Product allocation of warehousing and cross docking: a genetic algorithm approach

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Abstract: In spite of the vast amount of researches on product allocation to distribution centres, allocating different products by considering different scenarios to plan the cross docking and warehouse operations is less investigated. To fill this gap, this research was conducted rationally to allocate different products to a distribution centre aligned with analysing different scenarios. The research case study was a distribution centre located in the South East of Asia supplying 19 different products (Li et al., 2008). A genetic algorithm was used to allocate different products to both cross dock and warehouse considering processing cost, demand, capacity and related constraints.

Keywords: distribution centres; product allocation; cross dock; warehouse; genetic algorithm.

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1 Introduction

Today's competitive market has forced managers and practitioners to consider the vital need of allocating different products to different markets. With the advent of technology, supply chain management can be considered as a successful strategy for all echelons from the first supplier to the final customers to achieve supply chain surplus (Chopra and Meindl, 2007). A supply chain consists of different components comprising suppliers, manufacturers, distributors, retailers and customers. Supply chain revolution has changed the traditional approaches to deliver the product to the customer due to the complexity of current procurement networks. This can make the role of proper product allocation more significant. Although the concepts of product allocation have been discussed by many researchers (Ayer et al., 2007; Heragu et al., 2005; Sammons et al., 2008), only very few efforts have been conducted to allocate different products to distribution centres (DCs) considering different products and scenarios for both warehouse and cross dock. In this context, identifying, modifying and using the proper model to efficiently allocate different products to both cross dock and warehouse is a challenge for many practitioners, managers, and researchers (Boysen and Fliedner, 2010; Heragu et al., 2005). While proper product allocation models should be used to increase the preciseness of product assignment, it is less analysed and investigated in the literature. This is partially due to the intrinsic difficulty connecting with mathematical models. Additionally, different products are considered as a unique entity which may not be similar to the real world problem.

The different characteristics of products in addition to their allocating to DCs using mathematical models can be beneficial, since in the real world, different products have different demand, price and suitability that can justify the consideration of different scenarios. Additionally, mathematical models are the most popular approach to solve distribution problems considering different constraints to minimise operation costs (Lin et al., 2014). Allocation problems have different usage but all aims to minimise operation cost parallel to optimising the operation of supply chain. Precise decision making tool can guarantees the best robust solution and minimising rebalance cost for practitioners (Harris et al., 2014). Proper product allocation can efficiently improve facilities operation by cutting inventory handling cost and carrying cost inside facilities (Bhatnagar and Syam 2014). Many researchers have concluded that supply chain performance can be improved through proper product allocation (Mafakheri et al., 2011). Apart from dwindling operational costs in supply chain management especially for products that required fast delivery, delivery time can determine winner and loser in highly competitive markets. In this issue, precise product allocation can decrease operation time parallel to minimising costs (Gajjar and Adil, 2011).

Proper product allocation can also improve the DC's performance resulting in a supply chain surplus. Therefore, using a GA to allocate different products to cross dock and warehouse aligned with a scenario-based analysis is the focus of this study. The main objectives of this research are as follows:

1. Optimal product allocation for warehouse and cross dock in distribution system considering different demand and cost aligned with capacity constraints.
2. Determine the effect of different scenarios for product allocation.
3. Determine the optimum number and capacity of facilities.

4 Determine the best kind of products for cross docking and warehousing considering their demand and process costs.

The case study investigated in this study is a DC located in South East Asia adopted from Li et al. (2008). This study focuses on the relation between multi-functional manufacturers and a DC located in a supply chain. Although the case study is located in Southeast of Asia, the research structure, methodology and results can be helpful to other case studies which aim to allocate different products to cross dock and warehouse in the DCs using mathematical models. This study contributes to consider different characteristics of products such as cost and demand in addition to other related constraints and scenarios within the product allocation framework to provide the most optimal product allocation to facilities and to determine the most efficient capacity required to satisfy customers order. Based on our review, only a very limited works have been reported on this issue. The rest of this paper is organised as follows: Section 2 overviews the related literature on warehousing and cross docking, product allocation definition and proposed methods by other researchers; Section 3 describes the methodology used to achieve the objectives of this study; Section 4 presents the initial findings aligned with mix integer linear mathematical model for the product allocation; Section 5 discusses on the application of GA to solve the mathematical model; Section 6 describes the model solutions and results from the proposed heuristic approach. Finally, Section 7 concludes the work.

2 Literature review

Nowadays, as business environments are facing competitive challenges, some features of competitive environment have gained high attention, such as higher efficiency and lower operational costs. These factors affect the progress of improving companies' operations. Therefore, numerous companies are applying various decision support systems and computerised analysis tools, optimisation models and algorithms as a decision making tools to survive in competitive markets (Dargi et al., 2014; Sarmiento and Nagi, 1999). Supply chain management has been critically investigated by many researchers to find intact gaps to optimise the performance of the whole-long supply chain management by various pragmatic analytical approaches (Galankashi et al., 2015).

Undeniably, the cost minimisation is the focus of researchers at all stages of supply chain management from supplier selection to select best DC strategies. In this case, optimisation of DC capacities to satisfy both customer's demands and suppliers expectation is the most effective way to increase productivity of supply chain (Manimaran and Selladurai, 2014). One of the most effective ways for supply chain optimisation is cross docking (Cóccola et al., 2015). A traditional DC such as cross docking has four major functions – receiving, storage, order picking and shipping. Among the four major functions, storage and order picking are the most costly operations because of inventory holding costs and being labour intensive, respectively. Cross docking, as a relatively new logistics technique was first used by Wal-Mart, and then was widely applied in the retail and trucking industries to rapidly consolidate shipments from disparate sources and realise economies of scale in outbound transportation. Cross docking essentially eliminates the storage function of a warehouse while still allowing it to serve its consolidation and shipping functions (Van Belle et al., 2012). Warehouse performance is influenced by the strategy applied to allocate the products (products allocation problem – PAP). It is highly correlated to the layout that contributes many restrictions that need to be considered (Guerriero et al., 2013).

Heragu et al. (2005) suggested a mathematical model for warehouse design and product allocation. Their main goals were to present a mathematical model and a heuristic algorithm that jointly determine product allocation to the functional areas in the warehouse as well as the size of each area to determine the optimum capacity using data available to a warehouse manager. Li et al. (2008) investigated optimal decision-making on product allocation for cross docking and warehousing operations. A case study model and a prototyping system were introduced in their research. Fay and Xie (2014) applied probabilistic selling (PS) as an inventory management approach that specially concerned with the effect of timing of product allocation to buyers. They concluded that probabilistic products enterprises need to order fewer inventories in order to increase the profit.

Guerriero et al. (2013) suggested a mathematical model for the multi-levels product allocation problem in a warehouse with compatibility constraints. Katayama et al. (2013) proposed a product-to-plant allocation problem in logistics network design. The investigation was based on a Japanese tire company. A tabu search formulation and approximate solution method were developed in their study. Schirmer (2013) applied heuristic algorithm to solve allocation problems in decentralised networks to solve allocation problem in order to achieve maximum satisfaction. His research showed that operation research (OR) technique can be used to solve the problem non-optimally while keeping an eye on the runtime. Guerriero et al. (2015) noted that product allocation is one of the significant activities in warehouse management in order to maximise available warehouse space utilisation. Their problem was modelled as a mixed integer linear programming and solved by mixed of iterated local search-based heuristic (ILS) and cluster-based heuristic (CH). Ramtin and Pazour (2015) noted that by using different assignment approaches, practical assignments and optimal assignments can be quantified and applied for decision making procedures.

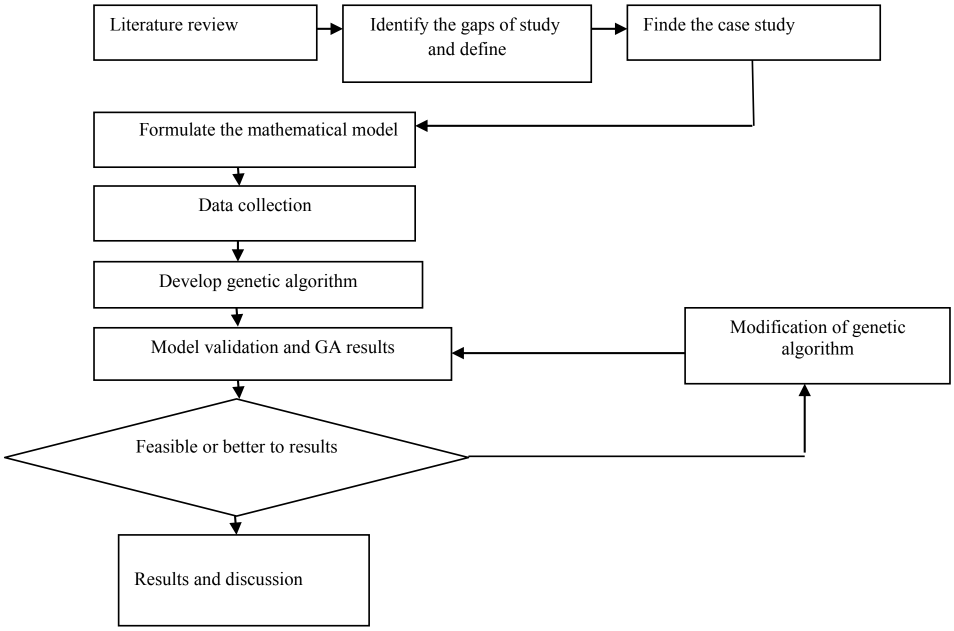
Zhou et al. (2002) investigated the allocation of customers to multiple DCs in supply chain network. They applied the GA method in order to maintain the DCs from underutilisation and deterioration of customer service. Sahu and Tapadar (2006) solved the assignment model using GA and simulated annealing. Farahani and Elahipanah (2008)used mixed integer linear programming and GA to find the best solution for DC's with minimise cost, on time delivery, and the best service level. Esparcia-Alcázar et al. (2009) proposed an algorithm to deal with allocation problem with both balanced constraints and capacitated constraints.

Based on the characteristics of the problem and available literature, GA seems to be a proper tool to solve the research model (Esparcia-Alcázar et al., 2008). In optimisation, there are many ways to find the best solution to a given problem. Genetic algorithm (GA) was introduced in order to deal with different kinds of decision problems that most business companies face in their routine operations. These challenges are included of vital supply chain issues such as supplier selection, marketing activities, selling and allocation of goods and services to pre-determined points (Min, 2015).

3 Research methodology

This section explains the research methodology and also the context of the problem. The summary of research methodology is shown in Figure 1.

Figure 1 Flowchart of research methodology



Industry needs guideline and model to support the assignment of various products to their facilities in a costly manner. In this regard, cross docking/warehousing and make an alternative plan for allocating products to cross docking and warehousing seems beneficial. In this paper, a systematic procedure and a model for evaluating cross docking distribution and warehouse has been presented. The main variables affecting the supply chain, warehouse and cross docking scenarios were determined according to operational costs. The considered constraints are physical capacity of the facility, the demand of each product and product capacity. GA has been applied to search the solution space and conclude with the best results.

3.1 Problem context

Business companies are highly depending on cost reduction in their everyday operation to survive in the market and be productive. According to the concept of cross docking, not all the products are suitable for cross docking since the operational costs of cross docking are relatively higher than traditional warehouses. Distribution manager has to decide which products need to proceed through cross docking and send to customers and which product can be stored in a warehouse. Making decision of how products can be sorted to cross docking and warehouse are complex decision making procedure since many factors such as product demand, facility's capacity, product life cycle and quantities need to be considered to satisfy customers demand and being a goodwill company while they can operate with the minimum possible cost. In this paper, the main objective was to provide strategic decision for supply chain manager to make optimal decisions for allocating products to cross docking and warehouse.

A mathematical model was proposed to optimise the product allocation process. In order to develop a GA for product allocation, the required data were compiled and treated accordingly. The required data were the number of products (jobs), the number of potential facilities for allocation and processing cost of product for each facility in addition to the demand and volume of each product. In addition, operational costs of the process for each products in both cross dock and warehouse were gathered. This step provided the necessary inputs for the GA. Necessary inputs of GA in static mode were the number of facilities, the number of products and the demand of each product.

4 Mathematical model and initial findings

Based on what discussed in research methodology, the case study of Li et al. (2008) was adopted in this study (Table 1).

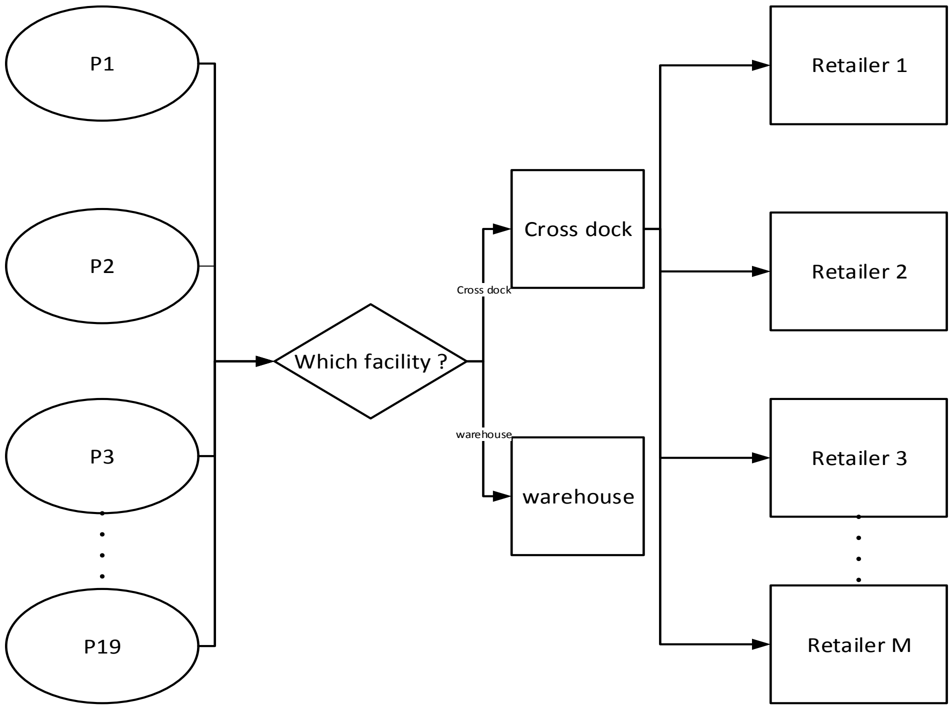
Table 1 Products data

Product name	*Demand (m^3)*	*Weigh (kg)*	*Cross dock cost ($)*	*Warehouse cost ($)*
Bread	36	50	19	38
Rice	32	5	20	37
Milk	20	5	21	36
Apple iPod	14	1	22	35
Coke drink	12	30	23	34
Nike shoes	15	0.1	24	33
Television	29	15	25	32
Nabisco biscuit	24	30	26	31
Lurker super	11	15	27	30
Detergent	20	40	28	29
FHM magazine	15	5	29	28
T-shirt	15	25	30	27
Coffee maker	33	30	31	26
Facial cotton	15	10	32	25
DVD player	15	2	33	24
Compel soup	10	20	34	23
Digital camera	9	1	35	22
Ricky powder	5	10	36	21
Facial cotton	9	10	37	20

Source: Li et al. (2008)

Figure 2 presents a conceptual model of the DC used in this study. As discussed in previous sections and shown in Figure 2, we have 19 different products (P1, P2, …, P19) that should be allocated to a cross dock and a warehouse located on a DC according to specific criteria (Figure 2).

Figure 2 DC conceptual mode



4.1 MILP mathematical model

We propose a mixed integer linear programming to optimise the DC operation. This model helps distribution channel to minimise the costs of operation through better allocation of products according to facilities constraint, anticipated demand and product process costs in each facility. Suppose there is a distribution channel decided to allocate N products to M facilities, C is the incurred process cost of product allocation to each facility and A is the capacity of each point for product allocation to satisfy all the points according to the order or anticipated demand and not to exceed each point limitation. The capacity of a and b is equal to (a_{ij}, b_{ij}) where $b_{ij} = (b_{ij1}, b_{ij2}, \ldots, b_{ijM})$ is the vector of requests product units from demand, and a is the amount of products that is interested to allocate for each facility.

Model:

$$\text{Minimise } z = \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{j=1}^{N} C_{ij} X_{ij} p_{ij} \tag{1}$$

Subject to:

$$\sum_{i=1}^{M} \sum_{j=1}^{N} p_i X_{ij} = \sum_{j=1}^{N} b_i \tag{2}$$

(Balanced condition between demand and capacity)

$$\sum_{i=1}^{M} \sum_{j=1}^{N} p_{ij} X_{ij} \le a_i \qquad \forall i = 1, 2, 3, ..., M \tag{3}$$

$$\sum_{j=1}^{N} X_{ij} \le 1 \qquad \forall j = 1, ..., N \tag{4}$$

$X = 1$ if allocated to the facility

$$0 \text{ otherwise } X \in \{0, 1\} \quad \forall i = 1, 2, 3, ..., M \quad \forall j = 1, ..., N \tag{5}$$

Notation:

X binary variable

M number of assignments points ($M = 1, 2, 3, \ldots, M$)

N number of products ($j = 1, 2, 3, \ldots, N$)

a_i capacity of assignment points

b_j demand at each point product

c_{ij} cost of process for each assignment

p_m is the number units allocated at point M.

Since there are 19 products and each one has a different process cost in each facility, the objective function (1) aims to allocate products to cross dock and warehouse with least cost. Constraint (2) is a balanced condition that guarantees the product demand is satisfied by both cross docking and warehouse. Constraint (3) ensures that total product allocated to cross dock or warehouse does not exceed their capacity. Constraints (4) and (5) are a binary variable and determines which product is allocated to which point.

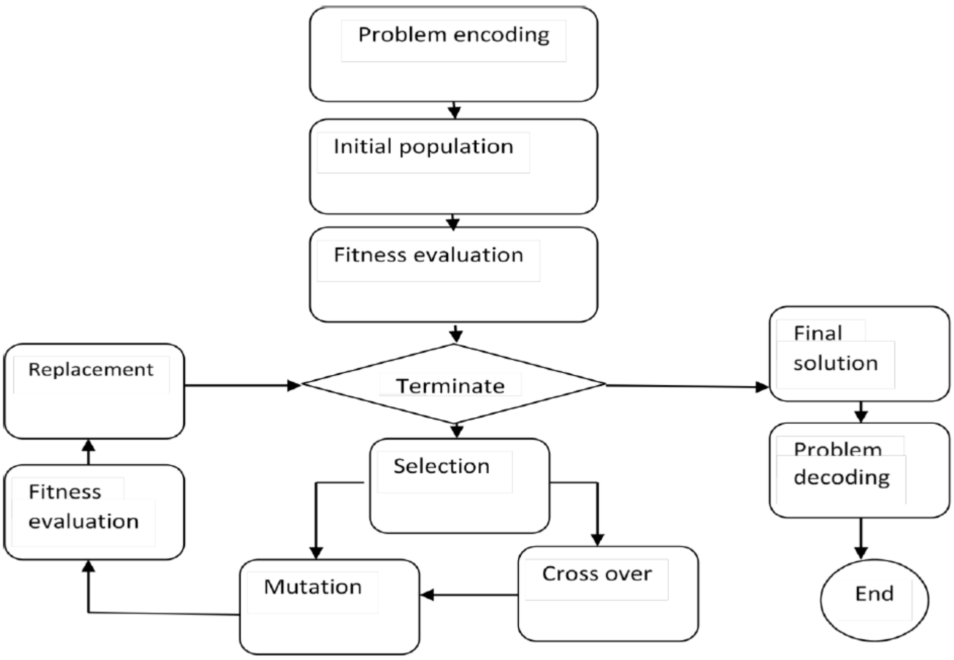
5 GAs for solving product allocation

GA was used in order to solve the model. The main mechanisms of GA are creating the chromosome representation, creating the primary population, creating the adjustment function for fitness evaluation, defining the selection strategy, selecting genetic operators for creating a new generation, defining the parameter values. The summarised process of GA is shown in Figure 3. By considering the above-mentioned procedures, the created GA solver was simply described in general programming languages as shown in Table 2.

Table 2 General programming concepts

Begin	
N:	Population size
E:	Elite number
Pc:	Crossover probability
Pm:	Mutation probability
G:	1 // No. of generation
I:	1 // No. of generation without improvement
S.C1:	Stop Criteria 1 // No. of generation
S.C2:	Stop Criteria 2 // No. of generation without improvement
B1:	The best answer in each iteration
F:	The final result
End	

Figure 3 Flowchart of GAs process



5.1 Chromosome structure

Through classical GA, the chromosomes are bit strings and include 0s and 1s. Straight forward procedure to define a bit vector for our solution of this problem was to create vector (v_1, v_2, …, v_p) ($p = n.\ k$) in which every component v_i ($i = 1, 2, \ldots, p$) is a part of vector (w_1, w_2, …, w_s) and exhibits an integer associated to column m(which is 2) and row j(which is 19) in the allocation matrix by which j can be defined as $j = [(j - 1) / k - 1]$ and $m = (i - 1) \bmod k + 1$. In this case, two-dimensional structures for the chromosome have been chosen. A matrix $V = (x_{ij})$ $(1 \geq I \geq K1 \geq j \geq n)$ that every (x_{ij}) are real number.

5.2 Initial population

In this part, initial population in line with bounds and constraint was determined and set to 50.

5.3 Fitness function

The evaluation or fitness function aims to find the total allocation cost of item to cross docking and warehouse and the formula was given as follows:

$$Eval(x_1, x_2, ..., x_n) = \sum_{i=1}^{n} x_i \cos t[j][m],$$

The developed GA solver goal was based on minimising the total cost of the fitness function.

5.4 Selection strategy

The roulette wheel selection was selected as selection strategy. This was one of the genetic operators for selecting all the potential solution in each iteration. Roulette wheel selection, a possible solution is assigned to the fitness function. The fitness function quantity of each individual was used to associate a probability of each individual to be selected. The probability of being selected for each individual was found through $P_i = \frac{F_i}{\sum_{j=1}^{N} F_i}$ in which N shows the number of individuals in the population and determine each individual's fitness function value.

5.5 Elite number

The elite number indicates the number of privileged chromosomes in each generation that is directly transferred to the next generation. This amount can be specified in 'GA Setting' in the menu bar of the created GA solver (in this study it was considered as 5).

5.6 Genetic operators

Crossover operation was done for two parents that was selected by the roulette wheel selection strategy. The algorithm generated a random integer 'i' between 1 and the length of chromosome-1, selected genes numbered less than or equal to 'i' from the first parent, and selected genes numbered from $i + 1$ to the length of chromosome from the second parent. The algorithm then merged these genes to form a child. By selecting the first I number of genes from the second parent and the remaining genes from the first parent, and merging them, the second child was shaped. The mutation was performed in two steps. Moreover, it was conducted in two segments of the chromosome separately. First, the algorithm generated a random number between 0 and 1 for each gene in the first section of the chromosome. Wherever this number was less than or equal to the mutation probability, the related gene was chosen for mutation. In the second step, the algorithm substituted each selected gene with a random number taken uniformly from the acceptable range. For the second part of the chromosome, first, the algorithm generated a random number between 0 and 1 for each of the second sections of the chromosomes. If this number was less than or equal to the mutation rate, the related section was chosen for mutation. Then, the algorithm generated an additional integer random number, j between 1 and the number chromosome-1 for shifting each gene of the selected second section to the j^{th} gene.

5.7 Termination criteria

Şahman et al. (2009) applied new generations using the GA operators like selection, crossover and mutation. Generally, the role of generation is to be the parent of the next generation and this trend keep continuing until attaining a predetermined generation number or meeting an object. The most critical issue in this case is selecting stopping criteria which requires the evaluation of problem accordingly. They set the generation number as stopping criterion. Once the stopping criteria is reached and the loop completed, the optimisation results are displayed (Akif Şahman et al., 2009). The algorithm will be stopped if it reaches the specified maximum number of generations or if it reaches the specified number of iterations without any improvement (it was considered as 15,000 generations in this study). Furthermore, the following procedures are required, and are called while the main procedure is running.

1 Save: this procedure was developed to transfer decoded chromosome to the database.

2 Sort: this procedure was developed to sort chromosomes in each generation.

3 Part-cell-update: this procedure was developed to allocate product to cells of cross docking and warehouse.

4 Delete-repetitive-chromosome: this procedure was developed to delete repetitive chromosome in the initial generation.

5 Delete: this procedure was developed to delete previous results.

By considering the above-mentioned procedures, the developed GA solver was simply described in general programming languages as follows. Also, the GA pseudo code for allocation of product is presented in Figure 4.

Figure 4 GA pseudo code for product allocation

```
Genetic algorithm in allocation problem
Input:
Size of population (n)
Mutation rate (b)
Elit number (y = 5)
Number of iterations (m)
Crossover percentage (pc = 0.7)
Mutation percentage (pm = 0.05)
Output:
Response:
Cost(p)
// Initialisation
1.    Generate n number of feasible solution randomly;
2.    Save them in population (pop)
3.    Repeat the loop until termination criteria is reached
4.    For i = 1 to m do it
      // Elite number for subsequent selection
5.    Ne = 5
6.    Select the best Ne solutions in population and save them in n Pop1;
      //Crossover
7.    Number of crossover c = (n – y) / 2
8.    For j=1 to nc do it
9.    randomly select two solutions x and x from op;
10.   generate and by one-point crossover to and;
11.   save and to op2;
12.   endfor
      // mutation
13.   For j = 1 to nc do it
14.   Number of mutation nm = (pm*npop)
15.   Select a solution from pop2;
16.   Mutate each bit of under the rate pm and generate a new solution ′;
17.   endif;
      //endfor
18.   update o = o1 + o2;
      //endfor
19.   Return to the best solution
20.   If the iteration reached 15,000 stop
```

6 Computational results and discussion

The proposed model belongs to a special class of mixed integer linear problems (MILP). The majority of algorithms used to optimise this class of problems have an exponential time. The computation time increases exponentially with the problem size. Metaheuristics algorithms such as GA can solve these problems more efficiently. The parameters required to run the algorithm are population size, number of generations, crossover and mutation probabilities. These parameters have a crucial role in the performance of the GA. The number of generations is a function of the size of the problem. As the solution space increases, the GA will require a higher number of generations to possibly reach a convergence point. Population size may vary depending on the application. The number of iterations must be set properly to allow the GA to complete the convergence process. The crossover operator has a significant effect on the performance of GA and therefore, a relatively large probability value is considered for this parameter. Mutation operator is basically used to maintain diversity in the population and a low probability is set to this parameter. The proposed model was solved for 19 parts, two facilities and with different probabilities for crossover and mutation. However, the model can be used for larger problems and as a consequence the computation time increases accordingly. The population size and elite number were 50 and 5, respectively. The stopping criteria were 15,000 generations. The best answer was selected after observation of convergence. These results are presented in Table 3. The best result was obtained by using a crossover and mutation probability of 70% and 5%, respectively.

Table 3 GAs solutions

Crossover probability	*70%*	*90%*	*80%*	*85%*
Mutation probability	5%	15%	10%	20%
Population size	50	50	50	50
Elite number	5	5	5	5
Fitness function ($)	7,045	7,089	7,192	7,210

The best fitness function occurred when crossover and mutation was set to 70% and 5%, respectively. It should be mentioned that elite number and population size were constant. When the premature convergence occurred, their production was stopped and crossovers and mutations did not produce new generations. Using the appropriate GA operators and selection rules terminated to the premature convergence. The average fitness function is fluctuating between $7,045 and $7,210 in generations. It means that the GA solver did not stop in a local optimum in the last generation. Furthermore, to certify that the final answer was not a local optimum, the problem was solved four times with different population size, crossover and mutation rates. After generating 15,000 generations, the GA solver found the optimum answer equal to $7,045. The optimum product allocation is shown in Table 4.

Table 4 Optimum GA solution

	Cross dock	*Warehouse*	*Unallocated*	*Demand*
Bread	36	0	0	36
Rice	32	0	0	32
Milk	20	0	0	20
Apple iPod	14	0	0	14
Coke drink	12	0	0	12
Nike shoes	14	0	1	15
Television	22	0	7	29
Nabisco biscuit	0	0	24	24
Lurker super	0	4	7	11
Detergent	0	20	0	20
FHM magazine	0	15	0	15
T-shirt	0	15	0	15
Coffee maker	0	33	0	33
Facial cotton	0	15	0	15
DVD player	0	15	0	15
Compel soup	0	10	0	10
Digital camera	0	9	0	9
Ricky powder	0	5	0	5
Facial cotton	0	9	0	9
Total cost: $7,045				

According to Table 4, it can be seen that the total cost is improved to $7,045 which identifies GA solver is appropriately working for this problem. According to the solver solution, it can be inferred that all first products (bread, rice, milk, Apple iPod, Coke drink and Nike shoes) were completely allocated to cross docking without any un-allocation. It was obvious that cross docking is more suitable for these kinds of products. These are the most perishable products and need to get to a destination quickly. The only unallocated or lost located product is in the middle of the table. Television has eight unallocated units, while Nabisco biscuit is completely lost. The rest of products locating in the down side of the table was completely allocated to the warehouse since the cost of warehouse for this type of product was more appropriate and they could be stored in a warehouse. Figure 5 exhibits the allocation of product to cross docking and warehouse based on results provided by GA solver.

Figure 5 Current best individuals (see online version for colours)

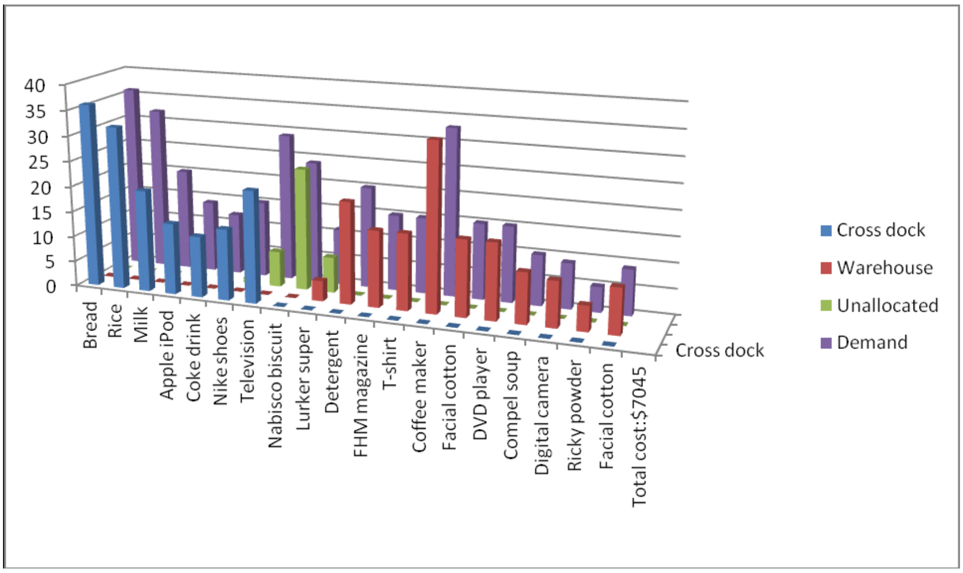


Figure 5 shows which product is allocated to which facility in addition to its quantity. There are vacancies for products that were not allocated. Moreover, the iteration of solution generation was set to 15,000 generations. According to the initial run, there has been some penalty in 100 first iteration since allocation to cross docking and warehouse was more than their capacities that caused the penalty. Next, from 5,000 generations, it was seen that GA solver found optimal solution and subsequently there was a little improvement in the results. In this research, the model is solved based on different scenarios. These scenarios depend on the type of distribution strategy applied to distribute products from sources to facilities. The scenarios are shown as follows:

- cross dock and warehouse with capacity constraints
- cross docking and warehouse without capacity constraints
- two cross docking facility and having one warehouse.

Cross docking and warehouse has limited capacity to satisfy predetermined demand imposed by the market. Scenario analysis is applied to provide satisfying demand management situation to increase profit and decrease process costs in a logical manner. The planner can make decision under different scenarios and analyse the impact of supply source over different organisation objectives and facilitate the flow of products from source to facilities based on scenario vision and giving prospective on requiring capacity and the number of facilities in strategic, tactical and operational decision making. It is required to highlight that developing capacity means physical capacity, human resources and technologies available to each facility.

6.1 Comparison of facilities with capacity constraint and without capacity constraint

When organisations are making key decisions regarding manufacturing facilities, the important aspect to be considered is capacity. We considered a set of investment alternative available for the protection of the facility. The strategic decision dealt was to find an optimum approach to allocate the protective resources and extra capacity among the facilities to be efficient as much as possible with the least cost, knowing that these facilities are exposed to external demand enhancement. The idea of using the extra capacity to indirectly protest supply networks was used with the objective of finding the best trade-off between direct investments by increasing capacity or adding another facility.

6.2 Cross docking and warehouse without capacity limitation

In contrast to previous discussion, there are some occasions that lost product has negative consequences on both company reputation and responsiveness because of insufficient capacity to satisfy demand. In this case, companies need to make appropriate decisions regarding the additional facility which can be another warehouse or cross docking or increasing the capacity of the facility to cover the demand and be more responsive. In this case, and also for similar issues where the quantity and types of product is extremely widespread, a company needs to make a decision regarding the amount of increasing cross docking or warehouse capacity in order to cover their demand. In this part, cross docking and warehouse will determine the product and capacity to allocate to both facilities in a very cost effective manner. So, the mathematical formula with eliminated capacity constraint was formulated as follows:

$$\text{Minimise } z = \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{j=1}^{N} C_{ij} X_{ij} p_{ij} \tag{6}$$

$$\sum_{i=1}^{M} \sum_{j=1}^{N} p_i X_{ij} = \sum_{j=1}^{N} b_i \tag{7}$$

(Balanced condition between demand and capacity)

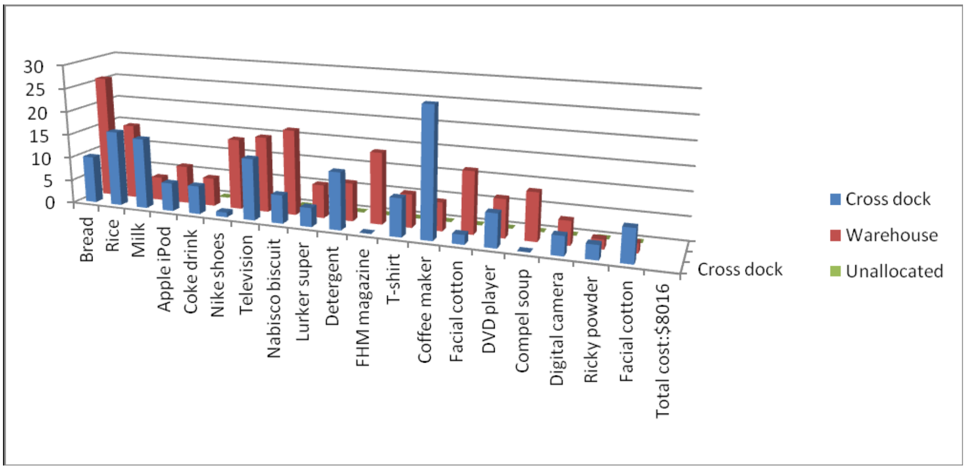
$$\sum_{j=1}^{N} X_{ij} \leq 1 \qquad \forall j = 1, ..., N \tag{8}$$

$X = 1$ if allocated to the facility; 0 otherwise

$$X \in \{0, 1\} \qquad \forall i = 1, 2, 3, ..., M \quad \forall j = 1, ..., N \tag{9}$$

Therefore, GA solver was used once more for this problem. However, in this case, the capacity constraint for both facilities was assumed as 150 cubic metre, so we could make the appropriate decision to identify sufficient capacity to cover the demand. According to GA solver, the initial feasible solution was first determined around 9,000 iterations and afterward it was set to 300 iterations. The optimum solution terminated by approximately \$8,016 and obviously did not change later, which can be interpreted as reaching a global solution. Therefore, further iteration was not helpful and could increase the run time without any improvement, so the GA solver was set to 500 iterations. Finally, the best answer for individuals is exhibited in Table 5.

Figure 6 Current best individuals without capacity limitation (see online version for colours)



As shown in Table 5, it is apparent that the entire products have been assigned without any lost product. In addition, regarding the eliminated capacity constraints, GA process became more sophisticated and had to assign the entire product to both facilities. Figure 8 shows the quantity of the allocated products.

Table 5 GAs solution for without capacity limitation

Products	*Cross dock*	*Warehouse*	*Unallocated*
Bread	10	26	0
Rice	16	16	0
Milk	15	5	0
Apple iPod	6	8	0
Coke drink	6	6	0
Nike shoes	1	15	0
Television	13	16	0
Nabisco biscuit	6	18	0
Lurker super	4	7	0
Detergent	12	8	0
FHM magazine	0	15	0
T-shirt	8	7	0
Coffee maker	27	6	0
Facial cotton	2	13	0
DVD player	7	8	0
Compel soup	0	10	0
Digital camera	4	5	0
Ricky powder	3	2	0
Facial cotton	7	2	0
Total cost: $8,016			

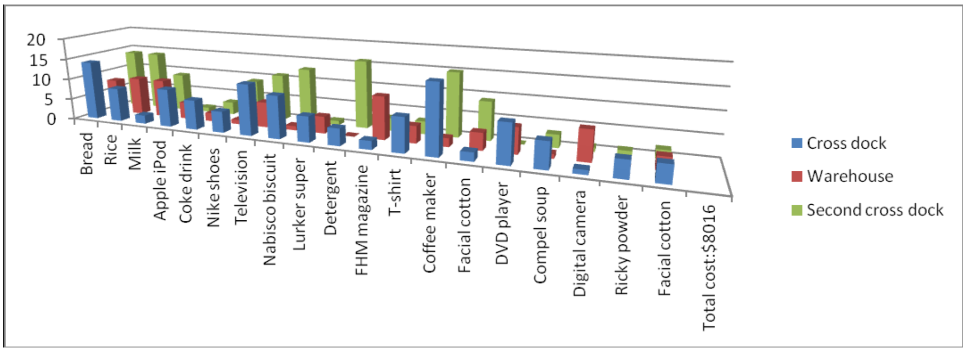
6.3 Adding another cross docking

In this part, another cross docking with the same processing cost evaluated through proposed GA solver. It was added to make an evaluation of changing processing cost. In the previous part, we observed that eliminating warehouse and cross docking capacity would increase the cost. Elimination of capacity constraint increases the cost, but it increases the responsiveness and consequently decrease the product lost and positively affect the company reputation. Hence, GA solver was set in the new scenario of one warehouse and two cross docking to check the modification in product allocation and total cost of processing. Therefore, the final solution of adding another cross docking facility can be seen in Table 6. Table 6 exhibits the best solution attained by GA solver with the best setting of GA parameters (crossover 70%, mutation 5%, initial population 50, elite number is 5 and the same iteration generation of 15,000). According to the GA solver, the best cost is $8,016 with no dramatic change instead of increasing cross docking capacity. Figure 9 graphically demonstrates products allocation. The comparison of different scenarios can be seen in Table 7 and Figure 8.

Table 6 Final solution with second cross dock

Products	*Cross dock*	*Warehouse*	*Second cross dock*
Bread	14	8	14
Rice	8	9	14
Milk	2	9	9
Apple iPod	9	4	1
Coke drink	7	2	3
Nike shoes	5	1	9
Television	12	6	11
Nabisco biscuit	10	1	13
Lurker super	6	4	1
Detergent	4	0	16
FHM magazine	2	10	3
T-shirt	8	4	3
Coffee maker	16	2	15
Facial cotton	2	4	9
DVD player	9	6	0
Compel soup	6	1	3
Digital camera	1	7	1
Ricky powder	4	0	1
Facial cotton	4	3	2
Total cost: $8,016			

Figure 7 Current best individuals for second cross dock (see online version for colours)



Based on the GA results, the best obtainable cost is $7,045. Based on the manager's viewpoint, increasing the capacity has priority over minimising cost regard to their intention to decrease the lost product. In this case, managers have to make appropriate decisions regarding the current facility capacity or adding another capacity. The comparison was done based on increasing the capacity. So, the main issue was to identify which facility has to be increased or decreased to satisfy customer demand by a cost effective manner. According to the GA solver, cross docking capacity need to be decreased to 147 cubic metres and warehouse capacity need to be increased to 193 cubic metres which incurs around $8,016 cost. Here, we also considered adding another cross docking to identify and compare the incurred processing cost. It was identified that first cross dock needs a capacity around 129 cubic metres, the second one needs around 128 cubic metres and warehouse needs 81cubic metres. Based on GA results, it is clear that adding facility or increasing capacity has the same cost. There is product lost in these two scenarios, but the cost is higher. Therefore, the lowest cost is for capacity constraint with $7,045 and total lost product is 39. However, increasing capacity will increase the processing cost to around $8,016 but there would be no lost product.

Table 7 Comparison of results for different scenario

	Li et al. (2008)	*GA solver for capacity constraint*	*GA solver without capacity constraint*	*GA solver for second cross dock facility*
Cross docking capacity (m^3)	150	150	147	129
Warehouse capacity (m^3)	150	50	193	81
Unallocated product (m^3)	39	39	0	0
Second cross docking capacity (m^3)	-	-	-	128
Total processing ($)	7,260	7,045	8,016	8,016

Figure 8 Comparison of results (see online version for colours)

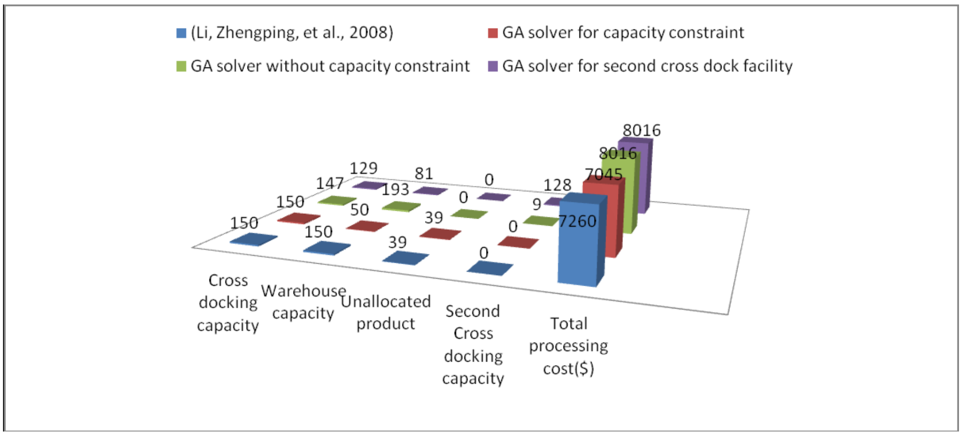
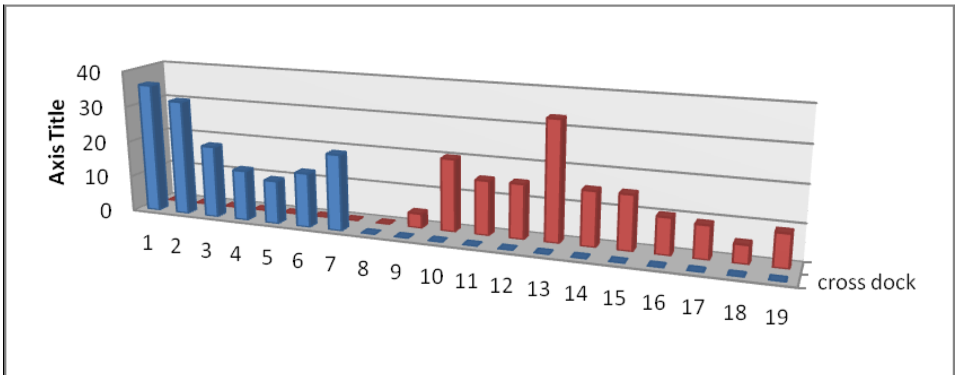


Figure 9 Ranges of objective function (see online version for colours)



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
cross dock	36	32	20	14	12	15	21	0	0	0	0	0	0	0	0	0	0	0	0
warehouse	0	0	0	0	0	0	0	0	4	20	15	15	33	15	15	10	9	5	9

7 Validation of the model

The model was validated using ‘risk solver’ which is an optimisation and simulation package in Microsoft Excel©. The intelligent engine of this software chooses an appropriate method for solving the problem.

Based on the solution attained from ‘risk solver’, it can be clarified that the model has been verified since both GA solver and risk solver results were approximately equal and consequently the little difference was negligible. After inserting all input data into the database, the created GA solver and also ‘risk solver’ was applied to solve the basic model with 19 kinds of products and two facilities (cross docking and warehouse). The population size and elite number were 50 and 5, respectively, and the stopping criteria were set to 15,000 generations. In addition, crossover and mutation probability were 90% and 15%, respectively. According to both solvers, Nabisco Lurker and super biscuit, had higher opportunity to be the loosing products.

8 Conclusions

A model for designing supply chain DC is presented in order to minimise the total system operating costs. The model presented in this study has the capability to determine the number and size of the facility along with allocation of different products to DCs via considering different criteria and constraints. This model provides guidelines for logistic planners for their decision making procedures, especially when they intended to make plans to modify the inventory capacity and setting rules for product allocation to facilities based on customers' demands. Expanding the capacity of the facility is another point of this research according to different scenarios. Product allocation aims to assign different products to DCs via considering different criteria and constraints. However, it is difficult to manage all these aspects simultaneously. Mathematical models provide insights for managers and decision makers to consider all these aspects jointly. Consequently, based on the case study data, a new approach of allocating different products to the warehouse and cross dock was proposed. In order to consider the different characteristics of products aligned with their related constraints, this study used an integer linear programming to conduct the product allocation task. GA was used to solve the mathematical model and provided the solution for the aim of product allocation. The results were compared, the best combination of facilities was proposed and the model was validated by using 'risk solver'. As a direction for future research, the proposed model can be extended in fuzzy or stochastic environments.

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