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Replenishment Decision Support System Based on Modified Particle Swarm Optimization in a VMI Supply Chain

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This paper proposes a replenishment decision support system, based on response surface methodology (RSM) and modified traveling particle swarm optimization (TPSO). Cross-border cooperation lengthens the distance for transportation and in turn widens the disparity in inventory cost among business partners, thus accentuates the importance of inventory management. Therefore, this paper solves a two-stage stochastic dynamic lot-sizing problem with two-phased transportation cost under a vendor managed inventory. Modified TPSO is proposed to solve a sub-problem, the nonlinear mixed integer programming. In this algorithm, which is executed with a perturbation policy, each move is a feasible solution. RSM is being used to determine the optimal replenishment condition. The result of the experiment indicates that the proposed approach lowers the cost for both the buyer and the vendor. Moreover, the solution quality using modified TPSO was tested and compared with that of the Solver tool in Excel and 3 lot-sizing decision rules.

Significance: The contributions of this paper include: (1) the decision support system based on RSM and PSO, (2) adding the perturbation policy to traditional PSO and analyzing the influence of the algorithm parameters on the solution quality, and (3) the probe into the impact of the replenishment policy on the VMI supply chain.

Keywords: Lot-sizing problem, Particle swarm optimization, Transportation cost, Response surface methodology, Vendor managed inventory

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1. INTRODUCTION

The order penetration point (OPP) is a stage in the supply chain where the suppliers allocate product orders in accordance with customers. Businesses at the pre-OPP operate under a make-to-stock environment (Olhager, 2003). Vendor managed inventory (VMI) model has been developing great momentum in upstream-downstream partnerships. This model allows a vendor to manage a buyer's inventory by formulating a replenishment plan and directly monitoring the buyer's inventory level, which can effectively decrease the bullwhip effect in the supply chain (Disney and Towill, 2003). Besides, globalization is an incentive for businesses to improve upstream-downstream integration so that cross-border cooperation and partnerships are becoming a trend. This has resulted in transportation cost becoming a critical issue in the replenishment policy. This paper proposes a decision approach for finding an optimal replenishment policy under the pre-OPP and VMI model.

The objective of the dynamic lot-sizing problem (DLSP) is to determine the optimal replenishment quantity to satisfy demand within the planning horizon. Wagner and Whitin (1958) used dynamic programming to solve this one-stage problem. One-stage DLSPs in discrete time include: Diaby (1995), Hindi (1995), Megala and Jawahar (2006), Hwang and Jaruphongsa (2006), and Martel (1998). Moreover, Zangwill (1969), Prasad and Krishnaiah Chetty (2001), Gencer (1999), and Özdamar and Birbil (1998) tried to solve multi-stage problems. Transportation cost, however, was not taken into account in these studies. Smith (2003) proposed a multiple-inventory loading problem for transportation operations. This problem is not designed for VMI supply chain, and it doesn't include forecasting models. Studies on DLSP that considered transportation cost are Osman *et al*. (2003), Yano and Newman (2001), Jaruphongsa *et al*. (2004), and Kaminsky and Simchi-Levi (2003), but in these models the demand is considered to be deterministic. Chiu and Chin (2005) proposed a production lot-sizing problem with the reworking and shortage not allowed. Their proposed problem is related to economic production quantity. The result shows that when the production lot-sizing becomes larger, the inventory cost becomes larger as well. In their literature, the consideration for time is continuous. Hashemipour et al. (1999) proposed a production lot-sizing problem. Their model is designed for make-to-order garment manufacturers.

This study solves a two-stage stochastic dynamic lot-sizing problem with two-phased transportation cost under a non-deterministic demand in which the vendor uses the exponential smoothing method for forecast. This paper also proposes a replenishment system based on particle swarm optimization (PSO) and response surface methodology (RSM). In the traveling particle swarm optimization (TPSO), particles must travel every variable (Su and Wong, in process). In performing the modified TPSO, *perturbation policy* is proposed for the velocity of the particles. Therefore, the main aspects of paper are to: (1) Formulate a decision approach applicable to stochastic model, here using RSM to determine the replenishment condition (e.g. the replenishment cycle) and than proposing modified TPSO to solve an NP-hard problem; (2) Examines how the parameters of modified TPSO influence the solution quality, which is then compared with the Solver tool in Excel; (3) Compare the performance of the proposed replenishment decision support system and traditional VMI model.

2. MATHEMATICAL FORMULATION FOR THE PROBLEM

Let t and T respectively denote the index of planning periods and the length of the planning horizon. For modelling the problem, the notations used in this paper are defined as follows:

x_t : the procurement quantity at the vendor at the end of period t

y_t : the replenishment quantity at the buyer at the end of period t

α : the constant of exponential smoothing method

k : the variable for extra order quantity to satisfy demand variation

T_0 : the length of the replenishment cycle

q_t : the decision variables for expand transportation capacity in period t

θ : interest rate

K_1 : the set-up cost of a procurement at the vendor

K_2 : the set-up cost of a replenishment at the buyer

p_1 : the unit procurement cost at the vendor

p_2 : the unit replenishment cost at the buyer

h_1 : the unit cost of holding inventory at the vendor

h_2 : the unit cost of holding inventory at the buyer

w : the unit waiting cost for shortage

c_t : original capacity in period t

G : the fixed cost of transportation for 3PL

u_1 : the unit transportation/holding cost for each period under original capacity

u_2 : the added unit transportation/holding cost for the over capacity in each period

L_1 : the transportation lead time at the vendor

L_2 : the lead time of transportation from the vendor to the buyer through 3PL

S_t : the order-up-to level at the end of period t

O : the quantity of expanded transportation capacity

I_{1t} : the inventory level at the vendor at the end of period t

I_{2t} : the inventory level at the buyer at the end of period t

D_t : the demand in period t

$\hat{d}_t$: demand forecast at the end of period t

$\mathbf{Z}_0^+$: a non-negative integer

$\lfloor\ \rfloor$: the greatest integer less than or equal to the variable

There is a buyer and a vendor, and a third-party logistics (3PL) service provider is responsible for the distribution. The main assumptions include: (1) the simulation is based on discrete unit time; (2) backlogging is provided at the buyer's consent, which increases cost because of customer waiting; (3) the inventory management adopts the order-up-to policy and forecasts with the exponential smoothing method; (4) the lead time is a constant. The decision variables include: the buyer's replenishment quantity (y_t), the variable of the extra order (k), the replenishment cycle (T_0), and q_t.

The expected total cost includes: the vendor's cost, buyer's costs, and transportation cost, as shown in Equation (1). The problem is as follows:

Minimize

$$\mathrm{E}(Z)=\sum_{t=1}^{T}\Big\{\Big[K_1\delta(x_t)+p_1x_t+h_1I_{1t}+G\delta(y_t)+u_1y_t\eta(L_2)+u_2(y_t-c_t)^+q_t\eta(L_2)\Big] + \Big[K_2\delta(y_t)+p_2y_t+h_2(I_{2t})^+ + w(I_{2t})^-\Big]\Big\}(1+\theta)^{-t} \quad \ldots (1)$$

Subject to:

$$I_{1,t-1}+x_{t-L_1}-y_t=I_{1t} \qquad t=1,2,\ldots,T \quad \ldots (2)$$

$$I_{2,t-1}+y_{2,t-L_2}-D_t=I_{2t} \qquad t=1,2,\ldots,T \quad \ldots (3)$$

$$y_t\le c_t+q_tO \qquad t=1,2,\ldots,T \quad \ldots (4)$$

$$T_0\in\mathbf{Z}_0^+ \qquad t=1,2,\ldots,T \quad \ldots (5)$$

$$q_t\in\{0,1\} \qquad t=1,2,\ldots,T \quad \ldots (6)$$

$$x_t,y_t,I_{1t},(I_{2t})^+,(I_{2t})^-\ge 0 \qquad t=1,2,\ldots,T \quad \ldots (7)$$

Note that $\delta(x)=1$ if $x>0$ and 0 otherwise; $(x)^+=\max\{x,0\}$; $(x)^-=-\min\{x,0\}$; $\eta(x)=1$ if $x\le 1$ and x otherwise; D_t is a random variable.

Equation (2) shows the inventory balance constraint at the vendor, Equation (3) is the constraint of the buyer's inventory balance, and Equation (4) is the capacity constraint at 3PL. Equation (5) is a non-negative integer constraint. Equation (6) is a binary variable constraint that is either 0 or 1. Equation (7) is a non-negative real number constraint that implies backlogging is not allowed for the vendor, but is allowed for the buyer.

In the order-up-to policy, the replenishment quantity provided by the vendor within a replenishment cycle is $x_t = S_t -$ *inventory position*. Therefore, the vendor's replenishment quantity is as follows:

$$x_t=S_t-I_{1t}-I_{2t} \qquad t=nT_0\,;n=1,2,\ldots \quad \ldots (8)$$

According to Chen *et al*. (2000), in addition to the forecast demand in the replenishment cycle, in practice, additional k orders will be placed for the forecast demand to satisfy any variation in the demand. Therefore, the vendor's order-up-to level is as follows:

$$S_t=(T_0+k)\hat{d}_t \qquad t=nT_0\,;n=1,2,\ldots \quad \ldots (9)$$

where the smoothing exponent forecasts $\hat{d}_t=\alpha D_t+(1-\alpha)\hat{d}_{t-1}$, $0\le\alpha\le 1$.

3. REPLENISHMENT SYSTEM

The proposed replenishment system is composed of RSM and modified TPSO, which determines the optimal replenishment condition through simulation.

3.1. Framework of the proposed approach

Meta-heuristic algorithms, such as genetic algorithms, ant colony optimization, and PSO, are derived from the observation of animal behavior or evolution and have been widely used. PSO, initially proposed by Kennedy and Eberhart (1995), was an evolutionary computation based on the observation of animal behavior like bird flocking. In executing the PSO, every particle moves at a randomized velocity based on the flight experience of its own and its neighbors'. Unlike traditional genetic algorithms, PSO has memory; consequently, the best solution for the swarm during the execution will be memorized, and so will the personal best solution of individual particles. Individual particles move in accordance with these two memories. PSO was used by Abido (2002), and Salman *et al*. (2002) to solve optimization problems. Su and Wong (in press) proposed the concept of TPSO and applied it in the development of the controller of the processing parameters. This paper proposed the modified TPSO based on Su and Wong's (in press) algorithm. After the vendor determines the replenishment amount through forecast, the particle determines the replenishment amount of each period at the buyer within a replenishment cycle, as shown in Figure 1.

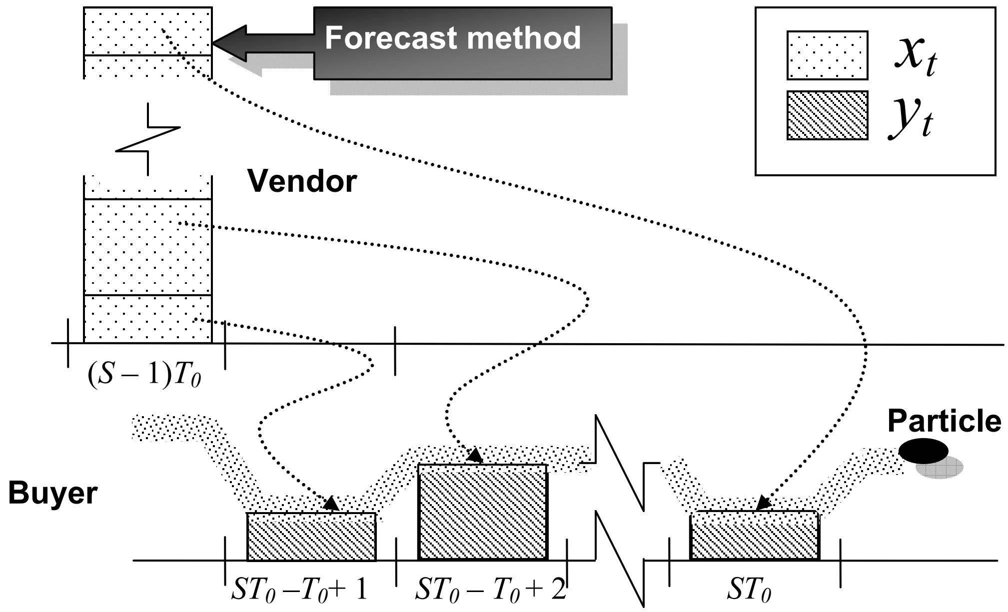

Figure 1. The diagram of TPSO application on the optimized replenishment policy

RSM, an integration mathematical and statistical method, is a methodology for finding the optimal condition in experimental design methods. RSM is a mathematical model that uses parameters and quality characteristics to establish the relationship of the two and to find the optimal condition. There is more detail on RSM presented in Myers and Montgomery (2002).

This paper solves a nonlinear mixed integer programming sub-problem of the proposed problem and proposes a meta-heuristic algorithm based on TPSO to determine the decision variables pertaining to be NP-hard (i.e. y_t). RSM is used to find the optimal combination of decision variables T_0 and k, as shown in Figure 2.

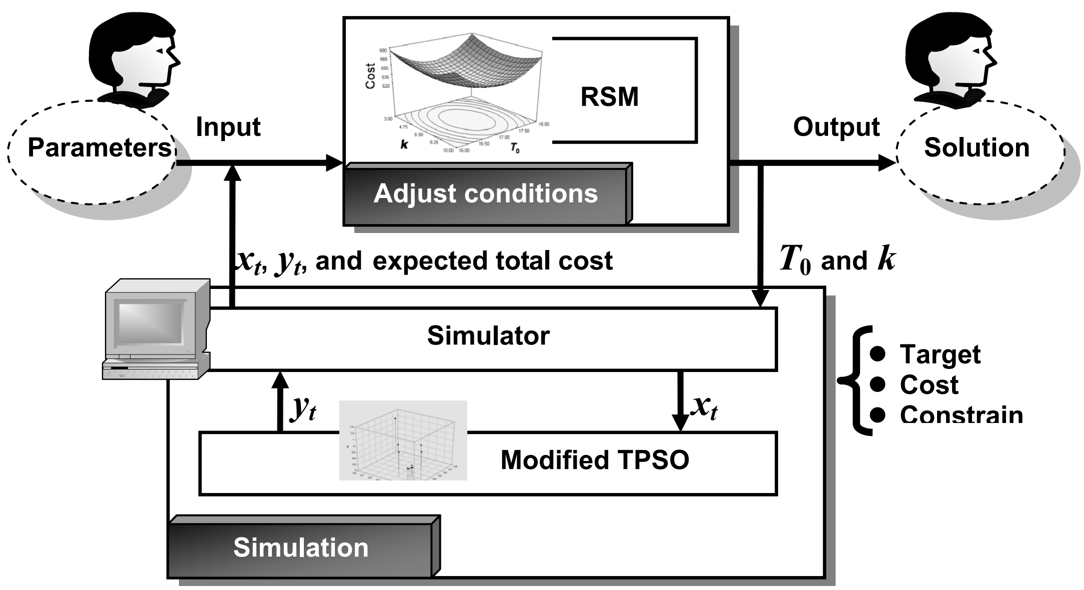

Figure 2. Schematic diagram for the proposed system

3.2. Modified TPSO algorithm implementation

In this paper, the modified TPSO with a perturbation policy is used to determine the optimal replenishment period and quantity for the buyer under the VMI model. The modified TPSO algorithm is being performed on this problem as follows:

Step 1. Input: the parameter of modified TPSO (i.e. number of iterations B, number of particles E, perturbation rate ϑ, ρ, ϕ_1, and ϕ_2).

Step 2. Set initial iteration $b = 1$ and the initial velocity v_{et} of particle e during the replenishment period t. v_{et} = random numbers, for $\forall$ e, t.

Step 3. Randomly generate the initial solution $\boldsymbol{Y} = \{ y_{et} \mid \forall\, t, e = 1, 2,\ldots, E \}$, and calculate the cost.

Step 4. Determine the current best solution y_{et}^{P} of particle e and the current best solution y_t^G of the entire swarm.

Step 5. Update the velocity of the particle as follows:

$$v_{et} = \rho v_{et} + \phi_1 r_1 \left(y_{et}^{P} - y_{et} \right) + \phi_2 r_2 \left(y_t^G - y_{et} \right), \qquad \ldots (10)$$

where ρ is an adjustable parameter between 0 and 1, r_1 and r_2 are random numbers between [0, 1], ϕ_1 and ϕ_2 are constants.

Step 6. Update the new solution as follows:

$$y_{et} = y_{et} + v_{et}. \qquad \ldots (11)$$

Step 7. Perform the perturbation policy. If $r \le \vartheta$, then v_{et} = random numbers of uniform distribution between 0 and c_t, for $\forall$ e, t, else next step, where r is a random number between [0, 1].

Step 8. Update the new solution as follows so that the new solution is feasible: $y_{et} = \begin{cases} I_{1t} & \text{if } y_{et} \ge I_{1t} \\ y_{et} & \text{if } I_{1t} > y_{et} \ge 0 \\ 0 & \text{if } 0 > y_{et} \end{cases}$ for $\forall$ e, t.

Step 9. Calculate cost and update y_{et}^{P} and y_t^G.

Step 10. If $b = B$, then next step, else $b = b + 1$ and go to the step 5.

Step 11. Return y_t^G and end.

3.3. Simulation procedure

The analysis is done through simulation. First, RSM is used to determine replenishment conditions T_0 and k, then the modified TPSO algorithm is used in simulation to determine $\boldsymbol{x} = \{x_t \mid t = nT_0, n = 1, 2,\ldots\}$ and $\boldsymbol{y} = \{y_t \mid t = 1, 2,\ldots, T_0\}$. The steps are as follows:

Step 1. Input simulation parameters including all cost and forecast constant.

Step 2. Determine the decision variables T_0 and k by RSM.

Step 3. Determine $\boldsymbol{x}$ and $\boldsymbol{y}$ as follows:

Step 3.1. Generate the demand: $\boldsymbol{D_i} = \{D_{it} \mid t = 1,2,\ldots,T\}$ $i = 1, 2, \ldots, Q$.

Step 3.2. Determine $\{x_t \mid t = (n-1)T_0\}$ in the n-th replenishment cycle by the forecast method.

*Step*3.3. Determine $\left\{ y_t \mid nT_0 - T_0 + 1 \le t \le nT_0 \right\}$ in n-th replenishment cycle by modified TPSO.

Step 3.4. Update I_{1t} and I_{2t}.

Step 3.5. Repeat steps 3.1–3.4 $\lfloor T/T_0 \rfloor$ times to obtain:

$$\left\{ x_t, y_t \mid 1 \le t \le \lfloor T/T_0 \rfloor T_0 \right\}.$$

Step 3.6. If the remainder of T/T_0 does not equal 0, then adjust the planned periods and execute optimization to obtain:

$$\left\{ x_t, y_t \mid \lfloor T/T_0 \rfloor T_0 + 1 \le t \le T \right\}.$$

Step 3.7. Calculate the objective value Z_i.

Step 3.8. Repeat steps 3.1–3.7 Q times to obtain $\boldsymbol{z} = \{Z_1, Z_2,\ldots, Z_Q\}$.

Step 3.9. Return the $\sum_{i=1}^{Q} Z_i / Q$, ***x***, and ***y***.

Step 4. Repeat step 2 until the RSM experiment is complete.

4. COMPUTATIONAL RESULTS

The first part of the experiment is an analysis of how the modified TPSO parameters would influence the solution quality, which is also compared with some lot-sizing decision rules and the Solver tool in Excel. The second part of the experiment is a simulation to compare the performance of the traditional VMI model and the proposed replenishment policy.

4.1. Modified TPSO test

This paper proposes a modified TPSO algorithm to solve the nonlinear mixed integer programming in the lot-sizing problem. This sub-section examines how parameters ϑ and ρ of the modified TPSO influence the quality of solutions in this sub-problem. The objective function of this sub-problem is as follows:

Minimize

$$\mathrm{TC}(y_t) = \sum_{t=1}^{T} \Big\{ \Big[h_1 I_{1t} + G\delta(y_t) + u_1 y_t \eta(L_2) + u_2 (y_t - c_t)^+ q_t \eta(L_2) \Big] + \Big[K_2 \delta(y_t) + p_2 y_t + h_2 (I_{2t})^+ + w(I_{2t})^- \Big] \Big\} (1+\theta)^{-t} \quad \ldots (12)$$

In order to test the modified TPSO algorithm, the Solver tool in Excel and three lot-sizing decision rules were used as comparison. The design of the three lot-sizing decision rules (i.e. DR_1, DR_2, and DR_3) is as shown in Equations (13), (14), and (15) respectively.

$$y_t = D_t \quad \text{for } t = 1, 2, \ldots, T \quad \ldots (13)$$

$$y_t = 0 \quad \text{for } t = 1, 2, \ldots, T \quad \ldots (14)$$

$$y_t = \begin{cases} \sum_{i=1}^{T} D_i & \text{for } t = 1 \\ 0 & \text{otherwise} \end{cases} \quad \ldots (15)$$

In calculating the total cost, the design of DR_1 (i.e. lot-for-lot rule) will enable h_2 and w to be left out, the design of DR_2 will leave out K_2 and p_2, the design of DR_3 will leave out w, and G and K_2 will only be calculated once (i.e. in period 1).

Table 1. Test result of parameter ϑ

	TPSO			Excel tool
ϑ	Min	Mean	Max	= 429.480
0.016	260.606	271.0915	286.777	DR_1 = 428.873
0.008	260.455	267.9376	283.202	DR_2 = 4044.546
0.002	261.101	272.7277	283.566	DR_3
0.000	261.931	270.4193	286.777	

Table 1 is the result of the parameter ϑ in modified TPSO in the thirty runs of each test. In this test, final customer demand is generated with discrete uniform distribution of [16, 25], and T = 20. Moreover, $I_{1,0}$ of the sub-problem is a constant. The parameters of modified TPSO are set E = 30, B = 5000, ϕ_1 = 1.2, ϕ_2 = 1.2, and ρ = 0.9. Table 1 shows that an adequate perturbation rate can improve the solution quality. When the perturbation rate = 0.008, its average objective function value is less than the solutions of the Excel tool and three lot-sizing decision rules. The convergence process, as shown in Figure 3, indicates that when the perturbation rate = 0, caving into the local optimum may be unavoidable.

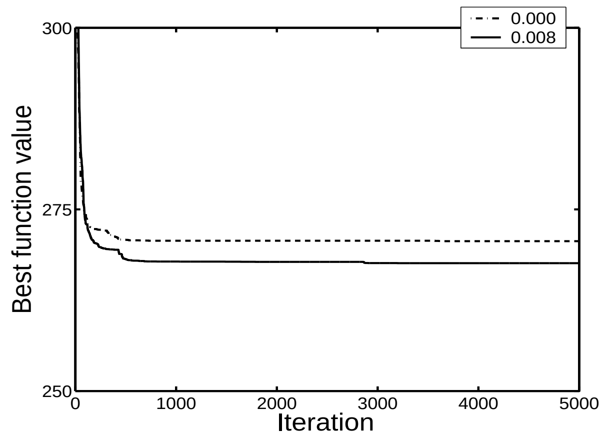

Figure 3. The improvement of the average best solution on parameter ϑ = {0.000, 0.008}

Table 2 shows the testing result of parameter ρ in the modified TPSO, with similar demand settings as Table 1. The parameters of the algorithm are set E = 30, B = 5000, ϕ_1 = 1.2, ϕ_2 = 1.2, and ϑ = 0.008. Compared with Tables 1 and 2 indicates that when ρ = 0.9, the solution quality is better.

Table 2. Test results of parameter ρ

ρ	TPSO		
	Min	Mean	Max
0.8	262.862	271.812	284.045
0.7	266.786	280.826	289.455
0.6	271.557	282.809	307.349
0.5	274.246	291.361	320.873

Table 3. Testing results of TPSO in 40 examples

Methods		Case 1_1	Case 1_2	Case 1_3	Case 1_4
TPSO	Min	148.62	117.14	448.09	330.24
	Mean	165.21	122.73	505.08	367.25
	Max	187.04	142.99	553.82	417.63
Excel tool	Min	236.99	216.00	648.15	582.85
	Mean	248.56	218.80	681.55	606.78
	Max	259.53	222.05	717.83	633.21
DR_1	Min	236.99	212.57	635.46	581.75
	Mean	244.61	215.36	645.61	586.82
	Max	258.00	218.79	659.78	591.16
DR_2	Min	1293.06	832.60	9934.14	6611.86
	Mean	1472.01	897.27	10578.57	6981.71
	Max	1697.80	991.55	11034.15	7284.57
DR_3	Min	148.62	117.14	513.72	398.10
	Mean	166.05	121.28	535.17	409.28
	Max	187.04	126.18	570.60	421.19

The solution quality of modified TPSO is being tested in four different cases, with 10 examples in each case. In case 1_1 the demands of the final customer are generated with discrete uniform distribution of [16, 35]. In case 1_2, the demands are generated from Equation (16) under T = 10. In case 1_3 and case 1_4, the final customer's demands are generated with discrete uniform distribution of [16, 35] and Equation (16) under T = 30, respectively. It is clear that Equation (16) is a distribution of demand with tendency. Table 3 shows the results of this test, which indicate that when the Excel tool is used to solve this sub-problem, the solution quality is not as good as expected, whereas the algorithm proposed by this paper renders better performance. This may be attributed to the fact that the greater the planning horizon T is, the more the carrying cost h_2 would undermine the performance of DR_3. On the other hand, the solution quality of the proposed algorithm is superior to that of the Excel tool and these three lot-sizing decision rules.

$$D_t = 15 + 0.1D_{t-1} + 0.1t + \varepsilon_t \qquad \ldots (16)$$

where ε_t is normally distributed with mean 0 and variance 2.

4.2. Comparative test

This experiment is to test the proposed replenishment system, supposing that the vendor is responsible for the transportation cost so that the buyer will consent to the VMI model. The proposed system is compared with the traditional VMI model (i.e. policy 2) so as to see who will benefit from the proposed replenishment system (i.e. policy 1). In the traditional VMI model, replenishment is provided by the vendor with his demand forecasts and the determined replenishment cycle (i.e. replenishment is provided at the beginning of replenishment cycle). The simulated cases 2_1 and 2_2 are generated from discrete uniform distribution of [16, 25] and Equation (16), respectively. The RSM reflects that the optimal model uses quadratic model. In other words, the quadratic model, with a convex response surface, as shown in Figure 4 is statistically significant. Table 4 shows the output of the statistical data. The results indicate that the values of the adjusted R-square for the four models are all above 95%, and that the quadratic model is statistically significant, reflecting the appropriateness of this model.

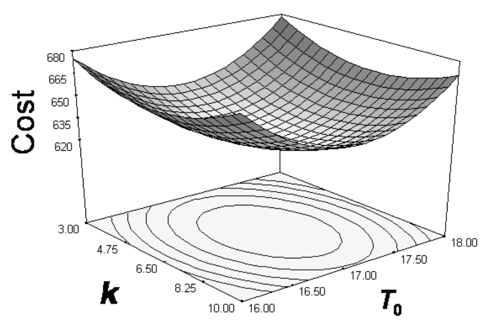

Figure 4. Response surface of case 2_1 in policy 1

Table 4. Output of the proposed model and the traditional VMI model

State	R-Squared (%)		Adjusted R-Squared (%)		P-value			
					Linear model		Quadratic model	
	Policy 1	Policy 2	Policy 1	Policy 2	Policy 1	Policy 2	Policy 1	Policy 2
Case 2_1	99.04	97.10	98.36	95.03	0.9431	0.8317	<0.0001	<0.0001
Case 2_2	99.32	98.56	98.84	97.54	0.7044	0.9221	<0.0001	<0.0001

Through RSM, the optimal replenishment condition (T_0 and k) is found, and Figure 5 is the output under the optimal condition. P1_1 and P2_1 are the results of using policy 1 and policy 2 respectively in case 2_1. P1_2 and P2_2 are the results of using policy 1 and policy 2 respectively in case 2_2. Figure 5 shows that in the simulation, the expected total cost of policy 1 is lower than that of policy 2, and that policy 1 lowers the cost for both the buyer and the vendor. The %τ of P1_1 and P2_1 = 10.23%. The %τ of P1_2 and P2_2 = 10.72%. Note that %τ = (the expected total cost of policy 2 – the expected total cost of policy 1)/the expected total cost of policy 1 × 100.

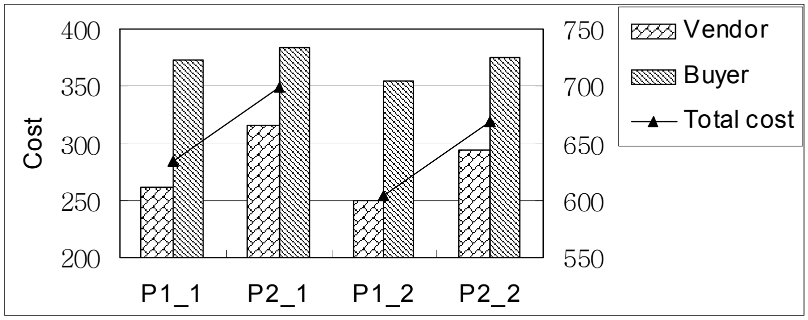

Figure 5. Output of the optimal condition

5. INDUSTRY APPLICATION

The replenishment system proposed in this paper is applicable for lot-sizing problems that consider transportation cost in VMI supply chain. In practice, VMI policy is a common approach for quick response (QR) from vendor to downstream demand. The main concept of VMI is that upstream partnership controls downstream partnership's inventory levels and order planning. Some famous high-tech enterprises, such as HP (Shah, 2000) and Dell (Baljko, 1999), implemented VMI policy to reduce inventory cost. Therefore, it's possible that VMI policy is applicable in practice. The methodology proposed is a replenishment system that is designed for VMI supply chain. To better meet the practical situations, the decision model also considers transportation cost.

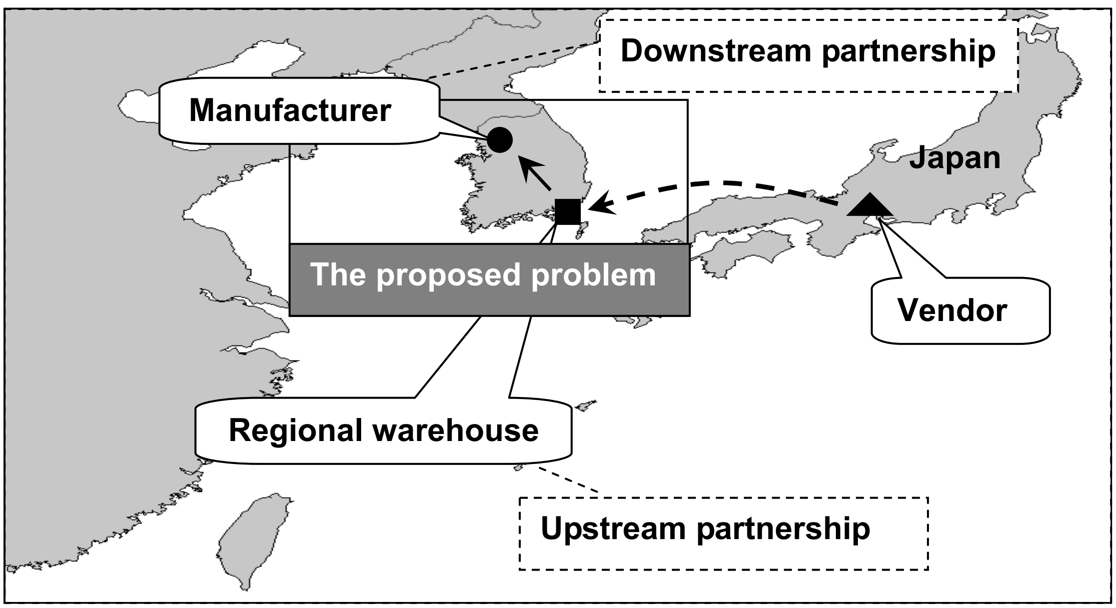

Figure 6.The VMI supply chain replenishment

We described an industry application scenario that the proposed methodology can be applied in. The background company in the illustrative example, *HC* Corporation, is a component raw material supplier in TFT-LCD industry. They produce single key material for polarizing sheets. The material is shipped from Japan to the regional warehouse in Korea. After some processing operations, these products can be sold to the downstream partnership *TG* in Korea. *TG* is an OEM manufacturer for polarizing sheets. In order to achieve QR, this simple supply chain adopts the VMI policy, and this example is shown in figure 6.In such scenario, decision makers face a non-deterministic replenishment problem for downstream, which is NP-hard. The approach proposed in this paper is applicable in the decision environment described above. In order to obtain an optimum replenishment policy, initially decision maker will acquire demand forecast by using forecasting model. Then, TPSO is used to determine optimal replenishment quantity. Finally, RSM is used to discover the best combination for other decision variables. In practical industrial application, the system proposed in this paper possesses some critical insights, which can be acquired by the experiments and problem characteristic in this paper, such as:

- In section 5.1, near-optimal solutions that TPSO obtains are: case 1 = 148.62, case 2 = 117.14, case 3 = 448.09, and case 4 = 330.24. In Excel tool, acquired near-optimal solutions for cases 1, 2, 3, and 4 are: 236.99, 216.00, 648.15, and 582.85. The result shows that TPSO performs better than Excel tool in different planning horizon and demand distribution.
- Table 1 shows that TPSO gains better performance when parameter ϑ is equal to 0.08. In practical application, decision makers should notice that the TPSO's perturbation rate. If the rate is too high or too low, the solution performance will be compromised.
- The replenishment model in this paper is applicable for VMI supply chain. Therefore, some practical execution issues are worthy to concern. For example, an experienced consultant should be hired to handle VMI policy. The power of supply chain partnership should be understood. Upstream and downstream partners should own complete and competent IT infrastructures. There should be complete reviews and communication channels for VMI policy executions (Tyan and Wee, 2003).
- Achabal et al. (2000) proposed a decision support system for VMI supply chain. Their system includes a forecasting model and an inventory decision model. The replenishment system in this paper is designed for simulation system includes NP-hard. In practice, different forecasting models and parameters should be applied for different environments. For this issue, please refer to the literatures of Achabal et al. (2000).
- In practice, vendors may persuade downstream partners to follow VMI policy by handling transportation cost. The experiment results in this paper also show that the proposed system can reduce cost for both upstream and downstream partners under VMI environment. Obviously, such approach doesn't consider the risk for information sharing.

6. CONCLUSIONS

The increasingly globalized marketplaces are creating more and more opportunities for transnational cooperation. As a result, the transportation distance has been stretched and the transportation cost has become an issue of increasing importance. This paper proposes a replenishment system based on modified traveling particle swarm optimization and response surface methodology to solve a two-stage stochastic dynamic lot-sizing problem with two-phased transportation cost. To solve the nonlinear mixed integer programming sub-problem therein, this paper proposes a modified TPSO algorithm with perturbation policy. In table 1, mean objective values for parameter ϑ = 0 and 0.008 are 270.4193 and 267.9376 respectively. The result indicates that perturbed strategy is beneficial for improving algorithm performance. The experiment shows that adequate perturbation rate prevents the modified TPSO from caving into the local optimum and renders better solution quality than Excel tool and 3 lot-sizing decision rules in problems with larger planning horizon. Figure 5 shows that the total costs when adopting the replenishment system proposed in this paper are all less than three hundred. All total costs acquired by traditional VMI policies are more than three hundred. The result of the replenishment system test shows that the cost in the proposed model is lower than that in the traditional VMI model. Even though the proposed method is being implemented on the condition that the vendor is responsible for the transportation cost, expected cost is lowered for both the buyer and the vendor. When managers confront a similar supply chain environment as the one examined in this paper, the proposed method and the testing result can serve as a good reference in the decision-making process.

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8. REFERENCES

1. Achabal, D., Mclntyre, S., Smith, S., and Kalyanam, K. (2000). A decision support system for vendor managed inventory. Journal of Retailing, 76(4): 430-454.
2. Abido, M.A. (2002). Optimal power flow using particle swarm optimization. International Journal of Electrical Power and Energy Systems, 24(7): 563-571.
3. Baljko, J.L. (1999). Dell: VMI catalyst for cooperation. Electronic Buyers' News, 1176: 1.
4. Chen, F., Drezner, Z., Ryan, J., and Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. Management Science, 46(3): 436-443.
5. Chiu, Y.-S.P. and Chin, S.W. (2005). The finite production model with the reworking of defective items. International Journal of Industrial Engineering – Theory, Applications and Practice, 12(1): 15-20.
6. Diaby, M. (1995). Optimal setup time reduction for a single product with dynamic demands. European Journal of Operational Research, 85(3): 532-540.

7. Disney, M.S., and Towill, D.R. (2003). The effect of vendor managed inventory (VMI) dynamics on the Bwllwhip Effect in supply chains. International Journal of Production Economics, 85(2): 199-215.
8. Gencer, C., Erol, S., and Erol, Y. (1999). A decision network algorithm for multi-stage dynamic lot sizing problems. International Journal of Production Economics, 62(3): 281-285.
9. Hashemipour, M., Magusa G., and, Kayaligil, S. (1999). Labor shifting and lot sizing in garment manufacturing: a simulation study. International Journal of Industrial Engineering, 6(3): 224–233.
10. Hindi, K.S. (1995). Solving the single-item, capacitated dynamic lot-sizing problem with startup and reservation costs by tabu search. Computers & Industrial Engineering, 28(4): 701-707.
11. Hwang, H.C., and Wikrom, J. (2006). Dynamic lot-sizing model with demand time windows and speculative cost structure. Operations Research Letters, 34(3): 251-256.
12. Jaruphongsa, W., Cetinkaya, S., and Lee, C.Y. (2004). Warehouse space capacity and delivery time window considerations in dynamic lot-sizing for a simple supply chain. International Journal of Production Economics, 92(2): 169-180.
13. Kaminsky, P., and Simchi-Levi, D. (2003). Production and distribution lot sizing in a two stage supply chain. IIE Transactions, 35(11): 1065-1073.
14. Kennedy, J., and Eberhart, R. (1995). Particle swarm optimization. IEEE International Conference on Neural Networks, pp. 1942-1948.Washington, DC, USA.
15. Martel, A., and Gascon, A. (1998). Dynamic lot-sizing with price changes and price-dependent holding costs. European Journal of Operational Research, 111(1): 114-128.
16. Megala, N., and Jawahar, N. (2006).Genetic algorithm and Hopfield neural network for a dynamic lot sizing problem. International Journal of Advanced Manufacturing Technology, 27(11-12): 1178-1191.
17. Myers, R.H., and Montgomery, D.C. (2002). Response surface methodology: process and product optimization using designed experiments. Wiley-Interscience.
18. Olhager, J. (2003). Strategic positioning of the order penetration point. International Journal of Production Economic, 85(3): 319-329.
19. Osman, O., Erkip, N.K., and Güllü, R. (2003). Optimal lot-sizing/ vehicle-dispatching policies under stochastic lead times and stepwise fixed costs. Operations Research, 51(1): 160-166.
20. Özdamar, L., and Birbil, S.I. (1998). Hybrid heuristics for the capacitated lot sizing and loading problem with setup times and overtime decisions. European Journal of Operational Research, 110(3): 525-547.
21. Prasad, P.S.S., and Krishnaiah Chetty, O.V. (2001). Multilevel lot sizing with a genetic algorithm under fixed and rolling horizons. International Journal of Advanced Manufacturing, 18(7): 520-527.
22. Salman, A., Ahmad, I., and Al-Madani, S.(2002). Particle swarm optimization for task assignment problem. Microprocessors and Microsystems, 26(8): 363–371.
23. Su, C.T., and Wong, J.T. (2007). Designing MIMO controller by neuro-traveling particle swarm optimizer approach. Expert Systems with Applications, 32(3): 848-855.
24. Smith, J.C. (2003). A genetic algorithm approach to solving a multiple inventory loading problem. International Journal of Industrial Engineering, 10(1): 7-16.
25. Shah, J.B. (2000). ST, HP VMI program hitting its stride. Electronic Buyers' News, 1309: 42.
26. Tyan, J., and Wee, H.M. (2003). Vendor managed inventory: a survey of Taiwanese grocery industry. Journal of Purchasing and Supply Management, 9(1): 11-18.
27. Wagner, H.M., and Whitin, T.M. (1958). Dynamic version of the economic lot size model. Management Science, 5(1): 89-96.
28. Yano, C.A., and Newman, A.M. (2001). Scheduling trains and containers with due dates and dynamic arrivals. Transportation Science, 35(2): 181-191.
29. Zangwill, W.I. (1969). A backlogging model and multi-echelon model of a dynamic economic lot size production system–a network approach. Management Science, 69(15): 506-527.

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