Modelling Integrated Multi-item Supplier Selection with Shipping Frequencies

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Abstract

There are many benefits for coordination of multiple suppliers when single supplier cannot satisfy buyer demands. In addition, buyer needs to purchase multiple items in a real supply chain. So, a model that satisfies these requests has many advantages. We extend the existing approaches in the literature that assume all suppliers need to be put on a common replenishment cycle and each supplier delivers exactly once in a cycle. More specifically, inspired by approaches that perform well for the Economic Lot Scheduling Problem, we assume an integer number of times a supplier can ship available items in an overall replenishment cycle. Because of complexity issue, a new approach based on genetic algorithm is employed to solve the presented model. Results depict that new model is more beneficial and practical.
Keywords: Integrated supply chain, Multi-item, Frequent shipping, Multi-supplier, Supplier selection.

1. Introduction

The design of the supply base is a core strategic area in *SCM*[1]. Following make-or-buy decisions, the determination of the size of the supply base and the selection of the suppliers are important decision problems (Benton, 2010). On the tactical level, the allocation of requirements to suppliers has to be determined and on the operational level, order quantities need to be determined and scheduled. An important trade-off when designing the supply base is the balance between Economies of Scale advocating few suppliers versus risk diversification favoring many suppliers.

Other than these arguments, especially for many industries where large buyers acquire and develop several small suppliers in developing countries, finite production rates where a single supplier is too small to satisfy the buyer's requirements drive larger supply bases.

The importance of integration in a supply chain was considered by Thomas and Griffin (1996). They argue that in order to achieve effective supply chain management, planning and coordination among all entities in a supply chain is needed.

Therefore, multiple supplier and inventory coordination problems have received considerable attention in the literature. The idea of joint optimization for buyer and vendor was initiated by Goyal (1976) and later supported by Banerjee (1986). Banerjee (1986) introduced *JELS*[2] model for a single vendor and single buyer to minimize joint total relevant cost. *JELS* was a single-source model that means all items should be purchased from selected supplier and allocation was ignored.

Kheljani et al. (2009) study the coordination problem between one buyer and multiple potential suppliers in the supplier selection process. In the objective function of their model, the total cost of the whole supply chain is minimized rather than only the buyer's cost. The total cost of the supply chain includes the buyer's cost and suppliers' costs. Finally, they solved their model by applying mixed integer nonlinear programming. The obtained model supports single-item to coordinate the supply chain.

Another problem that surfaces is integration of supply chain when multiple items should be ordered. Various interdependencies could exist among the different products and taking generated synergetic cooperation into account through multi-item models is profitable both for buyer and suppliers.

Aliabadi et al. (2013) develop Kheljani's model to coordinate an integrated supply chain when multiple item should be purchased from multiple supplier in integrated framework. They solve their model with a meta-heuristic approach which was based on hierarchical-structured

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1 Supply chain management

2 Joint economic lot size

genetic algorithm. Fig. 1, shows the stock and inventory levels of buyer and three suppliers when two items j and k should be purchased. The buyer follows EOQ[3] inventory policy and suppliers use EPQ[4] production policy. It is worth mentioning that if item k of second supplier is produced earlier, then it needs to wait in transportation system until buyer makes a request for it. Furthermore, holding costs of finished items during one cycle are included in fixed and variable costs of a transportation corporation as an independent entity outside of considered integration domain.

One major limitation of the Kheljani et al. (2009) model is that it puts all suppliers on the same order cycle. Minner and Pourghannad (2010) develop Kheljani's model by overcoming this limiting assumption. They assume that within a cycle of length T, each chosen supplier can ship an integer number of identical batches n_i of size Q_i. They prove their objective function is a convex function in each sourcing fraction X_i for given supplier and fixed shipping number n_i. They utilize Lagrangian relaxation method to solve the problem in hand for the given set of suppliers and multipliers.

Tiwari et al. (2010) consider multiple shipping/transportation into designing supply chain network. Moreover, their model integrates a five-tier supply chain. However, in their model allocations of items between entities are not considered. Finally, they solve their model with a new approach that benefits from Taguchi method in creating antibodies in artificial immune system.

Awasthi et al. (2009) consider a supplier selection problem for a single manufacturer. All the available suppliers may quote different prices and may have restrictions on minimum and maximum order sizes. In their study, the objective function is to find a low-cost assortment of suppliers which is capable of satisfying the demand. Pasandideh et al. (2011) use genetic algorithm to solve integrated multi-product EOQ model with shortages in which there is a single supplier and a single retailer.

Taleizadeh et al. (2011) study a multi-item multi-buyer model in which a given structural of supply chain is optimized and no selection is considered. Yang et al. (2011) examine supplier selection problem when multiple numbers of products should be supplied for a single buyer and the demand is stochastic. The authors considered service level and budget constraints in their model. Also, they assumed each product is supplied by a single supplier; therefore, splitting of demand between suppliers is not the case. Unfortunately, they have skipped vital details in scheduling by considering instantaneous production rate. They solved their problem by exploiting genetic algorithm.

In this paper, considering both integration and the multi-item assumptions, we develop an integrated multi-item supply chain in which the suppliers produce requested items and the buyer buys them according to EPQ and EOQ control inventory policies, respectively. The buyer buys products from the selected suppliers and sales them into the market. This model has advantages of both selecting the suppliers and then allocating the orders among them. Also, we extend our research by relaxing number of deliveries' constraint in one cycle. So, presented model let us schedule multiple shipments for each chosen supplier.

The rest of paper is organized as follows. In Section 2, assumptions of our model are discussed. In Section 3, the notations are introduced and the proposed model is derived. Section 4 describes structural properties of the model. After that, in Section 5 a new algorithm is constructed to solve the model effectively. The efficiency of the extended model will be demonstrated in Section 6 and, finally, Section 7 concludes the paper.

2. Model Assumptions

In the following section, we first follow the assumptions and notation used in this survey. Assume an infinite horizon inventory model with a single buyer who faces continuous demand with rate D_j for item j. The buyer should replenish constant and deterministic amount of items from multiple suppliers.

We assume that a replenishment cycle length is T_j^B and the total procurement volume of item j is Q_j which is repeated over cycles. Also, i^{th} supplier delivers n_{ij} times during the cycle. So, we could mention assumptions as follows:

1) Buyer consumption for all items are determined and fixed over time.
2) Buyer uses fixed slot storage to store items but suppliers use shared storage policy.
3) Inventory shortage for the buyer and suppliers is not allowed.
4) Buyer's Inventory surplus is not acceptable, so inventory cannot be delivered from the previous period to the next period.
5) Suppliers produce items and let the transportation corporations to transport items to the buyer at predetermined arriving time with certain fixed and variable costs. So, suppliers' holding cost only consists of work in processed (WIP) items. In other words, this assumption will allow suppliers to produce later demands of buyer within a cycle continuously without delay between them.
6) In each period, when entire i^{th} supplier's order quantity is consumed by buyer, $(i+1)^{th}$ supplier's order quantity can be entered by transportation system.
7) The lead time is assumed to be negligible.
8) Each supplier is characterized by a finite production rate of P_{ij}. Hence, the problem has feasible solution when $D_j \leq \sum_{\forall i} P_{ij}$ for all items.

3 Economic order quantity
4 Economic production quantity

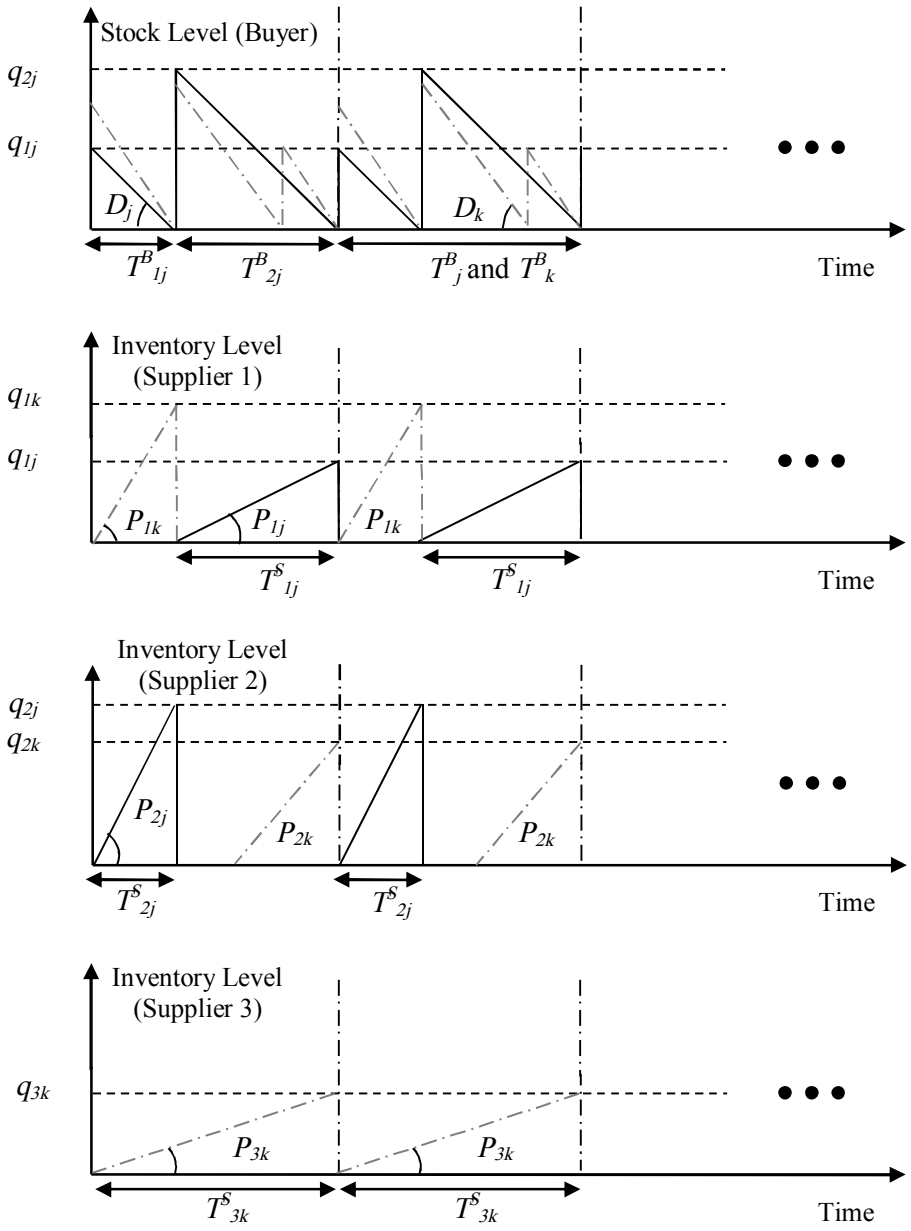

Fig. 1. Inventory levels of one buyer and three suppliers in multi-item model without shipping frequency

9) Suppliers' unsold opportunity cost is supposed intangible.
10) Finally, items quality is independent of their price. Hence, the only factor in the holding cost of buyer for items is related to types of items.

The buyer as a central decision maker has to take hierarchical interdependent decisions:

- As strategic decision, the choice of suppliers, modeled by a binary variable $Y_i \in \{0, 1\}$.
- As a tactical decision, the allocation of annual demand to i^{th} supplier for j^{th} item, modeled by sourcing fraction X_{ij}, $(0 \le X_{ij} \le 1)$. Also, the number of shipping from i^{th} supplier for j^{th} item is modeled by an integer number n_{ij}, $(n_{ij} \ge 1$ and integer).

3. A Multi-item Model with Shipping Frequencies

After reviewing the previous versions of integrated supply chain models in the literature and our modeling assumptions, we propose a new multi-item model that has advantages of both Aliabadi et al. (2013) and Minner and Pourghannad (2010) models. We will prove that our new model can outperform in terms of total benefit of whole chain.

First of all, we introduce the notations, used in the mathematical modeling. The mathematical model will be developed according to the following notations:

A. Parameters

n : The number of items

m : The number of suppliers

D_j : Demand rate of j^{th} item per unit time

A_{ij} : Fix order cost for j^{th} item when supplied by the i^{th} Supplier

q_{ij} : Order quantity of j^{th} item from i^{th} supplier

Q_j : The buyer order quantity of item j which will split between suppliers, that is $Q_j = \sum_{i=1}^{m} q_{ij}$

T^B_{ij} : The buyer cycle time for j^{th} item that is supplied from i^{th} supplier

T^B_j : The buyer cycle time of j^{th} item, that is $T_j^B = \sum_{i=1}^{m} T_{ij}^B$

T^S_{ij} : Cycle time of j^{th} item when i^{th} Supplier produces it

h^B_j : Buyer's holding cost for j^{th} item per unit per unit time

V_j : Buyer's sell price for j^{th} item

h_{ij} : i^{th} supplier's holding cost for j^{th} item per unit per unit time

S_{ij} : The i^{th} supplier's fixed set up cost to produce j^{th} item

Z_{ij} : Variable production cost for a unit of j^{th} item when i^{th} supplier produce it

P_{ij} : The i^{th} supplier's annual production rate when produce j^{th} item

b_{ij} : Constant Transportation cost to transport j^{th} item from the i^{th} Supplier to the buyer

t_{ij} : Variable transportation cost to transport a unit of j^{th} item from the i^{th} Supplier to the buyer

K_{ij} : Minimum permissible amount of j^{th} item which can order to i^{th} supplier.

$sgn(x)$: The Signum function of real number x.

B. Decision Variables

Y_i : Whenever i^{th} supplier Selected. 1, if i^{th} supplier select and 0, otherwise.

X_{ij} : The fraction of j^{th} item's demand that supply form i^{th} Supplier which is a real variable between 1 and 0.

n_{ij} : Number of shipping j^{th} item from i^{th} supplier (integer number).

The total cost function is the sum of the suppliers' costs and the buyer's ones. Costs at the buyer consist of purchasing cost, ordering cost, and inventory holding cost. On the other hand, costs at the supplier side are set up cost, production cost, inventory holding cost (work in process items), and transportation cost.

Buyer annual purchasing cost is intrinsic cost. So, in integrated model, we could neglect it.

Now, we calculate the Buyer Annual Inventory Holding Cost (BAIHC) and Supplier Annual Inventory Holding Cost (SAIHC).

$$BAIHC = \sum_{j=1}^{n}\sum_{i=1}^{m} \frac{h_j^B Q_j X_{ij}}{2n_{ij}} \left(\frac{T_{ij}^B}{T_j^B}\right) = \sum_{j=1}^{n}\sum_{i=1}^{m} \frac{h_j^B Q_j {X_{ij}}^2}{2n_{ij}} \quad (1)$$

$$SAIHC = \sum_{j=1}^{n}\sum_{i=1}^{m} h_{ij}\left(\frac{D_j {X_{ij}}^2 Q_j}{2P_{ij}n_{ij}}\right) \quad (2)$$

Then, we need to calculate Buyer Annual Ordering Cost (BAOC) and Supplier Annual Setup Cost (SASC). By factoring from X_{ij} and eliminating the common factor from numerator and denominator the expression is reduced. If we do not multiply signum of X_{ij} by expression (3) and (4), a problem occurs when X_{ij} is zero because BAOC and SASC will have a value greater than zero.

$$BAOC = \sum_{j=1}^{n}\sum_{i=1}^{m}\left(\frac{n_{ij}A_{ij}D_j X_{ij}}{q_{ij}} \times \mathrm{sgn}(X_{ij})\right) = \sum_{j=1}^{n}\sum_{i=1}^{m}\left(\frac{n_{ij}A_{ij}D_j}{Q_j} \times \mathrm{sgn}(X_{ij})\right) \quad (3)$$

$$SASC = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{n_{ij}S_{ij}D_j X_{ij}}{q_{ij}} \times \mathrm{sgn}(X_{ij})\right) = \sum_{j=1}^{n}\sum_{i=1}^{m}\left(\frac{n_{ij}S_{ij}D_j}{Q_j} \times \mathrm{sgn}(X_{ij})\right) \quad (4)$$

Also, supplier should be able to afford annual buyer's demands. Therefore, we have the following constraint for all suppliers.

$$\sum_{j=1}^{n}\frac{D_j X_{ij}}{P_{ij}} \le 1 \quad (5)$$

Thanks to assumption (5), scheduling sequence in suppliers can be omitted. Therefore, suppliers can produce items in one cycle earlier. Then, they can designate them to the transportation system.

The proposed model is a maximization model with *EPQ* constraints and minimum order quantity.

$$\max TB: \sum_{j=1}^{n} D_j V_j - \sum_{j=1}^{n}\sum_{i=1}^{m}\left[\frac{n_{ij} D_j (A_{ij} + S_{ij} + b_{ij}) sgn(X_{ij})}{Q_j} + \frac{X_{ij}^2 Q_j}{2 n_{ij} P_{ij}}(h_j^B P_{ij} + h_{ij} D_j) + D_j X_{ij}(Z_{ij} + t_{ij})\right] \quad (6)$$

Subject to :

$$\sum_{i=1}^{m} X_{ij} = 1 \qquad \forall j \quad (7)$$

$$\sum_{j=1}^{n} \frac{D_j X_{ij}}{P_{ij}} \le 1 \qquad \forall i \quad (8)$$

$$\frac{K_{ij} Y_i}{D_j} \le X_{ij} \le \frac{P_{ij} Y_i}{D_j} \qquad \forall i,j \quad (9)$$

$$int\ n_{ij} \ge sgn(X_{ij}) \qquad \forall i,j \quad (10)$$

As Q_j* is optimum order quantity and it is possible to substitute R_{ij} with $(A_{ij}+S_{ij}+b_{ij}) \times sgn(X_{ij})$; Q_j* for fixed X_{ij} and n_{ij} can be obtained by taking first derivative of Eq. (3) :

$$\frac{\partial TB}{\partial Q_j} = 0 \Longrightarrow Q_j^* = \sqrt{\frac{2 D_j \sum_{i=1}^{m} {n_{ij}}^2 P_{ij} R_{ij}}{\sum_{i=1}^{m} X_{ij}^2 (h_j^B P_{ij} + h_{ij} D_j)}} \quad (11)$$

Zence, the objective function is reformed as follows:

$$\max TB: \sum_{j=1}^{n} D_j V_j - \sum_{j=1}^{n}\sum_{i=1}^{m}\left[\frac{n_{ij} D_j (A_{ij} + S_{ij} + b_{ij}) sgn(X_{ij})}{\sqrt{\frac{2 D_j \sum_{i=1}^{m} {n_{ij}}^2 P_{ij} R_{ij}}{\sum_{i=1}^{m} X_{ij}^2 (h_j^B P_{ij} + h_{ij} D_j)}}} + \sqrt{\frac{2 D_j \sum_{i=1}^{m} {n_{ij}}^2 P_{ij} R_{ij}}{\sum_{i=1}^{m} X_{ij}^2 (h_j^B P_{ij} + h_{ij} D_j)}} \times \frac{X_{ij}^2 (h_j^B P_{ij} + h_{ij} D_j)}{2 n_{ij} P_{ij}} + D_j X_{ij}(Z_{ij} + t_{ij})\right] \quad (12)$$

As mentioned earlier, n is the number of suppliers and m is the number of items. X_{ij} is the fraction of j^{th} item's demand that is supplied by i^{th} supplier, Y_i is a binary variable that indicates decision of buyer to select i^{th} supplier and n_{ij} is an integer number that expresses number of shipment from i^{th} supplier for j^{th} item within a cycle.

The objective function (12) is used to maximize the total benefit of the aforementioned integrated supply chain. The total benefit is obtained from the difference between the incomes (the first term in the objective function) and the costs (the second term in the objective function) in the integrated supply chain model. The constraint set (7) ensures that the sum of orders from suppliers for j^{th} item is equal to the j^{th} item's demand. The constraint set (8) indicates that the i^{th} supplier is capable of producing all the items that the buyer orders. The constraint set (9) guarantees the minimum permissible order of j^{th} item from i^{th} supplier if the i^{th} supplier is selected by the buyer. Also, the constraint set (9) guarantees that the fraction of j^{th} item's demand that the buyer orders from the i^{th} supplier is not more than the i^{th} supplier's production capacity for j^{th} item. Also, this constraint set indicates that if a supplier is not selected, the fraction of j^{th} item's demand which is assigned to this supplier is zero. Finally, constraint set (10) states that the number of shipment should be considered whenever i^{th} supplier is selected to supply j^{th} item. Hence, from the constraint set (9) one can easily infer that X_{ij} is a bounded variable between $[K_{ij}Y_i/D_j,\ P_{ij}Y_i/D_j]$. It can limit our feasible space and accelerate our search. It is the lifeblood of our presented approach to solving the model effectively.

4. Structural Properties of Model

In this section, a research about structural properties of objective function is intended. For the first step, we should investigate convexity of objective function. If we prove that it is a convex function, we can solve the problem for given suppliers and fixed shipping numbers n_{ij} using standard convex analysis. On the contrary, we should develop a meta-heuristic algorithm to find a good solution in reasonable *CPU* time.

Our investigation shows that the objective function is not a convex function in general condition. (For more details see appendix A.) Also, we need to prove that our new model yields better results in terms of total benefits compared with Aliabadi et al. (2013).

Theorem 1. The proposed model always yields better or at least the same results in terms of objective function compared with the single shipment model.

Proof. Suppose S_1 be the feasible region of our problem when all n_{ij} be equal to 1 then S_1 will also be feasible for single shipment model. Therefore, the optimal solution of S_1 is the same in both models with the same value of *TB*.

Now, suppose there is a better solution in S_2 when at least one of n_{ij}s is equal to an integer number except 1. Then the new region is not feasible in single shipment model and therefore *TB* of S_2 would be better than S_1.■

5. Solution Algorithm

The proposed model that was studied in Section 3 is a nonlinear mixed integer programming model. The nonlinear nature of problem along with its binary and integer variables causes the model to be adequately hard to be solved by analytical methods. Even though *LINGO* has a powerful module to solve nonlinear and binary programming, it could not handle such an intractable model.

In order to solve such a problem, we employ a modified Two-Level Genetic Algorithm (*2LGA*). *2LGA* was initially introduced by Aliabadi et al. (2013). They show that *2LGA* could be a good choice to tackle with this kind of problem. The comparison of 2*LGA* and *LINGO* optimization package indicated that *2LGA* gives better results in terms of quality and time.

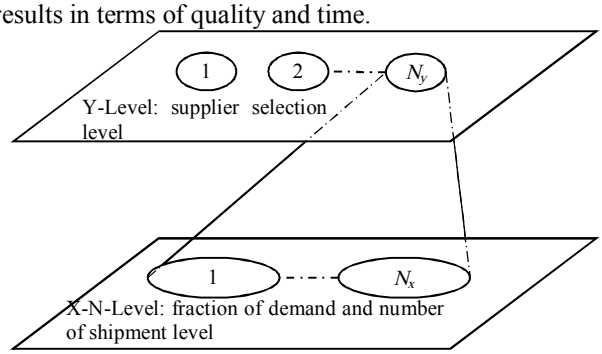

Fig. 2. Two-level GA's structure

Fig. 2 depicts the structure of our modified Two-Level Genetic Algorithm. The main difference between *2LGA* in Aliabadi et al. (2013) and ours is in the second layer that specifies not only their partnership in procurement of j^{th} item (X_{ij}) but also the number of shipment from i^{th} supplier for j^{th} item (n_{ij}).

In the following subsections, each operator of *2LGA* is explained in detail. Also, we decided to set values of *2LGA* parameters like Aliabadi et al. (2013) for ease of comparison between problems in Numerical examples.

5.1. Initialization

At the beginning, we need to initialize our parameters and find a bunch of feasible solutions for chromosomes in Y-Level and X-Level to start with. In Y-Level, after creating a random value between 0 and 1, we will check whether it is greater than 0.5 or not; if yes Y_i is 1 and otherwise 0, respectively. Also, we filter out those set of *Y* values which is infeasible. In X-Level, by considering constraint (9), a set of feasible numbers would be selected randomly. In addition to X_{ij}s, n_{ij} will be selected randomly between sgn(X_{ij}) and a capped value. This capped value can be imposed by transportation system limitation.

5.2. Crossover

Crossover operator is in charge of generating new population based on previous generation. Because of indigenous differences at Y-Level and X-Level, different crossover operators are implemented. The crossover is performed by randomly selecting a pair of chromosomes from the mating pool with probability of P_X^C and P_Y^C. In Y-Level, after choosing parent chromosomes, a tangent point is made, and then the gene values of two chromosomes are switched between each other. But in X-level, first, a random binary matrix is produced, then, the parent genes which have the same position as identity genes in random binary produced chromosomes are exchanged. The exchange between chromosomes includes X_{ij} and n_{ij} matrices together.

5.3. Mutation

Mutation is used to avoid local optimum. Hence by using mutation operator, the global search ability is improved. Due to structural differences between X and Y levels, they need different operators. In Y-Level, after generating a random vector between 0 and 1, we compare each value of that vector with a mutation probability value which is denoted by P_Y^M. Whenever generated gene is less than P_Y^M, we replace corresponding gene with its complementary value. In our implemented code, P_Y^M is set to 0.2.

For the X-Level, to perform mutation operator, for each gene a random real number between zero and one is produced. If this random number is less than P_X^M, X_{ij} of related gene is replaced with a new random value between $[K_{ij}Y_i/D_j, P_{ij}Y_i/D_j]$ and n_{ij} is replaced with a random value in $[sgn(X_{ij}), \overline{n_{ij}}]$. $\overline{n_{ij}}$ may be imposed by transportation system limitation.

5.4. Termination

The termination condition used here is the number of iteration without improvement in the best solution. The *2LGA* will terminate after 50 generation without improvement in binary layer and 40 generation without improvement in the best solution in real layer. The best solution may not appear in last generation but in transition iterations. Therefore, algorithm saves the best solution whenever it appears either in transition or final iterations.

6. Numerical Examples

In this section we assess the quality of solutions given by proposed *2LGA*. To achieve this aim, we extract the results of Aliabadi et al. (2013) samples and compare them with the new results.

Table 1 presents the comparison between these two solving methods. To analyze the results from two methods, we introduce the *%Benefits* as:

$$\%Benefit = \left(\frac{C_{new\ 2LGA} - C_{2LGA}}{C_{2LGA}}\right) \times 100 \qquad (13)$$

Where $C_{new\ 2LGA}$ is the cost of proposed *2LGA* and C_{2LGA} is the objective function which is obtained from previous *2LGA* in Aliabadi et al. (2013) model.

The results show efficacy in comparison to the previous model. The average improvement is about 1.68%.

From mathematical point of view, this improvement in global optimum is proved by Theorem 1. But when there is no guarantee to find global optimum, it is possible to find worse value for objective function due to intricacy of new model. But our proposed solution algorithm expresses good quality in proposed samples. Even in some instances, the efficiency is over 9%. Despite of small improvement in some instances, in general it depends on the problem's nature and in some cases a major benefit is achieved which is reasonable regarding to the insignificant increases in calculation time.

Also for more complicated problem, *CPU* time for solving problem sets #3, and #7 by *LINGO* are 13800 and 28800, respectively. As a matter of fact, we try larger samples; however, *LINGO* failed to solve these problems in a reasonable time and memory usage. This point, even, highlights the value of our work, because our proposed procedure can deal with big problems relatively fast.

Table 1
The comparison between new 2LGA and previous 2LGA with all n_{ij}=1

Problem Number	*n*	*m*	New *2LGA*		*2LGA* (n_{ij}=1)		*LINGO* (n_{ij}=1)	*%Benefit*
			Objective Function	*CPU Time (s)*	*Objective Function*	*CPU Time (s)*	*Objective Function*	
1	2	2	37461.81	49.59	37362.253	30.40	37388.69	0.266464
2	3	5	391401.29	190.8	358519.79	116.27	361801.1	9.17146
3	4	4	160414.32	157.2	159486.92	88.98	159460.7	0.58149
4	2	3	2230810.57	75.02	2229756.4	70.04	2207729	0.047277
5	3	2	2096214.68	97.18	2093837.4	45.92	2094784	0.113537
6	3	3	64448.741	93.96	63551.482	70.97	64464.54	1.411862
7	5	5	194591.04	175.038	194292.56	101.34	193263	0.153624

7. Conclusion and Further Research

We have extended the integrated supplier selection, supply allocation and order scheduling approach by Aliabadi et al. (2013) to allow for multiple shipments within an order cycle. Rather than using a general purpose non-linear programming solver (such as *LINGO*), we employed a multi-layer genetic algorithm derived from the structural properties of developed model. By considering the results, one can easily infer that the new modeling exposed more efficiency in comparison to the previous model. The average efficacy in the proposed *2LGA* is about 1.68%. This survey can be used as a starting point for extending the model into other directions making it more realistic.

Although our proposed *2LGA* works well and outperforms the method used by Aliabadi et al. (2013), in this paper, our purpose was not to find the best method to solve the problem. Hence, investigation to find a possible exact method or other heuristic methods to solve the problem is a valuable future work. On the other hand, in this study, all parameters are assumed to be deterministic. Considering stochastic demands is another worthwhile direction for the future works. Besides, further attention is also required to include the routing problem along with supplier selection problem.

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Appendix A. Checking objective function convexity

For simplicity, we rewrite objective function as Total Cost (TC) and check the convexity of Total cost function. After calculating second derivative, the convexity condition would be appeared. We cannot guarantee convexity with this condition in all X_{ij}.

$$V_{ij} = \left(\frac{h_j^B P_{ij} + h_{ij} D_j}{P_{ij}}\right), TC = \sum_{j=1}^{n} D_j V_j - TB \tag{A.1}$$

$$\frac{\partial TC}{\partial X_{ij}} = D_j\left(Z_{ij} + t_{ij}\right) + \frac{X_{ij} V_{ij} D_j n_{ij} R_{ij}}{Q_j\left(X_{ij}^2 V_{ij} + \sum_{k=1}^{m} X_{kj}^2 V_{kj}\right)} + \frac{X_{ij} V_{ij} D_j\left(\sum_{k=1}^{m} {n_{kj}}^2 P_{kj} R_{kj}\right)\left({X_{ij}}^2 V_{ij} - \sum_{k=1}^{m}\left(\frac{X_{kj}^2 V_{kj}}{n_{kj} P_{kj}}\right) nijPij - 2\left(\sum_{k=1}^{m} X_{kj}^2 V_{kj}\right)\right)}{Q_j n_{ij} P_{ij}\left(\sum_{k=1}^{m} {X_{kj}}^2 V_{kj}\right)^2} \tag{A.2}$$

$$\frac{1}{2}\sum_{k=1}^{m}\frac{X_{kj}^2 V_{kj}}{n_{kj} P_{kj}} \le \sum_{k=1}^{m}\frac{X_{kj}^2 V_{kj}}{n_{ij} P_{ij}} \le 2\sum_{k=1}^{m}\frac{X_{kj}^2 V_{kj}}{n_{kj} P_{kj}} \Rightarrow$$
$$\frac{1}{2m}\left(\sum_{k=1;k\neq i}^{m}\frac{n_{kj} P_{kj}}{X_{kj}^2 V_{kj}}\right)\left(\sum_{k=1;k\neq i}^{m} X_{kj}^2 V_{kj}\right) \le n_{ij} P_{ij} \le \frac{2}{m}\left(\sum_{k=1;k\neq i}^{m}\frac{n_{kj} P_{kj}}{X_{kj}^2 V_{kj}}\right)\left(\sum_{k=1;k\neq i}^{m} X_{kj}^2 V_{kj}\right) \tag{A.3}$$
$$\Leftrightarrow \frac{\partial^2 TC}{\partial {X_{ij}}^2} \ge 0$$