and $\gamma=0.3$. We assume that $\delta=\theta(u)$. Figs. 3(a) to 5(a) report the cases for $\theta_1(u)$ and Figs. 3(b) to 5(b) report the cases for $\theta_2(u)$.

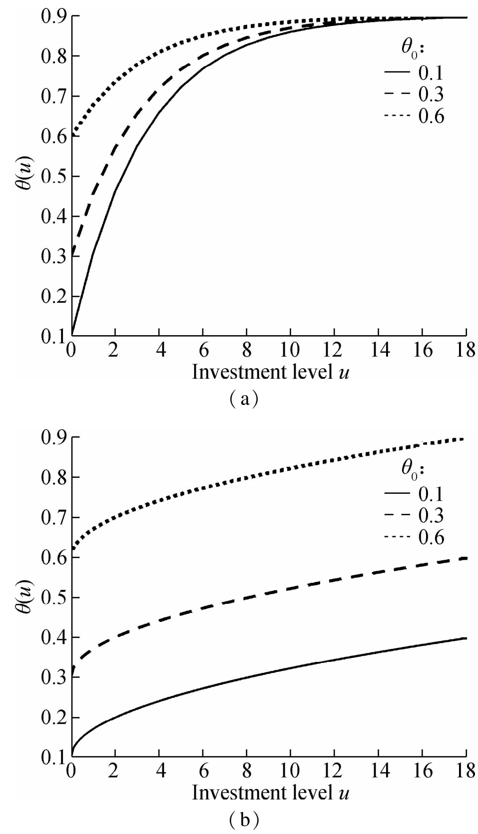

Fig. 3 Impact of investment level on order penetration point. (a) $\theta_1(u)=\theta_0+(\bar{\theta}-\theta_0)(1-\mathrm{e}^{-\gamma u})$; (b) $\theta_2(u)=\theta_0+c\sqrt{u}$

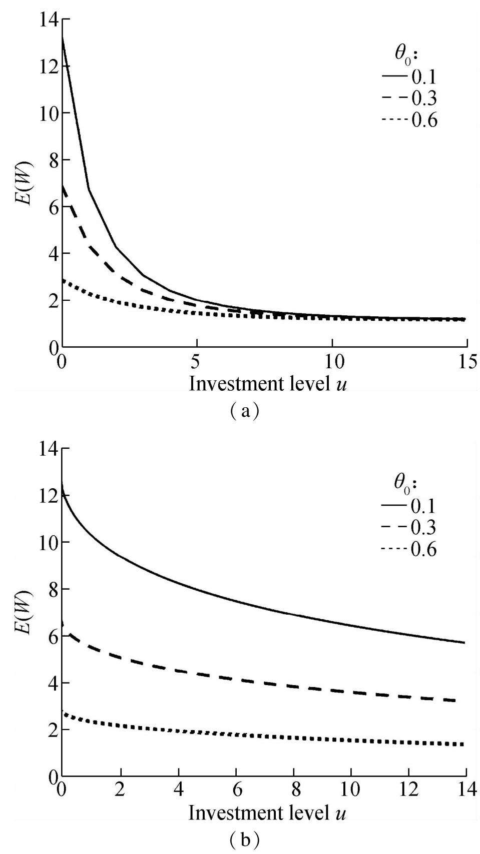

Fig. 4 Impact of investment level on expected customer order fulfillment delay. (a) $\theta_1(u)=\theta_0+(\bar{\theta}-\theta_0)(1-\mathrm{e}^{-\gamma u})$; (b) $\theta_2(u)=\theta_0+c\sqrt{u}$

From Fig. 4, we observe that a higher investment level results in a shorter expected customer order fulfillment delay. This observation implies that a smaller percentage of the production process is required to perform the customization task, which reduces the expected customer order fulfillment delay. Additionally, $E(W)$ is sensitive to θ_0. If the initial OPP is located at the front-end of the production process, the expected fulfillment delay registers a more marked reduction. However, when the process improvement is beyond a certain investment level, such as $u=10$ in Fig. 4(a), the expected customer order fulfillment delay remains unchanged, no matter where the initial OPP is located.

Fig. 5 shows how $E(O)$ is affected by u. A higher investment level is beneficial to hold a fewer expected number of semi-finished products. As the investment level increases, the initial OPP is pushed down; i. e., a larger

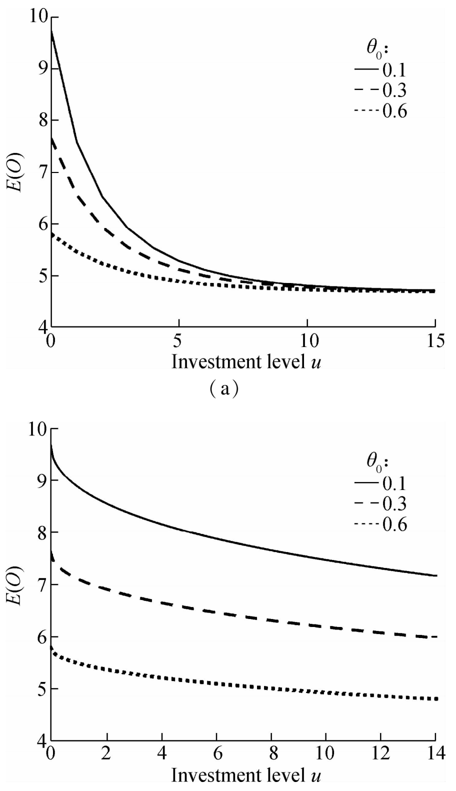

Fig. 5 Impact of investment level on expected number of semi-finished products. (a) $\theta_1(u)=\theta_0+(\bar{\theta}-\theta_0)(1-e^{-\gamma u})$; (b) $\theta_2(u)=\theta_0+c\sqrt{u}$

percentage of each product is completed in advance in phase one. Customers can receive their products much faster. As a result, it is not necessary to hold a more semi-finished products inventory. Similarly to Fig. 4, $E(O)$ is also sensitive to θ_0. The smaller the θ_0, the larger the $E(O)$.

2 Cost-Minimization Formulation

The manufacturer seeks to minimize the sum of the following costs when determining the optimal investment level u^*: The expected cost of customer order fulfillment delay; the expected inventory holding cost of semi-finished products; and process improvement cost. Mathematically speaking, the manufacturer intends to minimize its total cost (TC).

$$\min \mathrm{TC}(u)=C_{\mathrm{w}}E(W)+C_{\mathrm{h}}V(\theta)E(O)+gu^2 \quad (8)$$

where C_{w} is the average cost per time unit of customer order fulfillment delay; C_{h} is the average holding cost per time unit per semi-finished product; $V(\theta)$ is the average value per semi-finished product, assumed to be increasing in θ; and g is the cost coefficient of the investment. Here we assume that the cost directly associated with the investment level is quadratically proportional to the investment level. The customer order fulfillment delay may decrease as the investment level increases. However, an increased investment may also increase the inventory holding cost of semi-finished products and also increase spending on the investment. Hence, the manufacturer must weigh these conflicting factors when selecting the optimal investment level.

2.1 Optimization results

We present numerical experiments to investigate how the manufacturer's total cost is affected by the initial OPP and the investment level. In these experiments, we use $\theta_1(u)=\theta_0+(\bar{\theta}-\theta_0)(1-e^{-\gamma u})$. In our Matlab R2015a implementation, we used the following parameter values: $\lambda=0.55$, $\mu=1$, $s=3$, $\bar{\theta}=0.9$, $\varepsilon=10^{-100}$, $C_{\mathrm{w}}=1$, $C_{\mathrm{h}}=1$, $\gamma=0.3$ and $g=0.1$. We assumed that $\delta=\theta(u)$ and $V(\theta)=V\theta(u)$, where V is the value of the product and equal to 1. Since both $E(W)$ and $E(O)$ are unchanged when $u\geqslant 10$, as shown in Fig. 4(a) and Fig. 5(a), we use the enumeration method to calculate TC by selecting the value of u from 0 to 10.

Fig. 6 shows the manufacturer's total cost and the OPP under different investment levels when $\theta_0=0.1$. It is noted that the minimum total cost is 7.361 and it occurs when the investment level is 3, i.e., $u^*=3$. The manufacturer's total cost is reduced by 48.29% through process investment, which is remarkable. The corresponding optimal OPP $\theta(u^*)$ is 0.575. Increasing the investment level can indeed lower the manufacturer's total cost. However, when the investment level further increases, it no longer results in any cost reduction.

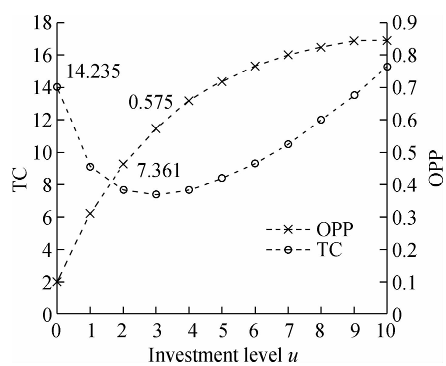

Fig. 6 Impact of investment level on total cost and OPP

Tab. 1 shows the optimal investment level u^* and the optimal OPP $\theta(u^*)$ with respect to varied θ_0. As θ_0 increases, u^* decreases and is greater than 0. Thus, it is beneficial to further delay product differentiation through process investment, since reducing the customer order fulfillment delay is the primary goal of the manufacturer. However, when $\theta_0=0.8$, u^* is reduced to 0. It means that there is no investment. The manufacturer's total cost increases in response to any further increase in investment, and thus the manufacturer is unwilling to further invest in the process improvement. On the other hand, the optimal OPP $\theta(u^*)$ does not strictly increase with θ_0. $\theta(u^*)$ declines from 0.615 to 0.571 when θ_0 increases from 0.2 to 0.3. The reason is that u^* decreases from 3 to 2. For a similar reason, $\theta(u^*)$ falls slightly when θ_0

increases from 0.5 to 0.6. Fig. 7 describes the relationship among $\theta(u^*)$, u^* and θ_0.

Tab. 1 The optimal decisions for various θ_0

θ_0	u^*	$\theta(u^*)$	$TC(u^*)$	Δ/%
0.1	3	0.575	7.361	48.29
0.2	3	0.615	7.147	35.91
0.3	2	0.571	6.884	24.89
0.4	2	0.626	6.598	15.89
0.5	2	0.680	6.364	8.38
0.6	1	0.678	6.075	3.95
0.7	1	0.752	5.820	1.20
0.8	0	0.800	5.587	0

Note: $\Delta = (TC(0) - TC(u^*))/TC(0) \times 100\%$ is the cost saving rate, and $TC(0)$ is the manufacturer's total cost without investment (i.e., $u=0$).

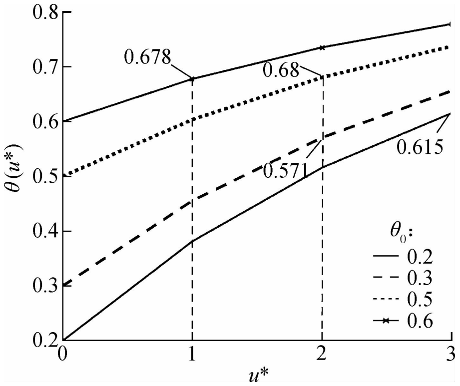

Fig. 7 The optimal OPP and optimal investment level under different θ_0

2.2 Sensitivity study

Next, we study the sensitivity of optimal solutions with the parameters changing.

Fig. 8(a) and Fig. 9(a) illustrate that as the unit-time cost of customer order fulfillment delay increases, the optimal investment level and the cost saving rate increase. This implies that, for a higher unit-time cost of customer order fulfillment delay, the manufacturer should more sensibly consider an investment in the process improvement. In other words, the OPP is likely to be further pushed downstream with impatient customers.

As the product value increases in Fig. 8(b) and Fig. 9(b), the optimal investment level and the cost saving rate decrease. This implies that the manufacturer is less willing to make an investment on process improvement when the product value becomes larger. This is due to an increase in the holding cost of the semi-finished products.

Additionally, as shown in Fig. 8(c) and Fig. 9(c), the optimal investment level and the cost saving rate decrease with the increase in the cost coefficient of the investment. A higher cost coefficient of the investment means that the manufacturer should invest more in order to achieve the same delivery lead time. To balance the customer order fulfillment delay cost with the investment cost, the manufacturer may set a reasonable investment level.

For more sensitive information, please see Tabs. 2 to 4.

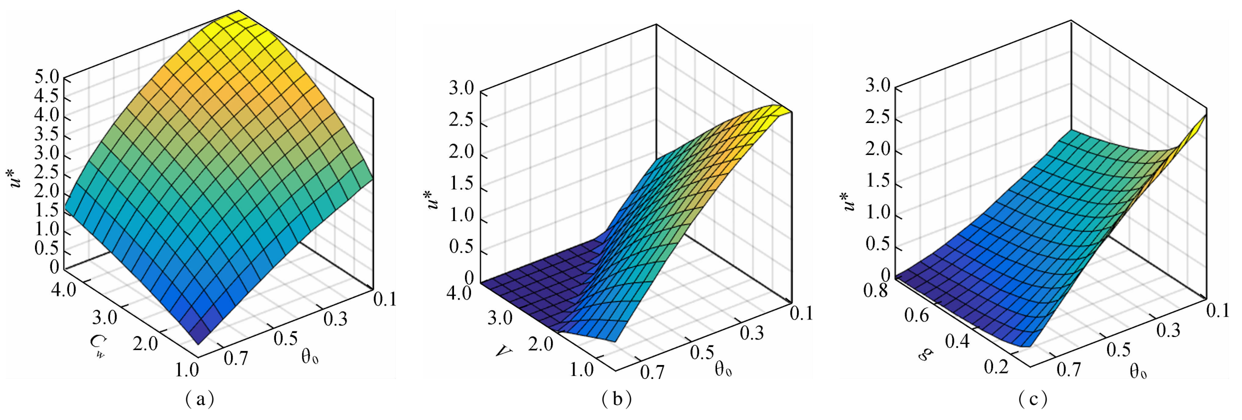

Fig. 8 Impact of C_w, V, g, θ_0 on optimal investment level. (a) $V=1$, $g=0.1$; (b) $C_w=1$, $g=0.1$; (c) $C_w=1$, $V=1$

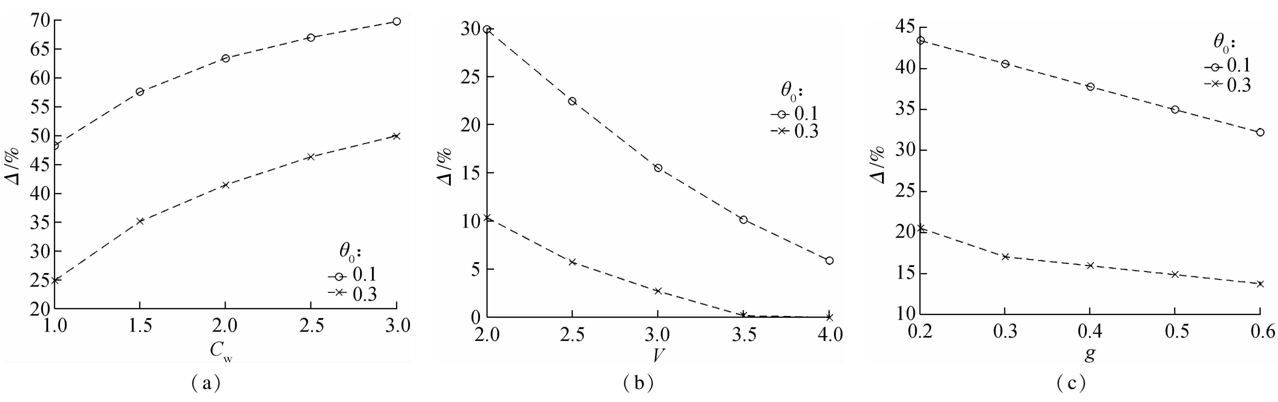

Fig. 9 Impact of C_w, V, g, θ_0 on cost saving rate. (a) $V=1$, $g=0.1$; (b) $C_w=1$, $g=0.1$; (c) $C_w=1$, $V=1$

Tab. 2 The optimal u^* and TC(u^*) for various C_w

θ_0	u^*			TC(u^*)		
	$C_w=1.5$	$C_w=2$	$C_w=2.5$	$C_w=1.5$	$C_w=2$	$C_w=2.5$
0.1	4	4	4	8.851	10.052	11.254
0.2	3	4	4	8.509	9.733	10.834
0.3	3	3	4	8.174	9.386	10.449
0.4	3	3	4	7.880	8.957	10.097
0.5	2	3	3	7.493	8.577	9.534
0.6	2	2	2	7.133	8.095	9.057
0.7	1	2	2	6.737	7.647	8.464
0.8	1	1	1	6.358	7.091	7.825

Tab. 3 The optimal u^* and TC(u^*) for various V

θ_0	u^*			TC(u^*)		
	$V=2$	$V=3$	$V=4$	$V=2$	$V=3$	$V=4$
0.1	2	2	1	10.665	13.672	16.141
0.2	2	1	1	10.438	13.517	16.199
0.3	2	1	0	10.271	13.378	16.044
0.4	1	1	0	10.091	13.344	16.132
0.5	1	0	0	9.895	13.248	16.398
0.6	1	0	0	9.773	13.280	16.758
0.7	0	0	0	9.649	13.406	17.163
0.8	0	0	0	9.588	13.588	17.588

Tab. 4 The optimal u^* and TC(u^*) for various g

θ_0	u^*			TC(u^*)		
	$g=0.2$	$g=0.4$	$g=0.6$	$g=0.2$	$g=0.4$	$g=0.6$
0.1	2	2	1	8.058	8.858	9.650
0.2	2	2	1	7.632	8.432	8.653
0.3	2	1	1	7.284	7.705	7.905
0.4	1	1	1	6.938	7.138	7.338
0.5	1	1	1	6.506	6.706	6.906
0.6	1	0	0	6.175	6.325	6.325
0.7	0	0	0	5.891	5.891	5.891
0.8	0	0	0	5.588	5.587	5.587

3 Conclusion

This paper mainly investigates the investment decision optimization for delayed product differentiation. A flexible manufacturing system modeled as a continuous time Markov chain is considered. Two important queuing performance measures by using the matrix geometric method are computed. Furthermore, our study leads to three managerial recommendations. First, the manager should consider the initial OPP when making a decision to invest or disinvest in the process improvement. Secondly, the manager should focus more on impatient customers as the cost of customer order fulfillment delay can have different impacts on the investment decision. Finally, the manager should take a more holistic viewpoint by considering the value of the products and the cost directly associated with the investment decision, especially when attempting to launch a high volume of investment.

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基于排队论的延迟产品差异化的投资决策优化

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摘要:为了平衡库存成本与多样化需求两者之间的矛盾,研究了延迟产品差异下必要工艺改进最优投资决策. 将两阶段生产柔性制造系统建模为连续时间马尔科夫链. 第一阶段采用备货型生产方式制造半成品,第二阶段采用订单型生产方式定制化第一阶段半成品. 利用矩阵几何方法得到柔性制造系统的绩效测量指标. 构建一个优化模型确定最优工艺改进投资水平以最小化制造商总成本. 结果表明:高投资水平能够降低期望顾客订单满足延迟以及期望半成品库存量. 当初始订单渗透点为 0.4 时,通过工艺改进投资能够节约制造商 15.89% 总成本. 此外,最优投资水平随单位顾客订单满足延迟成本的增加而上升,随产品价值和初始订单渗透点的增加而下降.

关键词:柔性制造系统;延迟策略;订单渗透点;工艺改进投资水平;矩阵几何方法
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