Chapter 22
Genetic Algorithm Model for Multi Product Flexible Supply Chain Inventory Optimization Involving Lead Time

P. Radhakrishnan

22.1 Introduction

Global competition, shorter product life cycles, dynamic changes of demand patterns and product varieties and environmental standards cause remarkable changes in the market scenario thereby forcing the manufacturing enterprises to deliver their best in order to strive (Sarmiento et al. 2007). Decrease in lead times and expenses, enrichment of customer service levels and advanced product quality are the characteristics that determine the competitiveness of a company in the contemporary market place (Mileff and Nehez 2006). The above mentioned factors have made the business enterprises to contemplate about their supply chains. An ensemble of organizations providing products and services to the market may be called as a supply chain. The effective management of the supply chain has become unavoidable these days due to the firm increase in customer service levels (Beamon 1998). The supply chain cost was immensely influenced by the overload or shortage of inventories. Thus inventory optimization has transpired into one of the most recent topics as far as supply chain management is considered (Joines et al. 2008; Adams 2004; Golden Embryo Technologies Pvt. Ltd. 2004).

In this paper, a novel and efficient approach using Genetic Algorithm has been developed for muti-product flexible supply chain inventory optimization. This paper supplements the supply chain inventory optimization analysis without raw material and multi product lead time considerations (Radhakrishnan et al. 2010). As the lead time plays vital role in the increase of supply chain cost, the complexity in predicting the optimal stock levels increases. In order to minimize the total supply chain cost, the proposed approach clearly determines the most probable excess stock level and shortage level that are required for inventory optimization in the supply chain. In practice, the dynamic nature of the excess stock level and shortage level over all the periods is the typical problem occurring in inventory management. The proposed approach of genetic algorithm predicts the emerging excess/shortage

P. Radhakrishnan (✉)
Wisdom School of Management, Pollachi, Tamil Nadu, India
e-mail: sp_radha@yahoo.com

M. K. Nandakumar et al. (eds.), *Organisational Flexibility and Competitiveness,* Flexible Systems Management, DOI 10.1007/978-81-322-1668-1_22,

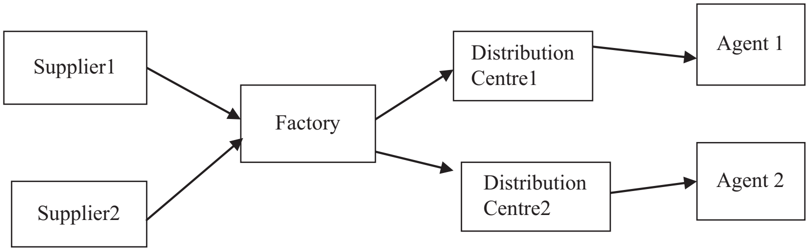

Fig. 22.1 Four stage-seven member supply chain

stock levels for the ensuing period by considering the stock levels of the past years, which is an essential information for supply chain inventory optimization as well as total supply chain cost minimization.

22.2 Method and Methodology

The proposed method uses the Genetic Algorithm to analyze the stock level that needs essential inventory control. In practice, the supply chain is of length *n*, means having *n* number of members in supply chain such as factory, distribution centers, suppliers, retailers and so on. Here the exemplary supply chain model consists of a four-stage supply chain having seven members as depicted in Fig. 22.1.

As illustrated in Fig. 22.1, the factory is the parent of the chain producing two products p1,p2 and it is having two distribution centers Distribution center 1 and distribution center 2, each having an agent. From the distribution center, the respective stocks will be moved to the corresponding agents. Also the raw materials required for manufacturing the products are sourced from 2 suppliers namely, Supplier1 and Supplier 2.

The methodology flow as illustrated in Fig. 22.2 is intended to determine the emerging excess or shortage amount of stock levels of the product at different members of the supply chain by analyzing the past records very effectively and thus facilitating efficient inventory management in order to minimize supply chain cost. The analysis flow is initiated by the selection of valid records. In the valid record set selection, records having nil values are neglected and the records having positive or negative values are selected for the analysis using clustering algorithm.

22.2.1 Generation of Individuals

A random individual generated along with the product representation for various members of the chain is illustrated in Fig. 22.3.

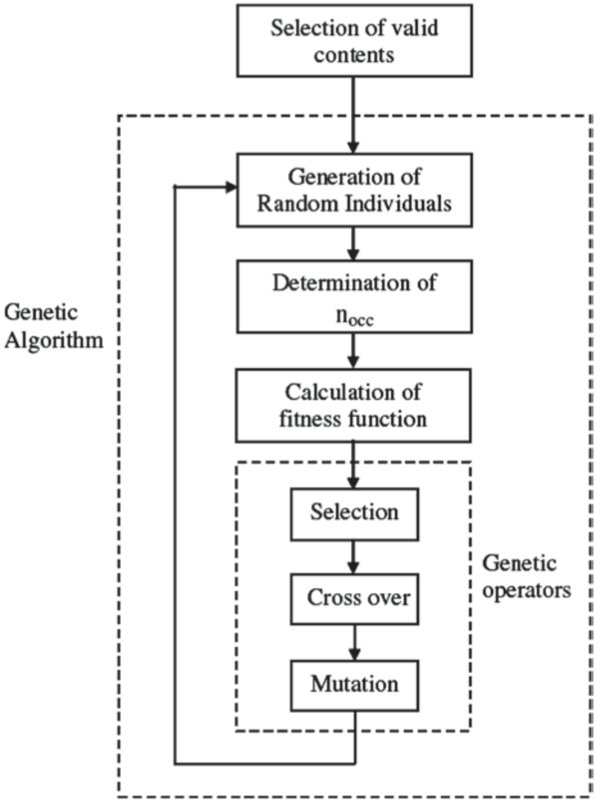

Fig. 22.2 Genetic Algorithm flow for the proposed inventory management analysis

Factory		Distribution center1		Distribution center2		Agent 1		Agent2	
p1	p2	p1	p2	p1	p2	p1	p2	p1	p2
100	−50	36	25	48	23	−79	100	−200	289

Fig. 22.3 The dataset format for the representation of a chromosome

In Fig. 22.3, the stock levels of the product at each member is represented with positive values representing excess stock levels of the product and the negative values representing shortage level of the product.

The database holds the information about the stock levels of products in each of the supply chain member, lead time of products in each supply chain member. For l members from factory to end-level-Agents, there are $l-1$ lead times for a particular product and these times are collected from the past records. Each and every dataset recorded in the database is indexed by a Transportation Identification (TID). For p periods, the TID will be $\{T_1, T_2, T_3, \cdots, T_p\}$.

Then each individual is queried into the database for obtaining the details regarding the TID and frequency of the individual. This will bring T_i and P(occ), number of periods of occurrence of that particular individual. This TID will be used as an index in mining the lead time information. After all these queries, the lead time of stocks is obtained as follows

$$T_s = [t_1\ t_2 \cdots t_{l-1}]$$

And the lead time for raw materials is obtained as

$$T_s = [t_1\ t_2 \cdots\cdots t_r]$$

where, r is the number of raw materials required for the product.

Then, for each individual the evaluation function is calculated.

22.2.2 Determination of Evaluation Function

The evaluation function is determined for each randomly generated individual. The function is given by

$$f(a) = w_1\left(1 - \frac{P(occ)}{T(periods)}\right) + \log(w_2.t_{stock} + w_3.t_{raw}) \tag{22.1}$$

where $a = 1,2,3,\ldots\ldots,m$

P(occ) is the number of counts of past records that occurs throughout the period.

T(periods) is the total number of periods of records in database.

m is the total number of chromosomes for which the fitness function is calculated.

In Eq. 22.1, w_1, w_2 and w_3 are the weightings of the factors, stock levels, lead time of stocks and lead time of raw materials in optimization, respectively and they are determined as

$$w_1 = \frac{R_1}{R_1 + R_2 + R_3}$$

$$w_2 = \frac{R_2}{R_1 + R_2 + R_3}$$

$$w_3 = \frac{R_3}{R_1 + R_2 + R_3}$$

R_1, R_2 *and* R_3 are the priority levels of influence of stock levels, lead time of stocks and lead time of raw materials in optimization respectively. Increasing the priority level of a factor increases the influence of the corresponding factor in the evaluation function. Hence this R_1, R_2 *and* R_3 decide the amount of influence of the factors.

The lead time of the stocks t_{stock} is determined as follows

$$t_{stock} = \sum_{i=1}^{l-1} t_i \tag{22.2}$$

And the lead time required to fill the raw materials is given as

$$t_{raw} = \sum_{i=1}^{r} t_i \tag{22.3}$$

When the values of t_{stock} and t_{raw} from Eqs. 22.2 and 22.3 are also substituted in Eq. 22.1, it gives an evaluation value for each individual chromosome.

The fitness function is carried out for each chromosome and the chromosomes are sorted on the basis of the result of the fitness function.

In the fitness function, the ratio (P(occ)/T(periods)) plays the role of finding the probability of occurrence of a particular chromosome; and [1−(P(occ)/T(periods))] will ensure minimum value corresponding to the maximum probability; t_{stock} will find the total lead time of stocks and t_{raw} will find the total lead time of raw materials in optimization respectively for the chosen record.

So, the fitness function is structured to retain the minimum value corresponding to the various chromosomes being evaluated iteration after iteration and this in turn ensures that the fitness function evolution is towards optimization.

22.2.3 Genetic Operations

Once fitness calculation is done, Genetic operations are performed. Selection, Crossover and Mutation comprise the Genetic operations.

Selection

The selection operation is the initial genetic operation which is responsible for the selection of the fittest chromosome for further genetic operations. This is done by assigning ranks based on the calculated fitness value to each of the prevailing chromosome. On the basis of this ranking, best chromosome is selected for further processing. The chromosome generating value as minimum as possible will be selected by the fitness function since the objective is to minimize the inventory levels and lead times.

Crossover

Among the numerous crossover operators in practice, for our complex operation, we have chosen two point crossover. From the matting pool, two chromosomes are

Before Crossover:

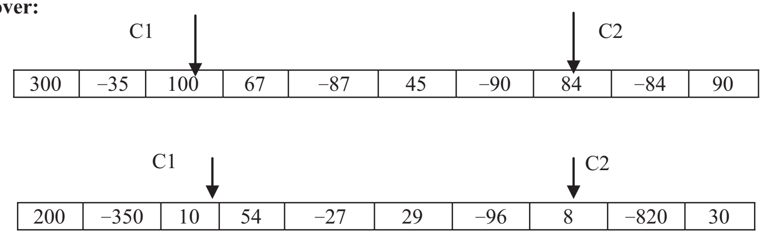

Fig. 22.4 Chromosomes before two-point crossover

After Crossover:

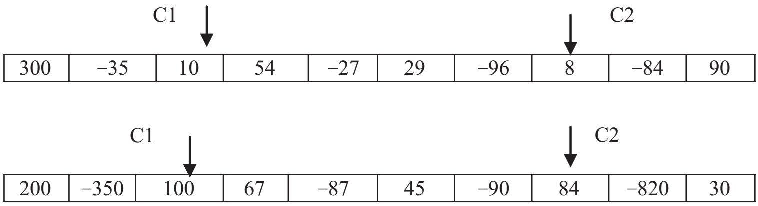

Fig. 22.5 Chromosomes after two-point crossover

subjected for the two point crossover. The crossover operation performed in our analysis is illustrated in Figs. 22.4 and 22.5.

As soon as the crossover operation is completed, the genes of the two chromosomes present within the two crossover points get interchanged. The genes before the crossover point C1 and the genes beyond the crossover point C2 remain unaltered even after the crossover operation.

Mutation

The crossover operation is succeeded by the final stage of genetic operation known as Mutation. In the mutation, a new chromosome is obtained. This chromosome is totally new from the parent chromosome. The concept behind this is the child chromosome thus obtained will be fitter than the parent chromosome. The performance of mutation operation is illustrated in the Figs. 22.6 and 22.7.

For mutation, four mutation points Mp1, Mp2, Mp3 and Mp4 are chosen randomly. The mutation is done on the particular gene present at the Mutation point. This pointing of gene is done randomly. Hence, the four mutation points may point any of the seven genes.

The mutation operation provides two new chromosomes corresponding to the initial two chromosomes from the crossover operation. Then out of the four chromosomes resulting from the first iteration, the chromosome with the minimum fitness function value will be chosen. To this chosen chromosome, another randomly

Before Mutation :

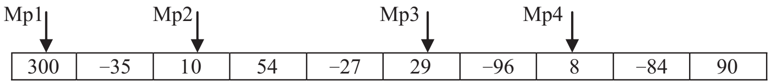

Fig. 22.6 Chromosome before mutation

After Mutation:

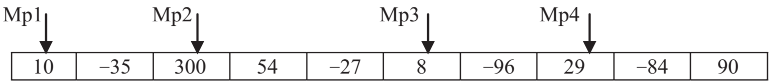

Fig. 22.7 Chromosome after mutation

Table 22.1 Sample data from database of different stock levels

TI	FP1	FP2	D1P1	D1P2	D2P1	D2P2	A1P1	A1P2	A2P1	A2P2
1	−12	−68	20	42	−91	−24	41	−32	02	50
2	−07	37	−81	−64	−31	99	−196	−146	−4	43
3	−12	−86	−20	42	91	24	41	−32	02	−40
4	−07	37	−81	−64	−31	99	−196	−146	−4	43
5	−07	37	−81	−64	−31	99	−16	−146	−4	43

generated chromosome will be added and subjected further to the genetic operations, crossover and mutation. This process repeats for a particular number of iterations or till convergence criteria is satisfied. Eventually the final best chromosome will represent the emerging excess or shortage of stock levels at different members of the supply chain thus giving the essential information for supply chain inventory optimization leading to cost minimization.

22.3 Implementation Results

The analysis based on GA for optimal inventory control is implemented in the platform of MATLAB using relevant past records in the format of Tables 22.1 and 22.2 which contain sample data of past records.

Table 22.1 is having the Transportation ID, the stock levels which are in excess or in shortage at each supply chain member. The transportation ID mentioned in table is used as an index in extracting the lead times for movements of stocks.

Table 22.2 depicts the sample data which is having the transportation ID and the lead times for stocks between the supply chain members.

Here T1 is the lead time of product1 from F to D1

T2 is the lead time of product2 from F to D1

T3 is the lead time of product1 from F to D2

Table 22.2 Sample data from database which is having lead times (number of days) for stocks

TI	T1	T2	T3	T4	T5	T6	T7	T8
1	2	4	5	1	4	6	2	4
2	4	5	2	4	1	6	7	2
3	3	5	2	8	5	7	9	6
4	4	6	2	7	9	10	3	8
5	3	4	5	10	4	6	12	3

Table 22.3 Sample raw material lead time (number of days)

TI	Supplier ID	RM1	RM2	RM3
1	1	20	7	19
	2	25	9	16
2	1	38	3	20
	2	25	25	9
3	1	38	4	15
	2	36	33	7
4	1	38	3	20
	2	25	23	9
5	1	38	4	15
	2	36	35	8

T4 is the lead time of product2 from F to D2
T5 is the lead time of product1 from D1 to A1
T6 is the lead time of product2 from D1 to A1
T7 is the lead time of product1 from D2 to A2
T8 is the lead time of product2 from D2 to A2

Table 22.3 represents the lead time to fill the raw materials which are essential to manufacture the products. In the Table 22.3, for Transaction period 1, for manufacturing the products three raw materials having the raw Material ID ‘RM1’, ‘RM2’ and ‘RM3’ are sourced and the lead times involved are ‘20’, ‘7’ and ‘19’ respectively for Supplier 1 and the lead times involved are ‘25’, ‘9’ and ‘16’ respectively for Supplier 2.

Table 22.4 describes two random individuals generated initially.

The simulation run on a large database of past records showing Fitness function improvement at different levels of iteration is as follows:

Simulation Result of GA showing Fitness function improvement with
$w_1=0.6250$; $w_2=0.3125$; $w_3=0.0625$;
For iteration 20: fitness = 5.7845
For iteration 50; fitness = 5.6450; Improvement: 2 %
For iteration 70; fitness = 5.3749; Improvement: 5 %
For iteration 100; fitness = 4.8220; Improvement: 10 %

As for deciding the total number of iterations required, the criteria followed is that as long as minimization of the fitness function is still possible, then the iteration continues till such a time that no improvement in the fitness function value is

Table 22.4 Initial random individuals

FP1	FP2	D1P1	D1P2	D2P1	D2P2	A1P1	A1P2	A2P1	A2P2
300	−35	100	67	−87	45	−90	84	−84	90
200	−350	10	54	−27	29	−96	8	−820	30

200	−350	10	66	−120	46	−9	40	−8	20

Fig. 22.8 The final best chromosome obtained from the analysis

noticeable. After a certain number of iterations, if the fitness function value is not improving from the previous iterations, then this is an indication that the fitness function value is stabilizing and the algorithm has converged towards optimal solution. For greater accuracy, the number of iterations should be sufficiently increased and run on the most frequently updated large database of past records.

The best chromosome obtained as result after satisfying the above mentioned convergence criteria is depicted in the Fig. 22.8.

The final individual thus obtained represents the emerging excess or shortage stock levels at each of the seven members providing essential information for supply chain inventory optimization.

This final chromosome obtained from the GA based analysis shown in Fig. 22.8 is the inventory level that has the potential to cause maximum increase of supply chain cost including lead time considerations. By taking necessary steps to eliminate the identified emerging excesses/ shortages at different members of the supply chain, the supply chain cost can be minimized to that extent. Thus by following the predicted stock levels, we can avoid the increase of supply chain cost.

22.4 Conclusion

Inventory management is an important component of supply chain management. The members of the supply chain are responsible for minimizing the costs of a supply chain by managing inventory levels in a number of production and distribution operations associated with different chain stages. As the lead time plays vital role in the increase of supply chain cost, the complexity in predicting the optimal stock levels increases. We have proposed an innovative and efficient methodology that uses Genetic algorithm presented that is aimed at reducing the total supply chain cost as it undoubtedly established the most probable surplus stock level and shortage level along with the consideration of lead time involved in supplying the stocks that are required for inventory optimization in the supply chain such that the total supply chain cost is minimal. The proposed approach was implemented and its performance was evaluated using MATLAB 7.4. The performance of Genetic Algorithm was well as predicted. By following the proposed genetic algorithm based approach for inventory management, we determined the products due to which the members of the supply chain incurred extra holding or shortage cost in the whole supply chain. The proposed approach of inventory management has achieved the objectives which are the minimization of total supply chain cost as well as lead time and the determination of the products due to which the respective supply chain members endured either additional holding cost or shortage cost with lead time consideration which is a vital information for supply chain inventory optimization.

References

Adams, C. M. (2004). *Inventory optimization techniques, system vs. item level inventory analysis*. 2004 Annual Symposium RAMS—Reliability and Maintainability, pp. 55–60, 26–29.

Beamon, B. M. (1998). Supply chain design and analysis: Models and methods. *International Journal of Production Economics, 55*(3), 281–294.

Golden Embryo Technologies Pvt. Ltd. (2004). *Optimization engine for inventory control* (White paper). Maharashtra: Golden Embryo Technologies Pvt. Ltd.

Joines, J. A., Thoney, K., & Kay, M. G (2008). *Supply chain multi-objective simulation optimization*. Proceedings of the 4th International Industrial Simulation Conference, Palermo, pp. 125–132.

Mileff, P., & Nehez, K. (2006). A new inventory control method for supply chain management. 12th International Conference on Machine Design and Production, Istanbul, PP. 393–409.

Radhakrishnan, P., Gopalan, M. R., & Jeyanthi, N. (2010). Design of genetic algorithm based supply chain inventory optimization with lead time. *IJCSNS International Journal of Computer Science and Network Security, 10*(4):238–246.

Sarmiento, A., Rabelo, L., Lakkoju, R., & Moraga, R. (2007). *Stability analysis of the supply chain by using neural networks and genetic algorithms*. Proceedings of the winter Simulation Conference, pp. 1968–1976, Washington DC, USA.