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Genetic Algorithm Parameters in a Vendor Managed Inventory Model

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***Abstract*— To handle the information exchange problem between a vendor and a retailer, Vendor Managed Inventory (VMI) provides a good approach to handle the problem. Information exchanges between both sides enhance supply chain performance. In a previous research work, a stochastic model for one vendor and one retailer has been developed. Simulation optimization using genetic algorithm (GA) has been use to solve the problem. There are 2 important parameters in genetic algorithm (probability of mutation and probability of crossover). This research aims at analyzing relations between GA parameters and optimal solutions. This research compares many combinations of GA parameters and the effects on optimal solutions and time to reach the optimal solutions. This research concludes that the best combination reaches the optimal solutions. Unfortunately, the best combination is only suitable for a certain condition and increasing/reducing GA parameters values do not automatically improve the optimal solutions.**

Keywords- Inventory, optimization

I. Introduction

There are many problems in a supply chain system. One of the basic problems in the supply chain system is lack of information exchanges between a retailer and a vendor. In a traditional inventory system, a retailer places an order based on his own interest. The vendor will fulfill the retailer order by delivering the product. Supply chain members have their own inventory control policies and they do not share their inventory information.

On modern supply chain networks, VMI has become an interesting topic in the management of the inventory system. VMI is different to the traditional inventory systems. In VMI, replenishment decision is delegate to the vendor. The vendor, therefore, monitors the retailer's inventory level and makes corresponding replenishment decisions. Applying VMI, the vendor will know the real demand and he does not rely on the retailer order, which may not be the real demand, and hence, bullwhip effect can be avoid. VMI has become an interesting topic in supply chain management since Wal-Mart and Procter & Gamble successfully implemented VMI in the late 1980s. VMI application helps reduce costs and improves service level [12].

Some research works have been done related to VMI environment. Research works on VMI have grown from one vendor-one retailer system into one vendor - multiple retailer system. Deterministic and stochastic demands have been considered in various VMI research works. Related to VMI models with one vendor and one retailer system, there are some research works focused on this area [1], [16], [11], [17], [8], [2], [7]. On the other hand, various VMI models with one vendor and one retailer system under stochastic demand have been developed by [4],[13],[15],[3],[6], and [10].

A VMI model using (t, q) policy has been developed by [10]. The research paper employed simulation-optimization technique using genetic algorithm to find optimal solutions. They use genetic algorithm parameters, which are recommended by the software. In fact, genetic algorithm parameter optimal settings follow model characteristics. Therefore, this research analyzes effects of genetic algorithm parameters on optimal solutions and time to reach the optimal solutions.

II. Literature Review

In the traditional inventory systems, a retailer places an order to his vendor based on his own interest. The vendor will fulfill the retailer order by delivering the product. In VMI, replenishment decision is delegated to the vendor. The vendor, therefore, monitors the retailer's inventory level and makes corresponding replenishment decisions.

Related to the research works with one vendor and one retailer system under deterministic demand, some research findings have been made. Profits after VMI implementation are always higher than the ones before VMI [1]. How profits distributed among a supplier and a buyer in a supply chain system was examined by [16]. By taking into consideration shipment cost in inventory costs [11] criticized [16]. In another direction, a multi-product EOQ model in which (R, Q) policy was employed and the model was solved by Genetic algorithm to find optimal solutions [8]. An integrated single product inventory model and shelf space arrangement under VMI and consignment stock has been developed by [2]. Related to green supply chain, integration of VMI policy and green supply chain aspects was proposed by [7]

Related to VMI research works for one vendor and one retailer system under stochastic demand, some research findings have been done. A VMI model, where Company A used (r, Q) policy to replenish the materials to company B and Company B produced Company A's order after a number of orders, has been developed by [4]. A Markov decision model was developed in this research. A VMI model for one vendor and one retailer with a third-party logistics service provider has been developed by [14]. Response Surface Methodology and particle swarm optimization was employed to find the optimal solutions through simulation. A VMI contract with consignment stock was designed by [5].

A VMI model for one vendor and one retailer using (t,q) policy was developed by [10]. Due to the complexity of the problem, simulation optimization using genetic algorithm (GA) was used to find the optimal solutions. They used GA parameters which were recommended by the software builder. In fact, the most suitable GA parameters follow model characterizations. This research, therefore, analyze the effects of GA parameter on optimal solutions and the time to reach the optimal solutions.

III. Methodology

This research analyzes the relation between genetic algorithm parameters and objective function value and the time to reach the optimal solutions. Some experiments have been conducted. This research uses the model which has been developed by [10]. The model aims at minimizing the total system cost. The total cost consists of vendor order cost, vendor holding cost, delivery cost, retailer holding cost and lost sales cost.

Data is collected using @RiskOptimizer software. The research steps are as follows.

1. Determining the genetic algorithm parameters

The objective of this research is to analyze the effects of GA parameter on optimal solutions of the model. There are four GA main parameters [9]:

1. Probability of crossover (Crossover rate)
2. Probability of mutation (Mutation rate)
3. Population size
4. Number of generations

Only two GA parameters will be analyzed in this research. The parameters are the probability of crossover (Pc) and the probability of mutation (Pm).

2. Determining values of each parameter

This research combines some values of probability of crossover (Pc) and probability of mutation (pm). The values for probability of crossover are 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9. The same values are used for the probability of mutation. So, this research has 81 sets of experiments for each scenario.

3. Conducting research experiments

In this research, Factorial experiment method is employed as recommended by [9]. The method is used to identify the best GA parameter values in order to find the optimal solutions.

4. Research results analysis and Concluding research results

In this research, effects of GA parameters on optimal solutions are studied. The value of optimal solutions and the time to reach optimal solutions are discussed in this paper.

IV. VMI Model Review

In this research, A VMI model, which was developed by [10], is employed. This section will describe the model. The model aims at minimizing the expected of total system cost. Simulation-optimization using genetic algorithm is employed to find the decision variables. The following notations will be use throughout this paper:

Q	vendor's order lot size
q	retailer's lot size
T	vendor cycle time
t	retailer cycle time
n	number of replenishments in a vendor cycle
AVO	average vendor order cost per time unit
VOC	vendor order cost per order
C_{VH}	unit holding cost at the vendor site ($/unit/unit time)
AT_V	average vendor holding cost per time unit
D_c	delivery cost per time unit
C_d	delivery cost per delivery
BIP_i	retailer beginning inventory position for cycle i
EIP_i	retailer ending inventory position for cycle i
D_i	customer demand for cycle i
RHC_i	the retailer holding cost per unit time in cycle i
t_1	time when the inventory position equals to 0
HR	unit holding cost at retailer site ($/unit/unit time)
ERHC	expected retailer holding cost per unit time
RLC_i	retailer lost sales cost for cycle i
LS	unit cost of lost sales ($/unit)
ERLC	expected retailer lost sales cost per unit time
D	average retailer demand per unit of time
SU_i	shortage amount for cycle i

The VMI system behavior is describe as follows.

1. The system starts with a vendor placing order to his external supplier with ample capacity. The vendor's order lot size is Q units.
2. The vendor delivers q units of product every t units of time to the retailer. The replenishment cycle time of the retailer (t) is fixed.
3. During a vendor cycle time (T), there is n replenishments. Consequently, T equals to the number of replenishments in a vendor cycle multiplied by the length of a retailer cycle (t).

The relations of the retailer's cycle time, the vendor's cycle time, the retailer's lot size, the vendor' lot size and number of replenishment in a vendor cycle are shown on Formulas 1 and 2 as follows.

$$T = n * t \quad (1)$$

$$Q = n * q \quad (2)$$

It is noted that, customer demand at the retailer is stochastic. The retailer inventory position will be reduced gradually due to stochastic demand. This VMI model is developed for a single non-deteriorating product. Demand observed by the retailer is assumed to follow Poisson distribution. The model is assumed that delivery lead time from vendor to retailer is negligible. The inventory policy considers shortage as lost sales. There is a lost sales cost which is incurred to the system when shortages occur.

The total system cost is the sum of the vendor costs and the retailer costs. The vendor costs consist of vendor order cost, vendor holding cost and delivery cost. On the other hand, the retailer costs consist of holding cost and lost sales cost. It is noted that all system costs are paid by the vendor.

Vendor order cost is incurred one time in a vendor cycle. The average vendor order cost per time unit (AVO) is calculated as vendor order cost (VOC) divided by the length of a vendor cycle (T) as shown by Formula 3.

$$AVO = \frac{VOC}{T} = \frac{VOC}{n * t} \quad (3)$$

The vendor inventory position is reduced due to the delivery of product from the vendor to the retailer. An illustration of vendor inventory position is presented in the Fig. 1 for the case when the number of replenishments equals to three.

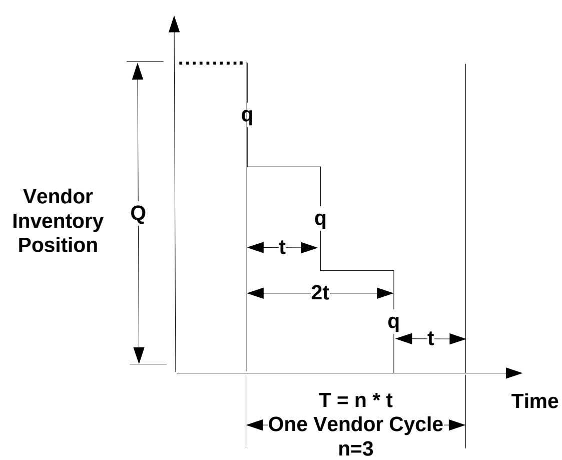

Figure 1. Vendor Inventory Position

The total vendor holding cost in a vendor cycle (T_V) is calculated by using Formula 4 as follows.

$$T_V = C_{VH} * t * q * n * (\frac{(n-1)}{2}) \quad (4)$$

From the above expression, the average total vendor holding cost per time unit (AT_V) can be determined by using Formula 5 as follows.

$$AT_V = \frac{T_V}{T} = \frac{C_{VH} * t * q * n * (\frac{(n-1)}{2})}{n * t} = \frac{C_{VH} * q}{2}(n-1) \quad (5)$$

Delivery cost is incurred one time per delivery. So the delivery cost per time unit (D_c) will be delivery cost per delivery (C_d) divided by retailer cycle time (t) as shown by Formula 6.

$$D_c = \frac{C_d}{t} \quad (6)$$

For retailer costs calculation, the simulation model developed will observe some data.

1. Retailer beginning inventory position for cycle i (BIP_i). BIP_i is defined as the retailer inventory position right after a replenishment in cycle i.
2. Retailer ending inventory position for cycle i (EIP_i). EIP_i is defined as the retailer inventory position right before a replenishment in cycle *i*.
3. Customer demand for cycle i (D_i). D_i is defined as a stochastic demand and its value will be generated through simulation process.

The model is simulated 40 cycles of retailer. The following procedure is used in the model.

a. For the first cycle, the beginning inventory position equals to retailer's lot size as shown by Formula 7.

$$BIP_1 = q \quad (7)$$

For the next cycles, the beginning inventory position of cycle *i* equals the ending inventory position of cycle (*i*-1) plus retailer's lot size as can be seen on Formula 8.

$$BIP_i = EIP_{i-1} + q \quad (8)$$

b. Demand for cycle *i* (D_i) follows Poison distribution with parameter lambda. Lambda is average retailer demand per unit of time.

c. Ending inventory position of cycle *i* (EIP_i) is determined by Formula 9 as follows.

$$EIP_i = \text{Max}\ \{0, BIP_i - D_i\} \quad (9)$$

d. Shortage amount at the end of cycle *i*, SU_i , is determined by Formula 10 as follows.

$$SU_i = Max\{0, D_i - BIP_i\} \quad (10)$$

e. Repeat step *a* - *d* for 40 cycles. However, the first 10 cycles are consider as warm up period, only the results of the last 30 cycles are used for data collection purpose.

For analyzing retailer's costs, the model considers retailer inventory positions at the beginning and at the ending of a retailer cycle. There are two possible scenarios that may occur for the ending inventory position in a retailer cycle (EIP_i).

a. The first scenario is the ending inventory position equals to 0, due to shortages are not backlogged.
b. The second scenario is the ending inventory position is more than 0.

Above scenarios can be describe in the Figs. 2 and 3 below.

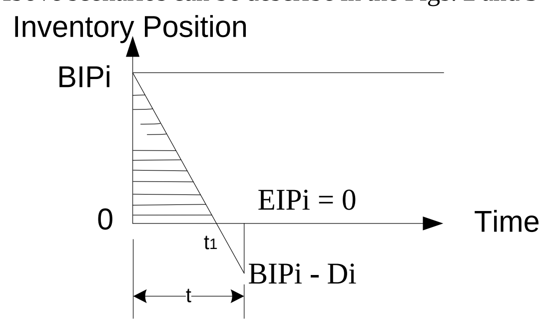

Figure 2. The first scenario

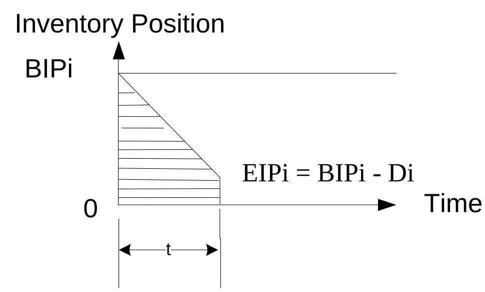

Figure 3. The second scenario

For both scenarios, the general formula for the retailer holding cost per unit time in cycle i (RHC_i) is expressed on Formula 11 as follows.

$$RHC_i = HR * \left(\frac{BIP_i + Max\{0, (BIP_i - D_i)\}}{2\left[1 - \frac{Min\{0, (BIP_i - D_i)\}}{BIP_i}\right]} \right) \quad (11)$$

where: HR is unit cost of holding retailer stock ($/unit/time unit).

Hence, the expected retailer holding cost per unit time (ERHC) is calculate by using Formula 12 as follows.

$$ERHC = \frac{\sum_{i=11}^{40} RHC_i}{30} \quad (12)$$

Retailer lost sales cost for cycle i (RLC_i) is calculated as the accumulated shortage amount at the end of the cycle multiplied by unit cost of lost sales. Therefore, retailer lost sales cost per unit time in cycle i (RLC_i) and expected retailer lost sales cost per unit time (ERLC) are calculated by using Formula 13 as follows.

$$RLC_i = LS * \frac{Max\{0, (D_i - BIP_i)\}}{t} \quad (13)$$

where : LS is unit cost of lost sales ($/unit) .

Expected retailer lost sales cost per time unit (ERLC) is calculated by using Formula 14 as follows.

$$ERLC = \frac{\sum_{i=11}^{40} RLC_i}{30} \quad (14)$$

For total system costs calculation, we can determine the total system cost per time unit as given by Formula 15 as follows.

$$\text{Total system cost} = AVO + \mathrm{AT_V} + \mathrm{D_c} + ERHC + ERLC \quad (15)$$

V. Results and Discussions

A. Results

In this research, A VMI model, which was developed by [10], is employ. The objective of this research is to analyze the effects of GA parameter on optimal solutions and the time to reach the optimal solutions. Two scenarios are developed. The input data for each scenario is show in the Table 1 below.

TABLE I. INPUT DATA

Input Data	Scenario 1	Scenario 2	Unit
Vendor Order Cost (VOC)	1000	1000	USD Per Pesanan
Vendor Holding Cost (CVH)	0,75	0,5	USD Per Unit Per Unit Waktu
Delivery Cost (Cd)	40	40	USD Per Pengiriman
Retailer Holding Cost (HR)	2	2	USD Per Unit Per Unit Waktu
Retailer Lost Sales Cost (LS)	4	4	USD Per Unit

Some software optimization settings are set as follows in the Table II.

TABLE II. SOFTWARE SETTINGS

Parameter		Values
Population Size		50
Random Number Seed		123
Number of Simulation (Max)		1000
Number of iterations		500
Stopping Criteria		
	Maximum Change	0.01%
	Number of Simulation	100

As the results of this research, 81 values of optimal solutions are found using simulation optimization software @RiskOptimizer for each scenario. The experiment results are show in the Table III, and IV below.

TABLE III. OPTIMAL SOLUTIONS (SCENARIO 1)

Parameter Values		Probability of Mutation 0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
Pc	0,1	924,487	924,091	924,203	924,600	948,551	933,903	926,142	940,179	955,782
	0,2	932,512	935,337	924,475	925,353	932,725	940,179	963,686	940,179	924,149
	0,3	955,247	938,966	940,179	926,254	958,096	924,309	927,111	940,179	958,096
	0,4	924,090	924,215	924,118	938,932	**924,089**	925,554	928,273	940,179	948,273
	0,5	934,480	924,190	931,328	924,711	958,096	931,675	963,686	940,179	958,096
	0,6	1051,218	924,090	927,327	928,691	924,254	924,166	958,096	940,179	948,273
	0,7	924,099	924,142	924,127	926,779	924,172	925,439	931,161	940,179	948,273
	0,8	924,099	954,002	940,179	924,483	946,809	950,464	934,476	940,179	948,273
	0,9	958,096	924,099	924,298	927,319	925,657	955,726	938,809	940,179	948,273

TABLE IV. OPTIMAL SOLUTIONS (SCENARIO 2)

Parameter Values		**Probability of Mutation**								
		0,1	**0,2**	**0,3**	**0,4**	**0,5**	**0,6**	**0,7**	**0,8**	**0,9**
Pc	0,1	1463,718	841,354	840,758	863,133	856,846	852,340	872,679	845,227	856,846
	0,2	840,785	852,893	840,773	841,721	848,341	840,835	866,084	856,846	848,153
	0,3	840,761	841,171	840,757	863,133	856,846	856,846	872,679	856,846	856,846
	0,4	840,962	840,848	840,810	908,512	854,506	856,846	872,679	856,846	848,153
	0,5	841,132	843,385	852,820	848,274	844,550	856,846	872,679	856,846	856,846
	0,6	864,496	853,433	855,894	844,944	841,533	852,236	872,679	856,846	840,766
	0,7	840,758	842,204	848,670	908,512	856,846	842,260	841,556	856,846	842,839
	0,8	840,759	840,769	841,023	844,006	853,606	856,224	868,659	856,846	856,430
	0,9	**840,756**	840,761	842,776	841,149	843,414	856,846	856,846	856,846	856,430

Each experiment needs different times to reach their optimal solution. Times to reach the optimal solution are shown in the Table V and VI below.

TABLE V. TIME TO REACH THE OPTIMAL SOLUTION (SCENARIO 1)

Parameter Values		**Probability of Mutation**								
		0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
Probability of Crossover	0,1	0:03:39	0:04:38	0:06:57	0:01:57	0:04:00	0:02:48	0:02:22	0:01:14	0:01:19
	0,2	0:01:47	0:02:45	0:03:26	0:01:36	0:03:07	0:01:30	0:01:04	0:01:10	0:02:53
	0,3	0:01:44	0:02:26	0:01:09	0:03:39	0:01:14	0:04:59	0:04:41	0:01:09	0:01:18
	0,4	0:10:08	0:01:43	0:01:40	0:02:00	**0:08:30**	0:03:19	0:01:37	0:01:09	0:03:04
	0,5	0:02:20	0:06:21	0:02:36	0:03:23	0:01:26	0:03:06	0:01:03	0:01:08	0:01:11
	0,6	0:00:08	0:07:46	0:02:43	0:02:41	0:05:21	0:08:03	0:01:27	0:01:07	0:02:56
	0,7	0:02:10	0:03:53	0:04:14	0:05:18	0:02:56	0:04:30	0:05:47	0:01:08	0:02:58
	0,8	0:07:46	0:02:19	0:01:38	0:03:20	0:04:20	0:05:51	0:03:40	0:01:11	0:02:56
	0,9	0:01:18	0:08:36	0:04:42	0:02:15	0:02:10	0:03:12	0:04:07	0:01:08	0:02:55

TABLE VI. TIME TO REACH THE OPTIMAL SOLUTION (SCENARIO 2)

Parameter Values		**Probability of Mutation**								
		0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
Probability of Crossover	0,1	0:04:08	0:04:18	0:04:08	0:01:01	0:01:06	0:02:07	0:01:21	0:01:27	0:01:09
	0,2	0:01:26	0:03:47	0:04:48	0:03:23	0:02:12	0:06:40	0:01:52	0:01:08	0:02:22
	0,3	0:03:39	0:05:08	0:06:46	0:01:01	0:01:07	0:01:08	0:01:23	0:01:08	0:01:09
	0,4	0:01:41	0:08:47	0:02:59	0:01:07	0:02:13	0:01:08	0:01:24	0:01:08	0:02:20
	0,5	0:02:28	0:03:53	0:02:17	0:05:59	0:03:34	0:01:07	0:01:21	0:01:08	0:01:10
	0,6	0:02:00	0:03:54	0:01:35	0:03:33	0:03:53	0:03:00	0:01:23	0:01:08	0:03:26
	0,7	0:07:21	0:02:11	0:01:16	0:01:06	0:01:07	0:02:16	0:02:26	0:01:08	0:03:37
	0,8	0:03:05	0:02:45	0:02:10	0:05:07	0:01:33	0:03:14	0:02:25	0:01:09	0:02:11
	0,9	0:06:18	0:05:05	0:02:28	0:03:17	0:02:08	0:01:05	0:01:24	0:01:07	0:02:12

To simplify the analysis process, the simulation results are plotted in the Fig. 4 to 11 as follows.

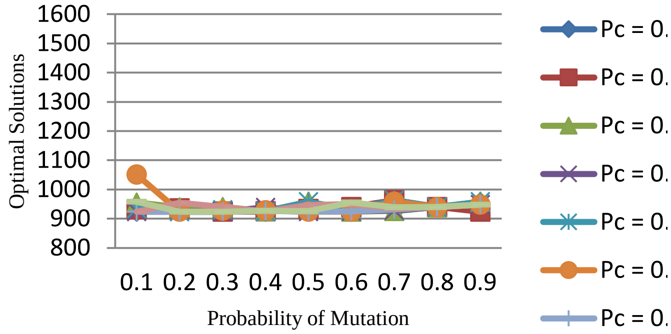

Figure 4. Effects of Pm values on optimal solutions (Scenario 1)

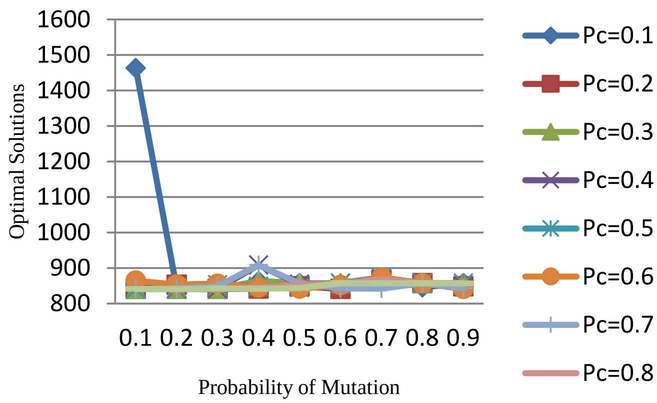

Figure 5. Effects of Pm values on optimal solutions (Scenario 2)

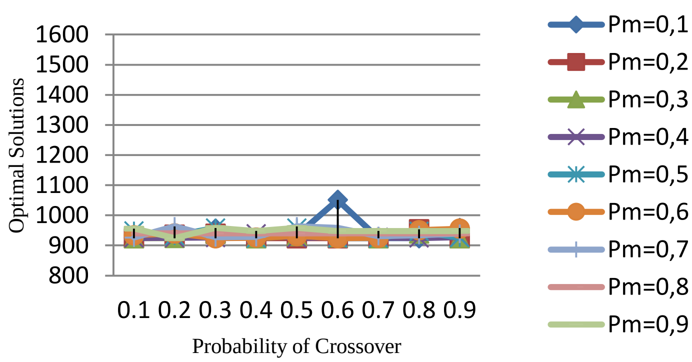

Figure 6. Effects of Pc values on optimal solutions (Scenario 1)

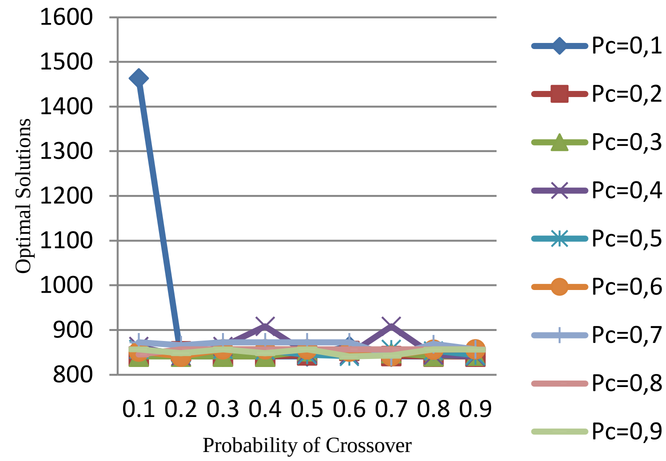

Figure 7. Effects of Pc values on optimal solutions (Scenario 2)

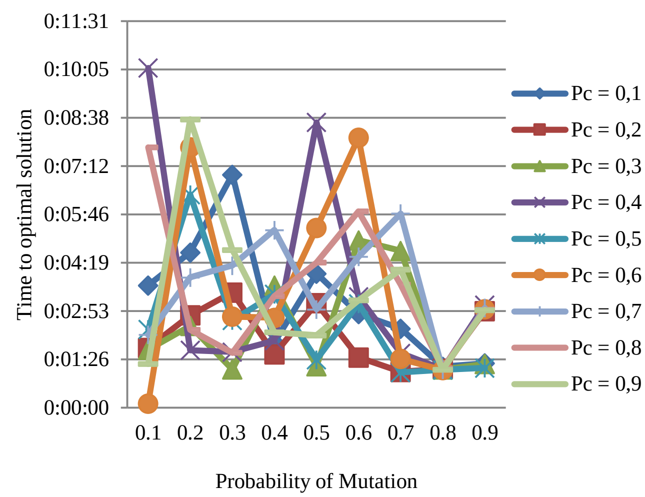

Figure 8. Effects of Pm on time to optimal solution (Scenario 1)

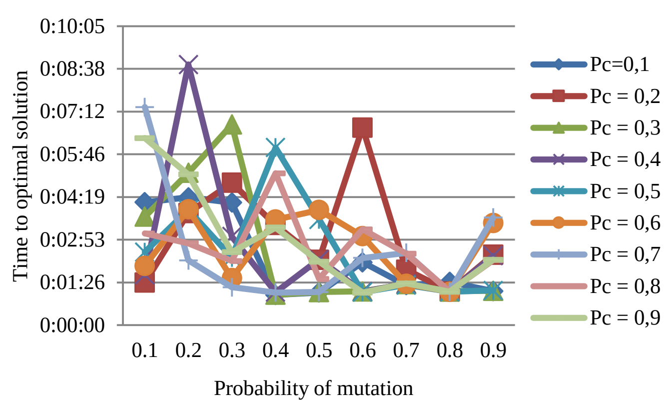

Figure 9. Effects of Pm on time to optimal solution (Scenario 2)

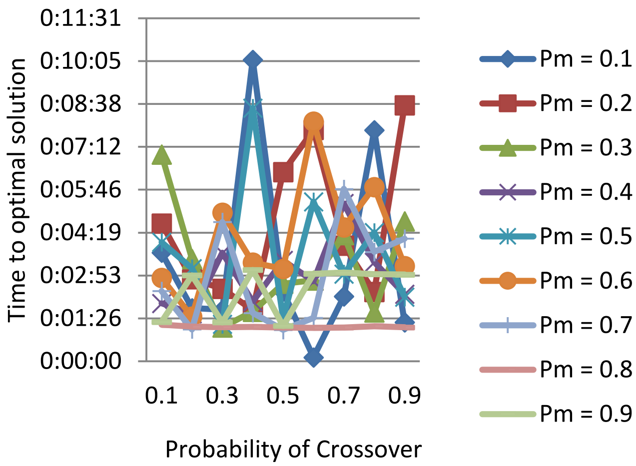

Figure 10. Effects of Pc on time to optimal solution (Scenario 1)

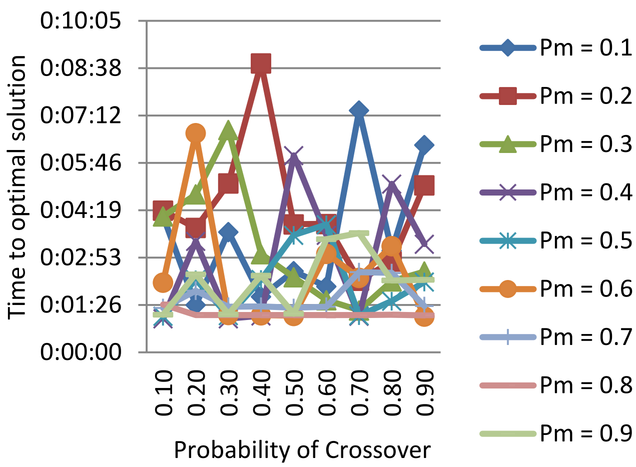

Figure 11. Effects of Pc on time to optimal solution (Scenario 2)

B. Discussions

The simulation results for scenario 1 are shown in Table 3. The best combination for scenario 1 is 0.5 for probability of mutation and 0.4 for probability of crossover. The total systems cost is 924.089 USD/time unit. Statistically, the optimal solutions have maximum values of 1051.218 USD/time unit, the average is 937,447 USD/time unit and the standard deviation is 17.675 USD/time unit (1,9% from the average). Fig. 4 and 6 confirm that changing of probability of mutation and crossover have small effect to optimal solutions.

The simulation results for scenario 2 are show in Table 4. The best combination for scenario 2 is 0.1 for probability of mutation and 0.9 for probability of crossover. The total systems cost is 840.756 USD/time unit. Statistically, the optimal solutions have maximum values of 1463.7180 USD/time unit, the average is 860.077 USD/time unit and the standard deviation is 69.141 USD/time unit (8% from the average). Fig. 5 and 7 confirm that changing of probability of mutation and crossover mostly have small effect to optimal solutions, except Pm and Pc equal to 0.1.

Times to reach the optimal solutions for scenario 1 are show in Table 5. The time to reach the best optimal solution for scenario 1 is 8 minutes 30 second (08:30). Statistically, the minimum time to reach optimal solution is 8 seconds, the average is 3 minutes 9 seconds, the maximum is 10 minutes 8 seconds and the standard deviation is 2 minutes 5 seconds (66% from average). Fig. 8 and 10 confirm fluctuations of times to reach optimal solutions.

Times to reach the optimal solutions for scenario 2 are show in Table 6. The time to reach the best optimal solution for scenario 2 is 6 minutes 18 seconds (06:18). Statistically, the minimum time to reach optimal solution is 1 minute 1 second, the average is 2 minutes 37 seconds, the maximum is 8 minutes 47 seconds and the standard deviation is 1 minute 42 second (65% from average). Fig. 9 and 11 confirm fluctuations of times to reach optimal solutions.

VI. CONCLUSION

This research aims at analyzing relations between GA parameters and the optimal solutions. The observed parameters are probability of mutation and probability of crossover. Based on the research results, the best optimal solutions are reach by different GA parameters. The best combination for scenario 1 is 0.5 for the probability of mutation and 0.4 for the probability of crossover. On the other hand, the best combination for scenario 2 is 0.1 for the probability of mutation and 0.9 for the probability of crossover. Statistically, the standard deviation of optimal solutions is 1.8% (from average) for scenario 1 and 8% (from average) for scenario 2. This means that the optimal solutions for scenario 2 are more diverse than scenario 1. For times to reach the optimal solution, scenario 1 are also more diverse than scenario 2. This research concludes that a combination of mutation rate and crossover rate is only suitable for a certain condition. In this research, increasing/reducing GA parameters values do not automatically improve the optimal solutions and time to reach the optimal solutions.

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