A Modified PSO to Optimize Manufacturers Production and Delivery

Liangyou SHU
School of Economics & Management,
Henan Polytechnic University, Jiaozuo, China
Email: lyshu@hpu.edu.cn

Lingxiao YANG
School of Electrical Engineering & Automation,
Henan Polytechnic University, Jiaozuo, China
Email: yanglx@hpu.edu.cn

***Abstract*—This paper presents a new approach to the solution of optimal Manufacturers Production and Delivery (MPD) scheduling problem, using improved particle swarm optimization (ISAPSO) technique. The producing and delivery system is highly complex and possesses nonlinear relationship of the problem variables, products storage, products transport delay and scheduling time linkage that make the problem of finding global optimum difficult using standard optimization methods. In this paper an improved particle swarm optimization (PSO) technique is suggested that deals with an inequality constraint treatment mechanism to accelerate the optimization process and simultaneously, the inherent basics of conventional PSO algorithm is preserved. To show its efficiency and robustness, the proposed ISAPSO is applied on the quick response (QR) manufacturing supply chain system using making to order (MTO) strategy. Numerical results are compared with those obtained by PSO and ISAPSO approaches. The simulation results reveal that the proposed ISAPSO appears to be the best in terms of convergence speed, solution time and minimum cost to the MPD problems.**

***Index Terms*—Particle Swarm Optimization; Optimization Model; Production and Delivery**

I. INTRODUCTION

The supply chain performance there is an intimate connection between supply chain profitability and other performance metrics such as flexibility, coordination, customer satisfaction, and responsiveness [1]. Reducing response time can enhance the response ability in market fluctuations [2]. For example, a responsive and flexible supply chain is more likely to capitalize from spot market opportunities than a supply chain with long lead times and limited flexibility. Quick response systems enable retailers to estimate customer demand more accurately, and improve stocking decisions for perishable products with uncertain demand [3]. Furthermore, tardy deliveries may lead to penalty costs and possibly loss of customer goodwill [4]. Order due dates were frequently missed resulting in penalties and/or loss of customer goodwill [5]. Therefore, the QR supply chain system has received a great deal of attention in the recent past because of the advances in many new technologies [6].

A MTO firm starts working on an order only after it has been placed by the customer. MTO is characterized by back orders with zero inventories as each customer order is unique and cannot be manufactured in advance. Because the main driver in MTO operations is customer orders [7]. In view of the various products and the changing demand, companies adopt MTO and Quick Response management strategies to be able response quickly to the users' demand through quick design and production of products.

A enterprises’ response speeds to changes of market demands can be improved from using generic parts under mass production mode [8]. Taken into impacts of the back distribution risk and time competition of manufacturers, the order fulfillment optimization model of manufactures based on time competition is set up [9]. The solution algorithm of the order fulfillment optimization model is not discussed. Therefore, in view of manufacturers' adopting of MTO management strategy and the users' requests of quick response, this article discusses the manufacturer production and delivery decision-making model and the method of solving of the model.

II. LITERATURE REVIEW

A. Production Scheduling

A poor production and delivery scheduling leads to high production cost, long production time and tardiness in the supply chain performance. The existing of tardiness in the production schedule significantly affects the harmony among the supply chain members. Ref. [4] models a manufacturing facility that considers a pool of orders, and chooses for processing a subset that results in the highest profit. Ref. [10] also proposes a genetic algorithm (GA) to solve the order acceptance problem with tardiness penalties.

Ref. [5] models a MTO operation of a job-shop with multiple resources having regular and non-regular capacity. A Mixed-Integer Linear Program (MILP) is

doi:10.4304/jsw.7.10.2325-2332

proposed to aid an operational manager to decide which orders to accept and how to allocate resources such that the overall profit is maximized. Recently, Ref. [11] investigates a QR supply chain via the mean-variance approach. By quantifying the pay off and risk of the QR supply chain by using the expected profit and variance of profits, they identify the analytical conditions under which the supply chain can be coordinated. A profit and risk sharing coordination mechanism is proposed to coordinate a QR supply chain [12]. A new mathematical model for virtual cell formation problem under condition of multi-period planning horizon is presented. The objective of the model is to determine the optimal number of virtual cells while minimizing the manufacturing, material handling, subcontracting, inventory holding and internal production costs in each period [13].

In order to address the production distribution coordination problem, Ref. [14] developed a model for a one-to-one supply chain whose solution resulted in an economic order quantity type formula for shipment size that optimizes the trade-off between transportation and inventory costs. Ref. [15] developed an analytical model to determine shipment size and production cycle length. Ref. [16] incorporates time and quantity dependent waiting costs into a direct shipping model with two customer classes and uncertain demand.

B. Application of Particle Swarm Optimization Algorithm

The PSO method is a well-established technique for global optimization. During the past years several variations of the original PSO have been proposed in the relevant literature. Because of the increasing necessity in global optimization methods in almost all fields of science there is a great demand for efficient and fast implementations of relative algorithms.

An improved PSO algorithm was developed for solving mixed-integer non-linear programming (MINLP) problems [17]. The novel technique called PSO is used to optimize routes for each care worker [18]. A self-adaptive framework is proposed to improve the robustness of the PSO. Within a framework that also includes other variants previously introduced by the authors, the algorithm’s parameters are co-evolved with the particles [19]. For enhancing global search capability, a method of incorporating a real-valued mutation operator into the PSO algorithms is proposed. Three variants of PSO algorithms are considered [20].

In order to increase the speed and its efficiency that can be applied independently in almost every PSO variant, three modifications of the original PSO method is presented [21]. Two kinds of PSO algorithms were applied in order to find the best way for taking into account the mixed-integer nature [22].

A PSO-based improved method is proposed. This method adopts a modified Particle swarm optimization (PSO) algorithm to optimize the fuzzy rule centroid of data covered area [23]. The PSO algorithmic is applied in the field of computational finance, namely portfolio optimization and time series forecasting [24]. A novel multi-objective endocrine particle swarm optimization algorithm based on the regulation of endocrine system is proposed [25].

Ref. [26] constructs a PSO for an elaborate multi-objective job-shop scheduling problem. The modified PSO was used to solve various benchmark problems. An improved chaotic particle swarm optimization algorithm is proposed to solve Dynamic economic dispatch with value-point effects [27]. An efficient linear programming embedded particle swarm optimization algorithm with a simulated annealing-based local search engine is proposed for solving the mathematical model for virtual cell formation problem under condition of multi-period planning horizon [13]. Ref. [28] presents a chaotic self-adaptive particle swarm optimization algorithm to solve dynamic economic dispatch problem with value-point effects. The proposed algorithm takes PSO as the main evolution method. It is not easy to express particle position and velocity.

III. Problem Description and Basic Assumption

In the given time, the manufacturers which adopt the MTO management policy will begin to produce after receiving the customers' order about some kind of products. Customers give lead-time to the order of the products and have request about the delivering time. They will ask delay fees if the manufacturer provide the goods late, and the manufacturers have original material purchasing lead-time. The products which have been completed can be delivered by transporters. The products which can't be delivered in time can temporarily be stored in the manufactory. When subjected to the demands of customers, requests of quick respond, the efficiency of manufacturers' produces and various delivery expenses and abilities, manufacturers optimize producing and delivery plans to reach the goal of total costs' minimum concluding the production cost, delivery cost, cost of storing in the manufactory and punitive fee of delaying.

In order to convenience of study, following assumptions are made:

(1) The costs and time can be different to different transporters in completing the task. The repeated use of transport vehicles considered as different vehicle;

(2) Storage costs during transport including into the transportation costs;

(3) Manufacturers doing production only for a single product orders;

(4) Products of manufacturer can be shipped immediately or in the following time. Products shipped in the following time can temporarily stored in the manufacturers’; the loading time of products is out of restrictions, the time needed during loading is omitted and loading completed at one-time;

(5) Only the punishment costs in distribution delay of users is considered;

(6) The internal transport between members is considered as the internal management of the members, the costs incurred included in the corresponding costs of its members.

In order to discuss conveniently, we provide two relevant concepts here:

Definition 1: the time of which per unit product delivery exceeds lead-time ordering a unit of time is defined as a unit for equivalent delay time.

Definition 2: a unit product stored per unit of time is defined as a unit for equivalent storage time.

IV. ORDER FULFILLMENT OPTIMIZE MODEL OF MANUFACTURERS

The notation used in the formulation is presented below.

A. Model notations

- *Indices*

j Indices for transporter

d Indices for transport vehicle

- *Sets*

E Set of product transporting companies from the manufacturer to the user

D_j Set of vehicles used by transporter j

- *Parameters*

Q Highest producing capacity of the manufacturers

C Cost of per unit production

CT_j The fixed cost of each vehicle of transporter j

QF_j The largest shipment capability of each vehicle of transporter j

U_j The per unit cost of product transportation of transporter j

T_j The time of the transporter j to complete one transport from the manufacturer to the user

YQ_j The largest transport capacity to the user of the transporter j

BQ The quantity of product which the user orders

ω The fee paying by manufacturers for a unit equivalent back-order

BT Lead time of user ordered

MT The longest-lead time for manufacturers ordering the raw material

PT The time of manufacturers needed to produce per unit product

h A unit equivalent cost for inventory time of product in the manufacturers

- *Decision variables*

z_{jd} The shipment amount of the d th-vehicle using by transporter j from the manufacturer to the users

γ_j The decision-making variable of transporter, If transporter j is choose to transport products, so, $\gamma_j = 1$; otherwise, $\gamma_j = 0$.

B. Model Constraints and Objective Function

Owing to that the above-mentioned hypothesis and the idea of the order fulfillment optimization model [9], the decision-making model of manufacturers' production and delivery can be founded.

- *The largest transport capacity constraints*

Constraint (1) allows that the shipment of each vehicle of transporter j cannot exceed the largest shipment of each vehicle of transporter j,

$$z_{jd} \le QF_j ,\ d = 1,2,\cdots,D_j ,\ j \in E . \tag{1}$$

- *The customer requirements constraints*

Constraint (2) indicates that the customer requirements need to be satisfied,

$$\sum_{j\in E}\sum_{d=1}^{D_j} z_{jd} \times \gamma_j = BQ . \tag{2}$$

- *The Selection of transporters constraints*

Constraint (3) allows only one transporter,

$$\sum_{j\in E}\gamma_j = 1 ,\ \gamma_j \in \{0,1\} \tag{3}$$

- *The variable non-negative constraints*

Constraint (4) indicates that the shipment number of each vehicle of transporter j cannot be negative,

$$z_{jd} \ge 0 ,\ d = 1,2,\cdots,D_j ,\ j \in E \tag{4}$$

- *Objective function*

The objective function of the problem is to minimize the total cost of order fulfillment (5). The total cost of order fulfillment consists of production costs, products transport cost; inventory cost and punishment fee of products back delivery. Moreover, transport costs can also be divided into fixed costs and variable costs.

$$\begin{aligned} \min\ & BQ\times C + \sum_{j\in E}\sum_{d\in D_{jv}}\left(z_{jd}\times U_{jv}\right) + D_j \times CT_j \times \gamma_j \\ & + \sum_{j\in E}\frac{h\times PT}{2}\left[\sum_{d\in D_j}\left(z_{jd}\right)^2 - \sum_{d\in D_j} z_{jd}\right]\times\gamma_j \\ & + \sum_{j\in E}\sum_{d\in D_j}\max\left(\left(PT\times\left(\sum_{l=1}^{d} z_{jl}\right) + T_j - BT + MT\right)\times z_{jd}\times\omega, 0\right)\times\gamma_j \end{aligned} \tag{5}$$

V. THE ORIGINAL PSO

PSO is based on the behavior research of birds preying[29]. PSO is fast and has high-quality solutions, and brevity code, etc., especially the field of multi-dimensional continuous space optimization problems, neural network training [30] and application in power system [31]. It is not easy to express particle position and velocity. This restricted its application in the combinatorial optimization field. Based on the traditional speed-displacement search model, Ref. [32] analyzed the particle swarm optimization mechanism, and proposed a generalized particle swarm optimization model, so that the particle swarm optimization algorithm can be applied to the fields of discrete and combinatorial optimization [32]. So, the author attempts to use the PSO algorithm to solve the model.

In this section, an improved particle swarm optimization algorithm is proposed for solving the decision-making of manufacturers' production and delivery.

PSO starts with a population of random solutions 'particles' in a D-dimension space. The i th particle is represented by $X_i = (x_{i1}, x_{i2}, \cdots x_{iD})$. Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fitness for particle i is stored as $P_i = (p_{i1}, p_{i2}, \cdots p_{iD})$ that its best value is represented by (P-best). The global version of the PSO keeps track of the overall best value (G-best), and its location, obtained thus far by any particle in the population. PSO consists of, at each step, changing the velocity of each particle toward its P-best and G-best according to (6). The velocity of particle i is represented as $V_i = (v_{i1}, v_{i2}, \cdots v_{iD})$. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward P-best and G-best. The position of the i th particle is then updated according to (7) [33, 34]:

$$\begin{aligned} v_{id}(t+1) = \omega v_{id}(t) + c_1 r_1(p_{id} - x_{id}(t)) \\ + c_2 r_2(p_{gd} - x_{id}(t)) \end{aligned} \tag{6}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{7}$$

where, ω is inertial factor. c_1, c_2 are the cognitive and social learning rates factors. $x_{id}(t)$ is the value of the d-th dimension of particle i in iteration t. r_1 and r_2 represent uniform random numbers between 0 and 1. p_{id} and p_{gd} are P-best and G-best. It is concluded that G-best version performs best in terms of median number of iterations to converge. However, P-best version with neighborhoods of two is most resistant to local minima. The results of past experiments about PSO show that x was not considered at an early stage of PSO algorithm. However, x affects the iteration number to find an optimal solution. If the value of x is low, the convergence will be fast, but the solution will fall into the local minimum. On the other hand, if the value will increase, the iteration number will also increase and therefore the convergence will be slow. Usually, for running the PSO algorithm, value of inertia weight is adjusted in training process. It was shown that PSO algorithm is further improved via using a time decreasing inertia weight, which leads to a reduction in the number of iterations [34]. In (6), term of $c_1 r_1(p_{id} - x_{id}(t))$ represents the individual movement and term of $c_2 r_2(p_{gd} - x_{id}(t))$ represents the social behavior in finding the global best solution.

The PSO algorithm is described as follows:

1: Initialize a population of N particles with random positions and random velocities with D dimensions in a given searching space.

2: While a specified stop condition (the optimal solution is found or the maximal number of iterations is reached) is not met do.

3: Evaluate the fitness of each particle in the populations according to the objective function of the problem, for each particle do.

4: Update the personal best position p_{id} for each particle and the global best position p_{gd} for all particles.

5: By (6), update the velocity of each particle.

6: By (7), update the position of each particle.

7: End for.

8: End while.

VI. AN IMPROVED PSO FOR MANUFACTURERS' ORDER FULFILLMENT OPTIMIZATION

A. Constraints Handling

In the operation of initialization or evolution, the shipment amount of every vehicle should satisfy the various constrains. The tradition constraints handling strategy is penalty function method, in which a penalty function is applied to convert a constrained problem into an unconstraint one. Though the penalty function is convenient and easy-implemented, the result of current solution may not always fully satisfy the equality constraints, and the procedure of multiple runs for the fine tuning of penalty factors would make a high computation cost.

In order to overcome the drawbacks of penalty function method for this problem, a randomness adjustment strategy is proposed in this paper. In the proposed strategy, the inequality constraints and the equality constraints are handled respectively. The shipment amount of every vehicle used by transporter j is firstly adjusted to satisfy the inequality constraints of the transporter j ($\gamma_j = 1$, $\gamma_i = 0$, $i \neq j$). Then, randomly adjust the shipment amount in the feasible region until the equality constraint is satisfied.

- *Handling the inequality constraints*

Consider the inequality constraints only. Through analyzing inequality constraints, the problem can be transformed into with no constraints. The object function the original problem (5) consisting of (1) and (4) can be transformed to:

$$\begin{aligned} \min \quad & BQ \times C + \sum_{j\in E}\sum_{d\in D_{jv}} \left(z_{jd} \times U_{jv}\right) + D_j \times CT_j \times \gamma_j \\ & + \sum_{j\in E} \frac{h \times PT}{2}\left[\sum_{d\in D_j}\left(z_{jd}\right)^2 - \sum_{d\in D_j} z_{jd}\right] \times \gamma_j \\ & + \sum_{j\in E}\sum_{d\in D_j} \max\left(\left(PT \times \left(\sum_{l=1}^{d} z_{jl}\right) + T_j - BT + MT\right) \times z_{jd} \times \omega, 0\right) \times \gamma_j \\ & + M\sum_{d\in D_j} \max\left(\left(z_{jd} - QF_j\right), 0\right) + M\sum_{d\in D_j} \max\left(-z_{jd}, 0\right) \end{aligned} \tag{8}$$

where M is a sufficiently large positive number. The optimal solution satisfied (5) is z_{id} * solved by ISAPSO.

- *Handling the equality constraints*

Equation.(2) is transformed to:

$$\sum_{j\in E}\sum_{d=1}^{D_j} z_{jd}\times\gamma_j - BQ = 0 \tag{9}$$

Let

$$\tau = \left|\sum_{j\in E}\sum_{d=1}^{D_j} z_{jd} * \times\gamma_j - BQ\right|$$

If $\tau < \varepsilon$ (ε is the accuracy of the optimal solution), z_{id} * is the optimal solution satisfied (5). Otherwise, calculate the optimal solution satisfied (9) again, until $\tau < \varepsilon$.

B. Initialization Parameters

Parameters are population size N , the maximum number of iterations $MaxIter$, dimension of variables D , the maximum of "fly" speed $V_{\max}$, the maximum of inertia weight $\omega_{\max}$, the minimum of inertia weight $\omega_{\min}$, the maximum of learning factor $c_{\max}$, the minimum of learning factor $c_{\min}$, and so on.

C. Structure of Individuals

The i -th individual is described as

$$X_i = \left\lfloor x_{i\,j1},\cdots,x_{i\,jD_j} \right\rfloor \tag{10}$$

where x_{ijd} is the shipment amount of the d th-vehicle using by transporter j from the manufacturer to the users ($d = 1,2,...,D_J$).

D. Initialization

The individuals are initialed randomly while satisfying the constraints (1) and (4), which is given by

$$x_{jd} = QF_j * rand() \tag{11}$$

Then, the proposed constraints handling strategy above is applied to adjust the position of each individual.

The velocity of each individual is initialed by:

$$v_{jd} = V_{\max j} * rand() \tag{12}$$

P-best is initialized equally to the individual. G-best is initialed as the best individuals among the population.

E. Update and Modification

In this paper, the rule of each particle updating its velocity is described by

$$\begin{aligned} v_{id}(t+1) &= \omega v_{id}(t) + c_1 r_1(p_{id} - x_{id}(t)) \\ &\quad + c_2 r_2(p_{gd} - x_{id}(t)) \end{aligned} \tag{13}$$

In order to improve the solution quality, the inertial weight ω , the cognition learning factor c_1 and the social learning factor c_2 are varying with time, not using the fixed coefficients.

Let ω be varying with time by the following self-adaptive function.

$$\omega = \begin{cases} \omega_{\min} + \dfrac{(\omega_{\max} - \omega_{\min}) * (f - f_{\min})}{(f_{avg} - f_{\min})}, & f \le f_{avg} \\ \omega_{\max} & , f > f_{avg} \end{cases} \tag{14}$$

Where $\omega_{\max}$ is the initial value of ω , $\omega_{\min}$ is the final value of ω , f is the valve of the object function for the particle, f_{avg} and $f_{\min}$ are the average and minimum of the object function for all particles.

$$\begin{cases} c_1 = c_{\max} - \dfrac{c_{\max} - c_{\min}}{MaxIter - 1} \times (Iter - 1) \\ c_2 = c_{\min} + \dfrac{c_{\max} - c_{\min}}{MaxIter - 1} \times (Iter - 1) \end{cases} \tag{15}$$

where $MaxIter$ is the maximum iterations during the evolutionary process, $Iter$ is the current iteration number, $c_{\max}$ is the maximum of learning factor, $c_{\min}$ is the minimum of learning factor.

The two sensitive parameter of PSO c_1 and c_2 is changed dynamically during the evolution procedure of proposed algorithm. According to the suggestion of the literature [29], $c_1 + c_2 = 4$. Generally, a large c_1 makes the particles flying to the P-best more probably. Similarly, a large c_2 makes the particles flying to the G-best more probably. Equation.(15) can make the proposed algorithm searching around P-best more probably at the earlier stage of the evolution progress and around G-best at the latter stage. For PSO, a large velocity makes the proposed algorithm explores globally, on the contrary, a small velocity will lead the algorithm searching in a local area [35]. So, to adequate the convergence of proposed algorithm, x is initialed with a large value at the beginning of run, and decreased rapidly in the process of evolution.

After updating and modifying the velocity and position of each particle, the position of each particle may not satisfy the various constrains. In this case, the constraint handling strategy above is applied to adjust the position of individuals.

F. Stopping Criteria

The proposed algorithm is terminated while the maximum iteration number or the precision of solution is reached. Otherwise, continue evolution until the terminate condition is reached.

G. Determine Transporter

Calculating the optimal solution of all transporters, the transporter, which object function valve is the best minimum, is choose.

H. Flow Chart of Proposed Algorithm

The flow chart of proposed ISAPSO is showed in Fig. 1.

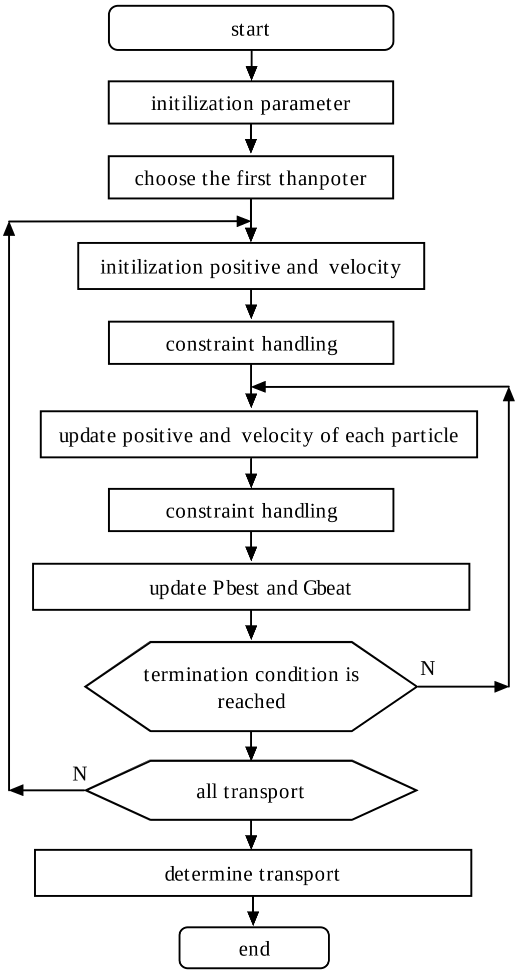

Figure 1. The flowchart of proposed ISAPSO

VII. Experimental Results

Assuming, a manufacturer has received order that the user needs 100 products, maximum production capacity of manufacturers is 260 in the period, cost of unit production is 200, lead time products order is 500 hours, the time consumed in producing one unit products by manufacturer is 2 hours, inventory costs per unit product is 0.5, back order cost of one unit product per hour is 0.5, lead time order of raw materials used by manufacturer is 30 hours. The basic data of transporters appears in the table I.

Table I.
The basic data of transporters

Transporter	1	2
vehicles number D_j	7	7
fixed cost of each vehicle CT_j	300	400
The largest shipment number of each vehicle QF_j	30	30
per unit cost of product transportation U_j	22	20
completing time of one transport T_j	6	7
the largest transport capacity YQ_j	210	210

The computation was implemented on a personal computer in MATLAB. The parameters of proposed algorithm for this test system are shown in Table II.

The proposed algorithm takes 20 trials to get the final best cost from the manufacturer to the user. And in each trial the population size takes 30.

The best results are obtained by ISAPSO. The first transporter is chosen. Total cost is 24967. The shipment numbers are showed in Table III.

Table II.
The parameters of ISAPSO

$c_{\max}$	$c_{\min}$	$\omega_{\max}$	$\omega_{\min}$	$MaxIter$	N	$V_{\max}$	D	div
2.5	0.5	0.9	0.4	1000	20	5	$D(j)$	20

Table III.
The shipment numbers

z_{11}	z_{12}	z_{13}	z_{14}	z_{15}	z_{16}	z_{17}
14.2	14.1	12.3	16.6	15.2	14.5	13.0

To validate the feasibility of proposed algorithm, ISAPSO is compared with PSO for the same test system, where PSO is implemented by classic PSO with the proposed constraint handling strategy. The best total cost by PSO is 24975. The proposed ISAPSO obtained the best fuel cost than PSO for this test system. The efficiency of ISAPSO and PSO is also compared in this paper.

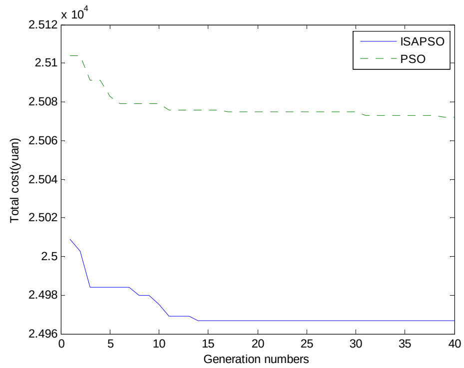

Figure 2. Convergence progress of PSO and ISAPSO for this test system.

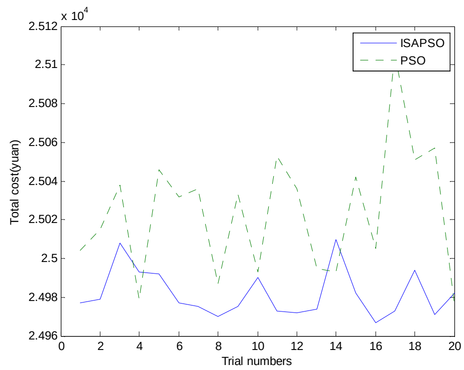

Figure 3. Distribution of total cost of each trial

From the convergence progress curves shown in Fig. 2, we can easily find that proposed ISAPSO have better convergence performance than PSO. The quality of solutions is also compared between ISAPSO and PSO by running 20 trials. The comparison results are shown in Fig. 3. It demonstrates that the result obtained by ISAPSO variation in a small range with trial numbers.

VIII. CONCLUSIONS

In this paper, we proposed an improved self-adaptive particle swarm optimization algorithm (ISAPSO) to solve MPD problem. A dynamic adjustment on the three sensitive parameters of PSO is imported to control the searching direction of each particle. Additionally, focus on the drawback of tradition method on constraints handling, a randomness adjustment strategy is proposed to handle the various constraints of MPD effectively. Especially, the proposed strategy can satisfy make the individual fully satisfying the various constraints of MPD problem. Finally, the feasibility and effectiveness of the proposed method is verified by a test system which contains two transporters. The experiment results show that the proposed ISAPSO can obtain better result with lower total cost along with fast convergence performance in solving MPD problem compared with PSO. So it can be a good and effective approach for MPD problem.

Owing to the idea of the order fulfillment optimization model[9], the article has founded the decision-making model of manufacturers' production and delivery and has given out the algorithm finding the solution based on Particle swarm optimization. Bat, the optimization decision-making model applied to variety of products is required to do further study.

ACKNOWLEDGMENT

This research was partially supported by the National Natural Science Found of P R China (Grant No. 61175066) and the Doctoral Research Fund Program of Henan Polytechnic University, P R China (Grant No. B2011-055) and the Literae Humaniores and Social Science Found Project of the Education Department of Henan Province, China (Grant No. 2011-zx-042).

REFERENCES

[1] B. M. Beamon, "Supply chain design and analysis: Models and methods," *International Journal of Production Economics*, vol. 55, pp. 281-294, 1998.

[2] B. D. J., S. T. P., and D. P. J., "Lean launch managing product introduction risk through response-based logistics," *Journal of Product Innovation Management*, vol. 16, pp. 557-568, 1999.

[3] D. A. Serel, "Optimal ordering and pricing in a quick response system," *International Journal of Production Economics*, vol. 121, pp. 700-714, 2009.

[4] S. A. Slotnick and T. E. Morton, "Order acceptance with weighted tardiness," *Computers and Operations Research*, vol. 34, pp. 3029-3042, 2007.

[5] S. Mestry, P. Damodaran, and C.-S. Chen, "A branch and price solution approach for order acceptance and capacity planning in make-to-order operations," *European Journal of Operational Research*, vol. 211, pp. 480-495, 2011.

[6] T.-M. Choi and S. Sethi, "Innovative quick response programs: A review," *International Journal of Production Economics*, vol. 127, pp. 1-12, 2010.

[7] B. Mehmet and V. Sridharan, "Revenue management in order-driven production systems," *Decision Sciences*, vol. 36, pp. 287-316, 2005.

[8] Y. Lin and S.-H. Ma, "A Study on Safety Stock Management of Component Commonality Based on Lead Time," *Systems Engineering*, vol. 21, pp. 71-75, 2003.

[9] S. Liangyou and Y. Lingxiao, "Order Fulfillment Optimization Model of Manufactures Based on Time Competition," *In: International Conference of Management Science and Information System*, vol. 3, pp. 393-396, 2009.

[10] W. O. Rom and S. A. Slotnick, "Order acceptance using genetic algorithms," *Computers and Operations Research*, vol. 36, pp. 1758-1767, 2009.

[11] T.M.Choi and P.S.Chow, "Mean-variance analysis of quick response program," *International Journal of Production Economics*, vol. 114, 2008.

[12] H. Chen, Y. Chen, C. H. Chiu, T. M. Choi, and S. P. Sethi, "Coordination mechanism for the supply chain with leadtime consideration and price-dependent demand," *European Journal of Operations Research*, vol. 203, pp. 70-80, 2010.

[13] H. Rezazadeh, R. Mahini, and M. Zarei, "Solving a dynamic virtual cell formation problem by linear programming embedded particle swarm optimization algorithm," *Applied Soft Computing*, vol. 11, pp. 3160-3169, 2011.

[14] L. D. Burns, R. W. Hall, D. E. Blumenfeld, and C. F. Daganzo, "Distribution strategies that minimize transportation and inventory costs," *Operations Research*, vol. 33, pp. 469-490, 1985.

[15] D. E. Blumenfeld, R. W. Hall, and W. C. Jordan, "Trade-off between freight expediting and safety stock inventory costs," *Journal of Business Logistics*, vol. 6, pp. 79-100, 1985.

[16] W. Jang, "Production and allocation policies in a two-class inventory system with time and quantity dependent waiting costs," *Computers and Operations Research*, vol. 33, pp. 2301-2321, 2006.

[17] L. Yiqing, Y. Xigang, and L. Yongjian, "An improved PSO algorithm for solving non-convex NLP/MINLP problems with equality constraints," *Computers & Chemical Engineering*, vol. 33, pp. 153-162, 2007.

[18] A. Chananes, Y. Pisal, and D. P. R, "PSO-based algorithm for home care worker scheduling in the UK.," *Computers & Industrial Engineering*, vol. 53, pp. 559-583, 2007.

[19] I. Montalvo, J. Izquierdo, R. Pérez-García, and M. H. ManuelHerrera, "Improved performance of PSO with self-adaptive parameters for computing the optimal design of Water Supply Systems," *Engineering Applications of Artificial Intelligenc*, vol. 23, pp. 727-735, 2010.

[20] H. Lu, P. Sriyanyong, Y. H. Song, and T. Dillon, "Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function," *Electrical Power and Energy Systems*, vol. 32, pp. 921-935, 2010.

[21] I. G. Tsoulos and A. Stavrakoudis, "Enhancing PSO methods for global optimization," *Applied Mathematics and Computation*, vol. 216, pp. 2988-3001, 2010.

[22] A. Ferrari, S. Gutierrez, and E. C. B. Jr, "Development of an optimal operation strategy in a sequential batch reactor (SBR) through mixed-integer particle swarm dynamic optimization (PSO)," *Computers and Chemical Engineering*, vol. 32, pp. 1994-1998, 2010.

[23] X. Yang, J. Yuan, J. Yuan, and H. Mao, "An improved WM method based on PSO for electric load forecasting,"

Expert Systems with Applications, vol. 37, pp. 8036-8041, 2010.
[24] S. C. Chiam, K. C. Tan, and A. A. Mamun, "A memetic model of evolutionary PSO for computational finance applications," *Expert Systems with Applications*, vol. 36, pp. 3695-3711, 2009.
[25] D.-b. Chen, F. Zou, and J.-t. Wang, "A multi-objective endocrine PSO algorithm and application," *Applied Soft Computing*, vol. 11, pp. 4508-4520, 2011.
[26] D.-b. Chen, F. Zou, and J.-t. Wang, "A multi-objective PSO for job-shop scheduling problems," *Expert Systems with Applications*, vol. 37, pp. 1065-1070, 2010.
[27] Y. Wang, J. Zhou, H. Qin, and Y. Lu, "Improved chaotic particle swarm optimization algorithm for dynamic economic dispatch problem with valve-point effects," *Energy Conversion and Management*, vol. 51, pp. 2893-2900, 2010.
[28] Y. Wang, J. Zhou, Y. Lu, H. Qin, and Y. Wang, "Chaotic self-adaptive particle swarm optimization algorithm for dynamic economic dispatch problem with valve-point effect," *Expert Systems with Applications*, vol. 38, pp. 14231-14237, 2011.
[29] K. J. and E. R. C., "Particle swarm optimization," *In: Proceedings of IEEE International Conference on Neutral Networks, Australia*, vol. 4, pp. 1942-1948, 1995.
[30] R. C., Eberhart, and J. Kennedy, "Swarm Intelligence." Morgan Kaufmann: San Diego, 2001.
[31] H. Yoshida, K. Kawata, and Y. Fukyyama, "A Particle Swarm Optimization for reactibe power and Votage controk considering voltage stability," *In: G L Torres, A P Alves da Silva Eds. ISAP'99, Rio de Janeiro, brazil*, 1999.
[32] G. H. B., Z. C., and G. L., "Generalized model of particle swarm optimization," *Chinese Journal of Computers*, vol. 28, pp. 1980-1987, 2005.
[33] H. Shayeghi, A. Jalili, and H. A. Shayanfar, "Multi-stage fuzzy load frequency control using PSO," *Energy Conversion and Management*, vol. 49, pp. 2570-2580, 2008.
[34] C. M. and K. J., "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE Trans Evolut Comput*, vol. 6, pp. 58-73, 2002.
[35] C. Sun and S. Lu, "Short-term combined economic emission hydrothermal scheduling using improved quantum-behaved particle swarm optimization," *Expert Systems with Applications*, vol. 37, pp. 4232-4241, 2010.

Liangyou SHU is the Professor in the School of Economics and Management at the Henan Polytechnic University since 2007. He received the B.S. degree in College of Mathematics and Information Science from Henan Normal University, Xin'xiang, He'nan, PR China in 1986, and the M.S. degree in the Graduate Department of China University of Mining & Technology, Beijing, PR China in 1989, and the Ph.D. degree in the School of Traffic & Transportation from Southwest Jiaotong University, Cheng'du, Si'chuan, PR China in 2009. His research interests include Management Decision-making, Logistics Management, and Supply Chain Management.

Lingxiao YANG is the Professor in the School of Electrical Engineering and Automation at the Henan Polytechnic University since 2009. She received the B.S. degree in Department of Electronic Engineering from Chengdu Institute of Radio Engineering, Chengdu, Sichuan, P R China in 1986, and the M.S. degree in Department of Electrical from Jiaozuo Institute of Mining and Technology, Jiaozuo, Henan, PR China in 1989. Her research interests include Optimization and Calculation, System Simulation.