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The investment strategy and capacity portfolio optimization in the supply chain with spillover effect based on artificial fish swarm algorithm

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A B S T R A C T

Spillover effect can lead to the free-riding behavior when joint investment takes place in the supply chain. This study examined the investment strategies of two competitive retailers who considered whether to invest a shared contract manufacturer (CM) or not. The supply chain members' operational decisions in four scenarios were analyzed through a Cournot competition model, and the paths of the retailers' investment strategies were examined. The CM's capacity portfolio optimization was NP-hard in nature, and was modelled by an investment portfolio problem. Results show that both retailers jointly invest the CM only when the difference of production costs is not high, and the intentions of joint investment will decrease when the coefficient of spillover and the degree of substitutability between products increase. The CM always benefits as long as one retailer invests, and allocates more investment on the capacity with highest revenue when he emphasizes more on the profit. For optimizing the CM's capacity portfolio problem, an artificial fish swam algorithm with uniform mutation (AFSA_UM) is developed and it shows better convergent performance and higher robustness than the basic AFSA.

A R T I C L E   I N F O

Keywords:
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1. Introduction

Joint investment has been frequently witnessed in the supply chain, where several members (e.g., retailers in the downstream) might invest to a shared partner (e.g., a manufacturer in the upstream). Investment could vary in different kinds, such as financial injection, advertisement subsidy, investment on the most up-to-date equipment, and cooperation on the R&D of new product etc. [1, 2]. Joint investment could benefit all members in the supply chain, such as lowering the production costs, increasing the market share by providing lower retailing prices to the customers, thus performing better than the price-based coordination [3].

Despite the merits of joint investment, there are two questions for both the investor and the investee in the supply chain. For the investor, she could be surprised to find that her effort in some activities could benefit her competitors in the same industries. For example, in 2012, Intel and Samsung jointly provided $4.4 billion to ASML (the largest manufacturer of wafer steppers and scanners for microchip fabrication in the world) through a "Customer Co-Investment Program" to accelerate a 450 mm technology and a next-generation EUV development project. However, the ASML claimed that the results of development projects and capacity investment would be available to every semiconductor company with no restrictions. For the ASML (the investee), he has to consider the loss brought by the obsolete risk of production capacity. For example, the capacity to produce 450 mm chips might be outdated quickly due to the change of market demand. When offered several kinds of capacity with different production rate and obsolete loss, the AMSL has to carefully determine the proportion of each capacity by balancing the revenue and loss with the consideration of budget constraint.

This study is motivated by the ASML case. In this study, Intel and Samsung are referred as the retailers, who have the incentives to invest the ASML or free ride the competitor's investment. The ASML is referred as the shared contract manufacturer (CM) who is at the upstream of the supply chain and optimizes the capacity portfolio after receiving the retailers' investment. There are two questions worthy of investigation: (1) What the retailers' investment decisions will be when spillover effect exists? Jointly invest, invests alone or free rides? (2) How could the CM optimize the capacity portfolio when given multiple production capacity with different combinations of production output (equivalently, revenue) and obsolete risk (equivalently, loss)? With these two questions in mind, this study considers a supply chain consisted of two competitive retailers and a shared CM. In this supply chain, both retailers compete to sell the products with a certain degree of substitutability in the market, either retailer could free ride the other one's investment in reducing the production cost due to the spillover effect. Once the CM receives the investment, he should appropriately spilt the retailers' total amount of investment on multiple production capacities for maximizing his revenue while minimizing the loss.

The rest of this study is organized as follows. In section 2, the relevant literatures are reviewed. In section 3, the supply chain members' decisions in four scenarios are firstly analysed under the Cournot model, and then the paths of retailers' investment decisions are investigated. The CM's capacity portfolio problem is described through a classic investment portfolio model, and an artificial fish swam algorithm (AFSA) improved by the uniform mutation is developed to optimize the problem. In section 4, numerical studies are carried out to investigate the managerial insights. In section 5, the conclusions and future researches are given.

2. State of the art

In recent decades, many researchers have carried out voluminous studies on the investment in the field of operation management (OM) [4]. The literatures related to this study can be categorized into the following two streams:

The first stream of studies mainly focused on the influence of spillover effect on the players' operational decisions when they compete in the same market. Due to the spillover effect, the player who did not invest could have the opportunity to free ride the outcome of the other one's investment on some activities (e.g., R&D and cost reduction). Actually, the spillover effect was so prevailing in the R&D investment that many researchers paid their attentions in this field in the past decade. Those who were interested in this topic, we refer the studies given by [5-8]. In recent decade, researchers found that the spillover effect also existed in the operational decisions in the supply chain field. For example, the spillovers in process knowledge increased the likelihood of observing decentralized channel structures under some conditions (e.g., spillovers were involuntary, firms' innovative activities were non-overlapping, and firms benefited directly from the results of competitors' innovations) [9]. In a supply chain where an original equipment manufacturer (OEM) and a CM competed in the finished goods market, the technology spillovers could strengthen the OEM's incentive to strategically outsource the production to the CM [10]. Under a wholesale price contract, both firms in the supply chain could achieve win-win via cartelization in R&D only if their contribution levels were Pareto matched (e.g., when each firm's contribution level was comparable to its partner's even when spillover existed) [11]. However, the degree of competition might change the players' operational decisions. For example, the manufacturer's improvement effort usually declined in market competition, market uncertainty or spillover effect, although its expected profit typically increased in spillover effect [12]. In the situation when two rival firms' operations and technology managers were given bonuses for cost reduction, the prisoner's dilemma occurred in case spillovers were less than 50%, or when spillovers were higher and process improvement capability was relatively high [13]. In the situation when two competing firms invested in a shared supplier, the spillover actually discouraged firms' investment despite that it supposedly intensified competition [14]. However, in the work of [15], after investigating the effect of learning, spillover and competition in affecting the optimal strategies for two firms to invest in their shared suppliers, the investment strategies of two firms were characterized by a region of preemption and a region of war of attrition.

The second stream focused on the optimization of capacity portfolio problem, which was a branch of capacity management and concerned with specifying the amounts or locations for the given multiple capacity types [16]. For some capacity-intensive industries (e.g., semiconductor manufacturing), capacity portfolio planning could significantly affect the capacity effectiveness and final profit via forecasting various demands of products [17]. From the point of investment's view, balancing the production system's revenue (profit) and risk (loss) was the critical consideration of the decision maker who aimed to optimize the capacity portfolio under different settings of environments [18]. However, it was difficult to optimize the capacity portfolio, because it was NP hard in nature to determine the sizes or proportions among different types of capacity with budget constraints. Some researchers modelled the capacity portfolio problems by various kinds of mixed-integer problems. For example, in [19], the capacity portfolio problem was formulated a two-stage stochastic mixed-integer model when the production system faced multiple demands with associated probability, then a robust stochastic programming approach was proposed to solve problem. Similarly, a mixed integer linear programming was proposed in [18] to seek an optimal capacity allocation plan and capacity expansion policy under single-stage, multi-generation, and multi-site structures. Some researchers modelled the capacity portfolio problem as a Markov decision process, and solved the optimal investment levels on two types of capacity (mainly the dedicated and flexible capacity) through efficient dynamical programming [20] or heuristic algorithm [21], or robust optimization [22, 23]. When there were multiple capacities (such as dedicated, flexible and reconfigurable capacity) to be invested, the capacity portfolio problem turned to be a mixed integer programming model [24], and hence, heuristic method could be adopted to obtain the optimal solution.

Most published studies on the spillover effect in the supply chain field focused on the investment decisions, supplier's reliability, or increasing the quality of product from the perspective of the investors (e.g., retailers in this study). Few studies paid attention to the spillover effect could alter the investors' decisions on investing or free riding, and hence, the path of investors' investment strategies were lack of investigating. On the other hand, investee (e.g., the shared CM in this study) might optimize the capacity portfolio when given more than two types of capacity associated with different combination of revenue and loss. In this study, we adopt the game model to analytically show the investors' (e.g., the retailers) investment decisions and the path of changing investment decisions when considering the competitors' advantage or disadvantage. We model the investee's (e.g., the CM) capacity portfolio problem by the classic investment portfolio problem, which is solved through an artificial fish swam algorithm (AFSA) improved by the uniform mutation.

3. Methodology

3.1 Operational decisions in four scenarios

In this study, we consider a supply chain with two competitive retailers and a shared CM. Each retailer is intent to lower the production cost by investing or free riding the competitor's investment due to the spillover effect. To describe the retailers' competitive behaviour, we follow the assumption in [25] where the Retailer *i*'s retailing price, p_i could be given by

$$p_i(q_i, q_j) = a - q_i - bq_j, \quad i = 1, or\ 2;\ j = 3 - i \tag{1}$$

where a denotes the potential demand of two products in the market, q_i and q_j are the ordering quantities, b is the degree of substitutability between two products. b ranges between 0 and 1. The larger value of b is, the more substitutable of the products are to the customers, thus the high market competition is.

c_i denotes the initial production cost when the Retailer *i* does not invest the CM. For simplicity but without loss of generality, we assume $c_1 = c$ and $c_2 = c_1 + \delta$. δ is the difference of production costs between two products. $\delta > 0$ denotes that the Retailer 1 enjoys a cost advantage over Retailer 2 in production cost, vice versa.

We assume that the spillover effect takes place in production process. Because both retailers share the same CM, one retailer could have the opportunity of enjoying a lower production cost by free riding. C_i denotes the production cost after the retailers provide the investment, which is given by

$$C_i = c_i - x_i - \alpha x_j \tag{2}$$

where x_i and x_j are the levels of cost reduction that the Retailer *i* and *j* want to achieve by investing the CM, respectively. α is the coefficient of spillover. α ranges between 0 and 1. The larger value of α is, the higher spillover effect is, thus leading to Retailer *i*'s higher free-riding behavior. By the Eq. 2, C_i is the result of both retailers' joint investment decisions. Furthermore, we assume the Retailer *i*'s investment is quadratic in the level of production cost reduction [11, 26]. Due to the spillover effect, each retailer has an incentive to free ride the other one's investment. Thus, $\rho_i x_i^2$ is the Retailer *i*'s investment on the CM for achieving x_i. ρ_i is a parameter related to the investment and $\rho_i \geq 1$. The Retailer *i* does not invest any when $x_i = 0$.

When the Retailer *i* invests the CM, her profit is given by

$$\pi_i(q_i, x_i) = (p_i - w_i)q_i - \rho_i x_i^2 \tag{3}$$

where w_i is the wholesale price that CM sets for Retailer *i*. The CM's profit is shown as follow:

$$\pi_M(w_1, w_2) = \sum_{i=1}^{2} (w_i - C_i)q_i \tag{4}$$

We assume that the retailers compete under Cournot competition model, thus the retailer's ordering quantities are determined simultaneously. The retailing prices could be determined through the backward induction. Note that, we assume that all members in the supply chain have complete knowledge of the game participants. Consider the question of whether to invest the CM or not, each retailer has two options: Yes or No (denoted as Y or N). Therefore, there are four scenarios: the YY scenario where both retailers invest the CM; the YN and NY scenarios where only retailer invests the CM and the other free rides; and the NN scenario where no one invests the CM.

We start with the derivation of the retailers' and CM's equilibrium decisions in the YY scenario. As both retailers invest the CM, the Retailer *i*'s production cost is given by the Eq. 2. The Retailer *i* aims to maximize her profit in Eq. 3. Take first and second order derivatives of π_i with respect to q_i, we could have π_i is convex in q_i. Therefore, the Retailer *i*'s optimal ordering quantity is given by $q_i(q_j) = \frac{1}{2}(a - bq_j - w_i)$, which can be reformulated in below:

$$q_i(w_i, w_j) = \frac{a(2-b) - 2w_i + bw_j}{4 - b^2} \tag{5}$$

By inserting the Eq. 5 into Eq. 3, we have the Retailer *i*'s profit, $\pi_i(x_i) = q_i^2 - \rho_i x_i^2$.

Now, it is the CM's turn to optimize his profit. The CM aims to maximize his profit by considering the Retailer *i*'s optimal ordering quantity $q_i(w_i, w_j)$. The CM's profit is given by $max \pi_M = \sum_{i=1}^{2}(w_i - c_i - x_i - \alpha x_j) q_i(w_i, w_j)$. By taking the first order derivative of π_M with respect to w_i, we have the optimal wholesale price $w_i(x_i, x_j)$ for the Retailer *i*, which is given by $w_i(x_i, x_j) = \frac{a + c_i - x_i - \alpha x_j}{2}$. Insert $w_i(x_i, x_j)$ into Eq. 5, and we have the Retailer *i*'s profit, which is $\pi_i(x_i) = \left[\frac{a(2-b) - 2c_i + bc_j + x_i(2 - b\alpha) - x_i}{2(4-b^2)}\right]^2 - \rho_i x_i^2$.

By summarizing the results above, we have the proposition 1.

Proposition 1: In the YY scenario,

(1) *To make sure that the Retailer i's ordering quantity is positive, the difference of production costs should be bounded, i.e.,* $\delta_1 \le \delta \le \delta_2$, *where* $\delta_1 = (a-c)(1-2/b)$ and $\delta_2 = (a-c)(1-b/2)$.

(2) $\frac{\partial q_i(x_i)}{\partial x_j} \le 0$ *when* $\alpha \le b/2$, *and* $\frac{\partial q_i(x_i)}{\partial x_j} \ge 0$ *when* $\alpha > b/2$.

(3) *the Retailer i's profit is strictly concave in* x_i. *Therefore, her optimal decision is* $x_i(x_j) = \frac{(2-\alpha b)[a(2-b)-2c_i+bc_j-x_j(b-2\alpha)]}{2\rho_i(4-b^2)^2-(2-\alpha b)^2}$ *for a given* x_j.

By Proposition 1, we could backwardly derive the retailers and CM's optimal decisions in the YY Scenario, which are given in Table 1.

The procedures of deriving the operational decisions in YN, NY and NN scenarios are same with those in YY scenario. Therefore, we omit the derivations for saving the pages. The retailers' and CM's operational decisions in four scenarios are summarized in Table 1.

Table 1 The Supply Chain's operational decisions in four scenarios

	YY Scenario	NY Scenario	YN Scenario	NN Scenario
x_1	$\frac{D_1(A_1B_2-A_2D_1D_2)}{B_1B_2-(D_1D_2)^2}$	0	$\frac{A_1D_1}{B_1}$	0
x_2	$\frac{D_1(A_2B_1-A_1D_1D_2)}{B_1B_2-(D_1D_2)^2}$	$\frac{A_2D_2}{B_2}$	0	0
p_1		w_1+q_1		
p_2		w_2+q_2		
q_1	$\frac{2(4-b^2)^2\rho_1(A_1B_2-A_2D_1D_2)}{B_1B_2-(D_1D_2)^2}$	$\frac{(A_1B_2-A_2D_1D_2)}{2(4-b^2)B_2}$	$2\rho_1(4-b^2)\frac{A_1}{B_1}$	$\frac{A_1}{2(4-b^2)}$
q_2	$\frac{2(4-b^2)^2\rho_2(A_2B_1-A_1D_1D_2)}{B_1B_2-(D_1D_2)^2}$	$2\rho_2(4-b^2)\frac{A_2}{B_2}$	$\frac{(A_2B_1-A_1D_1D_2)}{2(4-b^2)B_1}$	$\frac{A_2}{2(4-b^2)}$
w_1	$\frac{1}{2}\left\{a+c_1-\frac{D_1[A_2(B_1-\alpha D_1D_2)+A_1(\alpha B_1-D_1D_2)]}{B_1B_2-(D_1D_2)^2}\right\}$	$\frac{1}{2}(a+c_1-\alpha x_2)$	$\frac{1}{2}(a+c_1-x_1)$	$\frac{1}{2}(a+c_1)$
w_2	$\frac{1}{2}\left\{a+c_2-\frac{D_1[A_1(B_2-\alpha D_1D_2)+A_2(\alpha B_1-D_1D_2)]}{B_1B_2-(D_1D_2)^2}\right\}$	$\frac{1}{2}(a+c_2-x_2)$	$\frac{1}{2}(a+c_2-\alpha x_1)$	$\frac{1}{2}(a+c_2)$
π_1	$\frac{\rho_1B_1(A_1B_2-A_2D_1D_2)^2}{[B_1B_2-(D_1D_2)^2]^2}$	$\frac{(A_1B_2-A_2D_1D_2)^2}{[2(4-b^2)B_2]^2}$	$\frac{\rho_1A_1^2}{B_1}$	$\frac{A_1^2}{B_1^2}$
π_2	$\frac{\rho_2B_2(A_2B_1-A_1D_1D_2)^2}{[B_1B_2-(D_1D_2)^2]^2}$	$\frac{\rho_2A_2^2}{B_2}$	$\frac{(A_2B_1-A_1D_1D_2)^2}{[2(4-b^2)B_1]^2}$	$\frac{A_2^2}{B_1^2}$
π_M		$\sum_{i=1}^{2}(w_i-c_i+x_i+\alpha x_{3-i})q_i$		

3.2 Paths of the retailers' investment strategies

In this section, we start with the analysis of the path that the Retailer 1 changes her decision from NN to YN scenario. Apparently, Retailer 1 decides to invest the CM only when her profit increases in YN scenario compared with that in NN Scenario, i.e., $\pi_1^{YN}-\pi_1^{NN}>0$ should hold. From Table 1, $\pi_1^{YN}-\pi_1^{NN}>0$ holds only when $\delta>\delta_2$. Further, we have $q_1^{YN}-q_1^{NN}>0$, which means the Retailer 1 will always order more products when she invests the CM.

We investigate the CM's benefit when Retailer 1 invests. From Table 1, we have $w_i^{YN}-w_I^{NN}<0$, which means that the CM will lower the wholesale prices to both retailers as long as Retailer 1 invests. Let $\Delta P_{Mi}^{YN-NN}=(w_i^{YN}-C_i)-(w_i^{NN}-c_i)$ be the CM's difference of marginal profits when he wholesales the product to the Retailer *i* in YN and NN scenarios. We could prove that $\Delta P_{Mi}^{YN-NN}>0$. Obviously, the CM's marginal profits will always increase when the Retailer 1 invests the CM. Further, the difference of the CM's profits, $\pi_M^{YN}-\pi_M^{NN}$ is strictly positive. Therefore, the CM's profit always increases as long as one retailer invests.

Corollary 1 summarizes the results above.

Corollary 1: *Compared with the operational decisions in the NN* scenario*, in the YN scenario where the Retailer 1 invests the CM,*

(1) The CM offers lower wholesale prices for both retailers when only the Retailer 1 provides the investment. He could increase the marginal and total profits concurrently.
(2) The Retailer 1 always orders more in YN scenario than she does in NN scenario, and she enjoys a higher profit only when $\delta > \delta_1$; otherwise, she will not invest the CM.

Corollary 1 shows the path of the Retailer 1's investment strategy from NN to YN scenario. We find that, in YN scenario, the Retailer 1 could benefit in two folds: (i) she orders (also sells) more products, enjoys higher market share, thus deterring the competition from the Retailer 2. (ii) She could have higher profit by investment.

We could derive the path of Retailer 2 when she change her investment decision from NN to NY scenario in the same way. For saving pages, we omit the derivation and give the results in Corollary 2.

Corollary 2: *Compared with the equilibrium decisions in the NN scenario, in the NY scenario where only the Retailer 2 invests the CM,*

(1) The CM offers lower wholesale prices for both retailers. He could increase the marginal and total profit concurrently.
(2) The Retailer 2 will always orders more in YN scenario than she does in NN scenario, and she invests the CM when $\delta < \delta_2$; otherwise, she will not invest the CM.

Corollary 2 shows that the Retailer 2 changes her investment strategy from NN scenario to NY scenario under two situations: (i) the Retailer 1's cost advantage is not high, and (ii) the Retailer 1 is obvious cost disadvantageous. Both situations should satisfy $\delta < \delta_2$.

Since both retailers compete in the market, no one would like her investment to be free rode by the other one. Therefore, joint investment would be the ideal equilibrium state for both retailers. To investigate the dynamic path by which one retailer quits free riding and enters the equilibrium state of YY scenario, we compare the equilibrium decisions in NY (YN) and YY scenarios.

To make sure that the Retailer 1 stays in YY scenario, her profit in YY scenario should be more than that in NY scenario (i.e., $\pi_1^{YY} - \pi_1^{NY} > 0$ should hold). From Table 1, $\pi_1^{YY} - \pi_1^{NY} > 0$ holds when $\delta > \frac{(a-c)(2-b)(B_2-D_1D_2)}{bB_2+2D_1D_2}$. $q_1^{YY} - q_1^{NY} > 0$ always holds.

Corollary 3 summarizes the results above.

Corollary 3: *The Retailer 1 enters into the equilibrium state of YY scenario from NY scenario only when $\delta > \delta_3$, where $\delta_3 = \frac{(a-c)(2-b)(B_2-D_1D_2)}{bB_2+2D_1D_2}$. In this case, the Retailer 1 will not only increase the profit, but also increase the ordering quantities.*

Corollary 3 indicates that the Retailer 1 will jointly invest the CM with Retailer 2 only when her cost advantage is above a threshold over the Retailer 2's production cost (i.e., $\delta > \delta_3$).

Similarly, we could analyse the path of the Retailer 2 to jointly invest the CM with Retailer 1. For saving the pages, we only presents the results in Corollary 4.

Corollary 4: *The Retailer 2 will quit the equilibrium state of YN scenario and enter into the equilibrium state of YY scenario only when $\delta < \delta_4$, where $\delta_4 = \frac{(a-c)(2-b)(B_1-D_1D_2)}{2B_2+bD_1D_2}$. When compared with the YN scenario, the Retailer 2 will increase her profit, but increase her ordering quantities only when $\alpha > b/2$.*

Corollary 4 indicates that the Retailer 2 will jointly invest the CM with Retailer 1 only when the Retailer 1's cost advantage should not be above a threshold over her production cost (i.e., $\delta < \delta_4$).

3.3 The CM's capacity portfolio optimization based on AFSA_UM

Shown by Corollary 1 to 4, the CM always benefits as long as one retailer invests. However, the CM still has to carefully split the retailers' investment on different types of capacity before launching the production. The reasons is that each capacity varies in the production output and obsolete risk, thus the potential revenue and loss is different to each capacity.

For simplicity without loss of generality, we assume that the total amount of retailers' investment to be one, and the CM allocates the investment on n types of capacity ($S_j, j = 1, \dots, n$) with different proportion (y_j). For the capacity S_j, the potential revenue and loss are r_j and u_j. The total revenue of CM is given by $V = \sum_{j=1}^{n} y_j r_j$, and the maximal risk of CM's investment allocation is given by $U = max_{1 \le j \le n}\, y_j u_j$. Therefore, the CM's objective in allocating the investment turns into a classic portfolio optimization problem, which is maximizing the total revenue while minimizing the maximal risk. According to [27], the CM's capacity portfolio optimization problem could be modelled by

$$maxF = \beta V + (1-\beta)U, \qquad s.t. \sum_{j=1}^{n} y_j = 1, y_j \ge 0, j = 1, \dots, n \tag{6}$$

where β is the CM's attitude on revenue, and $0 < \beta < 1$. By introducing β, the multi-objective capacity portfolio optimization problem in Eq. 6 turns into single-objective problem.

Unfortunately, the optimization of CM's capacity portfolio given in Eq. 6 is NP hard in nature. It is rather time-consuming to optimize the problem when the numbers of decision variables and constraints increase. In this study, we develop an improved AFSA (named AFSA_MU) to optimize the CM's capacity portfolio.

The AFSA and its variants are widely used in the optimizations in the OM field [28-30]. The basic principle AFSA relies on the phenomenon that a fish can discover the more nutritious area by searching or following other fish, the area with more fish is generally most nutritious. The AFSA imitates the fish behaviours such as preying, swarming, moving and following with local search of an artificial fish (AF) for reaching the global optimum. The AF's behaviours are defined as follows:

Preying behaviour. An AF is generated with $Y(y_j, j = 1, \dots, n)$ being its current position, where y_j is the proportion of investment on the capacity S_j and y_j is the decision variable to be optimized. The AF randomly searches its neighbour's position Y_v in its vision.

$$Y_v = Y + Visual \cdot rand() \tag{7}$$

where $rand()$ is uniform distributed in 0 and 1, $Visual$ represents the AF's visual distance. The AF compares the value functions of $F(Y)$ and $F(Y_v)$. If $F(Y_v) > F(Y)$ in the maximum problem, then the AF goes forward a step in this direction and arrives at the position Y_{next}, which is given by

$$Y_{next} = Y + rand() \cdot step \cdot \frac{Y - Y_v}{\|Y - Y_v\|} \tag{8}$$

where $step$ is the step length. If $F(Y_v) < F(Y)$, the AF continues an inspecting tour in its visual range, which is described by Eq. 7.

Swarming behaviour. The AF will assemble in groups naturally, which is a kind of living habits. Let Y_c be the center position and N_f be the number of its companions in the current neighbourhood. n is the total fish number. Δ measures the crowdedness of the AF's neighbourhood. If $F(Y_c) > F(Y)$ and $\frac{N_f}{n} < \Delta$, which means that the companion center has more food and is not very crowed, the AF goes forward a step to the companion center, which is given by

$$Y_{next} = Y + rand() \cdot step \cdot \frac{Y - Y_c}{\|Y - Y_c\|} \tag{9}$$

Otherwise, the AF executes the preying step.

Following or moving behaviour. If the position Y_v is better than Y and the surrounding of Y_v is not crowded, the AF goes forward a step to the position Y_v, which is given in Eq. 8. If the AF cannot find a better position, it continues to search in its vision, which is given in Eq. 7.

The basic AFSA is an iterative algorithm, which gradually converges into global optimum. However, the AFSA could easily fall into the local optimum when the $step$ is fixed. For a larger value of $step$, the AF could quickly assemble in groups in the first iterations, but it could oscillate around the global optimum. However, for a smaller value of $step$, it will take a longer time for the AF to converge and could easily fall into the local optimum. To improve the performance of AFSA, we introduce the principle of uniform mutation to adaptively change the length of visual range and step. Therefore, the improved AFSA is called AFSA_UM in this study.

Let $kesi$ ($kesi < step$) be the threshold to trig the uniform mutation process. If the variation between the current and the previous positions is less than $kesi$, then keep the current position and add a uniform random number on the other fish. The uniform mutation allows us to use larger values of visual range and step at the beginning iterations and switch to the small values at the ending iterations. Therefore, it could greatly increase the convergent speed and precision in finding the global optimum.

To adaptively change the lengths of AF's visual range and step, we first calculate three kinds of vision ranges: (1) $Visual\_avg$ denotes the average distances between the AF and all its neighbour fish, (2) $Visual\_best$ is the distance between the AF and the best neighbour fish, and (3) $Visual\_nrst$ represents the distance between the AF and its nearest neighbour. The AF could use $Visual\_avg$ as the visual range in moving and swarming steps, and use $Visual\_best$ and $Visual\_nrst$ as the visual range in preying step. The adaptive step length could be given by $step\_adp = \gamma \cdot visual$, where γ is a constant between 0 and 1.

The procedure of AFSA_UM to optimize the CM's capacity portfolio is described below.

Step 1: Initialization. Set the fish number (*fishnum*), maximal generation ($maxgen$), the maximal try number (*try_num*), randomly generate an artificial fish swam with the population size *fishnum* ($Y_1, \dots, Y_{fishnum}$).
Step 2: The CM's capacity portfolio problem is served as the value function.
Step 3: Calculate the visual ranges (e.g., $Visual\_avg$, $Visual\_best$, $Visual\_nrst$) and the adaptive step ($step\_adp$).
Step 4: For Y_j, execute the swarming and following behaviours with $Visual\_avg$, and execute the preying behavior with $Visual\_best$ and $Visual\_nrst$. If a better solution Y_v is found, replace Y_j with Y_v.
Step 5: Update the optimal solution on the bulletin board. If the optimal solution reach the convergent precision, then terminate the iteration; otherwise, go to the next step.
Step 6: Uniform mutation. Calculate the variation between the current and previous optimal positions. If the variation is less than *kesi* (i.e., 0.01), then keep the better fish and add uniform random numbers on the other fish with worse positions.
Step 7: Termination criteria. $gen = gen + 1$. If gen > $maxgen$, or the optimal solution meet the convergent precision, then terminate the iteration.

Before using the AFSA_UM to solve the CM's optimal capacity portfolio, we use the $min\, f(x, y) = x^2 + y^2 - 10(cos2x + cos2y)$ and $5.12 \leq x, y \leq 5.12$ to test the robustness of the AFSA_UM in avoiding falling into the local optimum. The parameters settings are: *fishnum*=100, *step*=0.1, Δ=0.5, *kesi*=0.01, γ=0.5. The convergent precision to terminate is 1.0e-5.

To show the robustness of AFSA_UM, we test the performance of three algorithms: genetic algorithm (GA), the basic AFSA, and the AFSA_UM. We run each algorithm on the testing function for 20 times. Table 2 gives the results. Among three algorithms, AFSA_UM performs the best in convergent precision and speed.

Table 2 Precision and iterations of GA, AFSA and AFSA_UM on the testing function

	Precision_best	Precision _worst	Precision _avg	Iterations_avg	Success rate
GA	3.913e-5	9.16e-4	4.89e-5	97.5	70.3%
AFSA	3.213e-5	8.16e-4	4.34e-5	91.3	74%
AFSA_UM	2.53e-11	1.09e-11	6.73e-11	30.6	94%

4. Results and discussion

4.1 Influences of δ on the retailers' investment decisions

From Corollary 1 to 4, we have shown that the value of δ determines each retailer's investment decision. Recall the thresholds of δ in Corollary 1 to 4, we could have $\delta_1 < 0$ and $\delta_4 > \delta_2 > 0$. However, the sign of δ_3 depends on the values of α and b. Table 3 shows each retailer's investment decision under different values of δ.

As $(\delta_2 - \delta_1)$ denotes the region that both retailers jointly invest the CM, we investigate the influences of α and b on the value of $(\delta_2 - \delta_1)$ given in Table 3. From Corollary 1 and 2, we could obtain that $(\delta_2 - \delta_1)$ decreases with α and b. It means that, when the free-riding behaviour and the market competition are high, both retailers will lower their intentions to jointly invest the CM.

Table 3 Each retailers' investment decisions under the value of δ

In the situation when $a > b/2$
Both retailers jointly invest the CM when $\delta_1 < \delta < \delta_2$ Retailer 1 free rides and Retailer 2 invests the CM when $\delta < \delta_3 < 0$ Retailer 1 invests the CM and Retailer 2 free rides when $0 < \delta_4 < \delta < \delta_3$ Both retailers do not invest the CM when $0 < \delta_2 < \delta < \delta_4$ and $\delta_3 < \delta < \delta_1 < 0$
In the situation when $a \leq b/2$
Retailer 1 free rides, Retailer 2 invests the CM when $\delta > \max(\delta_3, \delta_4)$

4.2 Influence of β on the CM's capacity portfolio optimization

To investigate the CM's attitude on revenue (β) on the solution of capacity portfolio, we use the numerical studies where the AFSA and AFSA_UM are utilized. Table 4 gives the parameters of five types of capacity with different combinations of revenue and risk.

The parameters for the AFSA and AFSA_UM are: *Visual* = 2.5, *step* = 0.5, *firshnum* = 100, *maxgen* = 100, *try_num* = 100, Δ = 0.6, *kesi* = 0.01, *γ* = 0.6. The CM's attitude factor on revenue, β = {0.1, 0.2, 0.3, 0.4, 0.5}. Both algorithms are run for 20 times, and y_j is the average of the proportion of total investment on the capacity S_j. Table 5 gives the numerical results.

Table 4 The parameters of the capacity portfolio to be optimized

	S_1	S_2	S_3	S_4	S_5
r_i	0.28	0.23	0.21	0.05	0.25
u_i	0.025	0.055	0.015	0.00	0.026

Table 5 The results of CM's capacity portfolio optimization by AFSA and AFSA_UM

		y_1	y_2	y_3	y_4	y_5	R	U	F
$\beta = 0.1$	AFSA	0.401	0.003	0.437	0.053	0.106	0.2339	0.0100	0.0324
	AFSA_UM	0.327	0.18	0.493	0	0	0.2365	0.0099	0.0326
$\beta = 0.2$	AFSA	0.397	0.043	0.3	0.007	0.253	0.2477	0.0099	0.0575
	AFSA_UM	0.365	0.229	0.126	0	0.28	0.2450	0.0126	0.0591
$\beta = 0.1$	AFSA	0.539	0.056	0.206	0.009	0.19	0.2550	0.0135	0.0859
	AFSA_UM	0.505	0.18	0	0	0.315	0.2616	0.0126	0.0873
$\beta = 0.4$	AFSA	0.639	0.056	0.206	0	0.099	0.2598	0.0160	0.1135
	AFSA_UM	0.627	0	0.183	0	0.19	0.2615	0.0157	0.1140
$\beta = 0.5$	AFSA	0.754	0	0.006	0	0.24	0.2724	0.0189	0.1456
	AFSA_UM	0.773	0	0	0	0.227	0.2800	0.0210	0.1525

From Table 5, we have two findings:

- The AFSA_UM always outperforms the AFSA in two folds: (i) it provides a higher total revenue while lowering the maximal loss, and (ii) it provides higher value of objective function than the AFSA.
- The CM prefers to increase the proportion of S_1 when β increases. It means that the CM tends to increase the installment of the capacity with the highest revenue when he increase his attitude on the revenue.

4.3 Managerial findings of the study

In this section, we summarize the managerial findings of the study.

- From Table 3, we find that the retailer with obvious cost advantage over her competitor will invest the CM, because (i) she could increase her profit by enjoying a lower production cost, and (ii) she could dominate the market share by providing a lower price to the customers, thus deterring the competitor. Her competitor, who is disadvantageous in cost, will choose to free ride. Because, the competitive inferiority in production cost is so obvious that she gives up investing the CM. The competitor benefits from free riding in two folds: (i) she could enjoy a lower production cost, and (ii) order more products when $\alpha > b/2$. However, the competitor's profit is not surely to increase.
- In the situation when the absolute value of δ (i.e., $|\delta|$) is low (see Table 3), both retailers will jointly invest the CM. The reason is that, when the cost advantage (or disadvantage) is not obvious, the retailer who does not invest the CM will have a lower profit and a lower market share, and hence, be in a state of competitive inferiority. However, both retailers' intentions of jointly investment will decrease in α and b. The reason is that, high substitutable products and high spillover effect will increase both retailers' intention to free ride when the difference of production costs is not obvious.
- In the situation when $|\delta|$ is large, the retailer with obviously cost advantageous will continue to invest the CM, because she could dominate the market with even lower production cost and her profit will increase by investment. However, the retailer with obviously cost disadvantage will free ride, because the difference of production costs is so high that she will be in competition inferiority even she provides the investment.
- In the situation when $|\delta|$ is medium, both retailers will not invest the CM. The reasons are in two folds: (i) if the retailer with cost advantage invests the CM, then the competitor could benefit more through free riding, such as lowering the retailing price, increasing the profit and market share. (ii) Oppositely, if the retailer with cost disadvantage invests the CM, then her competitor could further lower the production cost, lower the retailing price, increase the profit and dominate the market. Therefore, both retailers will choose not to invest the CM as their investment decisions.
- The CM always benefits as long as one retailer provides the investment. The reasons are in two folds: (i) he will lower the wholesale prices for both retailers to incentivize the retailers to order more products, thus increasing the production quantity; and (ii) he could increase the marginal profit of wholesaling the product, and hence, increase the total profit. The numerical study shows that the CM prefers to install more capacity with the highest revenue in his capacity portfolio when his attitude on the revenue increases. AFSA_UM outperforms the AFSA in optimizing the CM's capacity portfolio problem in two folds: (i) it converges with higher speed and precision, and (ii) it provides higher revenue and lower risk, and higher value of objective function than the AFSA. Because the AFSA_UM has the ability to adaptively change the AF's searching step by introducing the uniform mutation.

5. Conclusion

In this study, the operational decisions of a supply chain with two competitive retailers and a shared contract manufacturer (CM) was firstly examined in this study. Then the paths of the retailers' investment strategies were investigated in detail. The CM's capacity portfolio problem was model as a classic investment portfolio problem which was solved by the artificial fish swarm algorithm modified by uniform mutation (AFSA_UM). The following conclusions were obtained in this study:

- For the CM, he always benefits from the retailers' investment, because both his marginal profit and total profit will increase. The CM will install a higher proportion of capacity with higher revenue when he emphasizes more on the revenue. The CM's capacity portfolio problem is optimized by the AFSA_UM which introduces the principle of uniform mutation to boost the convergent speed and precision. The numerical results show that the AFSA_UM is much more robust than the basic AFSA, and it could provide the CM a better capacity portfolio with higher revenue, lower maximal risk, and higher value of objective function.
- For the retailers, their investment decisions are significantly influenced by the absolute difference of production costs (i.e., $|\delta|$). Specifically, (i) both retailers jointly invest the CM when the value of $|\delta|$ is low. The retailers will lower their intentions to jointly invest when the free riding behaviour and the substitutability of the products are high. (ii) No retailer would invest the CM when the value of $|\delta|$ is medium. (iii) Only the retailer with obvious cost advantage will invest the CM when the value of $|\delta|$ is high.

Three research directions can follow from this study. First, no market uncertainty is considered in this study. It would be interesting to investigate how the downside risk of demand will influence the competitive retailers' investment decisions. Second, the information asymmetry phenomenon is not considered yet in this study. In the industrial practice, no retailer could have the compete knowledge of her competitors. However, the introduction of this phenomenon will greatly complicate the mathematic model and the procedure of analyses. Third, the optimization process of CM's capacity portfolio is independent of the retailers' investment decisions in this study. However, the value function of optimizing the CM's capacity portfolio will be complicated when the retailers' decisions are incorporated.

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