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Research Article

Mixed Replenishment Policy for ATO Supply Chain Based on Hybrid Genetic Simulated Annealing Algorithm

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Timely components replenishment is the key to ATO (assemble-to-order) supply chain operating successfully. We developed a production and replenishment model of ATO supply chain, where the ATO manufacturer adopts both JIT and (Q, r) replenishment mode simultaneously to replenish components. The ATO manufacturer's mixed replenishment policy and component suppliers' production policies are studied. Furthermore, combining the rapid global searching ability of genetic algorithm and the local searching ability of simulated annealing algorithm, a hybrid genetic simulated annealing algorithm (HGSAA) is proposed to search for the optimal solution of the model. An experiment is given to illustrate the rapid convergence of the HGSAA and the good quality of optimal mixed replenishment policy obtained by the HGSAA. Finally, by comparing the HGSAA with GA, it is proved that the HGSAA is a more effective and reliable algorithm than GA for solving the optimization problem of mixed replenishment policy for ATO supply chain.

1. Introduction

ATO (assemble-to-order) has become one of the most popular production modes adopted by manufacturing enterprises due to its ability of rapidly responding to customers' diversified and personalized demands at a low cost [1]. Under ATO mode, an ATO manufacturer just owns components inventory rather than an inventory of final finished products. Therefore, timely components replenishment is the key to ATO (assemble-to-order) supply chain operating successfully. There are two main component replenishment modes, (Q, r) and JIT. (Q, r) mode has little request on supplier's supply capacity but causes a higher inventory and holding cost [2]. JIT mode lowers the manufacturer's inventory and the probability of components being out of stock but has a high demand on supplier's supply capacity. In addition, it may raise the manufacturer's replenishment cost and total cost due to the increase in the number of replenishment times [3]. Therefore, a manufacturer should adopt different replenishment modes for different components.

There have been numerous researches on the (Q, r) and JIT replenishment policies. Harris is the earliest person who developed Economic Order Quantity model of (Q, r) mode [4]. Tersine and Wacker [5] proposed an (Q, r) inventory model under stochastic demand. Akçay and Xu formulated a two-stage stochastic integer program which is able to determine the optimal base-stock policy and the optimal component allocation policy for the ATO system [6]. Lu and Song studied a multi-item stochastic inventory system in which customers may order different but possibly overlapping subsets of items, such as a multiproduct assemble-to-order system, in order to determine the right base-stock level for each item and to identify the key driving factors [7]. Benjaafar and Elhafsi studied the optimal production and inventory control of an assemble-to-order system with m components, one end-product, and n customer classes [8]. Yang and Pan presented an integrated inventory model to minimize the sum of ordering/setup cost, holding cost, quality improvement investment and crashing cost by simultaneously optimizing the order quantity, lead time, process

quality, and number of deliveries while the probability distribution of the lead time demand is normal [9]. Wu and Low suggested that the advantages of JIT purchasing may have been overstated in theory and developed the JIT purchasing threshold value (JPTV) models, which overcomes two limitations of the existing EOQCJIT cost indifference point models [10].

However, the manufacturers in these researches only adopt either (Q, r) or JIT to replenish components, which runs counter to the fact that most ATO manufacturers adopt both (Q, r) and JIT modes to replenish components [11]. Betts and Johnston developed a tractable solution method for the decision problem of multiproduct manufacturing scenario under stochastic demand. They revealed several other ways in which JIT replenishment and component substitution can improve performance by limiting the cost of dealing with uncertainty [12]. In their research, they assumed that the manufacturer only replenishes one component by JIT. However, in reality, the manufacturer will replenish several components among all its n kinds of components by JIT. Therefore, the complexity of the mixed replenishment policy for ATO supply chain is 2^n. In automobile manufacturing industry, which is a typical ATO industry, the kind of components of a car is over 20,000. The complexity of replenishment policy for an automobile manufacturer can reach as high as 2^{20000}. Therefore, to make the mixed replenishment policy for an ATO supply chain not only needs to propose optimization models, but also to design an effective optimization algorithm to search for the optimal solution of the model.

One of the most popular algorithms for combinatorial optimization problem is genetic algorithm (GA), which has the ability of rapid global searching. Therefore, it is widely applied to production management and logistics management, such as production scheduling and path arrangement [13, 14]. Jalilvand-Nejad and Fattahi studied a flexible job shop scheduling problem with cyclic jobs, in which jobs must be delivered in determined batch sizes with definite time intervals. They proposed a genetic algorithm for the problem and proved its effectiveness [15]. Tasan and Gen proposed a genetic algorithm based approach to the vehicle routing problem with simultaneous pickup and deliveries and proved its performance [16]. Although GA has the ability of rapid global searching, it is easy to be premature. As a result, the optimal solution obtained by GA is not the real global optimal solution. On the other hand, simulated annealing algorithm (SAA) has the ability of obtaining the real global optimal solution. Therefore, it is widely adopted to production management and engineering field, for example production scheduling, control engineering, and so on [17, 18]. Mirsanei et al. studied the problem of sequence-dependent setup times hybrid flow shop scheduling with parallel identical machines to minimize the makespan. They developed a novel simulated annealing algorithm to produce a reasonable manufacturing schedule within an acceptable computational time [19]. Precup et al. discussed the design of fuzzy control systems with a reduced parametric sensitivity using simulated-annealing algorithms and proved the FCS performance by the experimental results [20]. However, it takes a long time to obtain the global optimal solution of mass scale problem by SAA. Therefore, some researchers proposed hybrid genetic simulated annealing algorithms (HGSAAs) by combining the advantages of GA and SAA and proved that the performance of HGSAA is better than the basic GA and SAA [21, 22].

In this paper, we develop a replenishment and production model of ATO supply chain, which consists of an ATO manufacturer and multiple component suppliers, in order to study the mixed replenishment policy, JIT and (Q, r), of the ATO manufacturer, as well as the component suppliers' production management policies. In addition, by combining the rapid global searching ability of genetic algorithm and the local searching ability of simulated annealing algorithm, we propose a hybrid genetic simulated annealing algorithm to search for the optimal solution of the model. Finally, we use a numeric example to illustrate the good performance of the HGSAA. This paper offers consultation and decision making support tools for ATO manufacturers and their components suppliers to make policies on production and replenishment policies.

The remainder of the paper is organized as follows. Section 2 is dedicated to the problem and assumptions. The model is developed in Section 3. We propose the HGSAA for the model in Section 4. An experiment is used to demonstrate the performance of the HGSAA in Section 5. Finally, conclusions are drawn in Section 6.

2. The Problem and Assumptions

An ATO supply chain consists of an ATO manufacturer and multiple component suppliers. The manufacturer adopts either (Q, r) or JIT mode to replenish a kind of component from a component supplier. The process of the ATO manufacturer and its suppliers making their policies is as follows. Firstly, aiming at maximizing the total profit of the supply chain, the ATO manufacturer makes its replenishment policy for every kind of component, including replenishment mode and order quantity under (Q, r) mode. Then, the component suppliers make their production policies according to the ATO manufacturer's replenishment policy in order to maximize their own profits.

The assumptions of this paper are as follows.

Assumption 1. The ATO manufacturer purchases m kinds of components, which are not substitutable for each other, from m component suppliers, and assembles these components into n kinds of final products. The duration of assembly is short and negligible.

Assumption 2. The ATO manufacturer assembles products according to customers' orders after receiving them and immediately sends the products to customers after finishing the assembly. Therefore, the ATO manufacturer owns no product inventory but components inventory, which means no product holding cost.

Assumption 3. The product demand is uncertain; therefore, there is a probability that some customers' demands are not satisfied. All these unsatisfied demands are lost.

Assumption 4. Arrange all the m kinds of components according to the replenishment mode applied to them, that is, applying JIT replenishment to the first k kinds of components and (Q, r) replenishment to the last m-k kinds of components.

Assumption 5. The component suppliers make their production management policies according to the ATO manufacturer's replenishment policy. If the ATO manufacturer replenishes components by JIT, component suppliers apply make-to-stock (MTS) to produce. If the ATO manufacturer replenishes components by (Q, r), component suppliers apply make-to-order (MTO) to produce due to the lead time of replenishment.

The notations related to the ATO manufacturer in this paper are as follows.

A_i: the annual expected demand of product i, $i = 1, 2, \ldots, n$;

S_i: the selling price of product i, $i = 1, 2, \ldots, n$;

b_i: the assembly cost of product i, $i = 1, 2, \ldots, n$;

p_i: the probability of product i being in shortage, $i = 1, 2, \ldots, n$;

k: the number of component kinds which are replenished by JIT, decision variable;

D_j: the annual expected demand of component j, $j = 1, 2, \ldots, m$;

C_j: the purchase price of component j, $j = 1, 2, \ldots, m$;

Q_j: the order quantity of component j replenished by (Q, r), $j = k + 1, k + 2, \ldots, m$, decision variable;

R_j: the replenishment cost per time of component j replenished by (Q, r), $j = k + 1, k + 2, \ldots, m$;

R'_j: the replenishment cost per time of component j replenished by JIT, $R'_j < R_j$, $j = 1, 2, \ldots, k$;

H: the holding cost per purchase price per time of all components;

r_j: the reorder point of component j replenished by (Q, r), $j = k + 1, k + 2, \ldots, m$, decision variable;

x_j: the demand of component j replenished by (Q, r) in its lead time, $j = k + 1, k + 2, \ldots, m$.

The notations related to the component suppliers in this paper are as follows.

P_j: the capability of the supplier producing component j per time, $j = 1, 2, \ldots, m$;

h_j: the holding cost per producing cost per time of component j, $j = 1, 2, \ldots, m$;

s_j: the setup cost of component j, $j = 1, 2, \ldots, m$;

c_j: the producing cost of component j, $j = 1, 2, \ldots, m$.

3. The Model

The ATO manufacturer makes its component replenishment policy for every component, including replenishment mode and replenishment quantity, aiming at maximizing the total profit of the whole supply chain. The sales revenue and costs consisting of profit function of the supply chain are as follows: (1) the sales revenue of the ATO manufacturer; (2) the ATO manufacturer's assembly cost; (3) the ATO manufacturer's total replenishment cost; (4) the ATO manufacturer's total holding cost of components replenished by (Q, r); (5) the suppliers' total holding cost; (6) the suppliers' total setup cost; (7) the suppliers' total producing cost, including the cost of raw materials for components.

Before we give the sales revenue function of the ATO manufacturer, we analyze the probability of product i and component j being in shortage, $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$. The ATO manufacturer adopts both (Q, r) and JIT to replenish components. The components replenished by JIT will not be in shortage, while the components replenished by (Q, r) may be in shortage during the replenishment lead time, which causes the final products to be in shortage. The expected shortage quantity of component j in replenishment lead time is $L(r_j) = \int_{r_j}^{\infty} (x - r_j) g_j(x) dx$, $j = k + 1, k + 2, \ldots, m$, where $g_j(x)$ is the demand distribution function of component j in replenishment lead time. Then, we can get that the probability of component j being in shortage is $L(r_j)/Q_j$. As the components are not substitutable for each other, the probability of final product i being in shortage, p_i, is

$$p_i = 1 - \prod_{j=1}^{m} \left[1 - \delta_{ij} \frac{L(r_j)}{Q_j} \right], \quad i = 1, 2, \ldots, n, \tag{1}$$

where

$$\delta_{ij} = \begin{cases} 1, & \text{the component } j \text{ is used in product } i \\ & \text{and replenished by } (Q, r). \\ 0, & \text{others.} \end{cases} \tag{2}$$

Then, we can get the sales revenue and costs of ATO supply chain as follows.

The sales revenue is

$$\mathrm{TR} = \sum_{i=1}^{n} \left[S_i A_i (1 - p_i) \right]. \tag{3}$$

The assembly cost of the ATO manufacturer is

$$\mathrm{TC}_a = \sum_{i=1}^{n} \left[b_i A_i (1 - p_i) \right]. \tag{4}$$

The component replenishment cost of the ATO manufacturer is

$$\mathrm{TC}_r = \sum_{i=1}^{k} R'_j D_j + \sum_{j=k+1}^{m} \frac{R_j D_j}{Q_j}. \tag{5}$$

The first part on the right side of (5) is the total replenishment cost of the k components replenished by JIT; the second is the total replenishment cost of the m-k components replenished by (Q, r).

The expected net inventory level of component j replenished by (Q, r) just before the replenished components arrive is $r_j - x_j + L(r_j)$, and the expected inventory level just after the replenished components arrive is $Q_j + r_j - x_j + L(r_j)$. Therefore, the expected average inventory level is $r_j - x_j + L(r_j) + Q_j/2$. Now, we can get the ATO manufacturer's total holding cost of the m-k components replenished by (Q, r) as follows:

$$\mathrm{TC}_{ah} = H \sum_{j=k+1}^{m} C_j \left[\frac{Q_j}{2} + r_j - x_j + L\left(r_j\right) \right]. \tag{6}$$

After the ATO manufacturer decides the replenishment mode of every component; the component suppliers make their production management policies. If the ATO manufacturer replenishes components by JIT, those component suppliers apply MTS to produce. If the ATO manufacturer replenishes components by (Q, r), those component suppliers apply MTO to produce due to the lead time of replenishment. Then, we can get that the total holding cost and setup cost of the suppliers are as follows.

The suppliers' total holding cost is

$$\mathrm{TC}_{vh} = \sum_{j=k+1}^{m} \frac{h_j c_j Q_j D_j}{2P_j} + \sum_{j=1}^{k} \sqrt{\frac{s_j c_j h_j \left(P_j - D_j\right)}{2P_j}}. \tag{7}$$

The suppliers' total setup cost is

$$\mathrm{TC}_{s} = \sum_{j=k+1}^{m} \frac{D_j s_j}{Q_j} + \sum_{j=1}^{k} \sqrt{\frac{D_j c_j s_j h_j \left(P_j - D_j\right)}{2P_j}}. \tag{8}$$

The first parts on the right side of (7) and (8) are individually the holding costs and setup costs for the components replenished by (Q, r), and the second parts are individually the holding costs and setup costs for the components replenished by JIT.

The suppliers' total producing cost is

$$\mathrm{TC}_{m} = \sum_{j=1}^{m} c_j D_j. \tag{9}$$

Then, we can get the total profit of the ATO supply chain as

$$\pi = \mathrm{TR} - \mathrm{TC}_a - \mathrm{TC}_r - \mathrm{TC}_{ah} - \mathrm{TC}_{vh} - \mathrm{TC}_s - \mathrm{TC}_m. \tag{10}$$

The target of the ATO manufacturer's decision making is maximizing the total profit of the ATO supply chain by deciding which k kinds of components are replenished by JIT and which m-k kinds of components are replenished by (Q, r), as well as the replenishment quantities and the reorder points of component j replenished by (Q, r). Therefore, the optimal model of ATO supply chain making its mixed replenishment policies is as follows:

$$\begin{aligned} \max_{k, Q_j, r_j} \quad & \pi. \\ \text{s.t.} \quad & m \geq k \geq 0, \\ & D_j \geq Q_j \geq 0, \\ & D_j \geq r_j \geq 0, \end{aligned} \tag{11}$$

where $j = k+1, k+2, \ldots, m$.

4. The Proposed Hybrid Genetic Simulated Annealing Algorithm

This paper proposes to incorporate the strengths of a genetic algorithm into a simulated annealing algorithm. GA is developed to rapidly search for an optimal or near-optimal solution among the solution space, and then SAA is utilized to seek a better one on the basis of that solution. Therefore, the weakness of the prematurity of GA and the time-consuming nature of SAA is overcome, and the global optimal solution is obtained rapidly.

HGSAAs have been increasingly used to obtain the optimal solution of combinatorial optimization problems. Elhaddad and Sallabi proposed new operations and techniques to improve the performance of GA and then combined the improved GA with SAA for implementing a hybrid algorithm (HGSAA) to solve Traveling Salesman Problem (TSP) [23]. Wang et al. studied the multivehicle and multicargo loading problem under limited loading capacity and used hybrid genetic simulated annealing algorithm to get the optimization solution [24]. Moussi et al. used three HGSAAs to solve the storage container problem in port [25]. Furthermore, Li et al. proposed an effective hybrid genetic simulated annealing algorithm to obtain the optimal solution for the location-inventory-routing problem considering returns under e-supply chain environment [26].

However, HGSAAs have been rarely used to solve the optimization problem of mixed replenishment policy for the ATO supply chain. As we discussed above, the complexity of this problem is 2^n and a little error may cause an ATO manufacturer a huge profit loss. Therefore, we utilize the particularities of HGSAA, which are converging more rapidly and obtaining the solution more accurately, to solve the mixed replenishment policy problem.

4.1. The HGSAA for the Mixed Replenishment Policy

4.1.1. Encoding. We use binary encoding in the HGSAA. If a component is replenished by JIT mode, the code of the component will be set as 0; if the component is replenished by (Q, r) mode, the code will be set as 1.

4.1.2. Fitness Function. Since the objective function is maximizing the ATO supply chain's total profit, and the fitness function values must be nonnegative, so we define the fitness function as $\mathrm{Fit}(k, Q_j, r_j) = \pi(k, Q_j, r_j) + \overline{\mathrm{TC}}$, where

(k, Q_j, r_j) represents a mixed components replenishment policy, $\pi(k, Q_j, r_j)$ represents the total profit of the ATO supply chain under the (k, Q_j, r_j) replenishment policy, $\overline{\mathrm{TC}}$ represents the upper limit of the supply chain's total cost, and $\overline{\mathrm{TC}} = \sum_{i=1}^{n}(b_i A_i) + \sum_{j=1}^{m}(c_j D_j) + \sum_{j=1}^{m}(HD_j C_j/2) + \sum_{j=1}^{m}(h_j D_j c_j/2) + \sum_{j=1}^{m}(R'_j D_j) + \sum_{j=1}^{m}(s_j D_j)$. $\sum_{j=1}^{m}(b_i A_i)$ is the upper limit of the ATO manufacturer's assembly cost, $\sum_{j=1}^{m}(C_j D_j)$ is the upper limit of the suppliers' total producing cost, $\sum_{j=1}^{m}(HD_j C_j/2) + \sum_{j=1}^{m}(h_j D_j c_j/2)$ are the upper limit of the ATO supply chain's holding cost, $\sum_{j=1}^{m}(R'_j D_j)$ is the upper limit of the ATO manufacturer's replenishment cost, and $\sum_{j=1}^{m}(s_j D_j)$ is the upper limit of the supplier's total setup cost. Therefore, $\overline{\mathrm{TC}}$ is a fixed constant used to guarantee the fitness function values to be nonnegative, which has no impact on the result of the algorithm.

4.1.3. Selection. The selection method in the algorithm is roulette-wheel-selection. The greater the individual fitness value is, the greater probability that the individual is selected. The process of selection is as follows. Firstly, calculate the selected probability P_i of the individual i, $P_i = \mathrm{Fit}_i / \sum_{l=1}^{S} \mathrm{Fit}_l$, where S is the population size. Then, generate a random number r which belongs to $[0, 1]$. Finally, the individual i is selected, if $\sum_{l=0}^{i-1} P_l \le r \le \sum_{l=0}^{i} P_l$, where $P_0 = 0$.

4.1.4. Crossover and Mutation. In this paper, we use sequencing crossover to exchange the sequence of the operations in the parent chromosomes and assignment mutation to change the assignment of a single operation in a single parent. The crossover probability $p_c = 0.8$; the mutation probability $p_m = 0.05$.

4.1.5. Simulated Annealing. Simulated annealing is based on the metropolis acceptance criterion, which models how a thermodynamic system moves from the current state to a candidate state, in which the energy content is being minimized.

In the genetic simulated annealing algorithm, only one of the parent individuals p and the child individuals c can be accepted to the next generation; simulated annealing is used to determine which one is accepted; the acceptance probability P is shown as follow:

$$P = \begin{cases} 1, & \pi_c > \pi_p; \\ \exp\left(\dfrac{\pi_c - \pi_p}{t}\right), & \pi_c \le \pi_p, \end{cases} \tag{12}$$

where π_p and π_c are the fitness values of individual p and c, and t is the current temperature.

4.1.6. Termination or Convergence Criterion. If the algorithm satisfies the following criteria, then terminate and output the best chromosome, that is, the optimal mixed replenishment policy.

(i) The fitness value has no significant change after successive iterations, which means the current policy is the optimal mixed replenishment policy.

(ii) The number of iterations reaches the set value.

4.2. The Steps of the HGSAA. The steps of the HGSAA are as follows.

Step 1 (initialization). get the encoding length according to the number of components; set the population size (S), the crossover probability (p_c), the mutation probability (p_m), the iteration number of the genetic algorithm (I), the start temperature (T_0), the stop temperature (T_e), andthe annealing rate (μ); then generate the initial population.

Step 2. Evaluate the fitness function for the current population (parent population).

Step 3. Make selection, crossover, and mutation operation on the parent population to generate an offspring population.

Step 4. Make simulated annealing operation on the parent population and the offspring population to generate a new population for next iteration; update the temperature.

Step 5. If the termination or convergence criterion is satisfied, terminate the process and output the best chromosome, together with the corresponding policy. Otherwise, go to Step 2.

The proposed hybrid genetic simulated annealing algorithm for the mixed replenishment policy is illustrated in Figure 1.

5. Experimental Analysis

5.1. The Solutions of the HGSAA. In an ATO supply chain, an ATO manufacturer replenishes 20 kinds of components (labeled as p_1 to p_{20}) from 20 suppliers (correspondingly labeled as s_1 to s_{20}) and assembles these components into 2 different products, namely, product 1 and product 2. The parameters of these products are as follows. The annual expected demands, selling prices, assembly costs, and holding cost per purchase price per time are individually $A_1 = 300$ units per year, $A_2 = 400$ units per year, $S_1 = 6500$ per unit, $S_2 = 7500$ per unit, $b_1 = 100$ per unit, $b_2 = 120$ per unit, and $H = 0.2$ per purchase price per year. The demands of all components are independent and follow a normal distribution. Other parameters of the components are shown in Tables 1 and 2.

The parameters in the HGSAA are set as follows: the population size (S) = 100; the crossover probability (p_c) = 0.8; the mutation probability (p_m) = 0.05; the iteration number of the genetic algorithm (I) = 10; the start temperature (T_0) = 100; the stop temperature (T_e) = 1; the annealing rate (μ) = 0.95.

In order to testify the performance of the HGSAA of this paper, we apply it to search for the optimal mixed replenishment policies under three conditions. Condition 1:

Table 1: The parameters of the ATO manufacturer.

Component	Quantity needed by Product 1 (units)	Quantity needed by Product 2 (units)	Annual expected demand (units per year)	Purchase price (per unit)	Demand in lead time (units)	Standard deviation of demand	Replenishment cost of (Q, r) (per time)	Replenishment cost of JIT (per unit)
p_1	1	2	1100	100	25	14	600	8
p_2	3	1	1300	150	53	22	750	9
p_3	1	3	1500	120	12	6	800	10.5
p_4	1	3	1500	130	33	16	720	8.8
p_5	2	2	1400	95	20	10	650	8.1
p_6	2	1	1000	90	17	8	680	8.3
p_7	1	3	1500	110	45	20	850	11.5
p_8	1	2	1100	85	39	18	780	9.3
p_9	2	1	1000	80	60	28	820	11.0
p_{10}	1	3	1500	140	48	24	700	8.5
p_{11}	4	2	2000	150	75	36	500	7.0
p_{12}	2	2	1400	200	43	21	900	12.0
p_{13}	1	1	700	180	65	32	1000	13.0
p_{14}	2	3	1800	160	37	20	1100	14.0
p_{15}	3	4	2500	170	29	12	950	12.5
p_{16}	1	1	700	190	19	8	550	7.5
p_{17}	1	1	700	185	73	34	880	11.8
p_{18}	3	2	1700	210	46	18	920	12.2
p_{19}	3	3	1700	135	58	26	1050	13.5
p_{20}	2	3	1800	175	69	33	980	12.8

Table 2: The parameters of the suppliers.

Supplier	Holding cost (per producing cost per time)	Setup cost (per time)	Producing cost (per time)	Producing capability (units per year)
s_1	0.21	500	70	2000
s_2	0.22	700	115	2200
s_3	0.21	750	100	3000
s_4	0.20	740	90	2900
s_5	0.23	730	95	2700
s_6	0.21	450	60	1800
s_7	0.22	740	110	2800
s_8	0.20	480	65	1900
s_9	0.23	460	68	1850
s_{10}	0.24	760	80	3100
s_{11}	0.25	600	77	2300
s_{12}	0.20	800	105	3500
s_{13}	0.23	900	84	4000
s_{14}	0.26	860	66	3800
s_{15}	0.21	770	73	3200
s_{16}	0.23	420	82	1600
s_{17}	0.24	710	98	2500
s_{18}	0.22	880	120	3900
s_{19}	0.22	720	88	2600
s_{20}	0.21	830	62	3600

Table 3: The results.

Number of components	The best chromosome	Replenishment policy	Complexity of the problem	The final number of iterations	The optimal solution of the HGSAA	The real optimal solution
10	1011111111	p_2 is replenished by JIT; others are replenished by (Q, r)	2^{10}	20	$5.7562e + 05$	$5.7562e + 05$
15	101111111101011	p_2, p_{11}, and p_{13} are replenished by JIT; others are replenished by (Q, r)	2^{15}	50	$1.1448e + 06$	$1.1448e + 06$
20	10111111110101100111	p_2, p_{11}, and p_{13} and p_{16} are replenished by JIT; others are replenished by (Q, r)	2^{20}	100	$2.2140e + 06$	$2.2140e + 06$

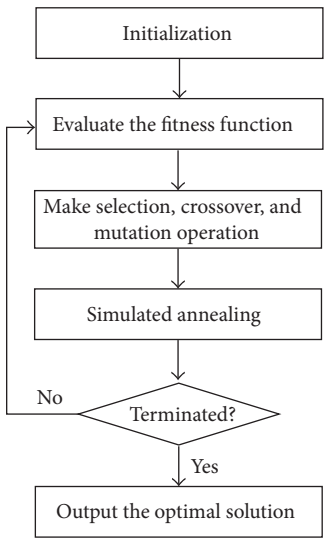

Figure 1: The hybrid genetic simulated annealing algorithm.

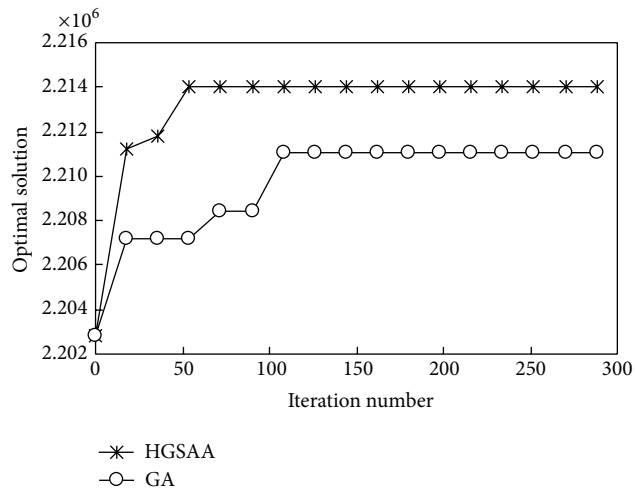

Figure 2: Comparison of the HGSAA and GA.

assemble components p_1–p_{10} (10 kinds of components) into product 1 and product 2. Condition 2: assemble components p_1–p_{15} (15 kinds of components) into product 1 and product 2. Condition 3: assemble components p_1–p_{20} (20 kinds of components) into product 1 and product 2. The results of the HGSAA under these three conditions are as in Table 3.

From Table 3, we can get that under the condition of 10, 15, and 20 kinds of components, the complexities of the mixed replenishment policy for the ATO supply chain are 2^{10}, 2^{15}, and 2^{20}, respectively. Though it just takes 20, 50, and 100 iterations to get the optimal solutions by HGSAA, the optimal solutions of the HGSAA are the real optimal ones. Thus it can be proved that the HGSAA is an effective algorithm for solving the optimization problem of mixed replenishment policy for the ATO supply chain.

5.2. Comparison of the HGSAA and GA. Now, we compare the HGSAA with GA to show the better performance of the HGSAA for solving the problem of mixed replenishment policy for ATO supply chain. Each algorithm is independently repeated 10 times, 20 times, 50 times, and 100 times, where dimension is 20. If the final searching quality is within 10^{-4} of the optimal value, the run is called a success run and its iteration number will be stored. Furthermore, Wilcoxon test [27, 28] is used to validate the statistical significance of the results.

Table 4 shows the means and standard deviations of the HGSAA and GA. Figure 2 shows the performance of the HGSAA and GA for solving the problem of mixed replenishment policy for ATO supply chain.

From Table 4, it can be found that the means of the HGSAA are closer to the theoretical optima, and the standard deviations of HGSAA are smaller than those of GA. Furthermore, Wilcoxon test shows the results of comparison are all statistically significant.

It can then be seen from Figure 2 that the curve of objective values of the HGSAA ascends faster than that of GA and the searching quality of the HGSAA is better than GA.

We use two indices named "number of successful hits" and "average valid iteration number" to analyse the robustness of the HGSAA and GA, while "number of successful hits"

Table 4: Means and standard deviations of HGSAA and GA.

Running times	HGSAA		GA		Wilcoxon test
	Mean	Standard deviation	Mean	Standard deviation	
10	$2.2140e+06$	87.0550	$2.2131e+06$	1273.9000	0.0910
20	$2.2140e+06$	$4.7776e-10$	$2.2137e+06$	509.3638	0.0042
50	$2.2140e+06$	38.9322	$2.2134e+06$	812.6267	0.0000
100	$2.2140e+06$	27.5292	$2.2134e+06$	926.2284	0.0000

Table 5: Means and standard deviations of HGSAA and GA.

Running times	HGSAA		GA	
	Number of successful hits	Average valid iteration number	Number of successful hits	Average valid iteration number
10	9	102	6	185
20	20	87	13	133
50	49	80	30	160
100	99	82	56	177

represents the number of successful runs among 10 runs, 20 runs, 50 runs, and 100 runs in which the optimal solution was obtained; "average valid iteration number" represents the average number of iterations for success runs among 10 runs, 20 runs, 50 runs, and 100 runs. The results of robustness analysis are shown in Table 5.

Table 5 shows that the HGSAA can find global optima with higher "number of successful hits" than GA, and for those valid runs, the HGSAA requires smaller "average valid iteration number" than GA.

From the above comparison, we can make the conclusion that the HGSAA is more effective and reliable than GA for solving the optimization problem of mixed replenishment policy for the ATO supply chain.

6. Conclusions

In this paper, we developed a replenishment and production model of ATO supply chain to study the mixed replenishment policy (i.e., JIT and (Q, r) mixed) of the ATO manufacturer, as well as the component suppliers' production management policies. In addition, through combining the rapid global searching ability of GA and the local searching ability of SAA, we proposed a HGSAA to search for the optimal solution of the model. Finally, an experiment was given to demonstrate the good performance of the HGSAA. This paper also offers consultation and decision making support tools for ATO manufacturers and their component suppliers to make policies on production and replenishment. It is proved that the HGSAA overcomes the prematurity of GA and the time-consuming nature of SAA; it has the ability of converging on the global optimal solution rapidly and is an effective algorithm for solving the optimization problem of mixed replenishment policy for the ATO supply chain.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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