Total Cost Reduction Using a Genetic Algorithm for Multi-Vendor and Single Manufacturer

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Abstract— The model configuration of the supply chain integration, which consists of multi-vendors and a single manufacturer under a shared transportation, is considered in this study. In finding the solution, the complexity increases as the number of actors in the supply chain increases. To address this complexity, several researchers typically use complex mathematical approaches (e.g., linear programming, non-linear programming, mixed integer programming, and derivatives) with model assumptions to simplify the model problem. However, under this assumption, most supply chain models cannot be implemented in practice. This paper proposes a heuristic approach based on Genetic Algorithm (GA) to solve the complex modeling. The objective is to minimize the total cost of the system by finding the optimal inventory replenishment decisions, which includes delivery quantities, batch production, and the number of shipments from multi-vendors to a single manufacturer. Moreover, numerical examples and experimentation are presented to illustrate the application of GA in finding the optimal or near optimal solution. Comparative analysis is conducted to compare the performance of GA with that of other approaches to determine the characteristics that are valuable in practical problems.

Keywords—Inventory replenishment, Genetic Algorithm; Optimization; Supply Chain, Total Cost.

I. Introduction

THE study of Supply Chain Management (SCM) is gaining considerable interest because of its application on industries in managing the flow of materials from the vendor to its customer. Several researchers have attempted to match and examine the theoretical aspects of solving the issues of the supply chain. One of the issues faced by industries is integration with vendors, because nowadays, competition is no longer characterized by “industry versus industry” but by “supply chain versus supply chain.” This phenomenon forces industries to find new ways of strengthening their positions in the business competition. To become fully aware of these issues, members of the supply chain must coordinate with one another toward a common goal [1]. A coordination through SCM attempts to optimize the streamlining materials from the vendor (purchasing), the manufacturer (production), and distribution [2]. The inventory for each stage of the supply chain must be managed efficiently by determining optimal decisions. Thus, a good inventory management reduces the total costs and produces a high customer service level [3].

Prior to the integration of the members of the supply chain, inventory replenishment decisions are conventionally treated independently from the perspectives of the vendor and the manufacturer, because members of the supply chain, focused on their own objectives, are conflicted with one another. Specifically, manufacturers use the Economic Order Quantity (EOQ) to order the material, and vendors consider the Economic Production Quantity (EPQ) to produce materials. Consequently, the optimal decision of the manufacturer is not suitable for the vendor, and vice versa [4], resulting in a trade-off between the vendor and the manufacturer. Thus, this study proposes a coordination decision to address this issue. To represent this coordination, an integrated inventory model is introduced for the planning tool to manage the inventory across the supply chain. In practice, this tool can be implemented if information is shared among members of the supply chain [5].

Goyal [6] introduced the first model of integrated inventory. The main objective of this model was to reduce the total cost for both the vendor and the manufacturer by managing optimal inventory replenishment decisions. Many researchers have attempted to extend this model by considering specific issues in the supply chain. For instance, Banerjee [7] developed an integrated model by assuming that a vendor produces an order

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on the basis of lot-for-lot decisions but that the shipment could be conducted after the production period is completed. To meet the practice, Banarjee and Kim [8] revised the previous model by splitting the batch production into sub-lot size instead of lot-for-lot decisions. In addition, this inventory model was extended to include the type of cost parameter, which affects the decision, such as the transportation costs linked to the number of shipments [4, 9, 10]. This decision is used to plan for the effective transportation of raw materials [11]. Existing integrated inventory models have not only considered the introduction of an additional costs parameter; several other parameter extensions can be integrated as well, such as product quality [12, 13, 14], lead time reduction [15, 16], stochastic demand or lead time [17, 18], multi-layer system [19, 20], and multiple actors for each stage [21, 22]. These extensions were discussed by Ben-Daya et al. [23] and Glock [1] in their comprehensive literature reviews. These studies revealed that the more parameters are included in the model, the more consistent is the theoretical approach with the practical problem. Additional parameters introduced into the model makes the solution procedure of the model become more complex. As such, complex theory, analytical approach, and computational experiments are integrated to find the solution of the model. These approaches include linear programming, non-linear programming, mixed integer programming, derivatives, and gradient-based non-linear programming. Nonetheless, integrating these approaches to find the model solution is challenging. Moreover, most inventory problems are difficult to solve [24]. For this reason, most researchers make several assumptions to simplify the model problem, thus reducing the complexity of the model in finding the solution.

Chen and Sarker [22] provided assumptions in the integrated inventory model. The study begins with the case of a single manufacturer purchasing single materials from multi-vendors. To deliver the materials, Third Party Logistic (TPL) is used with milk-run system. The TPL consolidates all of the materials from all vendors and then deliver them to the manufacturer. The problem lies in synchronizing the flow of materials from the vendors to the manufacturer that leads to the minimum cost of the supply chain. To reduce the complexity of the model, the manufacturer is assumed to operate synchronously with the vendors, meaning that the cycle time of each batch of the manufacturer was equal to that of the vendor. Although this assumption allows the model to easily find the optimal solution, such an assumption is contrary to the real practice because each vendor and manufacturer has a different cycle time in producing their product.

A number of researchers have proposed metaheuristic approach instead of analytical approach to address the complex model solution [24–28]. Most metaheuristic approaches provide reasonable computational time that can yield optimal or near-optimal solutions. Among these heuristic approaches, the Genetic Algorithm (GA) introduced by Holland [29] is one of the most effective techniques for solving complex modelling. Inspired by Darwin's principles, this algorithm mimics the process of natural selection or evolution and survival of the fittest [30]. The application of GAs to various disciplines prove that GA is flexible and simple [24]. For example, the application of GA in the field of production and operation management includes the inventory problem, as discussed by Aytug et al. [31] and Goren et al. [24] in their analysis of more than 100 papers. One of the studies that applied GA in the integrated inventory model is Lee et al. [3]. This study attempted to optimize the parameter of the supply chain by including multiple suppliers, multiple periods, and quantity discounts. This proves that the advantages of implementing GA in solving the inventory problems includes the following: easy implementation; a code that is easy to understand and modify; usefulness for both complex and loosely defined problems; an inductive nature that works using its own internal rules; a parallel nature of the stochastic search; ability to solve non-differential, multi-dimensional, non-continuous, non-linear programming, and non-parametrical problems; as well as the ability to easily deal with many constraints that other methods neglect in spite of their importance in practice [32, 33].

Considering the simplicity of GA, this study attempts to improve the solution procedure proposed by Chen and Sarker [22] with the GA approach. In this study, GA is proposed to blindly search the solution by compromising the assumption given in the previous model. The GA will optimize the parameter of the model to make inventory replenishment decisions for batch production size, delivery quantities, number of shipment, and consequently reduce the cost of the system.

The rest of this paper is organized as follows. Section 2 describes the problem in the supply chain system. Section 3 presents the problem the form of mathematical modeling. Section 4 describes the solution procedures based on GA. Section 5 provides a numerical example that was conducted by applying GA to find the optimal solutions. Moreover, comparative analysis of other approaches is also presented in Section 5. The conclusion and recommendations for further research are provided in Section 6.

II. Problem Descriptions

The following problems described are similar to those presented by Chen and Sarker [22]. Suppose a single manufacturer places an order to a multi-vendor. Procurement, production, and delivery systems under just-in-time circumstances were formed to illustrate the activities of interdependencies. In delivering the materials from the multi-vendor, the transportation mode used in this system is the milk-run system, in which the materials will first be consolidated before being shipped to the manufacturer. However, two problems occur as regards transportation, namely, incapacitated and capacitated. Incapacitated means that the capacity of the truckload is always larger than the shipping weight of the material. Conversely, capacitated indicates that the shipping weight is larger than the capacity of the truckload. Another problematic assumption in the previous model is that the cycle time of all vendors is equal to that of the manufacturer; this assumption is impossible to project in real practice. Therefore, this paper attempts to employ GA to solve the model problems.

In dealing with these issues, it needs to determine the optimal central decisions, including batch production lot-size policy, delivery quantities, and number of shipments from the vendors to the manufacturer. In this regard, the optimal determination of lot sizing was also used to synchronize the production flow along the supply chain for the total cost reduction of the system to be achieved. A short description of a manufacturer that interacts with multi-vendor is presented as follows:

1. This integrated system only considers the inbound logistics of the manufacturer. A multi-vendor will supply the raw materials to a single manufacturer.
2. The manufacturer and vendors have a regulated JIT philosophy on a long-term contract basis to supply raw materials as required.
3. Supply lead time, demand of parts, and finished products are deterministic.
4. Backlogs and no shortages are allowed.
5. The production rates of the vendor sites are greater than the demand rate of the manufacturer sites because the vendor produces on demand.

III. Problem Modelling

The situations of inventory problems are shown in Fig. 1 as the graphical representation of the inventory status of multi-vendor and single manufacturer. To mathematically formulate the problem, this study adopts the model from Chen and Sarker [22]. The model has a mathematical form that comprises vendor cost function, manufacturer cost function, and transportation cost function. Therefore, all cost functions are integrated into one model. As mentioned, the determination of the previous model solution used a complex analytical method with simplification of the model problem. Instead of proposing the analytical method, the present study proposes metaheuristic method-based GA to deal with the complexity in finding the solution. Before describing the model, all the required parameters and variables to model the problem are defined as follows:

Parameters:

C_0 Production cost of a finished product ($/unit).

C_s Setup cost of the manufacturer ($/setup).

C_i^v Production cost of a vendor i (i=1,2,…, n) ($/unit).

D Demand of the finished product (unit/year).

D_i Annual Demand of parts from a vendor i (i=1,2,…, n).

F_0 Fixed transportation cost per delivery trip (from a vendor to the manufacturer) ($/shipment)

H_i^M Holding cost of part i at the manufacturer's site ($/unit/year).

H_i^V Holding cost of part at the vendor i ($/unit/year).

H^M Holding cost of a finished product at the manufacturer ($/unit/year).

p Production rate of the manufacturer (unit/year).

P_i Production rate of vendor i (unit/year).

S_i Production setup cost of vendor i ($/setup).

F_y^{TPL} Variable cost due to the freight rate in dollar per pound per mile for the partial load.

F_x^{TPL} Freight rate in dollar per pound per mile for full truckload (FTL) of products.

α Small coefficient of adjusted inverse function.

w_i Weight of a unit part i (lbs/unit).

d_i Transportation distance of vendor i from the manufacturer (in miles).

W_x FTL weight.

W_y Actual shipping weight $W_y = \sum_{i=1}^{n} q_i w_i$.

A. Vendor Cost Function

The vendor cost functions are expressed in Eq. (1). These functions include setup cost, production cost, and work-in-process inventory cost. In the list of decision variables, the production and shipment-lot sizes of a vendor are given in the function $Q_i = m_i q_i$, thus, the total cost of vendor i (i=1,2,…, n) can be expressed as follows:

$$TC_i^v\left(q_i, m_i\right) = \frac{D_i}{m_i q_i} S_i + C_i^v D_i + \frac{q_i H_i^v}{2}\left(m_i\left(1-\frac{D_i}{P_i}\right) - 1 + 2\frac{D_i}{P_i}\right) \quad (1)$$

B. Manufacturer Cost Function

Incoming materials from a multi-vendor are processed in the assembly station to produce the finished product. The material process that incurs expenses include raw material inventory cost, machine setup cost, production cost, and finished product inventory. Thus, the manufacturer cost function is formulated as follows:

$$TC^M(Q, q_i) = \sum_{i=1}^{n} \frac{q_i}{2} H_i^M + \frac{D}{Q} C_s + C_0 D + \frac{Q\left(p-D\right)}{2p} H^M \quad (2)$$

C. Transportation Cost Function

According to Chen and Sarker [22], this transportation system was operated using independent third party logistics. Under JIT circumstance, a shared transportation was proposed using milk-run system to reduce the transportation cost. The product is consolidated first from all vendors and then delivered to the manufacturer. This situation states that all vendors have the same number of shipments $m_i = m$.

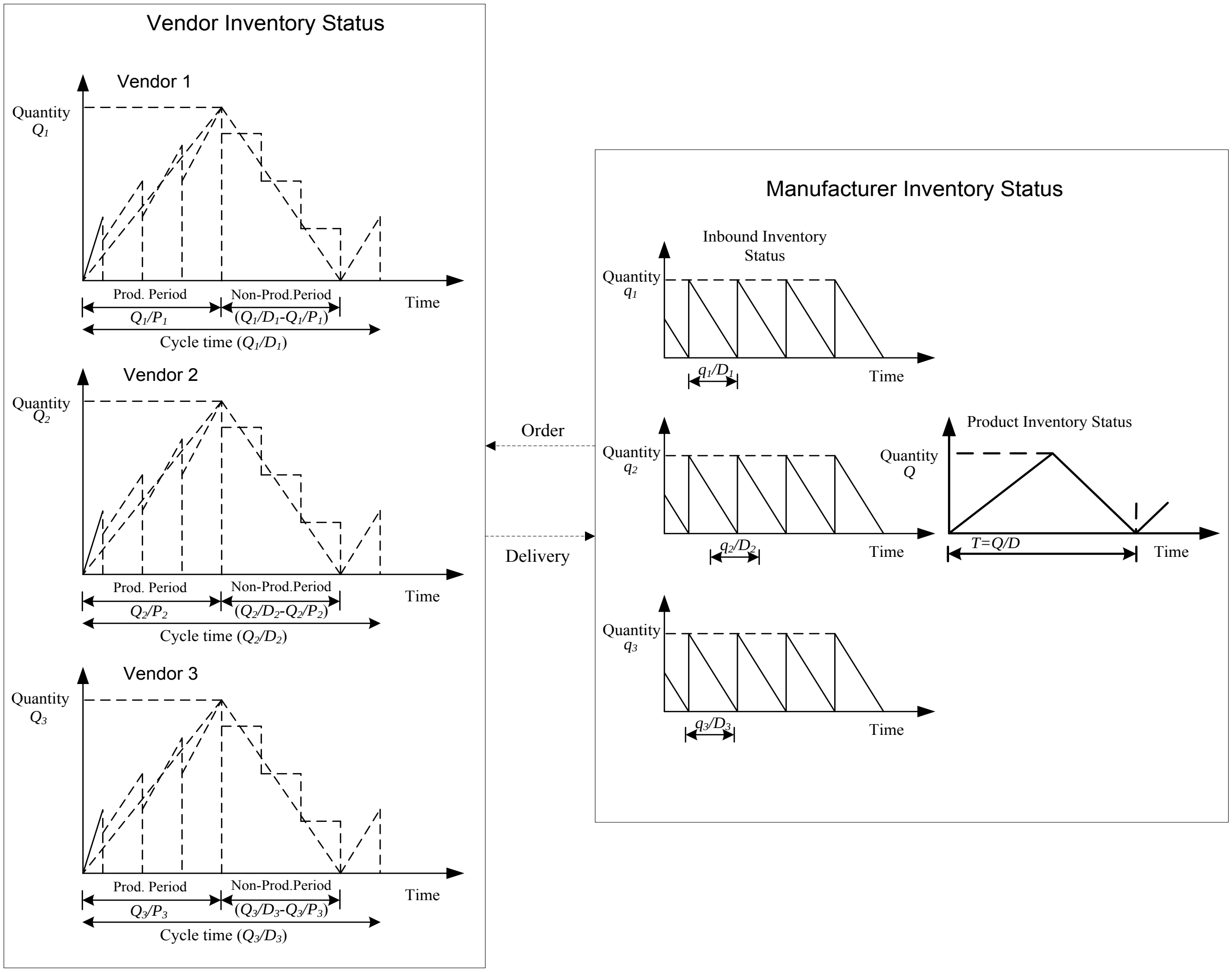

Figure 1: Inventory status of multi-vendor and single manufacturer [22]

The total transportation cost function includes fixed cost for preparing and receiving each shipment, and variable cost F_y^{TPL} from different freight rate volumes and distances. The transportation cost can be expressed as follows:

$$TC^{TPL} = \frac{\sum_{i=1}^{n} D_i}{\sum_{i=1}^{n} q_i} F_0 + \sum_{i=1}^{n} D_i d_i w_i (1+\alpha) F_x^{FTL} - \frac{\alpha F_x^{FTL}}{W_x} \sum_{i=1}^{n} \left(D_i d_i w_i \sum_{i=1}^{n} q_i w_i \right) \quad (3)$$

D. Total Cost Function

Equations (1), (2), and (3) are composed, and then the total cost functions based on Chen and Sarker [22] are written as follows:

$$\begin{aligned} Min\, TC(Q, q_i, m) = {} & \frac{D_i}{m_i q_i} S_i + C_i^v D_i \\ & + \frac{q_i H_i^v}{2} \left(m_i \left(1 - \frac{D_i}{P_i} \right) - 1 + 2 \frac{D_i}{P_i} \right) \\ & + \sum_{i=1}^{n} \frac{q_i}{2} H_i^M + \frac{D}{Q} C_s + C_0 D \\ & + \frac{Q(p-D)}{2p} H^M + \frac{\sum_{i=1}^{n} D_i}{\sum_{i=1}^{n} q_i} F_0 \\ & + \sum_{i=1}^{n} D_i d_i w_i (1+\alpha) F_x^{FTL} \\ & - \frac{\alpha F_x^{FTL}}{W_x} \sum_{i=1}^{n} \left(D_i d_i w_i \sum_{i=1}^{n} q_i w_i \right) \end{aligned} \quad (4)$$

Subject to $Q > 0$, $q_i > 0$, $m > 0$, and integer.

The objective of the model in Eq. (4) is to minimize the total cost of the supply chain. The total truck load (W_x) of shipped materials from the multi-vendor may be limited; thus, two case studies were suggested that had an incapacitated and capacitated model [22]. In the next section, GA is presented to efficiently solve the model given in Eq. (4) by considering two special cases for the incapacitated and capacitated problem.

IV. Genetic Algorithm

The model shown in Eq. (4) is categorized as a non-linear integer programming model, so this study attempts to find the solution procedures using different methods from previous work. GA is one of the searching algorithms that can successfully solve the model, which is similar to the model given in Eq. (4). It is one of the powerful metaheuristic or optimization techniques that determines the optimal or near optimal solution for complex multidimensional search spaces [34]. GA started from an initial population (*N*). An individual in the population is known as a chromosome (*Chr*), which potentially represents a solution. Each chromosome is evaluated using fitness value or objective function. The best fitness of chromosome is selected from the current generation as parents to generate an offspring. Each chromosome conducts regeneration through a genetic operator, such as crossover and mutation to produce offspring. Chromosome regeneration is conducted through iteration sequence. Furthermore, generation is terminated when the optimal solution or near optimal solution is obtained. In the next subsection, the detailed procedures of GAs are elaborated.

A. Chromosome Representation

As stated earlier, GA is initiated through the representation of chromosomes, in which each chromosome represents the solution. According to Eq. (4), the chromosome represents production-lot sizes, delivery quantities, and number of shipments for the vendors and manufacturer. Fig. 2 shows the structure of a chromosome.

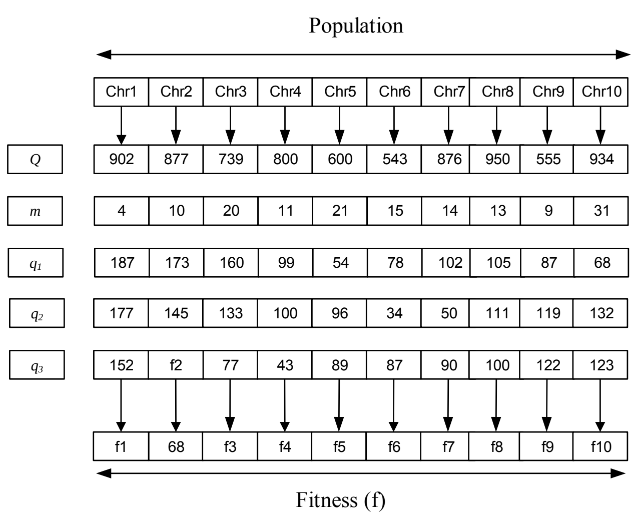

Figure 2: Chromosome representation

According to the case study by Chen and Sarker [22], incapacitated and capacitated problems refer to the total weight of quantity shipped (q_i). The total truck load (W_x) was larger than the total weight of quantity shipped; thus, the incapacitated problem can be solved easily using GA. Otherwise, if the total of weight shipped exceeds the total truck load given as $\sum_{i=1}^{n} q_i w_i > W_x$, then the searching space of GA refers to the value of delivery quantity that will be limited to avoid exceeding the total truck load. Therefore, determining the upper bound on the value of delivery quantities for each vendor is considered first for GA to search for q_i within the bound value that is already determined. To help GA in determining the upper bound value of delivery quantities, the Lagrange multiplier as approximation approach may be used to overcome this problem. The Lagrange multiplier steps can be described as follows:

1. First, assuming the function to be maximized as the function of quantity shipped for different vendor *i*, (*i*=1,2,…, *n*) is given as $z = \sum_{i=1}^{n} q_i^2$ and subjected to constraint $\sum_{i=1}^{n} q_i w_i = W_x$.
2. The constraint with zero is rearranged on one side of the equation because the Lagrange method only works if the constraint is in this form. Thus, the constraint becomes $W_x - \sum_{i=1}^{n} q_i w_i = 0$.
3. The Lagrange expression is defined as

$$V = \sum_{i=1}^{n} q_i^2 + \lambda\left(W_x - \sum_{i=1}^{n} q_i w_i \right) \tag{5}$$

   where V is obtained by adding the constraint to the objective function and multiplying the constraint by a new variable λ, which is known as the Lagrange multiplier.
4. To determine the value of q_i from vendor *i* (*i*=1,2,…, *n*), , Eq. (5) is set by obtaining the first partial derivatives with respect to q_i setting these derivatives as zero, and solving the resulting simultaneous equations for q_i

B. Initial Population

The initial population is generated randomly using a number of chromosomes (population sizes or pop sizes). The population is associated with the search space to find the optimal solution. Each individual in the population may be a candidate solution to the problem.

C. Fitness Function

At this stage, each chromosome in the population is evaluated using a measurement known as the fitness function. The total cost of the system (TC) that is shown in Eq. (4) becomes the fitness function that is directed for minimization.

D. Selection

This genetic operator is used to select an individual chromosome in the population with the best fitness from then current generation, and then this chromosome becomes the parent for the next generation. According to Pasandideh et al. [33], the selection process technique includes roulette wheel, tournament, ranking, and elitist. This study employs a roulette wheel operation technique based on the probability of selection with each individual chromosome.

E. Crossover

Crossover operation is employed to mate each chromosome in the population for an offspring or child chromosome to be produced. The crossover technique includes one-cut point, two-cut points, as well as multiple points and uniform that are already discussed in Pasandideh et al. [34]. This study employs the standard two-cut point crossover. An example of crossover operation is determined as follows:

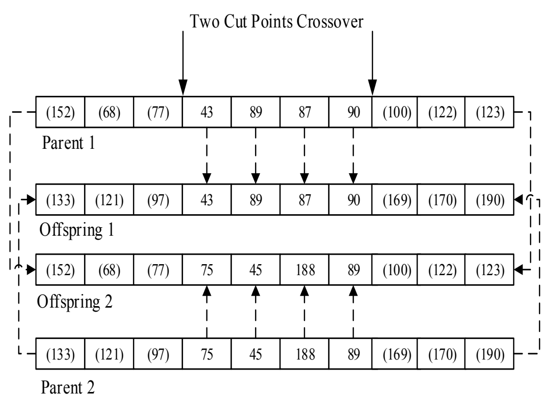

Figure 3: Example of crossover operation

F. Mutation

The mutation operator aids the GA process to avoid premature convergence and maintain enough diversity in the population by randomly changing the value of each element in a chromosome based on the mutation rate. The mutation rate is the probability of performing mutation in the GA method. Two mutation probabilities are determined randomly, which are mutation probability of population (P_m) and genes (P_g). An example of mutation is shown in Fig. 4.

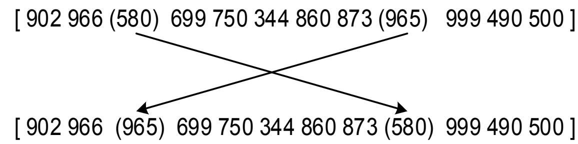

Figure 4: Example of mutation operation

G. Termination

At this step, terminating the GA process may be difficult to formally identify convergence criteria. Based on the work of Pasandideh et al. [34], the generation can be stopped (1) after a fixed number of generations or (2) when any significant improvement in the solution is obtained. To the present study, this paper conducts a fixed number of 200 generations to search the solution.

V. Numerical Example

A numerical example is given to illustrate the model solution procedure. Suppose the supply network consists of a single manufacturer, three vendors, and third-party logistic supports. The system parameter data adopted from Chen and Sarker [22] are shown in Table 1.

Microsoft Excel is used to model the formula in Eq. (4) using the data in Table 1. The problem that is formulated in Microsoft Excel is then connected to software using generator *GA* NLI-gen. To demonstrate the application of the solution procedure and evaluate the performance, GA solves two examples, including the incapacitated and capacitated models.

Example 1: Incapacitated problem.

The incapacitated model has been elaborated briefly in the previous section. The maximum quantity shipped (q_i) can be easily determined randomly because the total truckload (W_x) is a large number. Thus, GA can search within the maximum range of quantity shipped from the three vendors. Decision variables, such as Q, q_i, and m should be determined optimally using GA to obtain the low total system cost. The experiment was performed based on comparison among population (N), mutation probability of population (P_m), and mutation probability of genes (P_g).

Table 1: System parameter data [11]

Cost Unit			S_i	P_i	d_i	w_i	H_i^v	D_i	C_i^v	H_i^M
Vendors	i	1	500	12000	20	15	12	10000	32	25
		2	800	7000	15	10	23	5000	24	25
		3	900	18000	25	18	20	15000	15	25
Manufacturer			C_0	C_s	D	p	H^M			
			50	1000	5000	8000	50			
Third party logistics			F_0	F_x^{TPL}	W_x	α				
			100	0.0005	45000	0.2				

Table 2: Experiment results for example 1

No	N	P_m	P_g	Q	m	q_1	q_2	q_3	Q_1	Q_2	Q_3	TC
1	20	0.3	0.05	735	16	153	67	178	2448	1072	2848	970684.231
2	30	0.35	0.04	647	17	130	68	176	2210	1156	2992	970891.425
3	40	0.45	0.01	734	14	163	96	168	2282	1344	2352	970950.918
4	50	0.25	0.03	721	14	250	73	174	3500	1022	2436	971351.197
5	60	0.5	0.02	721	19	148	59	153	2812	1121	2907	970897.731
6	70	0.55	0.06	719	14	160	80	198	2240	1120	2772	970679.888
7	80	0.6	0.08	716	15	156	74	184	2340	1110	2760	970655.777
8	90	0.7	0.09	730	15	150	73	180	2250	1095	2700	970668.264
9	100	0.8	0.1	722	15	155	73	186	2325	1095	2790	970654.412

The results are summarized in Table 2. Based on these results, the best solution is obtained when population (N) is 100 with (P_m) and (P_g) at 0.8 and 0.1, respectively, in which the minimum total cost of the system is \$970,654.412. The convergence graph of GA is shown in Fig. 5 where the generation of new chromosomes is terminated by fixing the number of generations at 200.

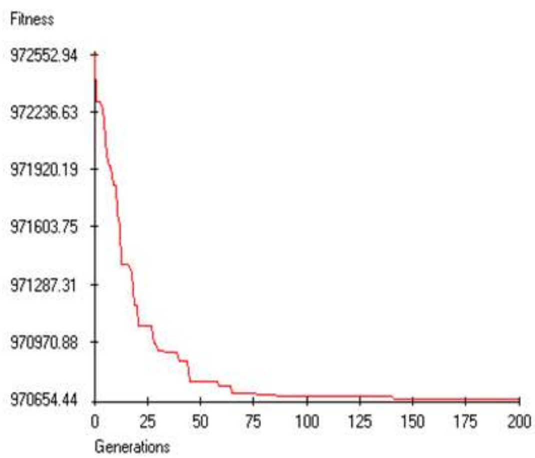

Figure 5: Convergence graph of GA

Example 2: Capacitated problem.

When facing an uncertain event in practical condition regarding the transportation problem, this study provides a case in which the total quantity shipped (q_i) from three vendors is larger than the total truck load (W_x). In this example and corresponding with Chen and Sarker [22], the data in Table 1 are used, and the value of W_x is revised. However, the other parameters remain unchanged. The value of W_x changes from 45,000 lbs to 5,000 lbs. Before the application of GA is introduced, bounding the search over q_i is highly important to avoid exceeding the total truckload. Therefore, Lagrange multiplier is used to determine the upper bound on the value of quantities that are delivered from each vendor. The application of GA was used in searching for the solution within the range of lower to upper bound value of quantities. Based on the step of the Lagrange multiplier mentioned in the previous sub-section, the solution can be given as follows:

1. The functions to be maximized are assumed to be the function of quantities shipped for the three vendors, which is given as
   $Z = q_1^2 + q_2^2 + q_3^2$
   subject to $q_1 15 + q_2 10 + q_2 18 = 5000$.
2. Likewise, the constraint with zero is rearranged as
   $5000 - q_1 15 - q_2 10 - q_3 18 = 0$.
3. The Lagrange expression is formed by adding the Lagrange multiplier (λ) as follows:
   $Z = q_1^2 + q_2^2 + q_3^2 + \lambda\left(5000 - q_1 15 - q_2 10 - q_3 18\right)$.
4. The Lagrange function is set by obtaining the first derivatives with respect to q_i for each vendor *i* (*i*=1,2,…, *n*), which is given as
   $\frac{\partial Z}{\partial q_1} = 2q_1 - 15\lambda = 0$, $q_1 = 7.5\lambda$,
   $\frac{\partial Z}{\partial q_2} = 2q_2 - 10\lambda = 0$, $q_2 = 5\lambda$,
   $\frac{\partial Z}{\partial q_3} = 2q_3 - 18\lambda = 0$, $q_3 = 9\lambda$.

The new formula for q_1, q_2, and q_3 are hence substituted with the constraint equation in step 2, and these formulas are solved simultaneously as follows:

$$5000 - (7.5\lambda)15 - (5\lambda)10 - (9\lambda)18 = 0$$

The values of λ, q_1, q_2, and q_3 are 15.4, 115, 77, and 138, respectively. $\sum_{i=1}^{3} q_i w_i = 4979 < W_x$, thus, the total quantities shipped are less than the total truckload. The q_1, q_2, and q_3 values are set as the maximum values for the searching space of GA in finding the optimum solution.

Table 3: Experiment results for example 2

No	N	P_m	P_g	Q	m	q_1	q_2	q_3	Q_1	Q_2	Q_3	TC
1	20	0.3	0.05	717	18	115	75	138	2070	1350	2484	970362.547
2	30	0.35	0.04	731	18	114	69	138	2052	1242	2484	970360.900
3	40	0.45	0.01	903	17	115	76	138	1955	1292	2346	970744.443
4	50	0.25	0.03	748	21	115	58	138	2415	1218	2898	970404.509
5	60	0.5	0.02	724	18	115	75	138	2070	1350	2484	970360.749
6	70	0.55	0.06	732	18	115	75	138	2070	1350	2484	970360.272
7	80	0.6	0.08	730	18	115	75	138	2070	1350	2484	970360.236
8	90	0.7	0.09	732	18	115	68	138	2070	1224	2484	970343.983
9	100	0.8	0.1	729	19	115	68	138	2185	1292	2622	970327.227

Table 4: The optimal result comparison of GA method and the model of Chen and Sarker [22]

Decision Variables	Chen and Sarker [22] Incapacitated Model	Proposed Model 1 (Incapacitated)	Chen and Sarker [22] Capacitated (5000 Lbs)	Proposed Model 2 Capacitated (5000 lbs)
Q	902	722	903	729
m	13	15	17	19
q_1	139	155	106	115
q_2	69	73	53	68
q_3	208	186	160	138
Q_1	1804	2325	1806	2185
Q_2	902	1095	903	1292
Q_3	2706	2790	2709	2622
TC	971,314.93	970,654.41	970,863.20	970,327.22
ΔTC	660.52=0.07%		535.98=0.06%	

As the experiment in example 1, a comparison among population (N), mutation probability of population (P_m), and mutation probability of genes (P_g) are conducted to find the best solution for capacitated problem. Hence, the results of example 2 are shown in Table 3. Moreover, the best solution is obtained when (N), (P_m), and (P_g) are 100, 0.8, and 0.1, respectively; thus, the minimum cost is $970,327.227. To show the performance differences between the GA method and the previous research, this study lists the optimal solution and corresponding total costs in Table 4. The result indicates that the GA method yields a lower cost than the previous model. For the case of minimizing the total cost, the GA method can indeed provide the multi-vendor and single manufacturer with the optimal production and shipment policy.

Moreover, GA can blindly search for the solution without any limiting assumptions. For this reason, GA ignores the assumptions of the previous research regarding the cycle time for each batch of the manufacturer that is equal to all vendors. The cycle time can be denoted as $T = Q/D = T_i = Q_i/D_i \, (i = 1,2,...,n)$. Moreover, GA yields different cycle times for each vendor and single manufacturer in producing the batch production. This result projects the real practical situation more than the result of previous work. The comparison of cycle time between the GA method and previous work is demonstrated in Fig. 6.

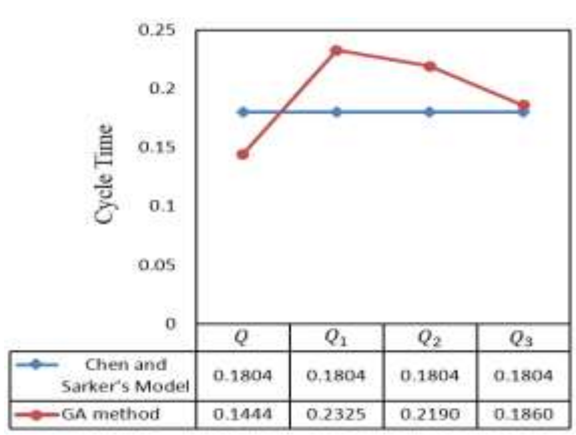

Figure 6: Cycle time comparison

Although GA can efficiently minimize the total cost of the supply chain, the cycle time is not yet synchronized. The supply chain system is still less effective in producing the batch production than previous research.

VI. Conclusion

This paper demonstrated a GA approach that improves the performance of the supply chain integration system consisting of multi-vendors and a manufacturer in the form of a complex inventory model. This approach attempts to reduce the total cost of the system by finding the optimal solution, which includes batch production-lot size, delivery quantities, and number of shipments. Unlike previous works that make assumptions to simplify the complexity of the model in finding the solution, GA is a good approach for solving the model problem without simplification of the problem based on limiting assumptions. The reason is that making assumptions in the model may cause the model to be inapplicable in practice.

Therefore, this study contributes to change the solution procedure of previous works by using GA so that the optimal or near optimal solution can be obtained without any limiting assumptions. The experiment results show that GA can effectively search the solution. Comparative analysis is also conducted to show how this approach differs from previous works. The comparison indicates that GA can better obtain the minimum total cost than previous works. The assumption that the cycle time of each manufacturer batch is equal to that of all vendors can be solved by using GA. The process of GA in finding the solution yields different cycle time in producing batch production, meaning that a manufacturer and all vendors do not have a synchronized cycle time. Although this result represents the real practice and leads to minimum cost, the supply chain system is less effective in producing the batch production of either vendors or manufacturer compared with previous findings. As such, the delivery of materials cannot be synchronized among vendors before being shipped to the manufacturer.

For future research in the area of modeling and optimization, this paper suggests to consider lead-time reductions for multi-vendor and single-manufacturer problems when producing batch productions to increase the customer service level. Incorporating the transportation schedule into the model is also highly important in facing different cycle times of each batch production for the manufacturer and all vendors. Moreover, employing other heuristic approaches, such as branch and bound, particle swarm optimization, and evolutionary strategies, can further challenge for improving the performance of the model, which includes branch and bound, particle swarm optimization, and evolutionary strategies that can be applied to solve inventory problems.

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