A Modelling of Genetic Algorithm for Inventory Routing Problem Simulation Optimisation

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***Abstract*— This paper presents the simulation optimization modelling for Inventory Routing Problem (IRP) using Genetic Algorithm method. The IRP simulation model is based on the stochastic periodic Can-Deliver policy that allows early replenishment for the retailers who have reached the can-deliver level and consolidates the delivery with other retailers that have reached or fallen below the must-deliver level. The Genetic Algorithm is integrated into the IRP simulation model as optimizer in effort to determine the optimal inventory control parameters that minimized the total cost. This study implemented a Taguchi Method for the experimental design to evaluate the GA performance for different combination of population and mutation rate and to determine the best parameters setting for GA with respect to the computational time and best generation number on determining the optimal inventory control. The result shows that the variations of the mutation rate parameter significantly affect the performance of IRP model compared to population size at 95% confidence level. The implementation of elite preservation during the mutation stage is able to improve the performance of GA by keeping the best solution and used for generating the next population. The results indicated that the best generation number is obtained at GA configuration settings on large population sizes (100) with low mutation rates(0.08). The study also affirms the premature convergence problem faced in GA that required improvement by integrating with the neighbourhood search approach.**

***Keywords*—** *Inventory Routing Problem, Genetic Algorithm, Simulation Optimisation, Supply Chain, Optimisation*

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1. Introduction

Inventory Routing Problem (IRP) integrates two phases of decision making in supply chain management (SCM) namely inventory planning and vehicle routine, into a single decision phase. IRP solution aims to obtain optimal replenishment timing and quantity for delivery, efficient route that minimize the average distribution cost during the planning period without affecting stock outs at any of the customers. IRP is widely applied in various supply chain environments and yielded a tremendous improvement in inventory policies and delivery associated costs. Such improvement has reported in many studies ([1], [2],[3], [4]and [5]. Thus, the IRP approach gained popularity and applied in various forms of SCM in various types of industries. The industries include maritime [6], vending machine [7], supermarket chains [8],road-based distribution of automobile components [9] and many more. Generally, most of the IRP related works is focused on minimizing the total cost by finding the optimal point that coordinates the inventory level and distribution frequencies. Coordination of these two costs exhibits a trade-off issue. This is due to the decreasing inventory cost leads to an increasing in the transportation cost since more frequent deliveries in small quantities of inventory are required or vice versa. The trade-off issue is also largely attributed by the inventory policies such as: when replenish, how much to replenish, and how often the inventory is reviewed and the dimension of the SCM itself. This trade-off issue has continuously attracted researchers to build new methods and approaches that yield an optimized cost solution. The solution techniques and approaches use in the literature include exact method, heuristic, metaheuristic; to name some of the approaches; and many more.

This work attempts to use genetic algorithm (GA) to obtain the optimal total cost a single echelon SCM scenario using periodic "Can Deliver" inventory policy. The following section discusses the previous approaches used by the researcher in solving IRP problems. The structure of GA used in solving the case study and its performance is discussed in the later sections.

2. IRP Solution Approaches

As brief in the previous section, the solution approaches of IRP proposed by researchers are ranging from exact method, simulation, heuristic, metaheuristic and hybrid approach. Apart from that, the scenarios of IRP are also varies and include different dimension of SCM including the inventory policies, demand pattern; stochastic or deterministic, and various delivery policies.

Exact methods have been used to solve IRP since the early stage of IRP, a variant of Vehicle Routing Problem (VRP) that includes inventory cost. The exact method used include integer programming, branch-and-cut, Lagrangian relaxation based method and Markov chain. Bell *et al*. [10], used mixed integer programming and Lagrangian relaxation algorithm for optimization proposed for the inventory routing problem at Air Products. Dror, Ball, and Golden [11], and Dror and Ball [1] applied integer programming to minimize the total cost of assigning customer to vehicle. Integer programing is also found promising in giving solution for large scale SCM and more complex scenario. For instance, Ramkumar *et al.* [12] used mixed integer programming to solve IRP with multiple commodities and multiple resources in two echelons SCM. Mirzaei and Seifi [13] used mixed integer non-linear programming to solve IRP with deteriorating products. Abdelmaguid *et al.* [14] in his work mixed-integer programming used primal heuristic to obtain an approximate solution for IRP. Coelho and Laporte [15] model the IRP for multi-products with mixed integer programming and find the optimal solution using branch-and-cut algorithm. Similar approach also adopted by [16] to solve IRP with order-up-to level and single vehicle problem scenario using branch-and-cut algorithm. Kleywegt *et al.* ([17], [18]) addressed the coordination of inventory-transportation and formulate the problem as Markov decision problem.

Another promising approach used by researcher to solve IRP is using simulation modelling ([19],[20],[21]). Golden *et al*. [19] used a simulation approach to investigate the interaction between inventory allocation and transportation decisions for a large energy-product company and proposed the heuristic method to design an integrated delivery system planning. They reported the improvement in delivering and minimizing the total costs.

Metaheuristic algorithm is often gained popularity in optimization problem class since it has potential to develop near optimal solution within necessary computational time compared to exact method. The algorithm include in metaheuristic is simulated annealing, Tabu search, population-based model such as evolutionary algorithm and Genetic Algorithm (GA) and Ant colony. GA however obtained more attention compared to other heuristic method. Fengjiao, W. and Qingnian, Z [22], used genetic algorithm in Matlab to solve IRP with Split Pick-Ups. GA used in ([23], [3], [24], [25]) is found giving promising solution in various dimension of IRP. For example Christiansen *et al*.[26] dealt with maritime inventory routing, whilst, Espacia-Alcazar et al. [27] used GA to obtain vehicle routing associated with a particular set of delivery pattern. Moin et al. [13] conducted a comprehensive study on GA application in IRP and found that GA performance on determining the best total supply chain costs, the number of vehicles and the CPU time is efficient regardless the problem size. More interesting fact is that the performance of the GA was increased as the problem size increased and the results were obtained in significantly less computational times. Beside genetic algorithm, ant colony is used in [28] for IRP daily visit to each customer are feasible due to fleet resources and resulted an optimal solution.

The optimal inventory cost solution is often obtained from hybrid approach. In particular, whenever a local minimum problem occurs in finding the solution. In most cases, hybrid approach attempt to exploit the best feature in both exact and metaheuristic methods. For instance, Yu *et al*. [29] used Lagrangan relaxation combined with local search techniques to solve large scale stochastic IRPs. The GA performance is further improved using two random neighbourhood search in the work conducted by (Abdelmaguid and Dessouky [30]. Archetti *et al.* [31] combines Tabu search scheme into mix-integer programming model of the IRP and resulted an effective solution over a set of benchmark instances.

3. Problem Formulation and IRP Simulation Model

The IRP model considered in this study is a centralized distribution system that consists of a single supplier with a single product and three retailers as discussed by Mustaffa (2009). The product demand at each of the retailer is stochastic and assumed to be independent and identically distributed over an infinite discrete planning horizon, *t*. The inventory level at each retailer is periodically reviewed at the end of each period, *t* The replenishment policy adopted in this model called periodic "Can Deliver" policy. This policy introduced three inventory control parameters called as order-up-to level, *S*, can-deliver level, *c* and must-deliver level, *s*. In this policy, the item at each retailer is replenished up to order-up-to level, *S*, each time the inventory position at retailer's inventory level reaches or falls below the *s* level The policy also allows supplier to make an early replenishment for the retailers with the inventory level reached the *c* level by consolidating the replenishment with retailers who have reach the *s* level. The amount of delivery sent to the "can-deliver" location is the difference between the current inventory level and the order-up-to level. However, no replenishment is required in the condition when retailers only reach the *c* level but neither has reached the *s* level. The distance travelled during replenishment is obtained using the Travelling Salesman Problem (TSP) approach. The IRP simulation model is developed in MATLAB.

4. A modelling of GA optimisation

Simulation alone is not an optimizer and it has to be incorporated with some specific techniques for the optimization process. Optimizer generally generates the searching concept for the best solution. Hence, the integration of optimization algorithm is required in order to obtain the best inventory control parameters *S*, *c* and *s* that minimise the total supply chain cost in IRP simulation model. Since GA potential to increase the optimization performance as explained in section 1, this work attempts to use GA to optimize the simulation of IRP in SCM scenario explained in section 2. Genetic Algorithm (GA) method is chosen in this study as the optimization technique as many studies have shown the effectiveness of GA in optimizing the supply chain management. The integration of GA and IRP simulation is illustrated in Figure 1.

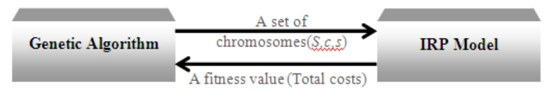

Figure 1 The integration of IRP simulation and GA.

Generally, the GA generates a set of chromosome that represents the optimal combination of value *S*, *s* and *c*, the inventory control parameters in the "can deliver" policy. These parameters give significant role in giving the most economical inventory total cost as they will determine the frequency of the delivery and the amount of stock hold by each retailer. Thus, these values deal the trade-off issues between delivery and inventory cost.

The IRP model acts as a core fitness function for calculating the fitness value. Whilst, the fitness value is the total cost, *TC* with regards of three inventory control parameters obtained from GA. The shortage, holding and transport costs are taken into account in calculating the total cost as shown in Eq 1

$$\text{Min. } TC = \sum \text{Holding Cost} + \sum \text{Shortage Cost} + \sum \text{Transportation Cost} \qquad \text{(Eq. 1)}$$

The transportation cost for the inventory replenishment is calculated according to the travel distances (*km*). Equation 1 highlights an equation of the total costs, *TC* that used as a fitness value.

GA generates solutions according to the natural genetic evolution operators which are selection, crossover and mutation. Figure 2 shows the process flows of modelling the GA in this study. Generally there are seven processes involved and each of this process will be further discussed in the following sub-section.

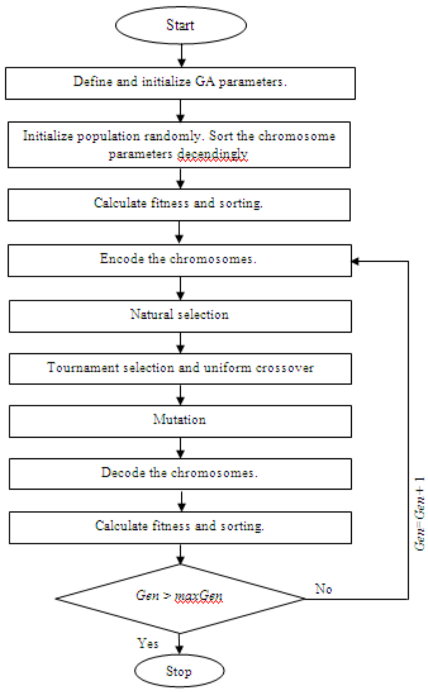

Figure 2 Genetic Algorithm flow

4. 1 Parameter Setting

Performance of GA depends on the initial value set for the parameters configuration.. The parameters involve in the initial setting are : 1) Population size, 2) crossover rate and 3) mutation rate. These parameters are required in the process of exploration and exploitation and give significant affect to the computational time. A good configuration of these parameters may produce a result that converge to the global optimum within a short period of time, while an ineffective parameter setting might cause either long runtime for finding the best solution, or it might unable to find a good solution.

Over the years, different researchers had used different parameters configuration setting according to their particular problem or based on the preference by other researcher. However, most of them agree that the crossover parameter should be fairly large to ensure occurrence of convergence, while mutation rate must be relatively small to allow the algorithm to search for better solutions (if any) close to the current solution. Some researchers prefer to iterate the algorithm in small number of generation in order to use a large population size as it can promise quick convergence. But, the computational time increases, as the size increases.

Thus, this study will conduct the sensitivity analysis in tuning the parameters of GA using various population size, mutation rate and crossover values to determine the best configuration GA parameters.

The experiment is designed based on Taguchi method using L_{25} orthogonal array to study the effects of population size and mutation rate factors with respect to the best generation number on determining the optimal inventory control as the performance measurements. Five levels for each factor are shown in Table 1**.**

Table 1 Experimental design

Factor/Level	1	2	3	4	5
Population Size, *Npop*	10	30	50	80	100
Mutation Rate, *mutrate*	0.01	0.05	0.08	0.10	0.20

4.1.1. Population Initialisation

Chromosomes value in the population represented in integer numbers and generated randomly within a specific range of feasible values. Feasible solution space is a set of all possible points (with a set of variable values) that satisfy the problem constraint. The structure of each chromosome, *X*, is depicted in Figure 3.

Chromosome, X= [*S, c, s*]

S	*c*	*s*

Figure 3 Chromosome representation

The feasible solution range for the chromosome *X* is based on the constraint of $S \geq c \geq s$. (repeated facts) .Through sorting function, the chromosomes are ranked according to their fitness value calculated in IRP model in descending order. The chromosome with minimum fitness value has a high priority of being selected to produce new offsprings since the objective function in this study is to minimise the total cost.

4.2 Encoding

At this encoding stage, each integer values in the chromosome will be encoded into binary representation. Each variable is represented by *Nbit* number of binary digit. As the number of bit string, *Nbit*, for each variable is 6-bit, the three dimension array of the integer chromosomes is transformed into 18 dimension array of binary chromosomes as shown in Figure 4.

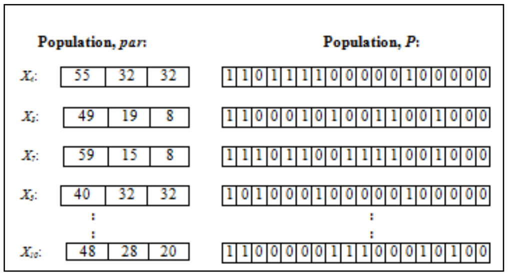

Figure 4 Chromosomes transformation into binary representation

4.3. Natural Selection and Tournament Selection

The role of this process is to select the survival chromosome in order to generate the next offspring of the chromosome in the next population. The selection for the survival chromosomes are performed via natural selection approach. Survival chromosomes are the chromosomes that have a lower fitness value compared to the threshold value. The threshold value is obtained from the mean value of population's fitness. These survival chromosomes are kept in the mating pool and l becomes potential candidate for parents to generate offspring in the next generation.

Parent candidate selection is conducted through tournament selection. Tournament selection involves with running several tournaments among a few individuals chosen at random from the population in the mating pool. In each tournament, a small subset of chromosome is randomly picked. Chromosome with the lowest fitness value in this subset will become a parent (mother, *ma* and father, *pa*). A parent is obtained from two tournaments by comparing two randomly picked chromosomes. The first tournament used to select the best mother whilst the next tournament will choose the best father. Figure 5 shows the tournament selections example for selecting parents. Two chromosomes; X_4 and X_7 are randomly selected for mother's tournament, while X_4 and X_7 are randomly selected for father's tournament. Chromosome X_4 is found to be best candidate for the mother since it fitness function value is less than X_7. Whilst in obtaining the best candidate for father, X_3 is selected due to similar reason.

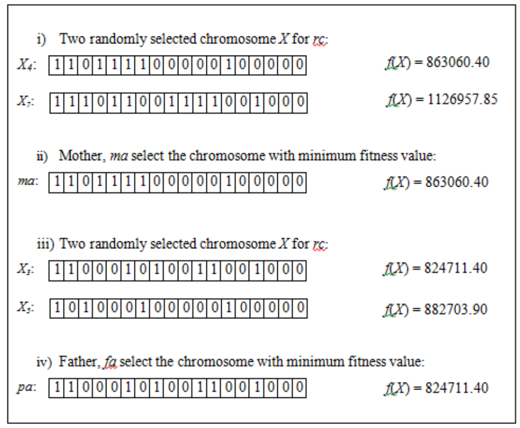

Figure 5 Tournament Selection

4.4. Crossover

Crossover operator is used to lead the population to converge on one good solution. It provides an exploitation ability to ensure the convergence of the population to the global optimum by using the process of mating that sharing the information between two individual chromosomes (parent). A single uniform crossover child approach is used in this study to increase the opportunity of finding better individual as it is offers a better chance for reproduction especially for more fitted individuals. The mating processes are influenced by crossover point that is randomly selected between the first and the last bits of the parents' chromosomes. Crossover point influenced by a crossover mask that has similar structure of chromosome, *X*. It is created randomly prior to mating process. The bit value in the mask will determine whose gene either father or mother will be inherited by the offspring. For example, bit 1 in the mask means gene obtained from the mother chromosome, *ma*, whilst bit 0 indicates gene inherits from the father chromosome, *pa*. Furthermore, the position of the bit the mask represents the position of gene in either *ma* or *pa*. Figure 6 show the example of uniform crossover implemented in this study. The first bit in the mask is 1, therefore gene at first position in *ma* chromosome is copied to the offspring. The second bit in the mask is 0. Hence, gene at the second position in *pa* chromosome is transferred to the respective offspring. The crossover continues until a complete chromosome of offspring is produced. The crossover process is repeated of the rest of the chromosome in the mating pool to produce a complete population of offspring.

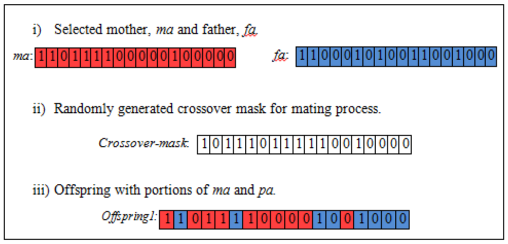

Figure 6 Uniform Crossover

4.5. Mutation

The next process is mutation, which is the second natural evolution operator in GA. While crossover make an effort to converge to the optimal, mutation does the best to prevent the convergence and searching any possible solution as much as possible. Mutations increase the diversity of the population and increase the exploration on more areas. The population is mutating randomly based on given mutation rate, *mutrate*, except for the best chromosome or elite, *el*, in order to guarantee that the best chromosome will survive. Introduced by De Jong [32], elite chromosome is the first ranked chromosome in the population. With the mutation rate of 0.2, the population will randomly mutated for about 20% of the population and the mutation will randomly pointed at any point and any of the chromosomes. In this case, the number of mutation, *Nmut* is calculated as in equation (2)

$$Nmut = mutrate \times (Npop - 1) \times Nbit \qquad \text{(Eq. 2)}$$

Figure 7 shows the example of chromosome mutation. The chromosome *NewX* is produced after the chromosome *X* has randomly mutated at point 17^{th} which mutates from bit string 1 to bit string 0.

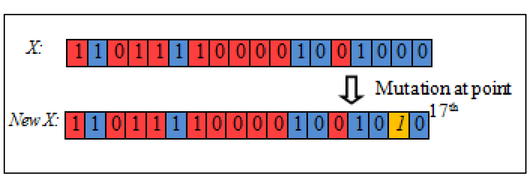

Figure 7 Mutation

5. Result and Discussion

The performance test is conducted to examine the performance of GA with and without the elite preservation during the mutation stage. Graph in Figure 8 shows that the GA performance without the implementation of elite parameter keeps losing the best solution (with the minimum total cost) as the generation number increased and sometimes leading to even worst solution as in Generation #57.

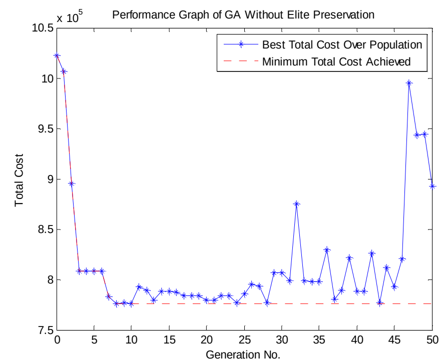

Figure 8 The performance of GA without elite preservation

The result of mutation with elite preservation as shown in Figure 9 has improved the performance of GA by keeping the best solution and used for generating the next population It indicates that the implementations of elite increase the chances of reaching global optimum early.

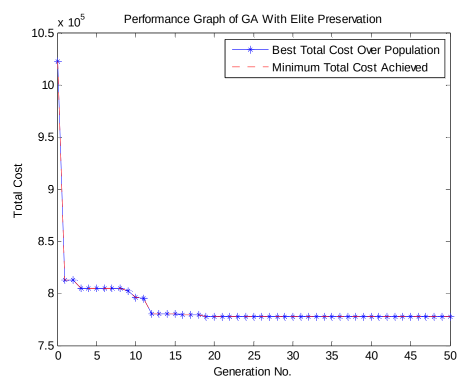

Figure 9 The performance of GA with elite preservation

The S/N ratio and ANOVA are employed to analyse the effect of the GA parameters on computational time. The S/N ratio for the computation times is considered as 'the lower-the-better' quality characteristic and calculated through the measurement of Mean-Square Deviation. Figure 10 presents a graphical overview on the impact of population size and mutation rate at each level.

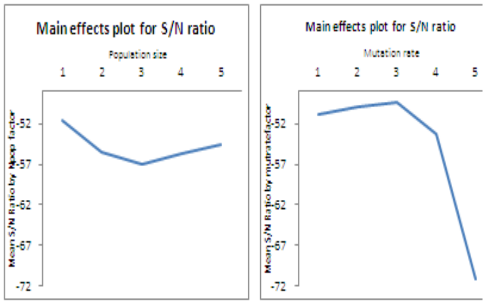

Figure 10 Effect of GA parameters

Based on the analysis, the mutation rate parameter significantly affects the performance of IRP model and the large effect occurred at high level of mutation rate. The effect in term of percentage contribution can further be investigated by using ANOVA technique. The ANOVA analysis presented in Table 2 shows that the variation of mutation rate parameter significantly contributes to affecting the output of computation times at 5% significant level with p-value of 43.370% compared to population size.

Table 2 ANOVA for GA Parameters

Factor	DOF	SS	MS	F_0	P Value (%)	SS'	New P Value
Npop	4	81.542	20.386	0.154	2.090	-449.140	-11.540
mutrate	4	1688.456	422.114	3.182	43.370	1157.774	29.740
Error	16	2122.729	132.671				
SST	24	3892.728					

The results for different combination of mutation rate and population size with regards to best generation number are shown in Table 3. Most research papers stated that the best configuration of GA can be obtained when using large population sizes and low mutation rates. On the other hand, Haupt [33] stated that the GA configuration settings on small population sizes with relatively large mutation rates is far superior compared to the low setting. Results for population size 10 in Table 3 proved that the best generation number for mutation rate 0.10 is 99.6% lower compared to generation number for mutation rate 0.01. The best setting of parameter for IRP model was found at population size 100 and mutation rate 0.08, which achieved the optimal result by 12 generation numbers.

Table 3 Best generation number for GA parameters

Mutation Rate / Population Size	0.01	0.05	0.08	0.10	0.20
10	7089	585	86	25	33
30	784	77	197	89	162
50	2351	78	66	36	326
80	233	123	84	86	16
100	56	26	12	189	91

Furthermore, the study also found the problem of local searching faced by GA as stated by [34] where GA tends to lead to premature convergence or may increase the probability of getting stuck in local optimum solution. This situation can be explained by Figure 11 where the algorithm is stuck at local optimum between Generation #70 until Generation #584 that affirms the problem. The algorithm converges to the global optimum at Generation #585 in 974 seconds as stated in Table 2 for mutation rate 0.05 and population size 10.

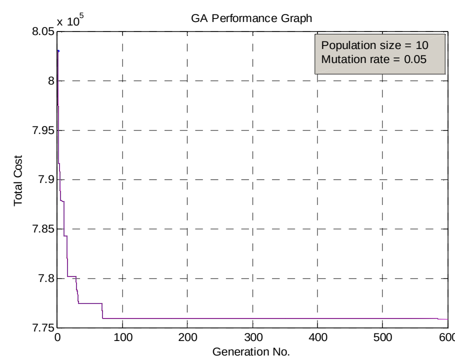

Figure 11 GA local searching performance graph

6. Conclusion and Future Research

This paper presents the modelling of Genetic Algorithm in order to determine the optimal total costs associated to IRP simulation model. Crossover operator performs the exploitative local search by selecting the best solutions and converge the population to the specific point. Mutation operator performs a global searching by exploring the solution search spaces, and it represent the ability of finding the potential solution which may not produce through the process of crossover. This study has evaluated the performance for different combination of population and mutation rate to determine the best parameter setting for GA with regards to the best generation number. The results shows that at 95% confidence level, mutation rate had 43.37% significant contribution on affecting the performance of results compared to the population size. The results indicated that the best GA parameter setting that minimized the total cost was at large population size and small mutation rate.

The study also proved that GA has problem on local searching that possible to be trapped in local optimum and leading to the premature convergence. As a result, it might substantially reduce the ability of the GA to continue searching for optimal solution.

Various techniques have been proposed with the strategy to regain the genetic diversity. Neighbourhood search is a recent popular techniques among metaheuristic which implement the local searching techniques. The basic idea is to explore the ‘ neighbours’ of the current solution and can also be defined as researching better solution among the current solutions. Bee algorithm (BA) has recently gaining attention in supply chain optimisation problem as it is good in local searching by using neighbourhood search strategy. Thus, GA need enhancement by integrating the neighbourhood search approach inspired by Bee Algorithm neighbourhood search in order to improve the local searching in GA by extending the GA exploitation space.

Acknowledgments

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