Research Article

The Genetic Algorithms for Dynamic Order Volume with Randomly and Inconsecutively Demands

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Abstract
The problems of inventory management demand which has random variation of products as well as demand in each interval which have many opportunities in discrete value are the problems that quite difficult to find quantity order as demand have many alternatives. If we did not receive products immediately after being ordered, we had to plan the long-term condition for a while on order to get a suitable option. The solutions for this problem have many ways, this report will thus present two solutions. They are 1) Stochastic Integer Linear Programming (SILP) and 2) Genetic Algorithm (GA) by defining the stable products prices that do not vary by the time before testing with 24 model problems. As a consequence, both solutions provided the right answer for random demand dynamic ordering problem. However, the time to find the answers are of difference. SILP can provide more accurate answer compared with GA, but SILP is proper for small problems which less than 6 periods and GA proper for big problems which has complexity of less than 11 periods.

Keywords: Dynamic order volume, Integer linear programming, Genetic algorithm

1 Introduction

In the current environment, consumer preferences are changing rapidly.Business competition and the higher amount of storage products to meet the needs of consumers is considered very important. Due to the storage reserves of too small amount make it impossible to meet the consumers' needs. Costs of inadequate product and losing the opportunity to sell their products in the storage reserves in excess amounts causes the costs of storage. Both cases will result in a competitive disadvantage, so plan has to be arranged in order to save the costs significantly.

As to characteristics of random needs, there are many options that occur with probability that are complicated and difficult to find appropriate answers. It has been studied in solution inventory in various forms. [1], [2] Problem solving inventory with random cannot determine the form of the probability by the application from the Dynamic Programming. It was found that the actual values can be found, but it will take more time to calculate when the size of the problem and the duration increases. Afterwards, the studies show how to use other method in solving the problem [3]–[7] presents a method of Dynamics programming, Stochastic linear programming, Bende division and Markov decision process to solve the problem. The panel concluded that the decision to act Markov is the most effective way to solve the problem. Later, Ding and Wang studied the problems with uncertainty by using a technique problem. Chance-Constrained Programming (CCP) was used to issue convertible models in the form of certainty. The uncertainty is equivalent to deterministic programming. Then the technique was used to find the optimal value

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for the problem under uncertainty. This technique has been used in dynamic inventory which added limitations, storage area under demand uncertainty of [8],[9] so as to compare with the technical schedule of linear mixed-integer. The finding showed the answer to powerful technique and calculating time was lower compared to a mixed integer linear schedule when the problem was more complicated. Also, the heuristic methods was used to resolve the problem, [10] presented three heuristic methods which are suitable for solving complicated problems in order to compare the other methods of finding the answers including Particle Swarm Optimization, Differential Evolution Algorithm and Harmony Search.

The results show that the method Particle Swarm Optimization and Differential Evolution Algorithm have a high efficiency in solving large problems. Later, [11] studied dynamic programming problems with uncertainty of many kinds under the limited level of service and limit production by applying a linear programming model that uses Piecewise functions in the estimation of the store and cost of backorder. In comparison with the Column Generation (CG) it was found the proposed method provides the answers better than CG method when the number of products is small and the productivity is of high limitation. Nevertheless, regarding the larger problem, CG is more effective in finding a good answer. According to the study, certain interesting issues have not been mentioned; that is, inventory management that is randomly required and possible to occur in any time with different probabilities in case that the delivery has to be waited. Therefore, this study aims to solve the aforementioned problem.

2 Research Methodology

In this section the mathematical model represent the problem and solution approach, the Stochastic Integer Linear Programming (SILP) and Genetic Algorithm (GA), are described as follow.

2.1 *Scope of research*

Notations

2.1.1 Index

$t = 1, 2, \ldots, T$	The planning time
$v = 1, 2, \ldots, S$	Demand level
$k = 1, 2, \ldots, K(t)$	Number of choice during the time t by $K(t) = S^t$
$i = 1, 2, \ldots, I(t)$	Number of choice during the time t by $I(t) = S^{t-1}$

2.1.2 Parameter

D_t^v	Demand under alternative v during the time t
O	Ordering cost
H	Holding cost
b	Product backlog
P_t^v	The probability that an event D_t^v under alternative v during the time t
E_t^k	Expected value of the probability under alternative k during the time t
M	Large numbers
L	Lead time

2.1.3 Decision variable

X_t^i	Order size under alternative i and gain at period t
I_t^k	Inventory size at the beginning under alternative k during the time t
B_t^k	The lack of inventory at the beginning under alternative k during the time t
Z_t^i	= 1 if being ordered = 0 if no order under alternative i during the time t

Scope of the problem

1. Start supply at the beginning period and get all product receipt at next lead time.
2. In the beginning period 1, the inventory is sufficient for the demand during lead time and the end product may be retained or not.
3. Demand will come at the beginning period. There are many different options in each period. They are shown in Table 1.
4. Acceptable case for example product stock outs when demand more than quantity available.
5. Have during lead time to send product.

Table 1: The general form of the problem

Period (i)	Demand (J)			
	Probability P_1	Probability P_2		Probability P_m
1	$\boldsymbol{d}_{1,1}$	$\boldsymbol{d}_{1,2}$	……	$\boldsymbol{d}_{1,m}$
2	$\boldsymbol{d}_{2,1}$	$\boldsymbol{d}_{2,2}$	……	$\boldsymbol{d}_{2,m}$
……	……	……	……	……
n-1	$\boldsymbol{d}_{n-1,1}$	$\boldsymbol{d}_{n-1,2}$	……	$\boldsymbol{d}_{n-1,m}$
N	$\boldsymbol{d}_{n,1}$	$\boldsymbol{d}_{n,2}$	……	$\boldsymbol{d}_{n,m}$

2.2 *Stochastic Integer Linear Programming (SILP)*

Stochastic Integer Linear Programming starts by creating a replica as to limitations mentioned. Common problems are shown in Table 1 and apply LINGO for problem solving.

Objective

$$Min \sum_{t=1}^{T} \sum_{k=1}^{k(t)} \sum_{i=1}^{I(t)} \left(OZ_t^i + HI_t^k + bB_t^k \right) E_t^k \qquad (1)$$

And define

$$E_t^{k'} = P_t^v E_{t-1}^k \qquad \forall\, v, k, \text{and } k' = (k-1)S + v$$

Conditions

$$I_0 = \sum_{t=1}^{T} D_t^1 \qquad \text{by } I_0 = 0 \text{ if } L = 0 \qquad (2)$$

$$X_{t+L}^{i'} \le MZ_t^i \quad \forall i, t = 1, \dots, T-L, \text{ and } i' = (i-1)S^L + j \text{ by } j = 1, \dots, S^L \quad (3)$$

$$I_{t-1}^k + X_t^i - B_{t-1}^k - I_t^{k'} + B_t^{k'} = D_t^v \qquad \forall\, v, i, k = i, \text{and } k' = (k-1)S + v \quad (4)$$

$$X_t^i + \mathrm{I}_{t-1}^k - B_{t-1}^k \ge D_t^1 \qquad \forall\, i, k = i, \text{and } t = L+1, \dots, T \qquad (5)$$

$$I_0 + \sum_{t'=1}^{t} X_{t'}^1 \ge \sum_{t'=1}^{t} D_{t'}^1 \qquad \forall\, t \qquad (6)$$

$$I_t^k, B_t^k \in N \cup \{0\} \qquad \forall\, t \text{ and } k \qquad (7)$$

$$Z_t^i \in \{0, 1\} \qquad \forall\, t \text{ and } i \qquad (8)$$

The objective of the model is Equation (1) to find the optimum solution to the problem with regard to inventory management. These included he expected cost 3 part i.e., 1) ordering cost 2) carrying cost and 3) the cost in case that the product cannot be shipped to customer or product backlog.

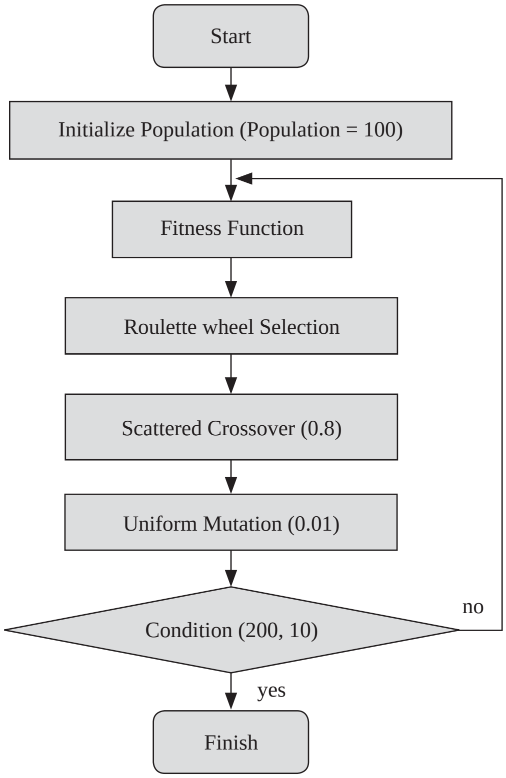

Figure 1: Genetic Algorithm Procedure.

The condition model includes Equation (2) which shows the beginning of the inventory that is sufficient to minimum requirements in the first period. Equation (3) shows the correlation of the purchase order and variables related to decisions of ordering. In other words, if the purchase order is carried out, there will be the volume purchase order. Equations (4) and (5) show the balance of the quantity of the product to order. Equation (6) shows the quantity of inventory that suffice for minimum requirement in each period. Equation (7) shows the inventory and product stock. Equation (8) shows decision for ordering which includes 2 possible choices i.e., order or no order.

2.3 Genetic Algorithm (GA)

Genetic Algorithm will make use of the GA application in Optimization tool of the MATLAB 2015b for solving the problem. The steps are as in Figure 1.

According to Genetic algorithm procedure, the first step starts with selecting the answer at random from 100. Then transforming the answer to chromosome binary bit string and moving to chromosome selection by roulette wheel selection and considering number of appropriateness for survival. If the number is high, it will get population selection in the next generation. For getting into genetic algorithm procedure that include 2 procedures. 1) Crossover that is taking 1 of 2 chromosomes from the population and exchanging genes between chromosome by scattered crossover with probability at 0.8 2) Mutation that is taking 1 chromosome and then randomly exchanging genes by uniform mutation with probability at 0.01. After this procedure, new chromosome called "offspring" will be taken. With the 2 procedures, all chromosome has been evaluated in terms of fitness value of probability of selection. Genetic algorithm procedure and selection has been repeated until they arrive the complete conditions. In this regard, there are totally 200 generations of population or the answer has not been changed for 10 generations.

3 Example Testing

In order to test the performance of proposed algorithm and model the 24 testing problems are generated with the parameter according to Table 2. The performance of SILP and GA will be investigated and compare both in solution quantity which represent by Total Cost and time consuming which indicate the algorithm efficiency.

Table 2: Variable discrete random demands in each period

Period (Week)	Demand Levels					
	Best		Majority		Minority	
	Occasion	Quantity	Occasion	Quantity	Occasion	Quantity
1	0.2	25	0.6	40	0.2	50
2	0.2	10	0.6	15	0.2	30
3	0.2	33	0.6	67	0.2	100
4	0.2	50	0.6	55	0.2	60
5	0.2	30	0.6	35	0.2	50
6	0.2	18	0.6	25	0.2	32

Table 2: (continued) Variable discrete random demands in each period

Period (Week)	Demand Levels					
	Best		Majority		Minority	
	Occasion	Quantity	Occasion	Quantity	Occasion	Quantity
7	0.2	25	0.6	40	0.2	50
8	0.2	10	0.6	15	0.2	30
9	0.2	33	0.6	67	0.2	100
10	0.2	50	0.6	55	0.2	60
11	0.2	30	0.6	35	0.2	50
12	0.2	18	0.6	25	0.2	32
13	0.2	10	0.6	15	0.2	30
14	0.2	33	0.6	67	0.2	100
15	0.2	50	0.6	55	0.2	60

Given Holding cost = 0.4 baht/piece/week
Back order cost = 0.6 baht/piece
Ordering cost = 100 baht/time

4 Operating Results

The results from SILP and GA indicate the exact solutions for 24 problems which spend different time as shown in Table 3 and Figure 2.

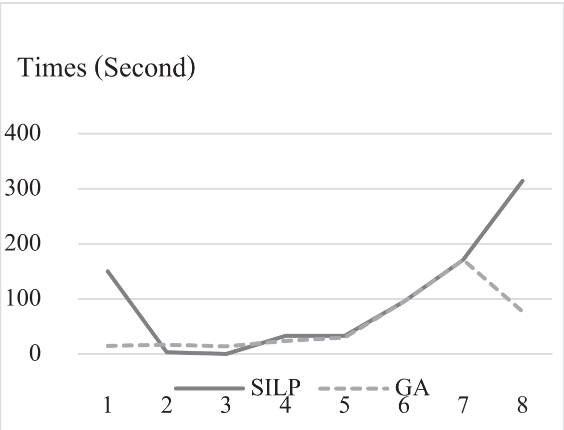

Figure 2: Processing times for SILP and GA

Table 3: Test results with SILP and GA

Problem (Period, Lead time)	Ordering	Cost (Baht)		Time (Second)	
		SILP	GA	SILP	GA
1 (4, 0)	Period 1: Order Period 3: Products receive on demand 150 pieces	257.00	258.16 0.45 %	150	15 -90 %
2 (4, 1)	Period 1: Order Period 2: Products receive on demand 180 pieces	228.76	228.76 0 %	3	17 466 %
3 (4, 2)	Period 1: Order Period 3: Products receive on demand 150 pieces	162.56	162.56 0 %	1	14 1,300 %
4 (5, 1)	Period 1, 3: Order Period 2: Products receive on demand 63 pieces Period 4: Products receive on demand 90 pieces	258.68	258.68 0 %	33	24 -27 %
5 (5, 2)	Period 1: Order Period 3: Products receive on demand 190 pieces	206.76	206.76 0 %	33	30 -9 %
6 (6, 1)	Period 1, 3: Order Period 2: Products receive on demand 63 pieces Period 4: Products receive on demand 128 pieces	290.55	290.55 0 %	95	95 0 %
7 (6, 2)	Period 1: Order Period 3: Products receive on demand 228 pieces	269.45	269.45 0 %	171	171 0 %
8 (6, 3)	Period 1: Order Period 4: Products receive on demand 128 pieces	198.67	198.67 0 %	314	77 -75 %
9 (7, 2)	Period 1: Order Period 3: Products receive on demand 150 pieces and order Period 5: Products receive on demand 107 pieces	NA	313.14	NA	317
10 (7, 3)	Period 1: Order Period 4: Products receive on demand 167 pieces	NA	250.38	NA	516
11 (8, 3)	Period 1, 3: Order Period 4: Products receive on demand 90 pieces Period 6: Products receive on demand 92 pieces	NA	310.30	NA	837
12 (8, 4)	Period 1: Order Period 5: Products receive on demand 142 pieces	NA	302.45	NA	1,581
13 (9, 3)	Period 1, 4: Order Period 4: Products receive on demand 128 pieces Period 7: Products receive on demand 113 pieces	NA	362.45	NA	3,339
14 (9, 4)	Period 1, 3: Order Period 5: Products receive on demand 68 pieces Period 7: Products receive on demand 113 pieces	NA	382.18	NA	3,455
15 (10, 1)	Period 1, 3, 5, 8: Order Period 2: Products receive on demand 63 pieces Period 4: Products receive on demand 90 pieces Period 6: Products receive on demand 92 pieces Period 9: Products receive on demand 149 pieces	NA	547.74	NA	2,536
16 (10, 3)	Period 1, 3, 6: Order Period 4: Products receive on demand 90 pieces Period 6: Products receive on demand 92 pieces Period 9: Products receive on demand 149 pieces	NA	455.86	NA	736
17 (10, 5)	Period 1, 4: Order Period 6: Products receive on demand 92 pieces Period 9: Products receive on demand 149 pieces	NA	440.72	NA	484
18 (11, 0)	Period 1: Order 113 pieces Period 4: Order 90 pieces Period 6: Order 92 pieces Period 9: Order 67 pieces Period 10: Order 90 pieces	NA	647.55	NA	14,277
19 (11, 1)	Period 1, 3, 6, 9: Order Period 2: Products receive on demand 63 pieces Period 4: Products receive on demand 128 pieces Period 7: Products receive on demand 113 pieces Period 10: Products receive on demand 90 pieces	NA	571.13	NA	9,946
20 (11, 3)	Period 1, 4, 7: Order Period 4: Products receive on demand 128 pieces Period 7: Products receive on demand 113 pieces Period 10: Products receive on demand 90 pieces	NA	479.25	NA	7,127

5 Conclusions

The suitable answers to the problems from SILP and GA are similar but the time to find the answers are different.The results find the proper answer is found that. The problem 1 SILP provides a lower cost than GA 0.45% but GA takes the processing time less than SILP 90%. The problem 2 SILP provides cost is not different from GA but SILP takes the processing time less than GA 466.67%. The problem 3 SILP provides cost is not different from GA but SILP takes the processing time less than GA 1300.00 The problem 4 SILP provides cost is not different from GA but GA takes the processing time less than SILP 27.27%. The problem 5 SILP provides cost is not different from GA but GA takes the processing time less than SILP 9.09%. The problem 6 SILP provides cost and takes the processing time is not different from GA. The problem 7 SILP provides cost and takes the processing time is not different from GA. The problem 8 SILP provides cost is not different from GA but GA takes the processing time less than SILP 75.48%. The problem 9 to problem 20 SILP cannot find the cost at proper. The problem 21 to problem 24 SILP and GA cannot find the cost at proper.

Thus, when the big problem happens, the GA is more effective than SILP in terms of finding the suitable and applicable answers. When more period of time is taken, the SILP is proper for small problems which has less than 6 periods and GA proper for big problems which has complexity of less than 11 periods.

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