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Optimization of Multi-Product Aggregate Production Planning Using Improved Genetic Algorithm

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Abstract— **Medium-term production planning with aggregate production planning (APP) is a crucial step in the manufacturing industry's supply chain. The essential phase determines the production size of each product over a planning horizon. Poor planning will undoubtedly directly impact the company regarding production costs and profits. The aggregate production planning is classified as NP-Hard combinatorial problem. Thus, a powerful approach is required. Most models in aggregate production planning consider a single product. This study modeled aggregate production planning to address a multi-period and multi-product. Thus, a more complex mathematical model is required. Implementing genetic algorithms (GA) may solve the problem with reasonably good solutions. This study aims to improve the GA by applying real-coded chromosomes and the adaptive change of crossover and mutation rates based on predetermined change criteria. The planning produced by the modified genetic algorithm is compared to the manufacturer's actual planning to prove the proposed approach's effectiveness. A set of computational experiments proves that adaptive evolution enables the genetic algorithm to balance its exploration and exploitation ability and obtain better solutions. The modified GA produces a less fluctuating pattern of the production amount. Even though the modified GA yields more inventory cost, the high cost of recruiting new workers can be eliminated. Using the proposed approach, the company can reduce 9 percent of the production cost.**

Keywords— **Aggregate production planning; adaptive genetic algorithm; crossover; mutation.**

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I. Introduction

Production planning is a vital process in manufacturing industries. It will significantly affect the costs incurred as well as the profits of the company. It is demanding for multi-product companies and considers production a combinatorial problem with many possible solutions [1], [2]. It may depend on processing inputs and outputs, influenced by some factors of an unknown nature [3]. In lead time, uncertainties may occur and trigger potential risks. The business may fail due to an expenditure expansion or a timetable extension [4]. In other words, the planning retains time and budget for production, optimal allocation of production resources, and reduces waste [5]–[7]. The precision of the production planning is thus of considerable significance.

Production planning for subsequent periods can use the term aggregate production planning. Aggregate production planning is a manufacturing and supply-related planning to satisfy market demand at reduced production costs [8]. The plan relates to the manufacturing resources used to respond to the anticipated market demand [5]. It aims to decide the output level in the medium term and to face unpredictable market demand. The multi-product aggregate production planning determines the production size of each product while considering inventory level, resource utilization, workforce levels, sale forecasts, and fluctuating demand requirements over a planning horizon. The planning horizon may range from 3 to 18 months [9]. The multi-product aggregate production planning should consider several constraints and rules that apply to the company. The position of the aggregate production planning, among other manufacturing stages for the case used in this study, is depicted in Fig. 1. As shown in Fig. 1, the focus of this study is depicted by gray shapes. The forecasting is required to obtain the quantity of consumer demand for each product type over a planning horizon. The aggregate production planning generates the number of each type that must be produced. The scheduling addresses the determination of starting time for producing each product type. Finally, the production process is carried out.

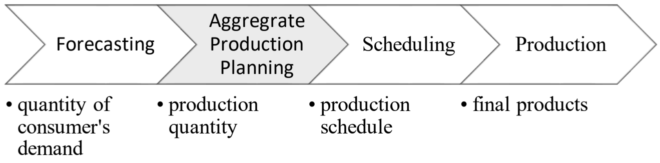

Fig. 1 Manufacturing Process Stages

Most of the research in this area considers maximizing profit or minimizing costs as their objectives. Most models in aggregate production planning consider single products. This study modeled aggregate production planning to address a multi-period and multi-product. Thus, a more complex mathematical model is required. This study proposes a modified genetic algorithm to solve the problem. The planning produced by the modified genetic algorithm is compared to the manufacturer's actual planning to prove the proposed approach's effectiveness.

Aggregate production planning is one of the examples of heuristic problems that exist in real life. The problem has attracted both practitioners and academics. Various approaches for aggregate production planning are in place, such as a staff capability strategy, a demand-driven strategy, and a hybrid strategy that combines various strategies for better performance. There are various ways to solve the problem; one of them is the application of computational methods. Various methods are applied to solve aggregate production planning problems: interval programming modeling [10], fuzzy linear programming [11], fuzzy multi-objective mixed integer linear programming [12], fuzzy TOPSIS and goal programming [13], variable neighborhood search [14], simulated annealing [15], and genetic algorithm [1], [8]. These computational approaches efficiently solve problems in complex mixed selection events, uncertainties [13], and long-term production planning [16]. It is practical yet potential to develop.

More specifically, the genetic algorithm (GA) overcomes the manufacturing problems of raw material classification [17], scheduling, planning, machine selection, production process [18], maintenance, and distribution of the final product [19], [20]. This approach can solve the composite issues of production planning and maintenance [21]. Such research indicates that GA can answer multi-product production planning problems. However, the random nature of GA's operator may lead to exploring unpromising search areas or falling in local optimum points. Furthermore, a conventional GA may require excessive computational time. Modifying a conventional GA may increase the quality of solutions [22]. The modification includes crossover mating scheme [23], [24], reproduction operators [25], [26], adaptive parameter values [27], and using a special strategy for generating an initial population [28]–[31]. This study offers the modification of GA with an adaptive change of crossover and mutation rates based on some predetermined change criteria. Another modification here is the genetic reproduction operator to find better solutions in a vast search area.

II. Materials and Method

A. Case Study

This research uses case studies of a school uniform manufacturing company. The company makes 18 different products, each of which has eight different sizes, is considered a multi-product. Planning is essential for future production, requiring consumer demand prediction in the upcoming 12 months [14], [32]. Here, we use a simple linear regression prediction due to its simplicity. Afterward, planning refers to the prediction result, which should consider the company restrictions and rules. This study uses a mixed strategy, so several variables are used in performing aggregate production planning, as shown in Table 1.

TABLE I
Parameters on Aggregate Production Planning

Parameters	Description
n	number of workers
rt	the average number of products produced by workers per day (regular time)
ot	the average number of products produced by workers per day (overtime)
sc	the average number of products produced by workers per day (subcontract)
wrt	working hours in a day (regular time)
wot	maximum overtime hours (overtime)
msc	maximum number of subcontract workers
crt	regular time cost production
cot	overtime cost production
csc	subcontract cost production
rw	number of new recruited workers (hiring)
pnw	average production amount per new worker in a day
crw	the cost of recruit workers
lo	number of workers laid off
clo	the cost of laying off workers
ps	the number of production shortages
i	number of products on storage (inventory)
ci	storage cost per product

For the considered case, there are two strategies for production planning. The first strategy is make-to-order, which starts when customer demands are received [33]. Thus, total production in a certain month equals the total of customer's demands in the month. The second strategy uses a fixed monthly production rate according to total product demand in a year based on forecasting. The first strategy will increase the cost of recruiting new workers and overtime hours when the production rate increase. The additional cost is also required for firing workers when the production rate increase. The second strategy will increase storage costs. The aggregate production planning is designed to reduce the weakness of the strategies. The difference between make-to-order strategy (MTO), fixed production rate strategy (FIX), and aggregate production planning is illustrated in Fig. 2. The figure shows that APP is less fluctuant than MTO. Thus, it will reduce the cost of recruiting new workers and overtime hours.

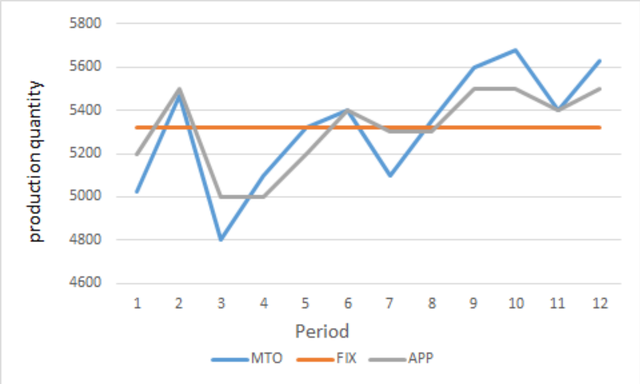

Fig. 2 Strategies for Production Planning

The overall stage in this study is depicted in Fig. 3. The first stage is determining the planning variables, as shown in Table 1. The second stage of aggregate production planning is to forecast the next period of demand in advance based on the data of the current period. Modeling of the genetic algorithm is done in the next stage so that the algorithm can effectively solve the aggregate production planning. A chromosome design is also developed in this stage to represent possible solutions to the problem. In this stage, the contribution of this study is also explained. The next stage is determining the best parameter values of the genetic algorithm to generate the optimal solution. The last stage is running the genetic algorithm several times to prove the effectiveness of the proposed approach.

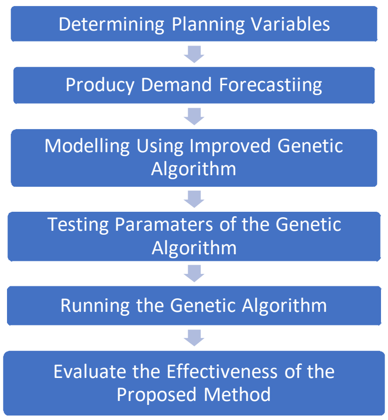

Fig. 3 Research Stages

B. *Numerical Illustration*

This section illustrates an example of APP from the start; demand forecasting to the application of modified genetic algorithms to determine the size of its production capacity. The sample data used are white shirt production data with eight different sizes for 12 months, starting from September 2015 to August 2016, as shown in Table 2.

TABLE II
SAMPLE PRODUCT DATA

Period	Size							
	II	III	IV	V	S	M	L	XL
Sep 2015	5	81	181	192	127	124	65	65
Oct 2015	0	60	137	136	163	144	46	75
Nov 2015	2	30	159	237	196	163	121	39
Dec 2015	10	10	115	188	168	135	75	25
Jan 2016	5	43	118	208	145	408	110	34
Feb 2016	10	30	91	100	101	95	85	50
Mar 2016	5	77	177	257	179	144	86	27
Apr 2016	20	190	299	830	244	224	138	71
May 2016	128	485	483	446	417	364	109	128
Jun 2016	211	548	611	575	236	181	176	122
Jul 2016	177	1024	1802	1142	978	821	831	333
Aug 2016	134	789	1243	824	690	571	455	166

The aggregate production planning process uses the following parameters:

- $n = 10$
- $rt = 17$
- $ot = 5$
- $sc = 15$
- $wrt = 8$
- $wot = 3$
- $msc = 3$
- crt = IDR 23,000
- cot = IDR 28,000
- csc = IDR 30,000
- $rp = 12$
- crw = IDR 2,700,000
- clo = IDR 500,000
- ci = IDR 500

After determining the planning variables, the next step of APP is to forecast the next period of demand in advance based on the data of the current period. The author uses simple linear regression as an example of forecasting calculations. The forecasting results using linear regression, as shown in Table 3.

TABLE IIII
FORECASTING RESULT

Period	Demand
Sep-15	5026
Oct-15	5471
Nov-15	5916
Dec-15	6362
Jan-16	6807
Feb-16	7252
Mar-16	7698
Apr-16	8143
May-16	8588
Jun-16	9033
Jul-16	9479
Aug-16	9924

After knowing the results of product demand forecasting in the next period, then further can be continued by doing aggregate production planning, as shown in Table 4. The production column contains the estimated value of production obtained randomly. The modified genetic algorithm will determine this value for optimal results with minimum cost. The insertion of production value involves some production parameters: regular time, overtime, subcontract, hiring workers, laying off workers as well as inventory. Previously note that each parameter has a maximum value based on a predetermined initial value. For example, the maximum value of regular time (rt) is obtained from the multiplication of the number of workers, the average production amount per worker in a day on regular time, and also the number of working days in the corresponding month. The maximum value for the first *rt* is 3570, while the maximum value of production overtime (*ot*) and a subcontract (*sc*) is 1050 and 3150, respectively.

TABLE IV
NUMERICAL EXAMPLE OF AGGREGATE PRODUCTION PLANNING

Period	**Demand**	**Day**	**Production**	**rt**	**ot**	**sc**	**rw**	**ps**	**lo**	**i**
Sep 2015	5026	21	8690	3570	1050	3150	4	920		3664
Oct 2015	5471	20	7856	7856						2385
Nov 2015	5916	21	5771	5771						-145
Dec 2015	6362	21	5801	4998	803					-561
Jan 2016	6807	21	7858	4998	1470	1390				1051
Feb 2016	7252	20	8189	5811	1400	978				937
Mar 2016	7698	22	9292	6173	1540	1579				1594
Apr 2016	8143	20	6416	6354	62					-1727
May 2016	8588	20	6860	4760	1400	700				-1728
Jun 2016	9033	17	9951	4046	1190	3570	6	1145		918
Jul 2016	9479	21	5410	5410						-4069
Aug 2016	9924	22	6148	6148						-3776

If the random production value remains after entering into the previous 3 phases, then the next step is recruiting workers. Each newly recruited worker also calculates the maximum value derived from the multiplication of the average production amount of new workers in 1 day to the working day. The number of workers to be recruited is calculated based on the remainder of the random production value divided by the maximum value of new worker production. The value of inventory (*i*) represents the residual number of products derived from the random value of production minus the forecasting result of the demand. A minus *i* is considered a loss, and it is assumed that each minus is multiplied by cost IDR. 3,000.

The production value in the first row is 8690. The value is sent to rt in advance of the maximum value of 3570 to leave 5120. The maximum value is inserted into the next phase *ot* at the maximum value of 1050 and still leaves 4070. Afterward, the value goes into the phase of *sc* at the maximum value of 3150. Since there is still a residual value of 920, then the process is continued into the recruitment phase of new workers. The maximum production value of each new worker in the first row is 252, which is derived from the multiplication of the average production amount of new workers in 1 day by 12 with the working day of the corresponding month (i.e., September 2016). The recruits can be calculated based on the remaining value of 920 divided by a maximum value of 252 so that if rounded will get results 4, which means recruiting as many as four new workers.

The value of *i* in the first row is obtained from a random value of production that is 8690 minus the value of forecasting results of demand of 5026, which later this value will affect the next process. The next process does not need the maximum value because it was added with *i* in the previous process. This stage was done continuously in sequence until the final line of production planning in August 2017. Such is the plot of the aggregate production planning process in general. Notable differences were seen in the proposed application when determining the amount of production.

C. *Improved Genetic Algorithm*

A genetic Algorithm (GA) is a method adapted from natural evolutionary processes. The GA uses evolutionary processes terms such as gene, chromosome, individual population, generation, and reproduction. Gene is the smallest part that represents the unit of solution. The chromosome is a collection of genes, is also called an individual. A generation, a group of individuals, is a living period of the population, which continues to move forward with the always-changing population. Reproduction is the process of generating new individuals. GA has two reproduction processes: crossover and mutation. The mechanism of solving the aggregate production planning using the genetic algorithm is depicted in Fig. 4.

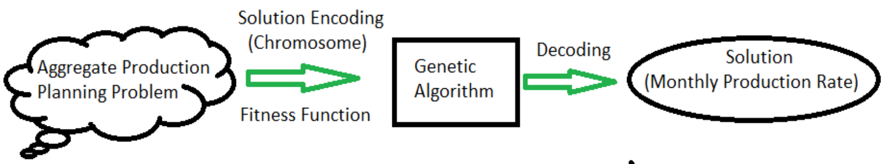

Fig. 4 Generating Solution Using Genetic Algorithm

Fig. 5 shows the representation of chromosomes. The fractional numbers on chromosomes will remain that way to show the amount of production in rounded fitness value. Each gene in a chromosome shows the quantity of production planning for the next year (12 months).

13.1	39.1	19.8	14.2	11.6	15.3	20.7	18.1	17.6	18.2	13.4	22.5

Fig. 5 Real-Coded Chromosome Representation for 12 Months

The first gene represents the first-period production, and so on. Every 12 genes are a chromosome segment, representing the same product until the 18th. So, the total chromosome length in this study is 216 genes. Fig. 6 illustrates the segment division on the chromosome.

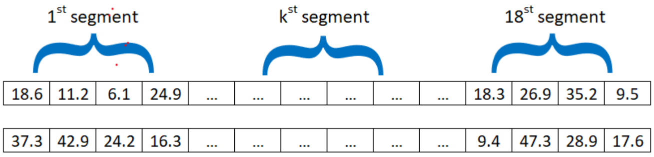

Fig. 6 Illustration of Segment Division on Chromosome

This evaluation process assesses the quality of each individual using the fitness function. The higher the fitness value, the greater the individual chances will be passed to the next generations, becoming a potential solution. Equation 1 shows the formula of the fitness value calculation.

$$Fitness\ Value = \frac{100000000}{Total\ of\ Production\ Cost + \sum Penalty} \quad (1)$$

$$Total\ of\ Production\ Cost = (\sum rt\,.\,crt) + (\sum ot\,.\,cot) + (\sum sc\,.\,csc) + (\sum rw\,.\,crw) + (\sum lo\,.\,clo) + (\sum i\,.\,cbi) \quad (2)$$

The fitness function indicates the individual quality, and the fitness value considers all costs with inverse proportions. The best solution will certainly have a high fitness value with minimum cost (Equation 2). The penalty, an unfulfilled condition, aggravates an individual to be the right solution.

The type of crossover used in this study is a one-cut-point crossover modification on each segment, referred to as segmented crossover. The first thing to do is generate random integer numbers in each section, ranging from 1 to 11. Fig. 7 illustrates the segmented crossover. For example, in the first segment, obtained random value = 2, then do the cutting on the second gene.

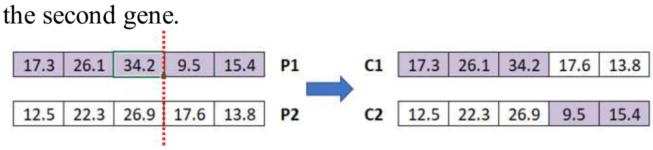

Fig. 7 Illustration of Segmented Crossover

The study modifies position-based mutations by generating random integer numbers in each segment ranging from 1-12. The modification is a segmented random mutation, and the random number indicates the gene position to be changed in value. Value changes will also be made randomly with a range of -10 to +10 of its initial value, as shown in Fig. 8. For example, the first segment obtains a random value = 1, then change the value of the first gene (between a predetermined range). While the new value derived from the random generation = 21.5, then there is a change in the value of the first gene. This modification is arranged to enable the GA to exploit possible better solutions around a current solution.

Fig. 8 Illustration of Segmented Random Mutation

The type of selection operator is elitism. In this selection method, the individual with the highest fitness value becomes a population in the next generation. The number of individuals retained depends on the predetermined population size. This simple method may not consume too much time during consuming computation. Also, elitism selection results always get the best individual for each generation.

Adaptive parameters in the genetic algorithm referred to in this study are the probability values of crossovers and adaptive or adaptable mutations depending on the situation and conditions that occur at that time. Easily the core of adaptive parameters is the change of probability value of crossover and mutation automatically based on predetermined change criteria. In this study, we gradually increase the crossover rate (*cr*) if there is no improvement in one generation, and this strategy will allow the GA to increase its exploration. If there is no improvement in 50 generations, the value of crossover rate is randomly generated between 0 and 1 while mutation rate (*mr*) is set equal to 1-*cr*.

III. Result and Discussions

The application of genetic algorithms determines the best parameters for generating the optimal solution. The test consists of testing the population and the number of generations. As with other meta-heuristics algorithms, different results will be obtained in every run [34]. Therefore, this study runs the test for ten cycles to take the average fitness value.

A. Population Size Testing

A higher population size will enable the GA to explore the wide search space. However, a higher computational time is also required, which may not be accepted for practical application. Thus, a proper population size must be determined [20]. In this population size testing, the authors determine the initial parameter number of generations = 1000, crossover rate (*cr*) = 0.5 and mutation rate (*mr*) = 0.5. The population size testing results as shown in Fig. 9.

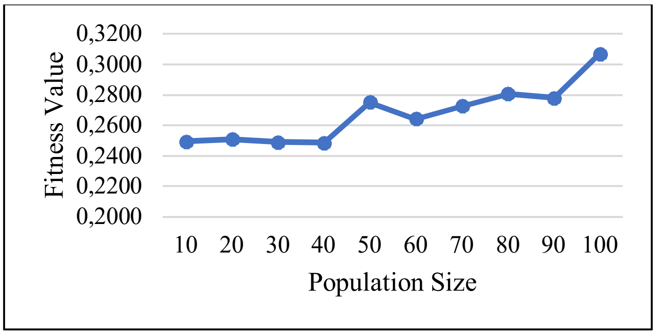

Fig. 9 Population Size Testing

Based on the test results, the highest point is in the population size of 100, with an average fitness value of 0.3071. The larger population size does not always produce a greater value of fitness. For example, when the population size = 60, there is a slight decrease, but it tends to increase. The pattern will likely recur in the next generation as the GA may obtain near optimum solutions.

B. Testing the Number of Generations

The number generation test finds out the best generation when it reaches the optimum point or the occurrence of early convergence. Early convergence occurs when the next generation has no significant increase in value. Some initial parameters (*cr* = 0.5 and *mr* = 0.5) are predetermined to test the population size. As for the size of the population, using the best results obtained in previous trials of 100. Fig. 10 shows the result of the test.

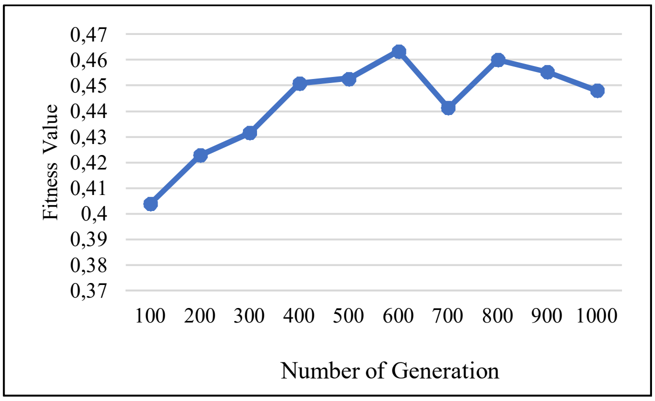

Fig. 10 Testing the Number of Generations

Based on test results, the highest point occurred at generation 600. Even though there is the possibility that a higher number of generations will produce better results, the computational time will also be higher which may be not accepted for practical use.

C. Effect of Adaptive Parameter

A proper crossover and mutation rate is an important input for the genetic algorithm to balance its ability to explore and exploit the search space[35]. The genetic algorithm will depend on its mutation rate and act as a random search method if its crossover rate is too low. In contrast, a high value of crossover rate and low value of mutation rate may not enable the genetic algorithm to maintain its population diversity and escape from local optima. The typical pattern of crossover rate and mutation rate change during generations for the adaptive rate is shown in Fig. 11.

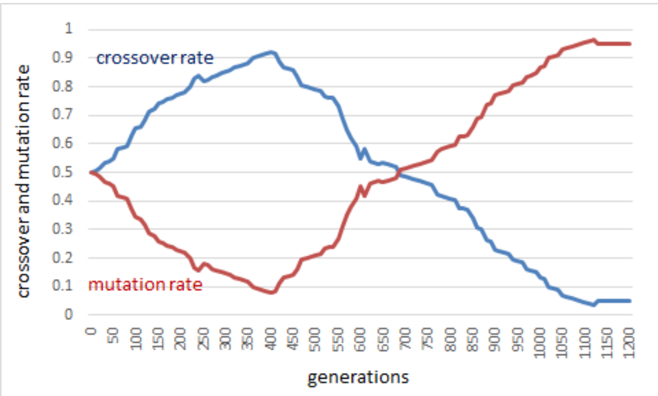

Fig. 11 Typical Pattern of Crossover Rate and Mutation Rate Change During Generations

In this computational experiment, we keep the value of the crossover and mutation rates between 0.05 and 0.95. Starting with crossover rate (cr) = 0.5 and mutation rate (mr) = 0.5, the crossover rate increases in the earliest generations as better solutions are achieved in each iteration. A fluctuation is happened after 400 generations as the genetic algorithm rarely obtains better solutions. After 800 generations, slight fluctuations are still happening as better solutions are sometimes obtained. The genetic algorithm achieves convergence after 1000 generations, and no better solution is found.

D. Results Using the Best Parameter Values

After knowing the best parameters based on the previous test results, the computer program is restarted ten times to take the average value using the best-obtained parameters. The final result is a near-optimal solution with a fitness value of 0.5319. Fig. 12 shows the production result of aggregate production planning using the proposed method. The result is compared with the original data owned by the company to discover the difference between the two-total amount of production, which will impact production cost and profit.

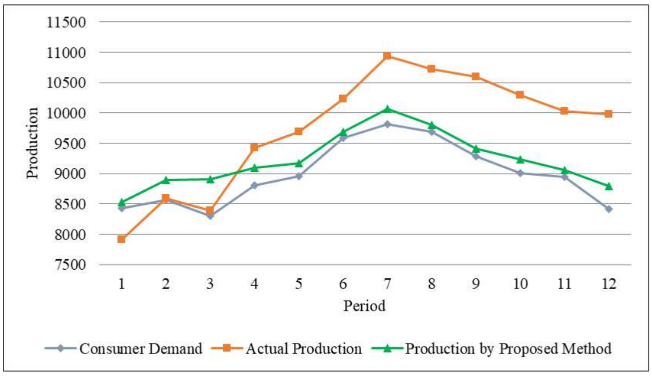

Fig. 12 Comparison of Total Production Amount

Based on Fig. 12, it is known that the production amount graph is actually fluctuating in accordance with demand and peak demand. This causes the production costs cannot to be planned properly. The result of the system can be more consistent in production, comparable to the cost efficiency incurred. The result of production cost is presented in Table 5.

TABLE V
COMPARISON OF PRODUCTION COST

Method	Cost
Actual Production	IDR 3,300,000,000
Genetic Algorithm (GA)	IDR 3,142,806,276
Modified GA	IDR 3,053,563,500

As shown in Table 5, the total cost incurred to produce 18 products by applying this modified GA is IDR 3,053,563,500. The amount is lower than the production costs incurred by the company to produce 18 products, which is around IDR 3,300,000,000. The cost is also lower than a result of a genetic algorithm without adaptive parameter values. Thus, it proves the effectiveness of the proposed approach.

E. Detail Cost Analysis on One Product

In determining which type of cost can be reduced using the proposed method, we compare an actual aggregate production planning for one product with the aggregate production planning using modified GA as shown in Tables 6 and 7. The detailed costs can be calculated using the tables shown in Table 8.

TABLE VI

ACTUAL AGGREGATE PRODUCTION PLANNING FOR THE FIRST PRODUCT

Period	Demand	Day	Production	rt	ot	sc	rw	ps	lo	i
Sep 2015	1843	21	2027	1764	263					184
Oct 2015	866	20	953	953						271
Nov 2015	1202	21	1322	1322						391
Dec 2015	1327	21	1460	1460						524
Jan 2016	744	21	818	818						598
Feb 2016	1304	20	1434	1434						728
Mar 2016	1393	22	1532	1532						867
Apr 2016	1650	20	1815	1680	135					1032
May 2016	1606	20	1767	1680	87					1193
Jun 2016	2367	17	2604	1428	510	666				1430
Jul 2016	4374	21	4811	1764	630	882	1535	7		1867
Aug 2016	6339	22	6973	4004	1430	924	615	3		2501

TABLE VII

AGGREGATE PRODUCTION PLANNING USING MODIFIED GA FOR THE FIRST PRODUCT

Period	Demand	Day	Production	rt	ot	sc	rw	ps	lo	i
Sep 2015	1843	21	2061	1764	297	0	0	0	0	218
Oct 2015	866	20	1432	1432	0	0	0	0	0	784
Nov 2015	1202	21	1432	1432	0	0	0	0	0	1014
Dec 2015	1327	21	1432	1432	0	0	0	0	0	1119
Jan 2016	744	21	1461	1461	0	0	0	0	0	1836
Feb 2016	1304	20	2061	1680	381	0	0	0	0	2593
Mar 2016	1393	22	2061	1848	213	0	0	0	0	3261
Apr 2016	1650	20	2632	1680	600	352	0	0	0	4243
May 2016	1606	20	2632	1680	600	352	0	0	0	5269
Jun 2016	2367	17	2632	1428	510	694	0	0	0	5534
Jul 2016	4374	21	2632	1764	630	238	0	0	0	3792
Aug 2016	6339	22	2632	1848	660	124	0	0	0	85

TABLE VIII

DETAILED COSTS FROM PRODUCTION AMOUNT

cost	actual	modified GA
regular time production	456,297,000	447,327,000
overtime production	76,375,000	97,275,000
production by subcontract workers	59,328,000	42,240,000
recruit new workers	49,450,000	0
laying off workers	0	0
production shortages	24,000,000	0
storage (inventory)	11,586,000	29,748,000
total	677,036,000	616,590,000

Based on Table 8, the actual aggregate production planning for the first product that the company manually determines produces a production cost of IDR 677,036,000. Better results are produced by applying modified GA to plan the aggregate production of the first product as shown in Table 7. The company's total production costs if applying the modified GA method is IDR 616,590,000. There is a reduction in production costs of IDR 60,446,000 in the production of the first product. Here, the company can reduce the production cost by 9% for one product which is quite significant for the company because the number of products of the company is 18 products. By implementing this modified GA, the company can effectively and efficiently carry out aggregate production planning to obtain optimal results.

A significant difference in the first product aggregate production planning is shown in Fig. 13. The modified GA produce a less fluctuate pattern of the production amount. Even though the modified GA yields more inventory cost, the high cost for recruit new workers can be eliminated. Furthermore, a significant cost reduction is obtained by eliminating a cost occurred from production shortages.

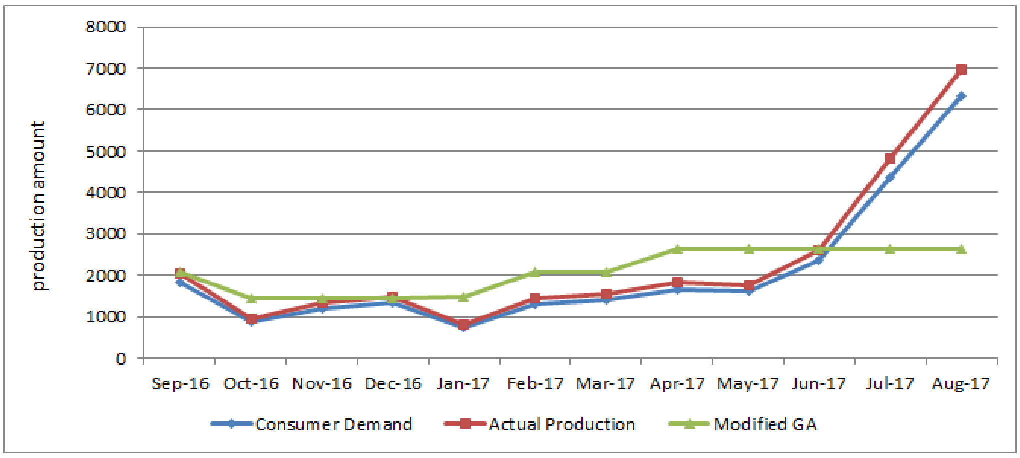

Fig. 13 Comparison of Production Value for Product 1

IV. Conclusion

The application of modified genetic algorithm methods can yield a reasonably optimal solution. The solution achieved has a high fitness value; it shows that the production costs that need to be issued by the company are minimal yet provide more benefits. Using the proposed approach, the company can reduce up to 9 percent of the production cost, and the modified GA produces a less fluctuation pattern of the production amount. Even though the modified GA yields more inventory cost, the high cost of recruiting new workers can be eliminated. Furthermore, a significant cost reduction is obtained by eliminating a cost that occurred from production shortages.

Companies can use solutions resulting from implementing this method in making decisions such as recruiting workers, laying off workers, and other rules related to the production process in the company due to the penalty as a clear benchmark. Combining GA with other approaches can be considered for future work.

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