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MULTI-ECHELON REVERSE SUPPLY CHAIN NETWORK DESIGN WITH SPECIFIED RETURNS USING PARTICLE SWARM OPTIMIZATION

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Abstract. *This paper focuses on the development of an optimization mathematical model for a reverse supply chain network that contains forward and reverse logistical plans in the multi-echelon system. In the reverse process, the defective products are returned to the original manufacture/supplier (specified returns) to be produced again. The next period covers the quantity of defective products for the present period, as well as the demands for the new period. To solve the mathematical model efficiently, a particle swarm optimization (PSO) solution is proposed, called PSOsm. The PSOsm introduces the saltation mechanism into the procedure of the original PSO to increase the search area, which prevents the solution being laid on the local solution. Finally, to illustrate the performance of the PSOsm, the original PSO and a genetic algorithm (GA) are employed to find the solution for the proposed problem and the performance of both methods is compared. The results show that the PSOsm provides a better solution.*

Keywords: Reverse supply chain, Specified returns, Particle swarm optimization, Genetic algorithm

1. Background and Related Works.

Supply chain management has become an important strategic process for the coordination of supply chain networks that increase a company's competitiveness in the current business environment [1-7]. Sadjady and Davoudpour [8] stated that designing distribution networks – as one of the most important strategic issues in supply chain management – has become the focus of research attention in recent years and Das and Chowdhury [9] pointed out consideration of reverse logistics as a significant part of overall business process has been gaining importance across the entire global market. Dowlatshahi [10] also pointed out that reverse logistics is an important concept for logistics and supply chain management and that efficient reverse logistics management can increase the competitiveness of an enterprise and prevent expulsion from the market, especially when facing intense competition and low profit margins.

Shih [11] suggested that the reverse logistics system is an essential part of business operations when the recovery rates and service coverage are broadened, in the future. Desai and Mital [12] suggested that enterprises should work on the reuse, reworking, recycling, and reutilization of products at the end of the product life cycle. Hu et al. [13] stated that reverse logistics involves the complex logistics of management procedures, which includes planning, management and control of the discarded logistics generated by rework and the disposal of discarded products. Imre [14] proposed that reverse logistics involves the recycling of materials that could be reused in the market. If reverse logistics is economically viable, it could protect the environment and reduce resources waste, which might provide a new use for recycled products. According to one conservative estimate, reverse logistics may account for 4% of total logistical costs [15]. According to Daugherty's study, the average reverse logistics may account for 9.49% of total logistical costs [16]. Therefore, reverse logistics may become critical to the success of many enterprises.

The traditional supply chain focuses only on logistics, which is the sale of products, and has neglected possible damage that may occur after the products are sold, seemingly ignoring the unavoidable fact that some non-conforming products would be generated in the production and transportation processes. Therefore, when customers discover that they have bought non-conforming products, they would surely want the original manufacturer to take responsibility. The distribution problem of returning the non-conforming products to the original manufacturers needs to be taken into account. The network for this specific return supply chain is shown in Figure 1.

To the best of our knowledge, no mathematical model for supply chain planning problems in multi-echelon networks that considers specified returns has been presented, even though it represents a better operational practice. Therefore, this paper emphasizes the development of an optimization mathematical model to deal with the problem of a reverse supply chain with specified returns.

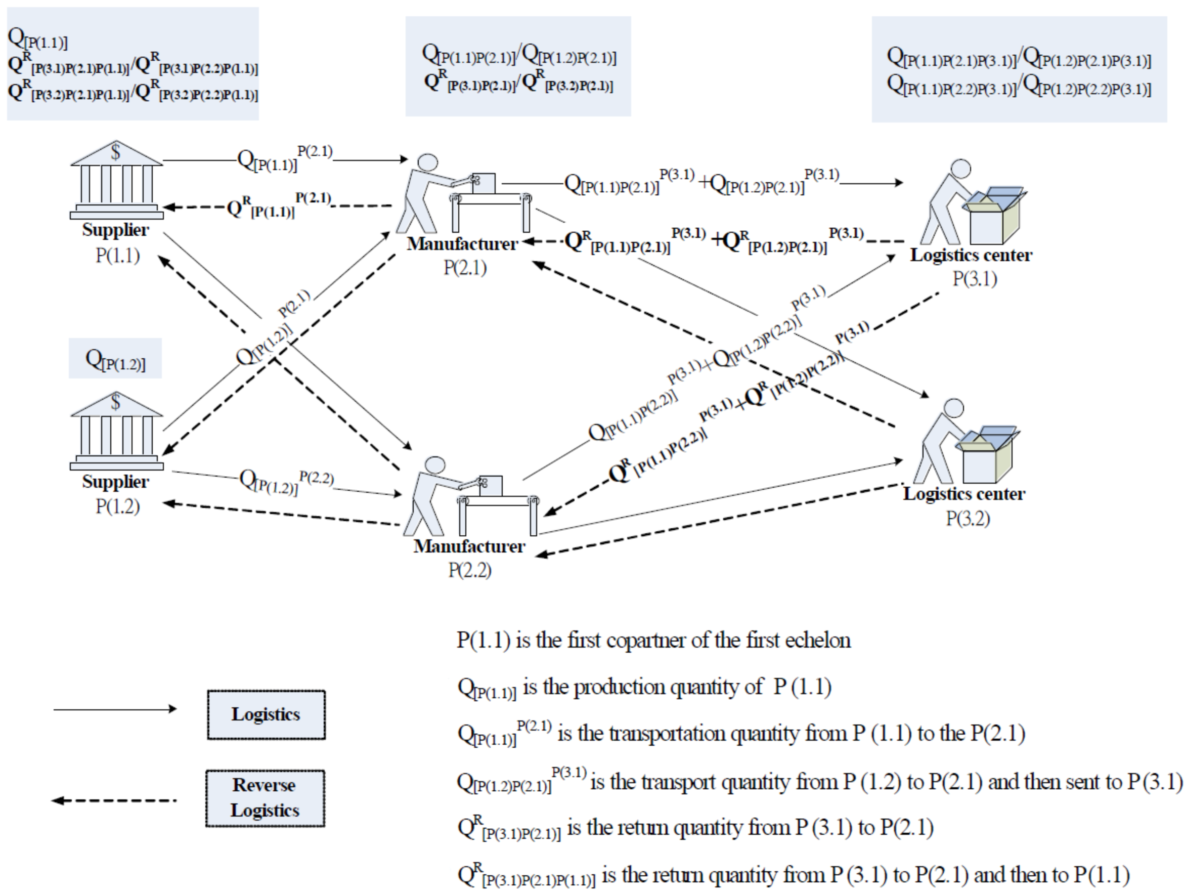


Figure 1. Network concept for reverse logistics with specified returns

Gen and Cheng [17] indicated that a multi-stage stage logistical problem can be treated as the combination of a multiple-choice Knapsack problem and a capacitated location-allocation problem as a NP-hard problem. In this study, every copartner has constrained information about not only capacity, but also rate of loss, rate of defective items and the specified returns. Hence, the task is more difficult for this problem.

Some previous research has proposed heuristic approaches for the design of forward/reverse supply chain networks, which can find near optimal solutions very quickly [18-21]. PSO has been proven as an effective and simple optimization algorithm [22]. Cui et al. [23] and Yu et al. [24] stated that PSO is a practicable method for the solution of optimization problems. Some studies [25-30] have also pointed out that PSO is a useful heuristic approach that can easily produce acceptable solutions to complex problems. Azadeh et al. [31] proposed a particle swarm optimization (PSO) algorithm to determine the optimal inspection policy in serial multi-stage processes. Che and Cui [32] proposed a PSO method for Unbalanced Supply Chain Design. Sinha et al. [33], Mahnam et al. [34], Yang and Lin [35] and Che [30] successfully applied the PSO to the solution of supply chain planning problems. However, the above studies did not deal with a multi-echelon supply chain planning problem that considers specified returns. Another purpose of this study, therefore, is to present a modified PSO method (PSOsm) for the solution of the optimization mathematical model developed for reverse supply chain network design with specified returns.

The remainder of this paper is organized as follows. Section 2 develops an optimization mathematical model to deal with the problem. The proposed heuristic solution model, PSOsm, is presented for the solution of the mathematical model in Section 3. Section 4 presents detailed applications of the proposed method. Section 5 compares the experimental results for PSOsm, PSO and GA, to determine the performance of PSOsm. Section 6 presents the conclusions.

2. **Optimization Mathematical Model for Supply Chain Network Design.** Cost and quality are the criteria used for the design of the supply chain network in this study. Before the data is used, a T-transfer technique is employed to transfer the original values of these two criteria to the standard T scores and to further integrate these scores. The T-transfer formula for the original value, C, is $Cs = (C - mean(C))/(Stand(C)/10) + 50$, where $mean(C)$ is the mean value of C and $Stand(C)$ is the standard deviation of C.

The notations used in the optimization optimizing mathematical model are as follows:

i	Supply chain echelons, $i = 1, 2, 3, \ldots, I$
p	Production periods, $t = 1, 2, 3, \ldots, T$
I	Total number of echelons in the supply chain
P	Total periods of production
j	Copartner index
k	Copartner index of the specified return
J_i	Total number of copartners at echelon i
K_i	Total number of copartners for the specified return at echelon i
$INC_{(i,j)}$	Inspection cost for copartner j at echelon i
$PC_{(i,j)}$	Production costs for copartner j at echelon i
$TC_{((i,j),(i+1,k))}$	Transportation cost from copartner j of echelon i to the original (specified) copartner k of echelon $i+1$
$TLR_{((i,j),(i+1,k))}$	Transport loss rate from copartner j of echelon i to the original (specified) copartner k of echelon $i+1$

$DR_{(i,j)}$ Defect production rate of copartner j at echelon i

$X^p_{(i,j)}$ Product quantity of copartner j at echelon i in period p

$X^p_{((i,j),(i+1,k))}$ Transportation quantity from copartner j of echelon i to the original (specified) copartner k of echelon $i+1$

$R^{p-1}_{((i+1,k),(i,j))}$ Quantity of non-conforming products from copartner j of echelon i at period $p-1$ to the original (specified) copartner k of echelon $i+1$

$MaxCAP_{(i,j)}$ Upper limit of maximal productivity of copartner j at echelon i

$MinCAP_{(i,j)}$ Lower limit of minimal productivity of copartner j at echelon i

$INT\{\}$ Integer function to obtain the integer value of the real number by eliminating its decimal

The mathematical model is formulated as follows.

Objective function: Minimize production costs, transportation costs, remake costs, inspection costs and quality (definition 1 of quality level was the best quality).

$$\begin{aligned}\text{Minimise} &\sum_{p=1}^{P}\sum_{i=1}^{I-1}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{i+1}}\left(PC_{(i,j)} \times X^p_{((i,j),(i+1,k))}\right)\\ &+\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J_1}\sum_{k=1}^{K_{i+1}}\left(TC_{((i,j),(i+1,k))} \times \left(X^p_{((i,j),(i+1,k))} + R^p_{((i+1,k),(i,j))}\right)\right)\\ &+\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{i-1}}\left(PC_{(i,j)} \times X^p_{((i-1,k),(i,j))}\right)\\ &+\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{i+1}}\left(INC_{(i,j)} \times X^p_{((i,j),(i+1,k))}\right) + \sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J_i} Q^p_{(i,j)}\end{aligned}$$

Constraints: The transportation quantities for suppliers are at the first echelon, the middle echelon suppliers of the second, third, etc., to the last echelon supplier, after considering the transportation loss rates. These also represent the quantity of specified non-conforming products returned to the original manufacturer.

$$\sum_{k=1}^{K_{i+1}} X^p_{((i,j),(i+1,k))} = INT\left\{\sum_{k=1}^{K_{i+1}} X^p_{((i,j),(i+1,k))} \times \left(1 - TLR_{((i,j),(i+1,k))}\right) + R^{p-1}_{((i+1,k),(i,j))}\right\},$$
$$i = 1; p = 1,2,3,\dots,P; j = 1,2,3,\dots,J$$

$$\begin{aligned}\sum_{k=1}^{K_{i-1}} X^p_{((i-1,k),(i,j))} = INT\Bigg\{ &\left[\sum_{k=1}^{K_{i-1}} X^p_{((i-1,k),(i,j))} \times \sum_{k=1}^{K_{i+1}} \left(1 - TLR_{((i,j),(i+1,k))}\right)\right]\\ &+ \sum_{k=1}^{K_{i+1}} R^{p-1}_{((i+1,k),(i,j))} - \sum_{k=1}^{K_{i-1}} R^p_{((i,j),(i-1,k))}\Bigg\},\end{aligned}$$
$$i = 2,\dots,I-1; p = 1,2,3,\dots,P; j = 1,2,3,\dots,J$$

$$\sum_{k=1}^{K_{i-1}} X^p_{((i-1,k),(i,j))} = INT\left\{\sum_{k=1}^{K_{i-1}} \left[X^p_{((i-1,k),(i,j))} \times \left(1 - TLR_{((i,j),(i-1,k))}\right) - R^p_{((i,j),(i-1,k))}\right]\right\},$$
$$i = I; p = 1,2,3,\dots,P; j = 1,2,3,\dots,J$$

The quantity of non-conforming products that must be returned to the original manufacturer of the last echelon is generated in the production process.

$$\sum_{k=1}^{K_{i-1}} R^p_{((i,j),(i-1,k))} = INT\left\{\left(\sum_{k=1}^{K_{i-1}} X^p_{((i-1,k),(i,j))} + \sum_{k=1}^{K_{i+1}} R^{p-1}_{((i+1,k),(i,j))}\right) \times DR_{(i,j)}\right\},$$
$$i = 2, 3, \ldots, I; p = 2, 3, \ldots, P; j = 1, 2, 3, \ldots, J$$

The restricted quantities apply to suppliers from the first to the last echelon, to meet the customer demands.

$$X_{(i,j)} = INT\left\{\sum_{k=1}^{K_{i+1}} X^p_{((i,j),(i+1,k))} \times \left(1 - DR_{(i,j)}\right) \times \left(1 - TLR_{((i,j),(i+1,k))}\right)\right\},$$
$$i = i; p = 1, 2, 3, \ldots, P; j = 1, 2, 3, \ldots, J$$

$$X_{(i,j)} = INT\left\{\sum_{k=1}^{K_{i-1}} X^p_{((i-1,k),(i,j))} \times \left(1 - DR_{(i,j)}\right) \times \left(1 - TLR_{((i,j),(i+1,k))}\right)\right\},$$
$$i = 2, 3, \ldots, I-1; p = 1, 2, 3, \ldots, P; j = 1, 2, 3, \ldots, J$$

The transportation volume must not be larger than the maximum productivity of the supplier and must not be less than the start-up productivity level.

$$MinCAP_{(i,j)} \le \sum_{k=1}^{K_{i+1}} X^p_{((i,j),(i+1,k))} \le MaxCAP_{(i,j)},$$
$$i = 1, 2, \ldots, I-1; p = 1, 2, 3, \ldots, P; j = 1, 2, 3, \ldots, J$$

The transportation volume must be equal to or larger than 0 and an integer number.

$$X^p_{((i,j),(i+l,k))} \ge 0 \text{ and } \in integer$$
$$\text{for } i = 1, 2, \ldots, I; j = 1, 2, 3, \ldots, J; k = 1, 2, 3, \ldots, K; p = 1, 2, 3, \ldots, P$$

Using multi-echelon production, no non-conforming products can be returned to the original manufacturer at the beginning of the production.

$$R^p_{((i,j),(i-1,k))} = 0$$
$$\text{for } p = 1; i = 1, 2, \ldots, I; j = 1, 2, 3, \ldots, J; k = 1, 2, 3, \ldots, K$$

3. **A Heuristic Method Based on PSO.** To solve the optimization mathematical model for the reverse logistics problem with specified returns, a heuristic method, PSOsm, is proposed, which obtains a near optimal solution under minimal objective function values. The step-wise description of PSOsm is as follows.

Step 1: Encoding scheme. Each particle is represented by a matrix-string of bits of integer numbers (Figure 2), which is used to illustrate the scheme for a feasible solution. Each bit represents the transportation quantity for each route between the upstream and downstream partners.

Step 2: Setting the relevant control parameters. Particle population and iteration times: larger particle populations and iterations times require extended computational time, but also generate better objective function values [36]. Maximum speed: by fixing the accuracy of particles in the solution space, if the speed of the particle is faster (larger value), the convergence rate of the solution is also faster, which may prevent the discovery of the optimal solution, due to the increased pace; if it is too small, it may not reach the local search space. A learning factor: usually $c_1 = c_2 = 2$, or between 0 and 4; c_1 regulates the flying step length of the particle towards its optimal location and c_2 regulates

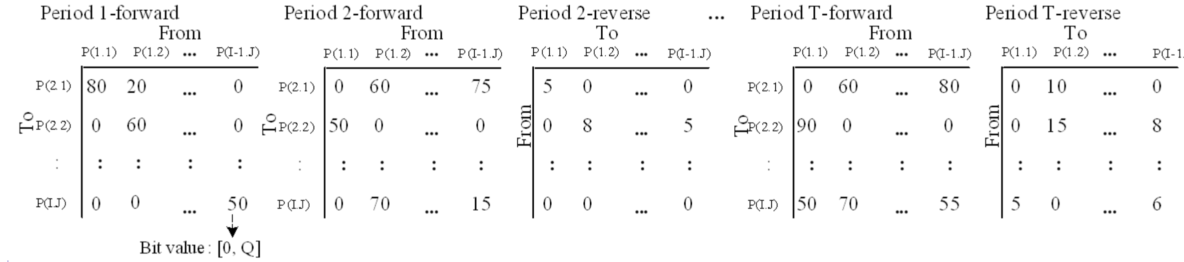


FIGURE 2. Particle scheme

the flying step size of the particle towards the global optimal location. Inertial weight: Shi and Eberhart [37] reported that w has a greater opportunity to discover the global optima, when it is between 0.9 and 1.2.

Step 3: Generating the initial population: The initial speed and location of each particle are generated in a random fashion. The range is regulated by the constraints of the mathematical models. These randomly generated values are called the parental generation. Each value has its own initial speed and location, substituting the particle swarm of parental generation in the objective function to obtain a fitness function value and then reordering and evaluating them to determine the optimal function value, $f(gbest)$, of the parental generation population.

Step 4: Updating the velocity and position of each particle: The formulae for velocity and position updating process for each particle are

$$v_{i+1} = wv_i + c_1 \times rand1() \times (pbest - S_i) + c_2 \times rand2() \times (gbest - S_i)$$
$$S_{i+1} = S_i + v_{i+1}$$

where v_i is the speed of the change in position of the particle i, v_{i+1} is the new speed of the particle i, S_i is the current position of the particle i, S_{i+1} is the new position of the particle i, $pbest$ is the best individual position of the particle i, $gbest$ is the best position of all of the particles, $rand1()$ and $rand2()$ are stochastic variables with a value between zero and one, w is the inertial weight and c_1 and c_2 are learning factors. The calculation shows that the population and individual optimal values are their current optimal location and velocity. The rest of the particles are updated towards the optimal value.

Step 5: Saltation. The saltation mechanism is used to update the particle. Saltation helps to broaden the area of the search space and prevents stalling at a local optimum. The procedure for the saltation mechanism can be algorithmically stated as follows:

Procedure – Saltation mechanism
{*Step 5.1: Randomly select n particles,* $P_n \in (P_1, P_2, \ldots, P_N)$;
//$n = q * r$, *q is the number of particles and r is the saltation rate;* P_n *is the set of selected particles.*//
Step 5.2: Randomly select k bits in each selected particle, $B_{k,P_n} \in (B_{1,P_n}, B_{2,P_n}, \ldots, B_{K,P_n})$; //$B_{k,P_n}$ *is the set of selected bits from particle* P_n.//
Step 5.3: Set $Value\_B^{new}_{k,P_n} = Value\_B^{old}_{k,P_n} + rand3()$, *for all k and* P_n;
//$Value\_B_{k,P_n}$ *is the value of the selected bit k from particle* P_n, $rand3()$ *is the independent random integer variable evenly distributed within* $[-S_{i,old}, U]$, *U is the upper bound of the transportation quantity.*//
Step 5.4: If (constraints of the mathematical model are not satisfied) Then go to Step 3;
Step 5.5: Calculate the new fitness value $f^{new}(P_n)$ *of the selected particles;*
Step 5.6: If $(f^{new}(P_n)$ *is not better than* $f^{old}(P_n))$ *Then go to Step 3;*

Step 5.7: If $(f^{new}(P_n)$ *is better than* $f(pbest))$ *Then* $\{pbest = P_n\}$;
Step 5.8: If $(f^{new}(P_n)$ *is better than* $f(gbest))$ *Then* $\{gbest = P_n\};\}$

Step 6: Repeat Steps 4 and 5, until the termination condition is met; that is to say, a new generation is generated.

Step 7: Obtain a suitable solution for the reverse supply chain network design problem with specified returns.

4. **Illustrative Example.** In a supply chain network, non-conforming products are unavoidable. All companies, no matter how high their yield rate, cannot guarantee a 100% yield. Product incidents in the manufacturing process and transportation losses in the transportation process may lead to non-conforming products. These non-conforming products may be returned to the original suppliers for rework using a reverse logistics network model.

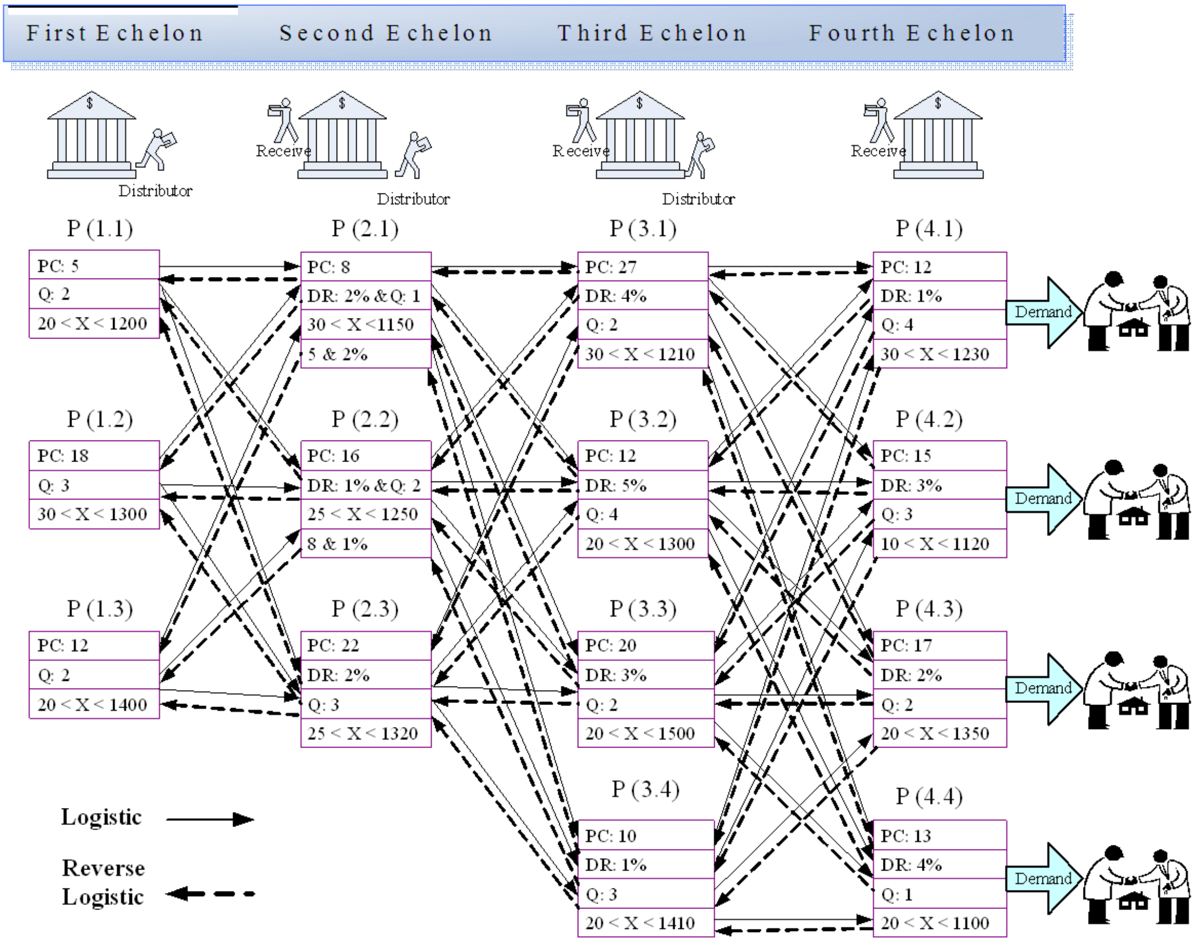
This study adopts the {3-3-4-4} network to simulate the return and rework of non-conforming products. The final customer demands for the first period are 400, 350, 450 and 400 units, those for the second period are 400, 250, 450 and 500 units and those for the third period are 400, 450, 400 and 350 units. Figure 3 shows the structure of the reverse logistics network, the return course of the product and the relevant parameter values, including production costs, transportation costs, inspection costs, quality, incident rates for the supplier, loss rates and the upper and lower limits of the productivity used in this case.

To solve this problem, experiments are carried out for different combinations of two population sizes (10 and 50), two generations (500 and 1000), two maximum velocities (0.95 and 1.25), two initial weights (1.25 and 2.15) and two saltation rates (0.07 and 0.08). The experimental results for all of the combinations are shown in Table 1. Using these parameter settings and depending on the evolutionary states, these results show that the minimum objective function is obtained when the settings are; population sizes = 10, generations = 1000, max velocity = 1.25, initial weight = 2.15 and saltation rate = 0.07. The experimental results for supply chain planning for this problem using PSOsm are shown in Tables 2-4. These results show that the best solution for all of the different combinations is 735670 and that the time spent is less than 60 seconds. For the illustrative case, the transportation quantities from 1.1 to 2.1, 2.2 and 2.3 are 407, 193 and 80, respectively, in the first period. The reverse logistics occur in the second period and the quantities shipped from 2.1 to 1.1, 1.2 and 1.3 are 11, 16 and 0, respectively. The detailed planning results for the case are shown in Tables 2-4.

Table 1. Experimental parameter combinations of PSOsm

Combination	A	B	C	D	E	F	G	H
Population Size	10	10	10	10	20	20	20	20
Generations	500	500	1000	1000	500	500	1000	1000
Max velocity	0.95	1.25	0.95	1.25	0.95	1.25	0.95	1.25
Initial Weight	1.25	2.15	1.25	2.15	1.25	2.15	1.25	2.15
c_1, c_2	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05
Saltation Rate	0.08	0.07	0.08	0.07	0.08	0.07	0.08	0.07
Avg. Fitness	746047	748008	738068	735670	742623	744620	743274	743746

5. **Evaluation of the PSOsm's Solution Performance.** To evaluate the performance of PSOsm in designing the multi-echelon reverse supply chain network with specified returns, the {3-3-4-4} network is chosen. The results for the PSOsm are compared with



	TC / TLR / INC
P(1.1) → P(2.1)	5 / 2% / 2
P(1.1) → P(2.2)	8 / 1% / 5
P(1.1) → P(2.3)	2 / 1% / 3
P(1.2) → P(2.1)	3 / 3% / 4
P(1.2) → P(2.2)	4 / 2% / 1
P(1.2) → P(2.3)	5 / 1% / 3
P(1.3) → P(2.1)	8 / 1% / 5
P(1.3) → P(2.2)	7 / 1% / 4
P(1.3) → P(2.3)	6 / 2% / 2

	TC / TLR / INC
P(2.1) → P(3.1)	6 / 4% / 1
P(2.1) → P(3.2)	2 / 2% / 1
P(2.1) → P(3.3)	2 / 2% / 3
P(2.1) → P(3.4)	1 / 2% / 3
P(2.2) → P(3.1)	2 / 1% / 1
P(2.2) → P(3.2)	3 / 5% / 2
P(2.2) → P(3.3)	5 / 1% / 4
P(2.2) → P(3.4)	7 / 4% / 3
P(2.3) → P(3.1)	9 / 2% / 2
P(2.3) → P(3.2)	6 / 3% / 4
P(2.3) → P(3.3)	6 / 3% / 1
P(2.3) → P(3.4)	8 / 2% / 5

	TC / TLR / INC
P(3.1) → P(4.1)	10 / 1% / 3
P(3.1) → P(4.2)	4 / 4% / 3
P(3.1) → P(4.3)	4 / 5% / 1
P(3.1) → P(4.4)	6 / 3% / 2
P(3.2) → P(4.1)	3 / 4% / 1
P(3.2) → P(4.2)	4 / 1% / 3
P(3.2) → P(4.3)	5 / 2% / 4
P(3.2) → P(4.4)	8 / 2% / 5
P(3.3) → P(4.1)	7 / 2% / 2
P(3.3) → P(4.2)	6 / 1% / 3
P(3.3) → P(4.3)	6 / 2% / 1
P(3.3) → P(4.4)	2 / 3% / 2
P(3.4) → P(4.1)	2 / 4% / 3
P(3.4) → P(4.2)	1 / 1% / 4
P(3.4) → P(4.3)	2 / 5% / 4
P(3.4) → P(4.4)	3 / 3% / 2

Production Cost (PC)
Defective Rate (DR) & Quality (Q)
MinCAP<X<MaxCAP
Transportation Cost & Transportation Loss Ratio (TC & TLR)
Inspection Cost (INC)

FIGURE 3. {3-3-4-4} reverse logistics network

those for the original GA and PSO. Table 5 shows the average value of the optimal parameter combinations for the GA and PSO, after obtaining the solution for the parameter combination. As shown, for the PSO, the average fitness value of 736211 is the minimal average fitness value of the parameter combinations. The optimal parameter combination is 10 particle populations, 1000 generation times, 1.25 maximal rate and 2.15 initial

Table 2. Production plan through PSOsm (1st period)

	To	Echelon 1			Echelon 2			Echelon 3				Echelon 4			
From		P(1.1)	P(1.2)	P(1.3)	P(2.1)	P(2.2)	P(2.3)	P(3.1)	P(3.2)	P(3.3)	P(3.4)	P(4.1)	P(4.2)	P(4.3)	P(4.4)
Echelon 1	P(1.1)				407	193	80								
	P(1.2)				601	99	247								
	P(1.3)				3	97	0								
Echelon 2	P(2.1)							181	304	171	334				
	P(2.2)							29	197	55	105				
	P(2.3)							112	71	71	68				
Echelon 3	P(3.1)											181	52	30	45
	P(3.2)											81	23	186	253
	P(3.3)											127	48	112	1
	P(3.4)											15	238	131	117

Table 3. Production plan through PSOsm (2nd period)

	To	Echelon 1			Echelon 2			Echelon 3				Echelon 4			
From		P(1.1)	P(1.2)	P(1.3)	P(2.1)	P(2.2)	P(2.3)	P(3.1)	P(3.2)	P(3.3)	P(3.4)	P(4.1)	P(4.2)	P(4.3)	P(4.4)
Echelon 1	P(1.1)				183	307	347								
	P(1.2)				155	156	29								
	P(1.3)		Reverse		48	37	429								
Echelon 2	P(2.1)	11	16	0				0	118	61	202				
	P(2.2)	2	1	1				63	117	13	295				
	P(2.3)	1	2	0		Reverse		67	507	87	123				
Echelon 3	P(3.1)				5	1	3					12	0	61	52
	P(3.2)				9	6	2					167	128	274	139
	P(3.3)				3	1	1					14	40	85	16
	P(3.4)				8	3	2		Reverse			203	85	25	304
Echelon 4	P(4.1)							4	2	3	0				
	P(4.2)							1	0	1	3				
	P(4.3)							1	6	3	4				
	P(4.4)							1	6	0	3				
Demand												400	250	450	500

weight, with a linear decrease to 0.4 and 2.05 learning factors. The optimal parameter combination for the GA is a parent population of 10, 1000 generation times, 0.8 crossover rate and 0.07 mutation rate. Its minimal average fitness is 739964. The average minimal fitness for the PSOsm of 735670, as shown in Table 5, is the smallest average fitness value of the three algorithms. As can be seen, the average fitness value for the PSOsm is the lowest of the three algorithms.

Tables 6 and 7 show the verification and comparison data tables for the three algorithms. The data is collected from 30 iterations of independent calculations of the optimal parameters and ANOVA verification is performed on the fitness value to check whether there are significant differences. Shen and Hsieh [38] used a single factor ANOVA to verify the differences between the response of different visitors and various different projects at a tourist attraction, in terms of satisfaction and loyalty. Scheffe's Multiple Comparison test was used to conduct the pairwise comparison [39-41]. If the diversity reaches a significant level, Scheffe's multiple comparison test is used to verify the differences between different groups.

As shown in Table 6, the P-value is 1.65E-13, which is smaller than the confidence level, α (The mean difference is significant at the $\alpha = 0.05$ level). Therefore, it can be inferred that the fitness values of these three algorithms display a significant variation,

TABLE 4. Production plan through PSOsm (3^{rd} period)

To		Echelon 1			Echelon 2			Echelon 3				Echelon 4			
From		P(1.1)	P(1.2)	P(1.3)	P(2.1)	P(2.2)	P(2.3)	P(3.1)	P(3.2)	P(3.3)	P(3.4)	P(4.1)	P(4.2)	P(4.3)	P(4.4)
Echelon 1	P(1.1)				46	75	316								
	P(1.2)				132	135	42								
	P(1.3)		Reverse		596	216	141								
Echelon 2	P(2.1)	4	4	1				93	304	91	266				
	P(2.2)	4	2	0				95	93	1	225				
	P(2.3)	5	0	7		Reverse		65	102	308	2				
Echelon 3	P(3.1)				0	1	1					105	54	76	6
	P(3.2)				4	4	16					235	7	237	0
	P(3.3)				2	0	2					28	122	66	174
	P(3.4)				6	9	4		Reverse			19	279	18	173
Echelon 4	P(4.1)							1	7	1	8				
	P(4.2)							0	1	0	1				
	P(4.3)							2	7	2	1				
	P(4.4)							1	4	0	8				
Demand												400	450	400	350

TABLE 5. Experimental parameter combinations of PSO and GA

PSO	Combination	A1	B1	C1	D1	E1	F1	G1	H1
	Population Size	10	10	10	10	20	20	20	20
	Generations	500	500	1000	1000	500	500	1000	1000
	Max velocity	0.95	1.25	0.95	1.25	0.95	1.25	0.95	1.25
	Initial Weight	1.25	2.15	1.25	2.15	1.25	2.15	1.25	2.15
	c_1, c_2	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05
	Avg. Fitness	757887	743386	739371	736211	746459	745624	746092	743423
GA	Combination	A2	B2	C2	D2	E2	F2	G2	H2
	Population Size	10	10	10	10	20	20	20	20
	Generations	500	500	1000	1000	500	500	1000	1000
	Crossover Rate	0.75	0.8	0.75	0.8	0.75	0.8	0.75	0.8
	Mutation Rate	0.08	0.07	0.08	0.07	0.08	0.07	0.08	0.07
	Avg. Fitness	745835	747472	741094	739964	746964	745175	744937	745107

TABLE 6. Verified results for fitness value

	Average	Variance
PSO	735899.8	6801490
GA	740350.3	7841043
PSOsm	734215.7	6844191
P-value = 1.65E-13, Critical value = 3.101296		

so Scheffe's Multiple Comparison is used to conduct the pairwise comparison between different algorithms. Its formula is

$$\left(\overline{x_i} - \overline{x_j} - \sqrt{(k-1)F_{\alpha(k-1)(n-k)}}\sqrt{MSE\left(\frac{1}{n_i}+\frac{1}{n_j}\right)},\right.$$
$$\left.\overline{x_i} - \overline{x_j} + \sqrt{(k-1)F_{\alpha(k-1)(n-k)}}\sqrt{MSE\left(\frac{1}{n_i}+\frac{1}{n_j}\right)}\right)$$

Table 7. Scheffe's multiple comparison results for fitness value

	Fitμ_{PSO}	Fitμ_{GA}	Fitμ_{PSOsm}
Fitμ_{PSO}		$(-,-)$	(+,+)
Fitμ_{GA}	$(-,-)$		(+,+)
Fitμ_{PSOsm}	(+,+)	(+,+)	

Fitμ_{PSO}: mean of fitness value of PSO
Fitμ_{GA}: mean of fitness value of GA
Fitμ_{PSOsm}: mean of fitness value of PSOsm

$\overline{X_i}$ and $\overline{X_j}$ are the average values of the projects to be compared, k is the freedom, $F_\alpha(k-1, n-k)$ is the critical value and n_i and n_j are the sample numbers.

When the obtained value is $(+,+)$, $\mu1 > \mu2$ and that there is a significant difference; when the obtained value is $(-,+)$, $\mu1 = \mu2$ and there is no significant difference; when the obtained value is $(-,-)$, $\mu1 < \mu2$ and there is a significant difference. The result of Scheffe's Multiple Comparison is Fitμ_{PSOsm} < Fitμ_{PSO} < Fitμ_{GA}, as shown in Table 7. Therefore, the fitness value for the PSOsm is better than those of the PSO and GA.

6. Conclusions.

This paper addresses a novel reverse supply chain network design problem, which also considers specified returns. After an extensive literature survey of studies of forward and reverse supply chains, very few references were found to similar problems. In this study, the problem was completely defined through an optimization mathematical model. A modified PSO algorithm PSOsm is presented and is evaluated against the original PSO and GA algorithms, through an experimental study. The main results of this study show that the PSOsm has better performance on fitness value than the PSO and GA. Possible extensions of this study could explore more complex multi-criteria decision making algorithms and consider price discount and information sharing in the problem.

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