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Article

Research on Intelligent Sensor Networks Based on Machine Learning Algorithms in Advance Financing Modeling

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Abstract: This paper conforms to the development characteristics of the digital era and studies the improvement and application of artificial fish swarm algorithm in the advance financing model. Firstly, the relevant parameters are defined and the bank financing model is constructed. Subsequently, the artificial fish swarm algorithm with good ability to find global extreme value is selected and optimized by integrating taboo search. Combine the above to complete the construction of the prepayment financing model. The solution process of the model algorithm is presented through specific numerical examples. Finally, the model is used to analyze the financing strategy of farmers and the financing strategy of manufacturing suppliers to verify the effectiveness of the prepayment financing model. The study points out that in the prepayment financing of manufacturing suppliers, the price discount coefficient is less than 0.42 when the demand fluctuation is low, which can make the manufacturer and retailer profits reach Pareto optimization. The feasibility of the prepayment financing model in real case applications is demonstrated.

Keywords: advance payment financing model; artificial fish swarm algorithm; financing strategy; forbidden search

1. Introduction

When the upstream suppliers of the supply chain are in financial constraints, the downstream buyer (or retailer) pays for the goods in advance through financial institutions, so that the upstream suppliers can obtain funds instantly to alleviate the financial pressure that they may face in their production and operation, and this model is called prepayment financing [1-3]. The prepayment financing model not only accelerates the suppliers' capital turnover, but also enhances the stability and resilience of the supply chain, especially in the face of market fluctuations and potential supply chain disruption risks, it can ensure the continuous operation of the supply chain, and reduce the risk of production stagnation and delayed payment due to the capital rupture [4-8]. However, in the traditional supply chain advance financing model, it is difficult for financial institutions to obtain complete transaction information between upstream and downstream enterprises in the supply chain, and information asymmetry leads to inaccurate credit assessment [9-10]. The opacity of transaction information and fund flow makes it difficult to track and verify the authenticity of the transaction among the subjects in the supply chain, which directly increases the financing risk [11].

The empowerment of information technology provides strong technical support for the prepayment financing model, which significantly improves the efficiency and transparency of capital flow in the supply chain, and reduces transaction costs and credit risks [12-15]. Through the application of machine learning algorithms, cloud computing, blockchain and other technologies, financial institutions can more accurately assess the credit status of both parties to the transaction and realize real-time response to the demand for funds in the supply chain, thus providing suppliers with rapid financial support and alleviating the pressure of capital liquidity [16-17]. The introduction of information technology can also optimize the payment process, reduce human error and fraud risk, and improve the security and traceability of payment [18-19]. Therefore, the digital technology-enabled supply chain finance innovation model plays a crucial role in enhancing the stability of the supply chain and improving the overall competitiveness of the supply chain.

This paper discusses the definition of parameters in the financing model, makes theoretical assumptions, and establishes a bank financing model. Taking this model as a benchmark, the artificial fish school algorithm is chosen as the global optimal solution method. For the defect that the diversity of the fish population deteriorates in the later stage of the artificial fish school algorithm, the improvement based on forbidden search is designed, from which the prepayment financing model is constructed. In order to test the feasibility of the model, the optimal strategy analysis and parameter change impact analysis in the financing of farmers, and the arithmetic example analysis and parameter sensitivity analysis in the financing of manufacturing suppliers are carried out successively.

2. Bank financing model

This section constructs a bank financing model by briefly analyzing the definition of parameters in the financing process and making relevant assumptions. It serves as a research baseline for the prepayment financing model below.

2.1. Parameter definitions

The symbols used in this paper are summarized in Table 1.

Table 1. Symbolic summary

Symbol	Definition interpretation
P	Unit selling price
D	The market is not sure how much is needed
w	Unit wholesale price of goods
π_j^i	Expected returns of different roles j in different modes i
r^i	Financing rates under different modes i
c	Unit production cost of goods
B	Dealer's initial funding level
q^i	Distributor order quantity under different mode i
β	Margin ratio under guarantee delivery prepayment financing model
r_B	Bank risk-free investment rate of return

Table 1 serves as a summary of the use of symbols in this paper. First, the meaning of the subscripts of the symbols is explained: subscript $j = m, d, b$ represents the manufacturer, the distributor, and the bank, respectively. The superscript $i = E, I, T, SC$ represents different financing modes: commercial bank financing as external financing, commercial credit as internal financing, and guaranteed pickup advance financing modes with the participation of three parties, e.g., π_D^I represents the distributor's revenue under the commercial credit financing mode, and q^E represents the optimal order quantity under the traditional bank financing mode.

Secondly, the relationship between the symbols is explained: in terms of price, there exists a relationship of $P > w > c > 0$, which is a guarantee that the transaction can be carried out smoothly. In terms of time, $T = 0$ or 1 represents the starting and ending moments of a single stage. The margin ratio ranges from $0 < \beta < 1$. In terms of loan interest rate, the lender has set different loan interest rates according to different financing modes, specifically, the different loan interest rates are composed of the base loan interest rate plus the corresponding loan interest rate upward fluctuation coefficients, and in this thesis the following relationships exist between the loan interest rates of the three financing modes: $r^E > r^I$ and $r^E > r^T$. The reason why these relationships are established is that the core firms are usually aware of the information of their more information about their downstream distributors, resulting in higher interest rates for both the traditional bank financing model than for the to the traditional commercial credit financing model and the secured pickup advance financing model. Moreover, industry practice divides interest rates into two components: a fixed interest rate base and a variable interest rate. When a small or medium-sized distributor applies for a bank loan, the bank will substantially increase the variable rate due to lack of collateral or poor credit history. On the contrary, banks are willing to offer financing at a much lower lending rate because of the guarantee provided by the core business.

2.2. Model assumptions

Assumption 1: The stochastic demand D obeys the probability density function $f(\xi)$ and the cumulative distribution function $F(\xi)$, while $F(\xi)$ is continuously derivable and has a finite mean, and conforms to the Incremental Failure Rate (IFR) property as in equation (1):

$$h(\xi)=\frac{f(\xi)}{\bar{F}(\xi)} \tag{1}$$

$\bar{F}(\xi)=1-F(\xi)$ of them.

Assumption 2: Manufacturers, distributors and banks are risk neutral and perfectly rational and completely moral hazard averse.

Assumption 3: The unit selling price of goods $P=1$.

Assumption 4: Risk-free investment returns are considered in the discussion of bank returns, while risk-free returns are not considered in the discussion of manufacturer and dealer returns.

Assumption 5: The preconditions for having dealers involved in the transaction are as in equations (2)-(4):

$$(1+r^{T})\beta w<P-(1-\beta)w \tag{2}$$

$$(1+r^{E})w<1 \tag{3}$$

$$(1+r^{I})w<1 \tag{4}$$

Otherwise the dealer cannot make a profit on normal transactions.

Assumption 6: Neglect the pickup cost.

Assumption 7: The dealer's inventory at the beginning of the period is zero and the stock is not replenished after the order is placed.

Assumption 8: The product is in short supply in the market.

Among them, Assumption 1 is a common demand distribution assumption in supply chain finance research. Assumption 2 is to ensure that manufacturers, distributors and banks all maximize their own expected returns as the basis for decision-making, to ensure the normal order of transactions. Assumption 3 is to simplify the calculation without loss of generality. Assumption 4 is because risky investment behavior is one of the methods for banks to obtain income, but not the main method for manufacturers and distributors to obtain income. Assumption 5 is made to ensure that dealers are able to profit from arm's length transactions and thus are willing to participate in them. Assumption 6 is based on the fact that the value of air-conditioning goods is high and the cost of delivery is ignored in order to simplify the formula. Assumption 7 is based on the characteristics of the guaranteed pickup advance financing model. Assumption 8 is a guarantee that the dealer will vigorously pursue the sale of goods produced by the manufacturer.

2.3. Modeling

This paper first analyzes a manufacturer's access to financing from a bank and uses the bank financing strategy as a benchmark for the comparison of financing strategies later in the paper. In bank financing, the manufacturer applies for a bank loan and then needs to repay the principal and interest at the term of the loan, and this paper assumes that the bank is in a competitive market and assumes that the risk-free rate is zero. In addition, this paper assumes that the bank's risk premium is also zero, such an assumption does not affect the main conclusions of this paper, and at the same time will simplify the model solution.

In the bank financing strategy game, the retailer first decides on the wholesale price w_b, and the manufacturer decides on the output Q_b. Therefore, there are market frictions and the bank's information about the manufacturer is incomplete, so the manufacturer is only able to obtain part of the bank loan $\eta c Q_b$, and the manufacturer's profit function can be expressed as in equation (5):

$$\pi_m^{BF}(Q_b)=E[w_b\min(\eta\theta Q_b,D)-\eta c Q_b] \tag{5}$$

The retailer's profit function can be expressed as equation (6):

$$\pi_r^{BF}(w_b)=E[(P-w_b)\min(\eta\theta Q_b,D)] \tag{6}$$

Through the inverse solution, it is found that the profit functions are all concave functions, i.e., there exists an optimal solution in the feasible domain, and then this paper solves the optimal decision variables of the manufacturer and the retailer, and puts forward the first proposition of this paper.

Proposition 1: In the case of bank financing, the retailer's optimal wholesale price decision w_b^* and the manufacturer's optimal output decision Q_b^* are solved as in equation (7):

$$w_b^* = \frac{A_0^2 - \sqrt[3]{3}}{\sqrt[3]{9}\theta A_0} \tag{7}$$

and equation (8):

$$Q_b^* = \frac{2h(\sqrt[3]{3}A_0^2 - 3A_0 - \sqrt[3]{9})}{\sqrt[3]{3}\theta\eta(A_0^2 - \sqrt[3]{3})} \tag{8}$$

Proposition 1 shows that the retailer's optimal wholesale price decision is affected by the manufacturer's production compliance rate, while the manufacturer's optimal output decision is affected by market frictions in addition to the manufacturer's production compliance rate. Here it is necessary to ensure the manufacturer's production pass rate $\theta \geq \underline{\theta}$, where there is equation (9):

$$\underline{\theta} = 1/P \tag{9}$$

This is because manufacturers still have incentives to participate in production when the wholesale price set by the retailer is the retail price. In addition, it is also found that the optimal decision under the bank financing strategy under competitive conditions is the same as the optimal decision under unfunded constraints, which confirms the market power hypothesis that a competitive banking market can further improve the overall efficiency of the supply chain.

Corollary 1: The retailer's optimal wholesale price decision is monotonically decreasing with respect to the manufacturer's production compliance rate under the bank financing strategy. The manufacturer's optimal output decision is a concave function of the manufacturer's conformity rate, i.e., there exists a threshold $\hat{\theta}_b$ such that Q_b^* is monotonically increasing with respect to θ when $\underline{\theta} \leq \theta < \hat{\theta}_b$ is present and Q_b^* is decreasing with respect to θ when $\hat{\theta}_b \leq \theta < 1$ is present. In addition, the manufacturer's optimal output decision is monotonically decreasing with respect to the market friction coefficient (η).

Corollary 1 shows that the retailer's optimal wholesale price decision is monotonically decreasing with respect to the manufacturer's production compliance. From the manufacturer's point of view, a too low product conformity rate implies a higher unit production cost, which leads to a decrease in the manufacturer's marginal profit. From the retailer's point of view, if the manufacturer's product conformity rate is too low, then the retailer has to set a higher wholesale price to increase the manufacturer's profit, and thus increase the manufacturer's output, which is beneficial to the whole supply chain. Conversely, if the manufacturer's product pass rate is relatively high, this means that the manufacturer's unit cost of production is low, so the retailer has an incentive to set a lower wholesale price and increase its own marginal profit margin. However, doing so reduces the manufacturer's marginal profit.

Corollary 1 also shows that the manufacturer's optimal output decision is a concave function of the manufacturer's production pass rate. This is because when the manufacturer's production pass rate is very low $\left(\theta < \hat{\theta}_b\right)$, the manufacturer benefits from lower unit production costs as the production pass rate continues to increase. And when the production pass rate is large enough $\left(\theta > \hat{\theta}_b\right)$, the manufacturer's profits continue to shrink as the wholesale price continues to fall, and the reduction in the marginal profit margin due to the fall in the wholesale price outweighs the benefit from the lower unit cost. In addition, it is easy to understand that the manufacturer's optimal product output decreases with market frictions because when the degree of market frictions is high, in order to achieve the target output, the manufacturer will set a higher output to facilitate access to sufficient production funds from the bank.

Corollary 2: With bank financing, the retailer's optimal profit function π_r^{BF*} is monotonically increasing with respect to the manufacturer's compliance rate. The manufacturer's optimal profit function π_m^{BF*} is a concave function of the manufacturer's conformity, i.e., there exists a threshold $\dot{\theta}_b$

such that the manufacturer's optimal profit is monotonically increasing with respect to the conformity at $\underline{\theta} \le \theta < \dot{\theta}_b$. Otherwise, the manufacturer's profit function is monotonically decreasing with respect to the conformity. Otherwise, the manufacturer's profit function is monotonically decreasing with respect to the production pass rate.

Corollary 2 shows that the manufacturer's optimal profit is a one-peak function of the production pass rate. This is because when the production pass rate is low $\left(\underline{\theta} \le \theta < \dot{\theta}\right)$, the manufacturer benefits from a larger marginal profit margin from lower production costs as the production pass rate increases. However, when the production pass rate is high $\left(\dot{\theta} \le \theta\right)$, the reduction in output from an increase in the production pass rate offsets the gains from an increase in the marginal profit margin and ultimately leads to a reduction in profits.

For the retailer, his optimal profit increases with the rate of product output. This is because when the manufacturer's production pass rate is low $\left(\underline{\theta} \le \theta < \hat{\theta}\right)$, the retailer benefits from setting a lower wholesale price as the production pass rate grows. And when the manufacturer's production pass rate is high $\left(\hat{\theta} \le \theta\right)$, despite the fact that the manufacturer's output is declining at this point, the increase in marginal profit due to the decline in the wholesale price outweighs the decrease in profit due to the decline in output, thus allowing the retailer's profit to increase as the manufacturer's production pass rate continues to increase.

3. Algorithm design for the advance financing model

In this chapter, based on the bank financing model proposed above, the artificial fish swarm algorithm is introduced as the solution method of the model. Improvements based on forbidden search are made to address the shortcomings of the fish swarm algorithm that slows down the convergence rate in the later stages.

3.1. Description of Improvement Points of Fish Swarm Algorithm

3.1.1. Variable parameter strategy

(1) Step *step* change strategy

The step size is large, which is conducive to convergence as soon as possible, but if the step size is too large, it is easy to miss the global optimal solution, and the accuracy of the solution deteriorates, at the same time, it is easy to have oscillation phenomenon in the later stage, and the convergence speed is slowed down. A small step size is good for local search and slow for global optimization. In this paper, the step size is set as a decreasing function shown in equation (10). This setting ensures that the optimization process has a strong global search capability in the early stage and a strong local search capability in the later stage.

$$step_{gen+1} = \left(\frac{1}{2} + \frac{1}{gen}\right) \times step_{gen} \tag{10}$$

(2) Crowding degree factor *delta* change strategy

In the early stage of optimization, each artificial fish possesses a larger crowding degree factor for optimization, which speeds up the optimization speed while avoiding falling into the local optimum and precocity dilemma. In the iterative process, the crowding factor is reduced generation by generation to enhance the local search convergence speed. In this paper, the crowding degree decay function is set as equation (11):

$$\delta_{gen+1} = \varepsilon \times \delta_{gen}, \varepsilon \in (0,1) \tag{11}$$

(3) Perceived Distance *visual* Changing Strategies

Under the condition of fixed perceptual distance, large perceptual distance, tail chasing and flocking behaviors are prominent, and small perceptual distance, foraging and random behaviors are prominent. In this paper, we set the perceptual distance change function as equation (12), so that the perceptual distance decreases with the increase of the number of iterations.

$$visual_{gen+1} = \left(1 - \frac{gen}{maxgen}\right) \times visual_{gen} \tag{12}$$

3.1.2. Taboo optimality-seeking operators

The study of this paper belongs to the category of continuous problems, the number of neighbors in a continuous problem is infinite, so the contraindication method for discrete problems cannot be applied in this problem, for this reason this paper takes the contraindication of the neighborhood of the solution. In this problem, if a point enters into the taboo table, then all the points in the line segment centered on that point with the radius of the taboo as the radius will be taboo, so after discretizing the solution space, the length of the taboo table can be used to calculate the taboo search algorithm given the length of the taboo table.

The current solution space, $[T_{lb}, T_{ub}]$, is discretized into K domains centered at $\frac{(T_{ub}+T_{lb})}{2}$, with radius r, spreading in both directions, schematically shown in Fig. 1.

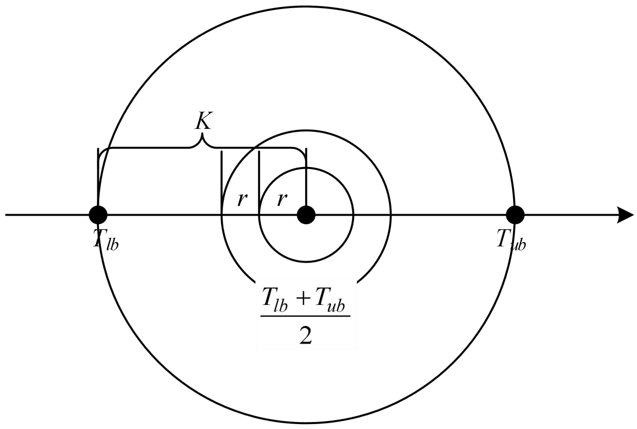


Figure 1. One-dimensional neighborhood concept schematic

In the gen st iteration, the current position of the i nd fish is T_i and the other position is T_j. T_j can be the optimal point in the field of view of the i th fish, the center point or other points. The number of optimization searches is $trynumber$, the optimization coefficient θ is a number between $(0,1)$ randomly generated by the system, and the next position of the i th fish is determined by equation (13):

$$T_{inext} = T_i + \theta \times (T_j - T_i) \tag{13}$$

3.1.3. Taboo optimization process

Step1: T_i is the current state of the artificial fish, n is the counter, $n=1$.

Step2: get a new point T_{inext} from equation (13), calculate AP_{inext}, $n=n+1$.

Step3: Compare the size of AP_i and AP_{inext}, if $AP_i < AP_{inext}$, go to Step4, otherwise go to Step5.

Step4: Judge T_{inext} belongs to the k nd neighbor, judge whether the k rd neighbor exists in the taboo table, if not, then the search is successful, the k th neighbor will be inserted into the taboo table, in the case that the taboo table is full, then update the taboo table according to the first-in-first-out rule, and the search process ends. If it exists, go to step5.

Step5: Determine whether n is greater than the maximum number of attempts $trynumber$, if so, the optimization process ends in failure, otherwise go to Step2.

3.2. Improvement of the general flow of the artificial fish schooling algorithm

Step1: Set the fish population size N, initial movement step $step$, initial perception distance $visual$, initial crowding factor δ, maximum number of attempts $trynumber$, taboo table length $Ntabu$, discretize the solution space into K neighborhoods, maximum number of iterations

$\max gen$, and let $gen = 1$.

Step2: Initialize the fish school $\left(T_1, T_2, T_3 \cdots\cdots, T_N\right)$ in the solution space, calculate the objective function value $\left(AP_1, AP_2, AP_3 \cdots\cdots, AP_N\right)$ of the current school, calculate the current optimal fish T_j , the historical optimal fish T_{best} , and record the historical optimal fish information with a bulletin board.

Step3: Each fish in the school obtains three positions T_{inext} through three behaviors: clustering, tail chasing and chasing the historical optimal fish, selects the one with the larger corresponding objective value T_{inext} , updates its position, and updates the bulletin board information by comparing it with the historical optimal fish.

Step4: If $gen \geq \max gen$, the algorithm terminates. Otherwise, make Eqs. (14)-(17):

$$step_{gen+1} = \left(\frac{1}{2} + \frac{1}{gen}\right) \times step_{gen} \tag{14}$$

$$\delta_{gen+1} = \varepsilon \times \delta_{gen} \tag{15}$$

$$visual_{gen+1} = \left(1 - \frac{gen}{\max gen}\right) \times visual_{gen} \tag{16}$$

$$gen = gen + 1 \tag{17}$$

Go to step3.

4. Test of validity of the advance financing model

In order to verify the correctness of the model on the prepayment financing strategy, this paper selects two examples of the financing strategy of farmers and the financing strategy of manufacturing suppliers, and carries out the analysis of optimal strategy and numerical experimental analysis using the prepayment financing model, respectively.

4.1. Farmer Financing Strategies

An agricultural supply chain decision-making system consisting of a farmer and a firm, in which the farmer has financial constraints and output uncertainty, and the farmer can apply for advance financing from the firm in order to alleviate financial pressure. Test the impact of different values of parameters on the decision-making of farmers, whether it is consistent with the description of the established prepayment financing model. Some scholars have studied the optimal decision of bank financing when farmers are subject to capital constraints and output stochastic situation, therefore, this paper selects some of their research data.

4.1.1. Optimal strategy analysis

By examining the agricultural supply chain, the parameter values that can be directly obtained are: x_L=3 tons/acre, x_H=12 tons/acre, and x_L=0.8. In addition to this, due to the fact that the production data is scattered and involves the confidentiality of the company's production, it is not possible to accurately obtain the research data related to the parameters of the cost-of-effort coefficient *c* in the production and the market size *a*. For this reason, it is assumed that *c*=10 and market size *a*=1000.

Choose three different bank interest rates *r* of low, medium and high, and three different *b* of small, medium and large, respectively, to compare and analyze the optimal decision volume, optimal expected profit and its rate of change of the farmer and the company under prepayment financing and bank financing when there is a bankruptcy risk of the farmer. Among them, the rate of change of farmers' optimal production inputs is shown in equation (18):

$$\Delta q_i^* = (q_i^* - q_i^*) / q_i^* \tag{18}$$

where *i* is the numerical subscript for bank financing and *j* is the numerical subscript for advance financing.

The optimal expected profit rate of change for farmers is shown in equation (19):

$$\Delta \pi_i^f = (\pi_i^f - \pi_j^f) / \pi_j^f \tag{19}$$

where i is the numerical subscript for bank financing and j is the numerical subscript for prepayment financing.

Similarly, the rate of change of the firm's optimal decision volume is equation (20):

$$\Delta\omega_i^* = (\omega_i^* - \omega_j^*) / \omega_j^* \tag{20}$$

The optimal expected profit is equation (21):

$$\Delta\pi_i^m = (\pi_i^m - \pi_j^m) / \pi_j^m \tag{21}$$

The optimal inputs, optimal expected profits and their rates of change for farmers are shown in Table 2.

Table 2. The optimal input amount, the optimal expected profit and change rate

r	***b***	q_2^*	q_1^*	π_2^f	π_1^f	Δq_1^*	$\Delta\pi_1^f$
0.1	0.04	203.58	203.11	318000	348000	0	0.08
0.1	0.4	77.38	77.31	46200	50700	0	0.11
0.1	4	10.76	10.76	888	979	0	0.11
0.25	0.04	203.58	182.68	3180005	322000	-0.11	0.02
0.25	0.4	77.38	74.15	46200	52800	-0.05	0.16
0.25	4	10.76	10.69	888	1100	-0.02	0.25
0.45	0.04	203.58	161.12	3180005	290000	-0.22	-0.08
0.45	0.4	77.38	70.33	46200	55300	-0.08	0.21
0.45	4	10.76	10.61	888	1260	-0.02	0.42

It can be observed from Table 2:

(1) In terms of farmers' optimal expected profit and its rate of change, the expected profit obtained by choosing bank financing will be greater in these cases, but the difference between the optimal expected profit values under prepayment financing and bank financing is not significant.

(2) When the price elasticity coefficient does not directly affect farmers' decisions, it still has an effect on the optimal input quantity q^* and the optimal expected profit π^f. When the price elasticity coefficient increases, the optimal input quantity and the optimal expected profit of farmers will decrease accordingly. This is because the firm is the core firm in the supply chain game process, and when the price elasticity coefficient increases, the firm's market price will be greatly negatively affected if the farmers' production inputs are large. The firm's measures to mitigate the negative impact will affect the farmers' optimal profit.

Table 3 shows the firm's optimal decision quantity, optimal expected profit and its rate of change.

Table 3. Optimal decision quantity, optimal expected profit and its rate of change

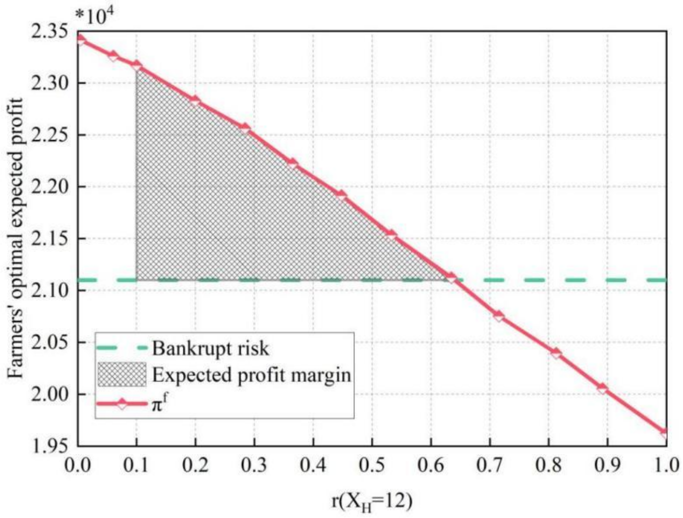
r	***b***	ω_2^*	ω_1^*	π_2^m	π_1^m	$\Delta\omega_1^*$	$\Delta\pi^m$
0.1	0.04	374	411	948000	945000	0.1	0
0.1	0.4	143	157	358000	358000	0.1	0
0.1	4	19.71	21.68	50000	50000	0.1	0
0.25	0.04	374	418	948000	850000	0.13	-0.11
0.25	0.4	143	171	67000	346000	0.21	-0.05
0.25	4	19.71	24.49	50000	49800	0.25	-0.02
0.45	0.04	374	429	948000	748000	0.16	-0.22
0.45	0.4	143	188	360000	328000	0.33	-0.08
0.45	4	19.71	28.19	50000	49400	0.44	-0.02

Table 3 can prove that in the case of high harvest output factor, if the bank interest rate is higher, the company expects farmers to choose prepayment financing more. On the one hand, it can reduce the financing pressure of farmers, and on the other hand, due to the more aggressive production of farmers under the prepayment financing mode, which negatively affects the price, the company can acquire more products at a lower purchase price, thus obtaining more profits. In addition, the incentives for the firm to adopt the prepayment financing model for the farmers can also be seen from the rate of change in the firm's optimal decision volume. All of the above numerical analysis results are consistent with the description of the prepayment financing model in this paper.

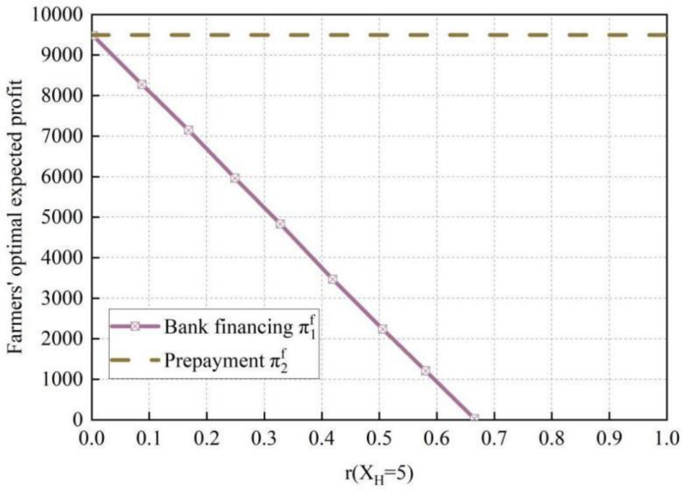
4.1.2. Impact of changes in bank interest rates on farmers' optimal decisions

The effect of changes in bank interest rate on farmers' optimal strategies is investigated by comparing and analyzing the magnitude of farmers' optimal expected profits in different scenarios when the output factor is high (x_H=12) versus low (x_H=5) in a good harvest year. Let c=90, b=1, and other parameters are kept constant.

Figure 2 shows the effect of x_H on the farmer's optimal expected profit under r variation.



(a) x_H=12



(b) x_H=5

Figure 2. The influence of x_H on the optimal expected profit of farmers

Observation of Fig. 2 leads to:

(1) In the case of farmers with bankruptcy risk, when the harvest year output factor x_H is small, the optimal expected profit of farmers under prepayment financing is larger, and the gap between the two is getting bigger and bigger with the increase of bank interest rate r. When the bank interest rate reaches a certain degree, the farmers will surely go bankrupt if they choose bank financing.

(2) For the harvest year output factor x_H is larger, when the bank interest rate r is lower, farmers in the bank financing under the optimal expected profit is larger; when r is larger, farmers choose the prepayment financing mode of revenue advantage will gradually show, and with the rise of the bank interest rate, the advantage is gradually enlarged.

4.2. Financing strategies for manufacturing suppliers

This section investigates a supply chain consisting of a financially constrained SME supplier s and an economically powerful and well-known e-commerce platform e to create a single-cycle operational supply chain decision system.

4.2.1. Example analysis

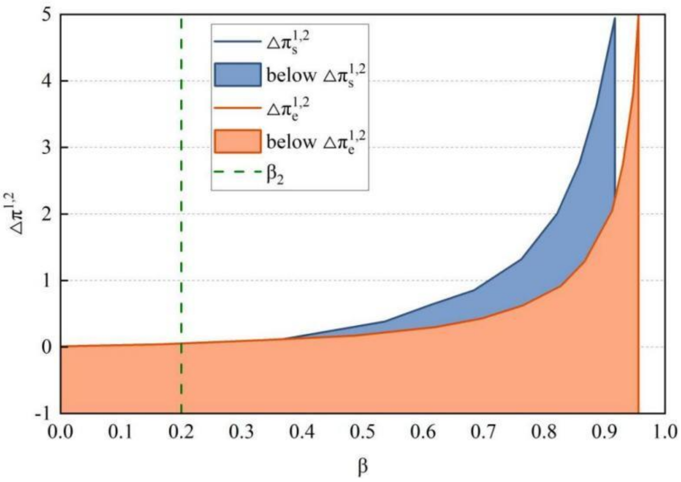
From the perspective of a manufacturing supplier with capital constraints and output certainty, we use the model in this paper to explore its channel choice and financing strategy in the face of capital constraints and word-of-mouth (WOM) spillovers, so as to help it make better decisions. Since the strategies and willingness of suppliers and platforms do not agree in all cases, the equilibrium outcome of their game is mainly affected by the spillover effect and the market share occupied by the supplier's platform. In this paper, we summarize the equilibrium results of the game between suppliers and platforms in Theorem 1.

Theorem 1: When suppliers and platforms discuss whether suppliers are stationed on the platform under the situation of bank financing, the equilibrium results of the game are mainly affected by the spillover effect and the market share occupied by the suppliers stationed on the platform:

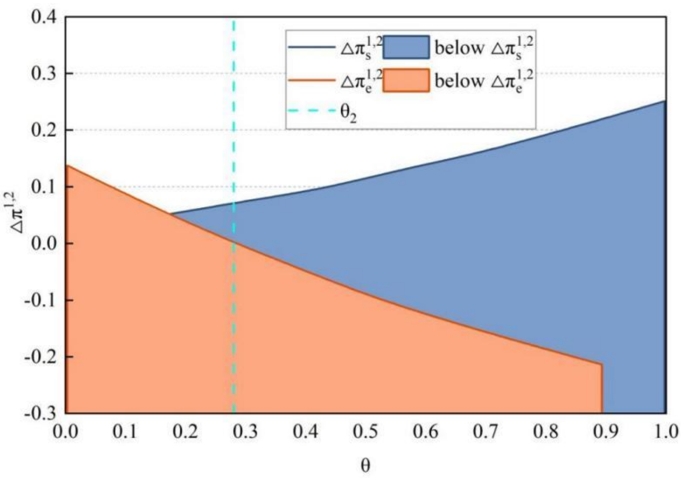
(1) When $\beta > \max[\beta_1(r_f,\theta), \beta_2(r_f,\theta)]$, $\Delta\pi_s^{1,2} > 0$, $\Delta\pi_e^{1,2} > 0$.

(2) When $\max[\theta(r_f,\beta), \theta_2(r_f,\beta)] < \theta < \theta_1(r_f,\beta)$, both parties reach a consensus and the supplier does not move into the platform.

Figure 3 shows the results of numerical experiments on Theorem 1.



(a) Equilibrium decision is affected by β



(b) Equilibrium decision is influenced by θ

Figure 3. Numerical experiment of theorem 1

In Fig. 3(a), according to the actual situation, let the platform commission rate $\lambda = 0.1$, the market share gained by the supplier on boarding the platform = 0.3, the production cost per unit of goods c = 0.4, and the bank interest rate r_f=0.03. The figure demonstrates $\beta=\beta_2$. Since $\beta_2<0$, which is out of the range of the parameter's value, the figure does not demonstrate it, and it is obvious that β, $\beta_2>\beta_1$. It can be concluded from the figure that when $\beta>\beta_2$, the supplier and the platform reach an agreement and both agree that the supplier is on the platform, which is consistent with the conclusion of Theorem 1. In Fig. 3(b), let the spillover effect β = 0.2, and other parameters remain unchanged. Since θ, $\theta_1<0$, it is not shown in the figure, and it is obvious that the market share is larger than θ, θ_1. The figure shows $\theta=\theta_2$, from which it can be concluded that when $\theta<\theta_2$, the suppliers and the platform reach an agreement, and all agree that the suppliers are on board the platform, which is consistent with the conclusion of Theorem 1.

In the case that all supply chain parties expect suppliers not to join the platform under bank financing, the equilibrium results of the supply chain parties' choices between suppliers joining the platform and choosing platform financing and not joining the platform are mainly affected by the financing interest rate. In this paper, the equilibrium results of the game of supply chain parties in this case are summarized in Theorem 2.

Theorem 2: After the supply chain parties exclude the strategy of suppliers joining the platform and adopting prepayment financing, the equilibrium results of the game between suppliers joining the platform and adopting bank financing and not joining the platform are mainly affected by the financing interest rate and the spillover effect:

(1) Due to $r_{f1}(\beta,r,\theta)>r_{f2}(\beta,r,\theta)$, if $r_{f2}(\beta,r,\theta)<r_f<r_{f1}(\beta,r,\theta)$, the parties reach a consensus that they do not expect suppliers to join the platform.

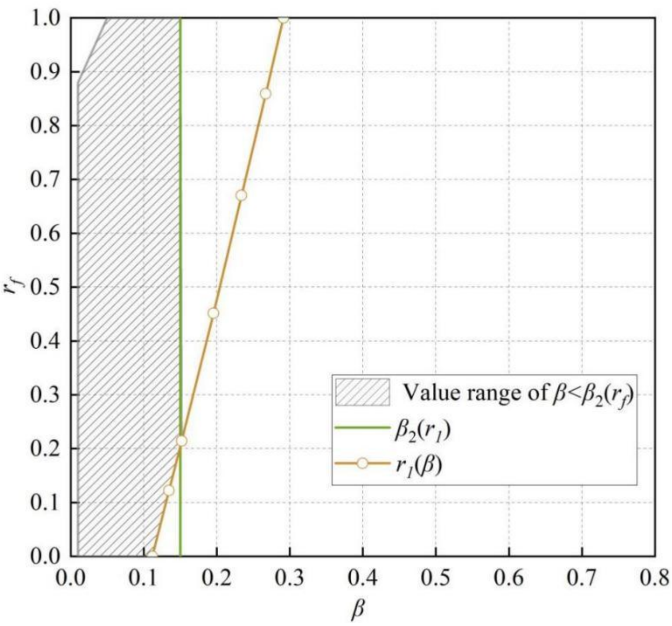
(2) When $\beta>\max[\beta_3(r_f,r,\theta),\beta_4(r_f,r,\theta)]$, all parties in the supply chain expect suppliers to join the platform. When $\beta<\min[\beta_3(r_f,r,\theta),\beta_4(r_f,r,\theta)]$, both parties do not expect suppliers to join the platform.

(3) When $r_2(r_f,\beta,\theta)<r<r_1(r_f,\beta,\theta)$, both supply chain parties reach a consensus that they expect suppliers to join the platform.

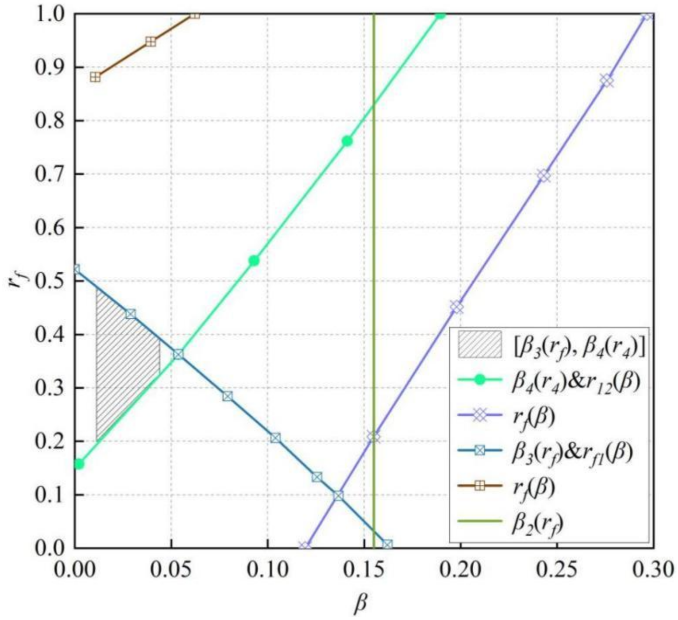
(4) When $\max[\beta_3(r_f,\beta,r),\beta_5(r_f,\beta,r)]<\theta<\min[\beta_4(r_f,\beta,r),\beta_6(r_f,\beta,r)]$, both parties reach a consensus that suppliers do not join the platform.

From Theorem 2, when the supply chain parties decide that the suppliers do not move into the platform under prepayment financing, the supply chain parties will not choose to let the suppliers move into the platform and take bank financing.

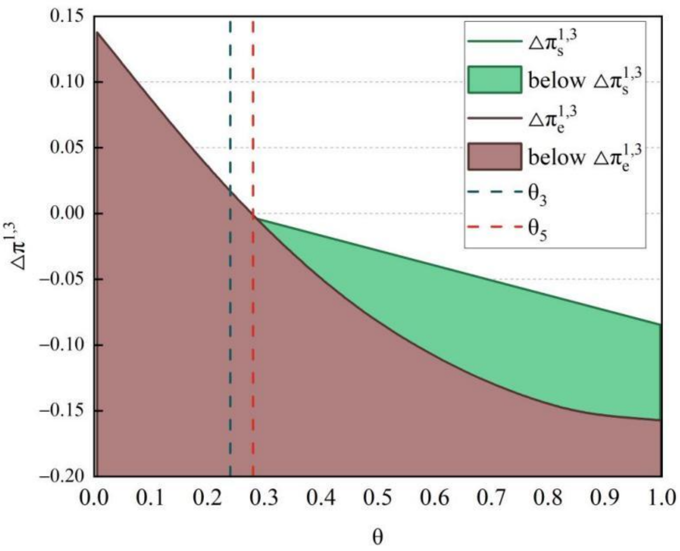
Fig. 4 shows the numerical experiment results about Theorem 1.



(a) Vendors will not opt to join the platform and take bank financing



(b) The supplier parties did not choose platform financing



(c) Equilibrium decision is influenced by θ

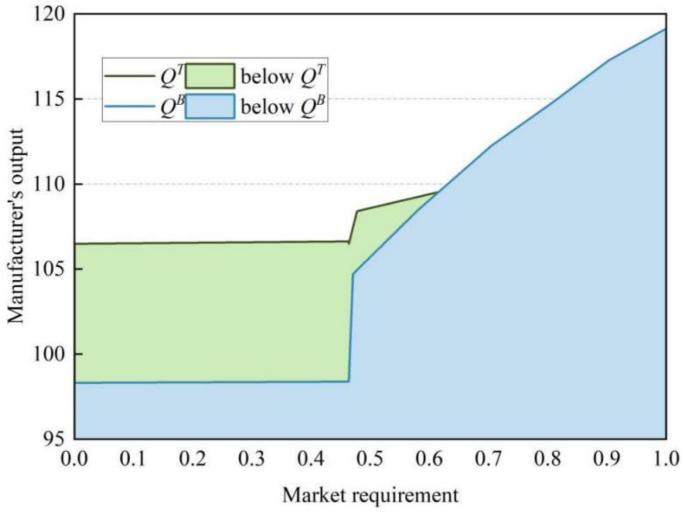
Figure 4. Numerical experiment of theorem 2

Fig. 4 shows the numerical experiment about Theorem 2, assuming that the platform commission rate λ=0.4, the market share θ=0.2 obtained by the supplier's admission to the platform, and the production cost per unit of goods c=0.3. According to Fig. 4(a), it can be seen that the two sides reach an agreement that the supplier won't be admitted to the platform under the bank financing when $r_f>r_f(\beta)$ and $\beta>\beta_2(r_f)$, which is in line with the conclusion of Theorem 2. On the basis that the supplier will not choose to move into the platform and take the prepayment financing mode, according to Fig. 4(b), when $r_2(\beta)<r_f<r_{f1}(\beta)$ or $\beta<\min[\beta_3(r_f),\beta_4(r_f)]$, both parties reach an agreement and the supplier does not move into the platform. From Fig. 4(c), it can be visualized that when $\theta>\max[\theta_3,\theta_5]$, both parties reach a consensus that the supplier does not move into the platform, and when $\theta<\min[\theta_3,\theta_5]$, the supplier moves into the platform, which is consistent with the conclusion of Theorem 2.

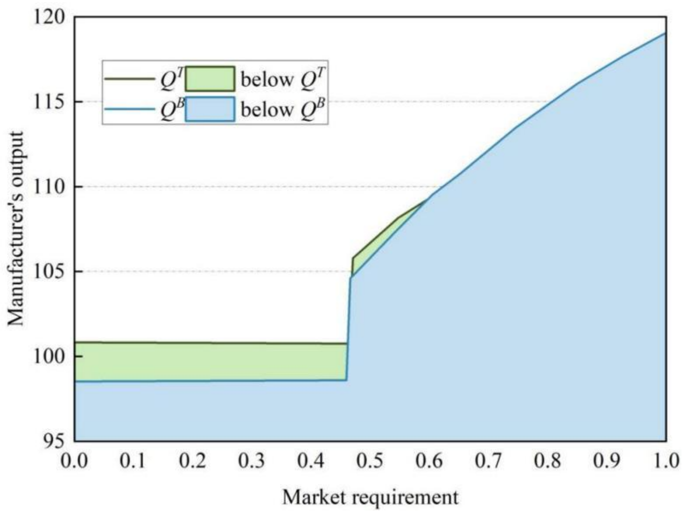
From the previous study, it is known that supply chain prepayment financing decision is affected by many factors such as upstream and downstream enterprises, market demand changes and so on. In this section, the price discount parameter is selected and the model of this paper is applied to study the impact of the change of this parameter on the equilibrium strategy and profit of supply chain financing.

Set A=60, k=0.5, ω=65, c=25, p=70, a=150, and b=1. μ=0.3 indicates a more stable market, and

μ=0.8 indicates a more volatile market. A comparison of the variation of the manufacturer's optimal output with the price discount factor under the two supply chain prepayment financing models is shown in Fig. 5.



(a) Market demand fluctuation is low

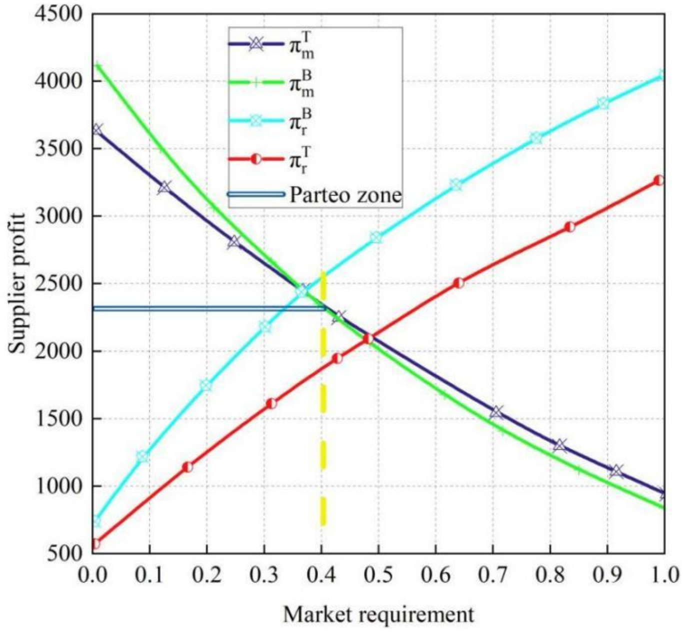


(b) The fluctuation of market demand is high

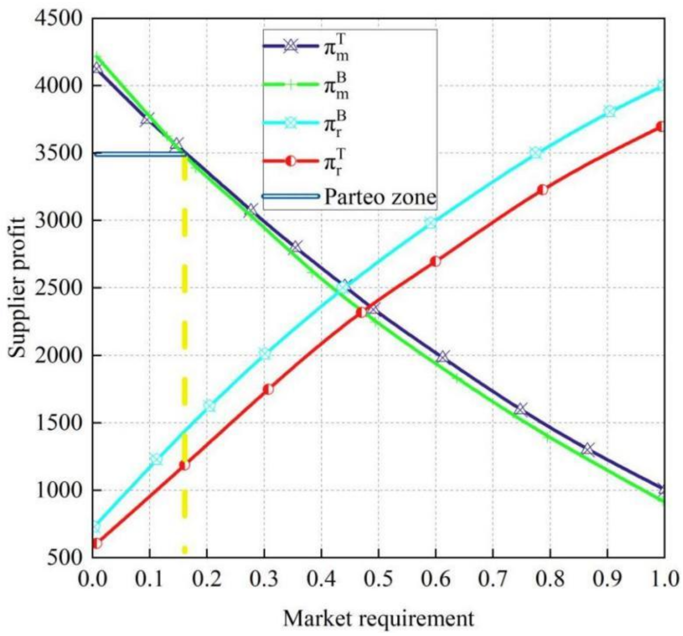
Figure 5. The effect of price discount coefficient on yield

As can be seen from Figure 5, the manufacturer's production volume can be increased only if the price discount is relatively low. This is because the manufacturer has to bear the costs and risks of the prepayment financing strategy on the one hand, and on the other hand, has to provide price discounts to the retailer, both of which lead to a decrease in the manufacturer's profit and thus lower production. The prepayment strategy can induce information sharing between the retailer and the supplier so that the production volume of the manufacturer will not fluctuate greatly even under different price discounts.

A comparison of the change in supply chain firms' profits with the price discount factor under the two supply chain prepayment financing models is shown in Figure 6.



(a) Market demand fluctuation is relatively low



(b) The fluctuation of market demand is relatively high

Figure 6. The influence of price discount coefficient on enterprise profit

As can be seen in Figure 6, when market demand fluctuations are low and price discounts are high, the use of the prepayment financing strategy increases the manufacturer's expected profit. As the price discount increases, the use of prepayment financing strategy reduces the manufacturer's profit. This is because on the one hand, the manufacturer has to bear the cost and risk of using the prepayment financing strategy, and on the other hand, the manufacturer provides higher price discounts to the retailer, which compresses its own profit margins and leads to a decline in profits. For the retailer, the prepayment financing strategy is always more favorable to the retailer, and with the increase of price discounts, the retailer's expected revenue gradually increases. Meanwhile, the prepayment financing model can realize the Pareto optimization of manufacturer and retailer's profit. When the demand fluctuation is low, μ=0.3, the price discount coefficient is less than 0.42, which can make the manufacturer and retailer profit Pareto-optimal. And when μ = 0.8, the price discount coefficient is less than 0.19 to make the manufacturer and retailer profits Pareto-optimal. Therefore, the model in this paper suggests that for a product market with stable demand, the manufacturer needs to give a higher price discount to incentivize the retailer to pay in advance to achieve a win-win situation for both the retailer and the supplier. On the contrary, when the market demand is more volatile, a lower price discount coefficient is needed to achieve Pareto-optimal profits for both parties.

5. Conclusion

This paper takes the bank financing model as the premise and constructs the prepayment financing model based on the improved artificial fish school algorithm. For the analysis of the farmers' financing strategy is recommended, the prepayment financing model calculates that when the bank interest rate is higher, the farmers choose the prepayment financing strategy as the optimal strategy. For manufacturing suppliers who choose the prepayment financing model, the prepayment financing model suggests that when the market demand is more stable, the price discount coefficient should be less than 0.42, so as to realize the optimal profit of manufacturers and retailers.

By improving the artificial fish swarm algorithm and example application, this paper realizes the effective combination of machine learning algorithm and prepayment financing model attempt.

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