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This paper proposes a multi-objective optimisation algorithm for solving the new multi-objective location-inventory problem (MOLIP) in a distribution centre (DC) network with the presence of different transportation modes and third-party logistics (3PL) providers. 3PL is an external company that performs all or part of a company's logistics functions. In order to increase the efficiency and responsiveness in a supply chain, it is assumed that 3PL is responsible to manage inventory in DCs and deliver products to customers according to the provided plan. DCs are determined so as to simultaneously minimise three conflicting objectives; namely, total costs, earliness and tardiness, and deterioration rate. In this paper, a non-dominated sorting genetic algorithm (NSGA-II) is proposed to perform high-quality search using two-parallel neighbourhood search procedures for creating initial solutions. The potential of this algorithm is evaluated by its application to the numerical example. Then, the obtained results are analysed and compared with multi-objective simulated annealing (MOSA). It is concluded that this algorithm is capable of generating a set of alternative DCs considering the optimisation of multiple objectives, significantly improving the decision-making process involved in the distribution network design.

Keywords: integrated location–inventory distribution; supply chain management; third-party logistics; NSGA-II; multi-objective simulated annealing

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1. Introduction

Supply chain management (SCM) is the coordination of production, inventory, location and transportation among the participants in a supply chain to achieve the best mix of responsiveness and efficiency for the market being served (Hugos 2006). If a company's strategy is to serve a mass market and to compete based on price, it had better have a supply chain that is optimised for a low cost. If a company's strategy is to serve a market segment and compete on the basis of customer service and convenience, it had better have a supply chain optimised for responsiveness. Therefore, the design of distribution networks plays an important role in a supply chain.

Plants usually use distribution centres (DCs) to distribute their products among final customers. In fact, DCs are an important link connecting plants and customers. In practice, there are many cases, in which each plant has its own set of DCs. Consider a distribution network configuration problem where a single plant, different DCs and customers are existed. DCs act as intermediate facilities between a plant and the customers, and facilitate the shipment of products between two echelons. In order to increase the efficiency and responsiveness, third-party logistics (3PLs) can be involved in distributing activities. The main role of the 3PL provider (or company) is to manage inventory in DCs and also deliver products to customers according to the provided plan. Therefore, the 3PL company is responsible for shipment of products from DCs to customers. The plant wishes to design the supply chain distribution network with incorporation of 3PL for its products, such as to select the best set of DCs to be opened to fulfil customers' demand. This problem considers both strategic and tactical decisions in the supply chain. The strategic decision involves the location problem, which determines the number and the locations of DCs and assigns demands to DCs and incorporating 3PL to distribute products from DCs to customers. Whereas the tactical decision deals with the inventory problem that determines the allocation of products to DCs in order to provide customers' demands and determination of transportation modes that makes trade-off between delivery time and deterioration rate, or in other words, makes trade-off between responsiveness and efficiency (Hugos 2006). Figure 1 shows the overall schema of a supply chain distribution network with different transportation modes and involvement of the 3PL.

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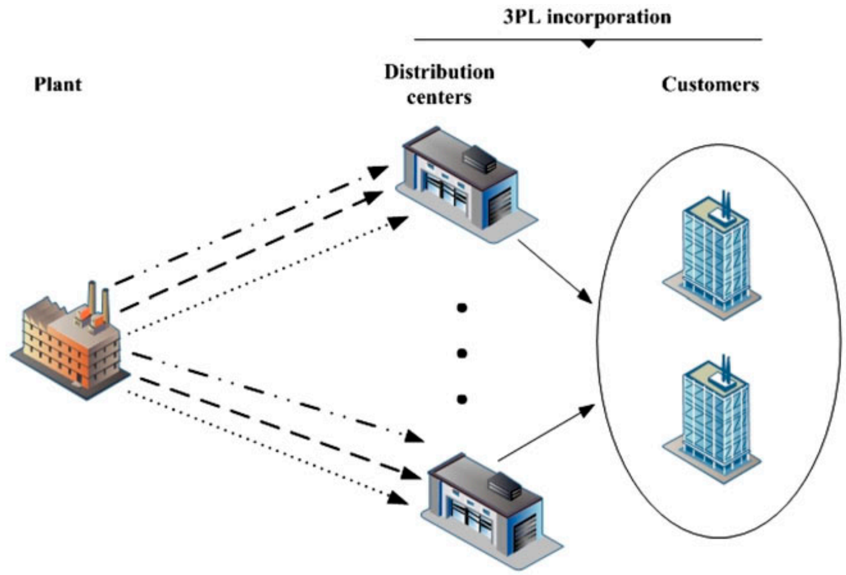

Figure 1. General schema of a distribution network with incorporation of 3PL.

As we discuss more in continue, there is a huge gap in integrating 3PL activities and planning the whole supply chain. To best of our knowledge, this gap still exists by reviewing the related literature. This paper not only focuses on integrating 3PL activities in the SCM tactical and strategic decisions, but also considers different transportation modes to cope with the trade-off between responsiveness and efficiency in the supply chain.

The primary goal of this paper is to present a mathematical model for integrated location-inventory distribution networks and adopt two meta-heuristics in order to solve this model and obtain Pareto-optimal solutions. Three objectives are considered; namely, (1) minimisation of the total costs consisting of transportation cost and set-up cost of DCs, (2) minimisation of earliness and tardiness and (3) minimisation of deterioration rates caused by different transportation modes.

Some noteworthy innovative aspects of this study are as follows: (1) proposing a multi-objective location-inventory problem (MOLIP) in the distribution network design, in which there are a few studies addressed this problem (Liao, Hsieh, and Lai 2011; Tancrez, Lange, and Pierre 2012), (2) considering responsiveness in design by incorporating earliness and tardiness, and transportation modes in the supply chain design and (3) applying evolutionary algorithms to solve the problem.

When the problem is large and the complexity increases, traditional methods (e.g. branch-and-bound method) are inefficient to solve the problem. Thus, evolutionary algorithms, which have been successfully developed for multi-objective optimisation problems, are considered to achieve a near-optimal solution, especially when the size of the problem increases in real-world problems (Liao, Hsieh, and Lai 2011).

2. Literature review

Increasing requests for logistics services imposed a strategic role for the 3PL companies. There are different definitions for 3PL in the literature. Coyle, Bardi, and Langley (2003) defined 3PL as an external organisation that performs all or part of a company's logistics functions. Many researchers have studied 3PL issues in a supply chain; however, there are limited numbers of studies about distribution network design problems and 3PLs. Jayaram and Tan (2010) investigated the integration of a supply chain and 3PLs, and mentioned that 3PL firms transformed the roles of DCs from storage facilities to channel assemblies by taking care of simple repair jobs that did not have to be sent back to manufacturers. Başligil et al. (2011) optimised a distribution network for 3PL service providers in two stages. In the first stage, they used mixed-integer programming and then outputs of the first stage were used as inputs for the second stage. In the second stage, a genetic algorithm was used.

Integration of 3PLs and SCM activities has been growing in importance in the recent years. 3PL companies are playing increasing roles in extended supply chains transforming from movers of goods to strategic value-added entities.

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The manufacturer has a full authority on DCs and 3PLs. Thus, integrating these two concepts to manage the downstream of a supply chain effectively is useful.

Ballou and Masters (1993) put forward four strategic planning areas in the design of a distribution network system as shown in Figure 2. The first issue deals with customer service levels. The second one deals the placement of facilities and demand assignments made to them. The third deals with inventory decisions and policies that involve inventory control. The fourth deals with transportation decisions of how transport modes are selected, utilised and controlled (Liao, Hsieh, and Lai 2011).

In supply chains, optimisation focus is usually on minimising costs. The efficiency was the major concern of companies for years; however, as mentioned above, responsiveness along with the efficiency was also crucial for a supply chain. It is not always desirable to reduce costs, if this causes a lower customer satisfaction.

Research on integrated location-inventory distribution network systems is relatively new. Jayaraman (1998) developed an integrated model that jointly examined the effects of facility location, transportation modes and inventory-related issues. However, the model did not contain any demand and capacity restrictions. Erlebacher and Meller (2000) formulated an analytical joint location-inventory model with a highly nonlinear objective function to maintain acceptable service while minimising operating, inventory and transportation cost. Nozick and Turnquist (2001) proposed a joint location-inventory model to consider both cost and service responsiveness trade-offs based on an uncapacitated facility location problem. Miranda and Garrido (2004) studied a mixed-integer non-linear programming (MINLP) model to incorporate inventory decisions into typical facility location models. They solved the distribution network problem by incorporating a stochastic demand and risk-pooling phenomenon.

Sabri and Beamon (2000) presented an integrated multi-objective, multi-product, multi-echelon model that simultaneously addresses strategic and operational planning decisions by developing an integrated two sub-module model including the cost, fill rates and flexibility. Gaur and Ravindran (2006) studied a bi-criteria optimisation model to represent the inventory aggregation problem under risk pooling, finding out the tradeoffs in costs and responsiveness. Shu, Teo, and Shen (2005) solved location-inventory model with risk pooling (LMRP) with a general stochastic demand. Shen and Daskin (2005) extended the LMRP model to include the customer service component and proposed a non-linear multi-objective model including both cost and service objectives. In contrast to LMRP and its variants that consider inventory cost only at the DC level, Teo and Shu (2010) and Romeijn Shu, and Teo (2007) proposed a warehouse-retailer network design problem in which both DCs and retailers carry inventory. These are actually the two major streams of integrated distribution network design problems.

Ghezavati, Jabal-Ameli, and Makui (2009) presented a new mathematical model for designing distribution networks in a supply chain system considering the service-level constraint optimising strategic decisions (location), tactical decisions (inventory) and assigning decisions. They first presented a new and robust solution based on a genetic search framework to solve non-linear integer programming model and then based on a GA results and some optimiser rules they proposed a new heuristic method. Shu, Ma, and Li (2010) proposed a two-stage stochastic model to address the design of an integrated location and two-echelon inventory network under uncertainty. They structured this problem as a two-stage non-linear discrete optimisation problem and solved the problem using column generation. Başligil et al. (2011) solved their approach in two stages. At the first stage, the assignment problem assigning the order of the vehicles was solved by mixed-integer programming. The output of the first stage was used as an input in the second stage. In this stage, routes were determined for vehicles by developing a genetic algorithm. Liao, Hsieh, and Lai (2011) formulated an integrated location-inventory distribution network problem which integrates the effects of facility location, distribution and inventory issues under the vendor-managed inventory (VMI) setup. They presented a MOLIP model and investigated the possibility of a multi-objective evolutionary algorithm based on the non-dominated sorting genetic algorithm (NSGA-II) for solving MOLIP.

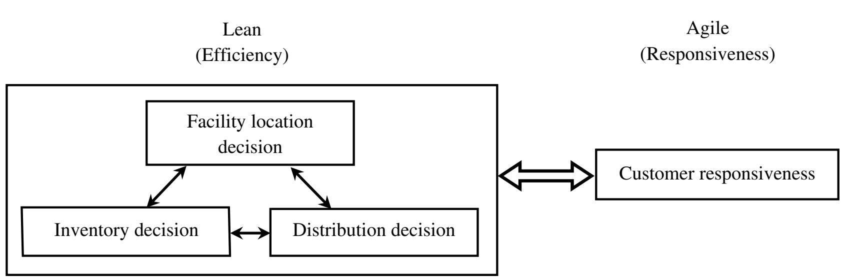

Figure 2. Four strategic planning areas in the distribution network design.

Chen, Li, and Ouyang (2011) proposed an integer programming model that minimises the sum of facility construction costs, expected inventory holding costs and expected customer costs under normal and failure scenarios. They developed a Lagrangian relaxation solution framework for this problem, including a polynomial-time exact algorithm for the relaxed nonlinear sub-problems. Lee, Moon, and Park (2010) studied the supply chain network design problem, which involves the location of facilities, allocation of facilities and routing decisions in order to minimise the related costs. They proposed two mixed-integer programming models, one without routing and one with routing, and a heuristic algorithm based on LP-relaxation in order to solve the model with routing.

Berman, Krass, And Tajbakhsh (2012) determined the location of the DCs to be opened, the assignment of retailers to DCs and the inventory policy parameters at the DCs such that the total system-wide cost is minimised. Their model was formulated as a non-linear integer-programming problem, and then a Lagrangian relaxation algorithm was proposed to solve it. Yuan, Low, and Yeo (2012) proposed a two-echelon network prototype for integrated production and distribution planning in which non-multifunctional plants supply multiple types of products with limited quantities to the customers via capacitated warehouses. Four variations of the prototype, formulated as individual mixed-integer programming models, were solved using the B&B algorithms by numerical experiments to examine the cost implications of production-distribution strategies involving single-sourcing constraints on different levels of the supply chain. Shavandi and Bozorgi (2012) developed a location-inventory model under a fuzzy environment. They considered the demand as a fuzzy variable and formulated the problem using a credibility theory in order to locate DCs and determining inventory levels in DCs. The proposed MINL problem was solved with a genetic algorithm.

Rajesh, Pugazhendhi, and Ganesh (2012) studied the balanced allocation of customers to multiple 3PLs warehouses. Since their problem developed to be non-deterministic polynomial-time hard, they used a SA algorithm to solve the problem. The balanced solution was achieved by using the min–max function. The effectiveness of the new algorithm was presented through simulation of large sets of problems. Jha et al. (2011) examined a problem to determine which retailers to be assigned as DCs, which retailers to receive direct shipments, how much of the retailer's demand to allocate to the DCs and how much of the DC's demand is to be met by different suppliers. Their problem was formulated as a mixed-integer model and solved by an adaptive differential evolution algorithm known as modified adaptive differential evolution. Tancrez, Lange, and Pierre (2012) proposed a non-linear continuous formulation, including transportation, fixed, handling and holding costs that decompose into a closed-form equation and a linear programme when the DC flows are fixed. They thus developed an iterative heuristic algorithm that estimates the DC flows a priori, solves the linear programme and then improves the DC flow estimations. Shu, Wang, and Zhang (2012) studied the design of a logistics distribution network consisting of a supplier, a set of potential warehouses and a set of retailers. They proposed a strongly polynomial time algorithm for the non-linear discrete optimisation problem, which must be solved in each iteration of the cutting plane algorithm.

3. Designing an integrated mathematical model

In this section, we present a mathematical model, which provides the foundation for our research.

3.1 *Model assumptions*

In this paper, a distribution network is considered in a supply chain to be designed in order to completely fulfil customers' demand. With a distribution network, it is meant that may be different number of distribution centres are available for company to be selected to support different customer zones. In addition, there are different transportation alternatives to ship products from company to the distribution centres. Therefore, selecting a set of distribution centres and allocating order via different existed transportation alternatives to achieve the objectives of the organisation and satisfy the demand is to be determined.

Let N be the number of distribution centres required to support K customer zones. Any customer zone r has a known average demand D_r. The company has M alternatives to ship products to distribution centres. It is important to emphasise that the problem of selecting distribution centres using different transportation modes is addressed and transportation of products from distribution centres to customer zones is done by 3PL. This paper assumes that the selected distribution centres are responsible to support the customer zones according to what allocated to them. In fact, each distribution centre has its own market share and should play his role in an effective manner. The following notations and definitions are used to describe the multi-objective mathematical model for the distribution network design.

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3.1.1 *Indices and parameters*

i	Index for distribution centres(i = 1, …, N)
j	Index for transportation alternatives (TA) (j = 1, …, M)
r	Index for customer zones ($r = 1, \ldots, K$)
D_r	Demand of the rth customer zone
C_i	Capacity of the ith distribution center
CP_j	Capacity of TA_j
n_j	Available quantity for TA_j
TC_{ij}	Transportation cost via TA_j to distribution center i
SC_i	Setup cost for TA_j
γ_j	Percentage of deteriorated items via TA_j
dd_i	Due date of delivering product to distribution center i
COT_{ij}	Completion time of delivery to distribution center i
ST_{ij}	Set up time of transportation to distribution center i using TA_j
TT_{ij}	Transportand merged to populationation time to distribution center i using TA_j
E_{ij}	Earliness for distribution center i via TA_j
T_{ij}	Tardiness for distribution center i via TA_j
α_i	Penalty cost for earliness of distribution center i
β_i	Penalty cost for tardinessof distribution center i

3.1.2 *Decision variables*

X_{ijr}	Number of products delivered to distribution centre i via TA_j for customer zone r
Z_{ij}	1 If product allocated to distribution centre i via TA_j; 0 otherwise

3.2 *Mathematical model*

Given the above-mentioned distribution network problem description, the objective is to find the best distribution centres minimising the cost with alternative transportations (i.e. Z_1), schedule minimising the total earliness and tardiness (i.e. Z_2), and minimising the total deteriorated items during transportations (i.e. Z_3). The following assumptions are considered in constructing the model.

- Demand of each customer zone is known.
- Current time of planning is considered as zero and due date of distribution centres is known.
- Capacity of each distribution centre and each transportation alternative is known.
- Multiple transportation alternatives can be selected by a company.
- Rate of deterioration by each transportation mode is known.

It is worth noting that three considered objectives conflict each other. To show the conflicted objectives, we solve the mathematical model with some small-sized problems and the sensitivity analysis on the objectives leads us to the conclusion that the objectives are conflicting. Hence, we can consider this model as multi-objective and trade-off between these objectives is another issue of concern that leads us to find Pareto-optimal solutions.

$$\text{Min } Z_1 = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{r=1}^{k} X_{ijr} \times \mathrm{TC}_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} Z_{ij} \times SC_j \tag{1}$$

$$\text{Min } Z_2 = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{r=1}^{k} \alpha_i \times E_{ij} \times X_{ijr} + \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{r=1}^{k} \beta_i \times T_{ij} \times X_{ijr} \tag{2}$$

$$\text{Min } Z_3 = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{r=1}^{k} X_{ijr} \times \gamma_j \tag{3}$$

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s.t.

$$\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ijr} \geq D_r; \quad \forall r \tag{4}$$

$$\sum_{j=1}^{m}\sum_{r=1}^{k} X_{ijr} \leq C_i; \quad \forall i \tag{5}$$

$$\sum_{i=1}^{n}\sum_{r=1}^{k} X_{ijr} \leq n_j \times CP_j; \quad \forall j \tag{6}$$

$$\sum_{r=1}^{k} X_{ijr} \leq M \times Z_{ij}; \quad \forall ij \tag{7}$$

$$\sum_{r=1}^{k} X_{ijr} \geq Z_{ij}; \quad \forall i,j \tag{8}$$

$$\mathrm{COT}_{ij} = \mathrm{ST}_{ij} + \mathrm{TT}_{ij}; \quad \forall i,j \tag{9}$$

$$\mathrm{COT}_{ij} - dd_i \leq T_{ij}; \quad \forall i,j \tag{10}$$

$$dd_i - \mathrm{COT}_{ij} \leq E_{ij}; \quad \forall i,j \tag{11}$$

$$T_{ij} \geq 0; \quad \forall i,j \tag{12}$$

$$E_{ij} \geq 0; \quad \forall i,j \tag{13}$$

$$X_{ijr} \geq 0 \text{ and Integer}; \quad \forall i,j,r \tag{14}$$

$$Z_{ij} \in \{0,1\}; \quad \forall i,j,r \tag{15}$$

Equation (4) guarantees that the sum of product quantities assigned to each distribution centre fulfils the customer zones' demand. Equations (5) and (6) specify the capacity constraints of DCs and transportation modes. Equations (7) and (8) define the relationship between product quantities allocated to DCs and transportation modes. Equations (9)–(11) are related to completion times, tardiness and earliness times of product delivery to DCs using different transportation modes.

4. Solution method

4.1 *Pareto-optimality*

Among the different ways of defining an optimal solution for a multi-objective problem, the concept of Pareto-optimality is useful. A solution is supposed as 'Pareto optimal' or 'efficient', if it is not dominated by any other solution in the whole search space (Ehrgott 1999). As for the identification of such a solution, a 'dominance' binary relation should be defined as follows: admitting minimisation is desired for all objective functions, a solution such as x_a dominates another solution x_b if:

$$x_a < x_b \quad \text{iff } f_i(x_a) \leq f_i(x_b); \quad \forall i \tag{16}$$

$$\exists i \quad \text{for which} \quad f_i(x_a) < f_i(x_b) \tag{17}$$

There is often a set of solutions in the decision space, which is non-dominated regarding any other solution in the given decision space. The above-mentioned set is called 'Pareto-optimal set', whose elements (i.e. alternative solutions), make a trade-off among themselves.

4.2 *Genetic algorithm*

Since the proposed model is a multi-objective mixed-integer linear programming (MOMILP), whose objective functions are completely in consistent, one of multi-objective optimisation techniques should be applied to solve the model. Also, because of the number of parameters and variables, traditional methods are not able to find the solution. To overcome this limitation, a genetic algorithm is used to obtain the result.

The non-dominated sorting genetic algorithm version 2 (NSGA-II) proposed by Deb et al. (2002) was applied to perform the search for Pareto-optimal solutions. In a few words, the logic of NSGA-II is as follows: given a population of solutions P_t, a derived population P'_t is generated by the application of genetic operators and merged to population P_t, forming $P_t + P'_t$. Thereafter, the solutions in $P_t + P'_t$ are sorted in subsets according to levels of non-dominance. All solutions, which share the same non-dominance level, are assigned the same rank. The less dominated, the lower the rank is. The population P_{t+1} for the next generation is filled by solutions from $P_t + P'_t$ in increasing ranks. Furthermore, the NSGA-II uses a parameter less-niching mechanism, based on the 'crowding' distance measure to maintain diversity among solutions.

4.2.1 *Solution codification*

Two matrices are considered to represent the solution. Binary matrix Z, in which row i corresponds to distribution centre i, and its column j corresponds to transportation alternative j, whereby an element Z_{ij} indicates if product is shipped to distribution centre using transportation alternative (value of 1) or not (value of 0). Integer matrix X, in which i corresponds to distribution centre i, and j corresponds to transportation alternative j, and r corresponds to customer zone, whereby an element X_{ijr} represents the allocated product using a transportation alternative to a distribution centre to support customers.

4.2.2 *Genetic operators*

According to Deb et al. (2002), evolutionary algorithms applied to multi-objective problems have to meet two requirements: converging to the Pareto frontier and finding a set of solutions, uniformly distributed along an approximation of the Pareto frontier. The former requirement is compiled by the mechanism of selection of solutions, as well as the genetic operators. Furthermore, in order to satisfy the latter requirement, a mechanism capable of avoiding the 'crowding' of solutions in some regions must be used.

For any two solutions, the dominant solution is the winner of the tournament and selected for mating. In case both are non-dominated, the selected solution is the one situated in a 'less crowded' region (i.e. a region with a lower density of solutions). This 'solution density' around a given solution may be evaluated by a quantity named 'crowding distance'.

The mutation operator randomly draws an element of a solution matrix. For the crossover, a two-point operator is implemented. It works in the following manner. For each position in the third dimension of matrix X, two indices in the interval of $[1, \dots, r]$ are selected and each parent divided into three equal parts. Two offspring are generated as follows:

Offspring 1. part 1 parent 1, part 2 parent 2, part 3 parent 1.
Offspring 2. part 1 parent 2, part 2 parent 1, part 3 parent 2.

4.2.3 *Initial population generation*

It is imaginable that a purely randomised generation method will generate too many infeasible solutions. On the other hand, a procedure that generates all initial solutions as feasible solutions will have a low probability of generating solutions near the 'borders' of the feasible region. This way, as a strategy of compromise, the following procedure pursuing with two-parallel neighbourhood search procedures is utilised:

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Step 0. Continue until all customers' demand fulfil

Step 1. Randomly generate indices i, j and r for distribution centres and transportation alternatives, which have free capacity, and for customer zones whom their demand is not satisfied yet

Step 2. Calculate the lowest possible value among these three elements and then put it in X_{ijr}. The corresponding Z_{ij} value should be converted to 1, if it is not

Step 3. Search for customer zones whose demands are not satisfied and if there is any, go back to Step 1; otherwise, go to Step 4

Step 4. End

The parallel neighbourhood search procedure includes two operators applied to the solution.

(1) First structure for neighbourhood search: indices i, j and r are selected randomly, and then X_{ijr} is equal to zero. Matrix Z is updated according to matrix X.
(2) Second structure for neighbourhood search: indices i and j are selected randomly, and then Z_{ij} is equal to zero. Matrix X is updated according to matrix Z.

4.2.4 *Feasibility correction*

Genetic algorithms are fundamentally unconstrained optimisers, since constraints contain problem-specific information. To handle constraints, some mechanisms have to be devised. A feasibility correction procedure is developed. Whenever an individual is generated or modified by an operator, the procedure cheques out, if it violates one of the three classes of constraints (Equations (4)–(6)) and correct it if necessary.

When the individual violates customers' demand (Equation (4)), DCs and transportation alternatives, which have free capacity, are selected to cope with the violation. The minimum value of the free capacity of distribution centres and transportation alternatives and unsatisfied demand is calculated, and the associated result is added to matrix X. When the individual violates capacity constraint of distribution centres (Equation (5)), related customer zones are investigated to resolve the violation. If any customer zone's demand is unsatisfied, it is selected. Otherwise, other distribution centres are considered to satisfy demand and remove violation from that distribution centre. The constraint on the transportation alternatives is in the similar way: related distribution centres are investigated to resolve the violation. If any distribution centre is free in capacity, it is selected. Otherwise, other transportation alternatives are selected to remove violation from the current transportation alternative.

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5. Model application and experimental results

5.1 *A base-line problem and its computational results*

There are no instances in the public domain and the previous studies for benchmarking. For this reason, a base-line problem is developed by taking a network size with transportation modes, DCs and customer zones. In this problem, 15 DCs are considered to support four customer zones. In addition, the company has five transportation alternatives to ship products to distribution centres. Furthermore, we consider the following assumptions.

(1) Demand of customer zones is integer and is generated from a uniform distribution on [1200, 2400].
(2) Capacity of DCs is integer and is generated from a uniform distribution on [800, 1200].
(3) Due dates of DCs are equal to 10 (current time is considered as zero).
(4) The penalty values for earliness and tardiness are five and six, respectively.
(5) Parameters related to the DCs regarding transportation modes are shown in Table 1.

The managers also need to evaluate trade-offs among three criteria, namely total cost, penalties for earliness and tardiness and deterioration rate. To obtain the approximate Pareto front, we attempt to solve the specified problem using the proposed NSGA-II approach. The input parameters are: population size = 100, generation number = 400, crossover rate = 70% and mutation rate = 20%. The approach programme is coded in MATLAB. The algorithm allows the decision-maker (DM) to rapidly find a set of Pareto solutions.

Figure 3 illustrates the approximate Pareto frontier obtained by the proposed NSGA-II algorithm. The final population comprises 29 individuals. We see the initial and final populations in objective space, which exhibits the improved quality in all three objective functions in comparison to the initial population.

From the 29 final non-dominated solutions, two of them are chosen to be analysed based on the trade-off that they exhibit as shown in Tables 2 and 3. Table 4 shows their objective values. Solution 1 is better in transportation and

Table 1. Model parameters and its values for the baseline problem.

Parameters	Transportation modes 1	2	3	4	5
Transportation cost to DC i using transportation mode j	U[1500, 2500]	U[3000, 5500]	U[7500, 10,000]	U[13,000, 16,000]	U[18,000, 21,000]
Setup cost of using transportation mode j	50,000	100,000	150,000	200,000	250,000
Deterioration rate of using transportation mode j	0.1	0.08	0.03	0.01	0.005
Transportation time to DC i using transportation mode j	U[7, 9]	U[8, 10]	U[5, 7]	U[6, 8]	U[2, 4]
Setup time for DC i using transportation mode j	U[1, 3]	U[1, 3]	U[1, 3]	U[1, 3]	U[1, 3]
Capacity of transportation mode j	50	160	510	1150	2050
Available quantity of transportation mode j	80	50	20	15	10

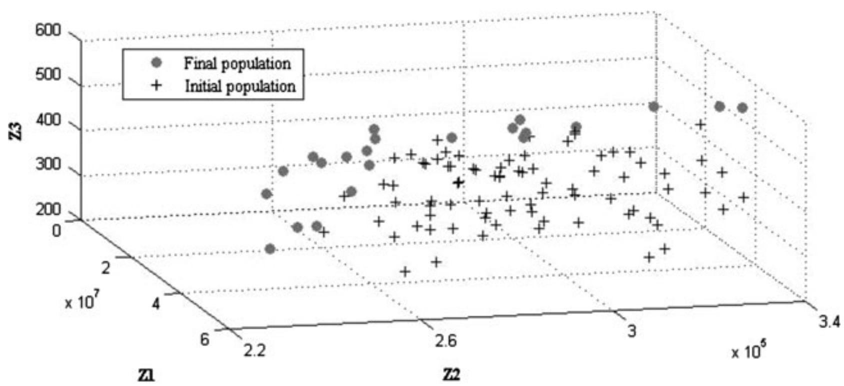

Figure 3. Initial and final populations.

Table 2. Non-dominated solution 1.

	Customer zone 1					Customer zone 2					Customer zone 3					Customer zone 4				
	Transportation modes					Transportation modes					Transportation modes					Transportation modes				
DCs	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
DC1	132																		532	
DC2			182												369	268				
DC3				116		293														
DC4																				
DC5																				
DC6				500	332						294									
DC7			79				684													
DC8				14													920			
DC9			785																	
DC10			38			323	73		22											
DC11								519												
DC12																				800
DC13														929						
DC14								442												
DC15																				

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Table 3. Non-dominated solution 2.

	Customer zone 1					Customer zone 2					Customer zone 3					Customer zone 4				
	Transportation modes					Transportation modes					Transportation modes					Transportation modes				
DCs	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
DC1															531					
DC2									327											335
DC3							705													
DC4																			915	
DC5			1097																	
DC6					672									326						
DC7																				
DC8		608															432			
DC9							734													
DC10																				
DC11			383									115								
DC12																		423	255	
DC13																				
DC14								547												
DC15													389							

Table 4. Chosen non-dominated solutions.

Solution	*Z*1	*Z*2	*Z*3
1	12,060,424	263,891	355.1
2	47,147,361	235,085	318.61

establishment costs, while solution 2 causes fewer penalties for earliness and tardiness (i.e. more on time delivery) and less deterioration rate.

There is significant difference regarding the first objective. Solution 1 exhibits 12,060,424 for expenses, while solution 2 exhibits 47,147,361, about four times more. If we take a look at Table 3, we can see that the first transportation mode is not used in any of them. Although it has a lower transportation cost; however, its transportation time and deterioration rate are more than other transportation modes. Therefore, solution 2 reduces earliness and tardiness, and deterioration rate in a cost of the increased cost. In other words, if the DM decides to design an efficient distribution network, solution 1 is a better choice. If the DM decides to design a responsive distribution network, solution 2 is a better choice.

5.2 *Performance evaluation*

Our goal here is to evaluate the efficiency and the effectiveness of the proposed NSGA-II. We establish a set of random instances and try to keep almost all model parameters the same as the base-case problem. We generate problem instances of different sizes of DCs and customers zones in the distribution network. In this experiment, we generate four sets of problem instances (i.e. SET 1 to SET 4) representing different sizes of the problem instances ranging from 30 DCs and 6 customer zones to 60 DCs and 12 customer zones (i.e. problem sizes n: 30 (SET 1), 40 (SET 2), 50 (SET 3), 60 (SET 4)). For each set of DCs, there are two different types of transportation modes scenarios. For instance, the problem instance 50_4_12 represents a problem, in which there are 50 DCs, 4 transportation modes and 12 customer zones.

To verify the effectiveness of the proposed NSGA-II algorithm, multi-objective simulated annealing (MOSA) is used to solve the problem. Table 5 summarises the performance results of two algorithms considered in this paper. The following three comparison metrics are considered. The quality metric (QM) is simply measured by putting together the non-dominated solutions found by algorithms and the ratios between non-dominated 500 solutions are reported. The space metric (SM) is defined by:

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Table 5. Comparison between NSGA-II and MOSA approaches.

Instances		Execution time (Sec.)		Quality metric		Spacing metric		Diversity metric	
		MOSA	NSGA-II	MOSA	NSGA-II	MOSA	NSGA-II	MOSA	NSGA-II
SET 1	30-5-6	0.0507	3.3066	5.8824	94.1176	1.1911	0.7282	3448	24,050
	30-5-8	0.1650	3.9136	0	100	0	0.7815	1753	22,752
	30-5-10	0.0057	4.4176	0	100	0	0.8750	1747	24,840
	30-5-12	0.0069	5.3018	0	100	NaN[a]	1.1952	0	25,187
	30-4-6	0.0076	2.8714	6.0606	93.9394	1.4252	0.6037	7463	23,095
	30-4-8	0.0067	3.3240	4.3478	95.6522	0.2404	0.4396	3457	26,074
	30-4-10	0.1036	3.8686	0	100	0.6912	1.0172	1624	25,637
	30-4-12	1.5271	4.3414	96.5517	3.4483	NaN	0.8774	0	22,291
SET 2	40-5-6	0.0231	4.5868	12.9032	87.0968	0.4005	0.5747	2121	28,922
	40-5-8	0.0848	5.4146	0	100	0.3811	0.7189	1611	30,539
	40-5-10	0.0205	6.2406	3.8362	96.1538	1.7676	1.0382	8710	20,735
	40-5-12	0.0092	7.0518	0	100	NaN	0.5059	0	18,190
	40-4-6	0.0053	3.8282	2.4390	97.5610	NaN	0.9014	0	34,965
	40-4-8	0.0944	4.4346	20.8333	79.1667	1.1470	0.7479	10,168	28,097
	40-4-10	0.4791	5.0958	7.5000	92.5000	0.8199	0.2339	1333	31,490
	40-4-12	0.2472	5.7184	3.2285	96.7742	NaN	1.0041	0	27,689
SET 3	50-5-6	0.0106	5.8454	5.1282	94.8718	0	0.8776	1267	28,441
	50-5-8	0.3452	6.5578	0	100	NaN	0.8206	0	28,211
	50-5-10	0.0090	7.6336	0	100	NaN	0.9052	0	27,294
	50-5-12	0.0128	8.8154	0	100	NaN	0.9237	0	28,099
	50-4-6	0.0062	4.7574	0	100	NaN	10,396	0	18,199
	50-4-8	0.0141	5.3756	0	100	0.8641	0.6654	3159	29,973
	50-4-10	0.0588	6.1716	5.8824	94.1176	1.0065	0.4023	3736	18,585
	50-4-12	0.0354	6.8750	9.0909	90.9091	1.0280	0.4603	3309	34,280

[a]NaN returns the IEEE arithmetic representation for Not-a-Number.

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$$\mathrm{SM} = \frac{\sum_{i=1}^{N-1} |d_{\mathrm{mean}} - d_i|}{(N-1) \times d_{\mathrm{mean}}}$$

where d_i is the Euclidean distance between consecutive solutions in the obtained non-dominated set of solutions and d_{mean} is the average of these distances. This metric allows us to measure the uniformity of the spread of the solution set points. Diversification metric (DM) measures the spread of the solution and is defined by:

$$\mathrm{DM} = \sqrt{\sum_{i=1}^{N} \max\left(\| x_t^i - y_t^i \|\right)}$$

where $\| x_t^i - y_t^i \|$ is the Euclidean distance between the non-dominated solution x_t^i and the non-dominated y_t^i.

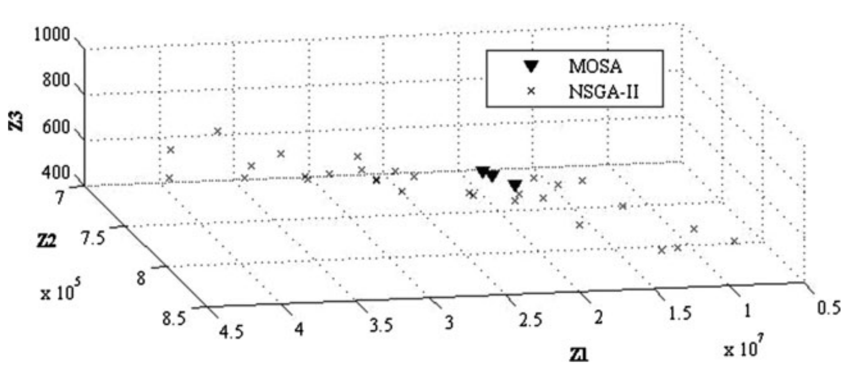

Figure 4. Approximate Pareto-optimal front for the problem instance 40_4_10.

From Table 3, we conclude that the larger the instances, the more time is devoted by both algorithms to solve the problem. Table 3 also lists the average values of the above-mentioned comparison metrics and shows the proposed NSGA-II is better in almost all of the instances. The proposed NSGA-II can achieve greater Pareto-optimal solutions with higher quality than MOSA. In addition, the values of diversification metric in our proposed NSGA-II are considerably greater than MOSA (i.e. NSGA-II finds non-dominated solutions that have more diversity). These data also reveal that in the majority of instances, non-dominated solutions obtained by NSGA-II are more uniformly distributed in comparison with MOSA. For example, in the 40_4_10 instance, NSGA-II runs slightly slower compared to MOSA, but favours in solution quality. Figure 4 illustrates the approximate Pareto frontiers obtained by the NSGA-II and MOSA algorithms for the problem instance 40_4_10. Visually, the trade-off curves of these two approaches show that NSGA-II results in the solutions covering a larger surface of the approximate Pareto solutions.

6. Conclusion

The aim of this paper was to propose a well-known multi-objective optimisation algorithm for the location-inventory distribution network design under the incorporation of 3PL and transportation modes. It was based on a multi-objective optimisation model solved by the application of meta-heuristics. The presented model was solved with a proposed a evolutionary algorithm, which is preliminarily based on a well-known NAGA-II evolutionary algorithm with an elitism strategy, a non-dominated sorting mechanism and two-parallel neighbourhood search procedures. First, we investigated the possibility of the proposed NSGA-II to solve the practical size of the given problems. Second, we compared our proposed NSGA-II with MOSA to understand the efficiency between two algorithms. Experiments indicated that the obtained Pareto frontiers by NSGA-II are almost better in terms of quality for all instances. However, MOSA was only efficient in terms of the execution time. This implied that the proposed NSGA-II could be an efficient algorithm for providing feasible and acceptable solutions to large-scale difficult-to-solve problems.

The major contribution of this paper is to focus on integrating 3PL activities in supply chain tactical and strategic decisions and consider different transportation modes to cope with the dilemma of responsiveness and efficiency in the supply chain. To best of our knowledge, none of the current papers considers these factors simultaneously in the supply chain network design. The major difficulty of implementing this model in real-world situations is the problem size. Because of the zero-one variables in the proposed model, increasing the size of the model, especially in real-life problem will increase the complexity of the problem exponentially. Hence, the authors tried to apply meta-heuristics to deal with this problem and it seems that other meta-heuristics also worth trying to find near-optimal solutions in an acceptable time.

Further research may consider the uncertain nature of the problem using stochastic programming, such as robust optimisation or fuzzy programming. The inclusion of other inventory decisions, such as VMI in the proposed model may be useful. Finding ways to adapt our evolutionary algorithm into such systems can be done in future research. Other possible research directions are to explore other MOEAs such as particle swarm optimisation (PSO) or other soft intelligent optimisation techniques. In addition to the meta-heuristic algorithm, some others techniques (e.g. Langrangean) is also suggested to solve this problem. Comparing the results of this study and the application of other analytical methods will provide more satisfactory conclusions, which can lead for the development of an expert system in designing a distribution network.

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Supplemental data

Supplemental data for this article can be accessed http://dx.doi.org/10.1080/00207543.2014.938836.

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