

Land-Use Planning for Farming Area in West Java to Divide Allocation of Vegetables Commodity Using Genetic Algorithm Approach

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Abstract—This research has created a model to determine the optimum allocation of land-use planning for farming in West Java by considering the two main components, i.e., production and cost. The method is essential in farming, especially in the COVID-19 situation, as it determines clearly which procedure needs to be involved for land-use farming optimization. The problem of land allocation lies in finding the optimum solution from the multi-objective functions. In this study, the method used to cope with the land-use design problem was the Genetic Algorithm (GA) and its expansion called Nondominated Sorting Genetic Algorithm (NSGA). The research results indicated that the best total fitness in GA and NSGA is relatively the same. It was shown that both NSGA and GA could make a planning scheme optimal for the farming commodities in West Java. Based on the maximum optimum value from the best fitness value of NSGA, around 37.35% of the farmland in West Java, it is the best fit for the big red chili commodity. The city where the land used for extensive red chili farming is found to have the maximum optimum value is Garut, with 98.73% of its total farm area.

Keywords— NSGA; GA; Land-use Planning; Fitness Value; Farming

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I. INTRODUCTION

West Java is one of the provinces with the highest vegetable production in Indonesia, besides Central Java, East Java, and South Kalimantan [1]. Consequently, West Java may be perceived as a province with high GDP. On the contrary, the Central Bank of Indonesia [2] had declared that the financial growth performance of West Java was lower in the first quarter of 2019, 5.43%, than in the fourth quarter of 2018, 5.50%. The decline, 5.90% in the first quarter of 2018, was also stated in the Central Statistics Bureau of West Java Province. The records reflect that the financial performance of West Java was getting slower within the timeframe. One of the causes was the declining economic activities of agriculture, forestry, and fisheries by 0.91%. The decrease was worsened during the COVID-19 condition, where thousands of medium-sized businesses, including the agricultural sector, collapsed. A study concerning the optimization of agricultural land is essential, especially in Indonesia, which is known as an agricultural country, especially by using the evolutionary concept, such as genetic algorithm (GA) [3] – [6]. Using the extent of the genetic algorithm approach, which was already known as Non-dominated Sorting GA (NSGA), was one of the solutions to improve in some cases to measure optimization of land use planning [7], [8]. Considering the agriculture aspect, optimum land-use planning is deemed one of the solutions to help solve the low procurement farming activities. Based on the critical reason mentioned above, the primary purpose of this study was to optimize the allocation of agricultural land in West Java using GA and NSGA to meet the vegetable needs the consumption of the people in West Java. In other words, during this research, the land use planning schemes will be modeled by optimizing the allocation of agricultural land for certain commodities in all districts or cities in West Java. The land-use planning design modeling GA and NSGA was adopted from AIMMS optimization modeling [9].

Several studies to better understand the solution of land-use planning using algorithm optimization have been carried out. They were starting from research [10] who had performed seeking the new solution of Pareto from some improvement at the artificial immune system for multi-objective land-use allocation. Moreover, a study from [11] [3] [7] had conducted experiments for several cases to answer the problem of sustainable development using GA as intensive and economical use of land resource's structure allocating. In other studies, writing from [13] [14] had said that mechanism models with meta-heuristic optimization algorithms could be used to design alternative land uses for sustainable agriculture. Then, research at [15] [16], [17] had made some improvements of formulation about crop planning problem as a multi-objective optimization model and solved two version algorithm MCA and NSGA. After that,

study [18] concluded that finding the best layout for city planners according to the transportation and land value effect could be solved in a reasonable time with the GA. The conclusion had been strengthened by research from [7], who proposed the improvement of NSGA-II algorithms for sustainable land-use optimization.

Recently, founding from research [19] had also developed a methodology that provides a feasible way to align the Ecosystem Services (ES) supply and spatial mismatch analysis. Meanwhile, a study from [4] [14] [17] had found that the multi-objective GA model LIR-MSO provided land-use planners with more realistic, efficient, and fitter land-use optimization through much more detailed patterns. Studies about land use optimization at Sulawesi in Indonesia using satellite imaginary also emerge to find out about balance determination of land use [21]. It is also enhanced by research from [10], [22], and [23] that monitor supply and demand at each study case of them are using an optimization approach. The statement that supports to use of genetic algorithms from research about machine learning had been said from [24] – [27] [28]. On the other side, talking about agricultural policies that consider production and consumption can be seen from research [4] [29] [30].

At last, the statement from research [31], [32] said that develop mathematic model-derived to optimize land use. My previous research about land use in Cianjur [33] enrich the necessities in a continuing study about optimization land use in West Java using GA and comparing it with another extent method of GA. The different goals in this research upon on the study case, in which it will optimize land use planning at west java to help farmers' vegetables there. Based on the previous research, this journal emphasizes finding the optimum solution from the multi-objective functions using the land-use design problem was Genetic Algorithm (GA). Its expansion is called Nondominated Sorting Genetic Algorithm (NSGA) for the farming area in west java to divide allocation of the vegetable commodity.

The main objective of this research is to evaluate the 16 land-use farming planning schemes in West Java using NSGA and GA methods. This objective states the gap from the previous study. The scheme results can also serve as an input on how to maximize profits on the sale and purchase activities of agricultural commodities in West Java. In the farming process production, there are benefits in the form of commodity sales and expenditures in producing agricultural products. An example of an agricultural cost is fertilizers to meet the nutrient intake of the crop's commodities. Considering the vast number of variables involved, the GA approach was used to obtain the optimal solutions for the problems. NSGA, the derivative of GA, was also employed

to solve multi-objective issues or use more than one objective search function [34]. Both schemes were then compared to see whether NSGA provides a better schematic result than GA.

The other output that will explain the differences of this study was the optimal allocation of the land area to produce the maximum profit, which is defined as the difference between the revenue and expenditure. In the author's hope, the study is one of the references in retaining the financial income stabilization at West Java in maximizing the land use for vegetable farming. The limitations of the problem in this study were the agricultural commodity type of vegetables and the location of the farm (city/district located in West Java). The vegetables were limited to red cayenne pepper, big red chili, shallot, cabbage, carrot, tomato, green bean, cucumber, and potato. The expenditure was limited to the cost of fertilizer use. The dataset processing used was the python programming languages where GA and NSGA were applied to build the model.

II. RESEARCH METHOD

General Overview of System

A general overview of the system in this research was put in Figure 1. On this figure was explained that this research has several steps. The first step was taking the dataset, and the details would be explained then. After taking the dataset, the next step was searching for the optimum results that used two methods, which are NSGA and GA methods. Continuously, after getting optimum results from both of those methods, then the results were evaluated to get the conclusion of this research. On the evaluation section, there was a comparison between solution and objective function value from NSGA and GA as value distribution of objective function in one population for some generations (for example 25-th, 50-th, 75-th, and 100-th generation from maximum iteration) also best fitness, second-best fitness, worst fitness, and mean fitness in every iteration.

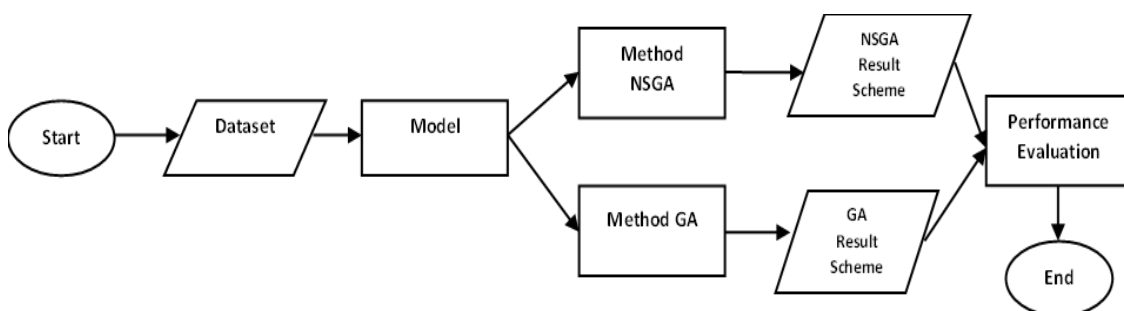


Figure 1. DESIGN SYSTEM OF GA IN OPTIMIZING LAND-USE PLANNING

The datasets on this research were taken from several sources. An explanation of raw data resources can be seen below. The collected data then moved inside the CSV format file to be processed with NSGA and GA methods.

1. There was average price data of vegetable commodity in West Java taken from West Java Department of Agriculture with the source link as follows: <http://distan.jabarprov.go.id/infoharga/>. The detail of the amount and the type of data can be seen figure 2.

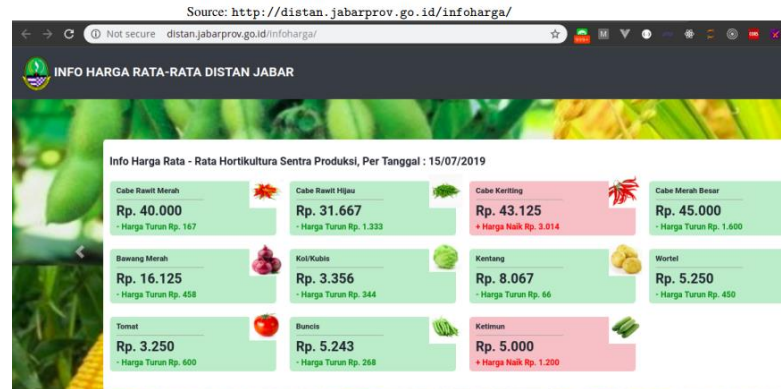


Figure 2. PRICE DATA OF VEGETABLE COMMODITY IN WEST JAVA

2. There was also extensive commodity data of regions in West Java and commodity production of regions in West Java from *Badan Pusat Statistik (BPS)*. The explanation of this data type was the average price data of vegetable commodities in West Java.
3. Another data was fertilizer price that taken from the Indonesian Republic Ministry of Agriculture Rules about the allocation of highest retail prices of fertilizer on the year of 2019 that from this link source mentioned below http://psp.pertanian.go.id/assets/file/2018/Permentan_No_47_%202018.pdf
4. Then there was fertilizer dosage data for commodities taken from PT Petrokimia Gresik from Source is <https://petrokimia-gresik.com/page/pupuk-tunggal>.

Based on the collected dataset as mentioned before, the model will be adjusted to be used in this research. This model is an optimization model for land use planning, as equation 1-3 from GA and NSGA.

$$\max_{\{x_{ij}\}_{i=0}^9} = C_i \sum_{j=1}^{27} P_{ij} X_{ij} - d_i \sum_{j=1}^{27} X_{ij} \quad (1)$$

$$\sum_{i=1}^9 X_{ij} \leq Y_j, \forall j = 1, 2, 3, \dots, 27 \quad (2)$$

$$\sum_{j=1}^{27} X_{ij} \leq Q_i, \forall i = 1, 2, 3, \dots, 9 \quad (3)$$

The model above aims to find the optimum value, where the optimum value of searching is from the maximum value from subtraction between production value and cost value. The searching model above has two limits: Y_j , the limit of commodity total on every region, and Q_i , which is the limit of wide region total on every commodity. These were to get optimum value on the searching process and not exceed a specified limit. The selection process of hyperparameters from both algorithms (NSGA and GA) was done to get a better generation. The process specification of that hyperparameter describes in Table 1.

Table 1. HYPERPARAMETER OF GA AND NSGA

Hyperparameter	Value
Iteration Maximum	100
Population Maximum	100
Gen Length on Chromosome	13
Total Population	50

The explanation why choosing the hyperparameter above will be explained here. The reason for the population total selected was 50 because if using so many populations taken on NSGA will impact overfitting in reaching optimum value during the searching process. In the evaluation section, there was the comparison between solution and objective function value from NSGA and GA as value distribution of objective function in one population for some generations (for example, 25-th, 50-th, 75-th, and 100-th generation from maximum iteration). It also tries to adjust fitness values about best, second-best, worst, and mean fitness in every iteration. Then, this research was set a gen length of about 13 because the limit of maximum commodity wide on the dataset is 7928. Where the two powers value near 7928 is 8192 because, in that range, the length of gen value is 13.

Agricultural Land Optimization Model

An agricultural land optimization model is used to assist farmers in determining what crops should be planted to get the maximum income from land use. The first step was to build the model and determine what inputs needed to be included. As explained by [9], the data needed to optimize agricultural land are 1. the area of agricultural land, 2. the labor costs, and 3. the volume of water use. A verbal model was formulated based on the input collected, as shown in Table 2.

Table 2. VERBAL MODEL

Maximize:	total agricultural profits in the form of the income minus the expenses derived from the farmers' salaries and the water purchases to water the plants.
With subject:	<ul style="list-style-type: none"> • for the whole month: the portion of the land used for activities must be less or the same as the available land area, • for the entire month: the number of farmers needed for the movement must be less or the same as a farmer's family plus a permanent farmer plus a temporary farmer, • for the whole month: the amount of water available must be less or equal to the amount monthly water limit, • the annual amount of water needed must be less or equal to the yearly water limit, and • for all parts of the land: the value of production must be less or equal to the amount of consumption plus the cost of expenses

After it was formulated into a verbal model, the next step was to convert it into a mathematics model. The agricultural allocation optimization model used here refers to the optimization model for conventional agriculture, as defined in [9]. Generally, there are two primary components in defining an objective function, namely elements of production and cost components, as stated in the optimization model below.

$$\max f(X_c) = \sum_c p_c s_c - r^F V^F - r^P V^P - r^T \sum_t V_t^T - p^W \sum_{tc} R_{tc} X_c \quad (4)$$

$$\sum_c l_{tc} x_c \leq L, \forall_t \quad (5) \qquad \sum_c v_{tc} x_c \leq h_t (V^F + V^P) + V_t^T, \forall_t \quad (6)$$

$$\sum_c R_{tc} x_c \leq w_t, \forall_t \quad (8) \qquad \sum_c R_{tc} x_c \leq W \quad (9)$$

$$y_c x_c = \sum_b d_{cb} z_b + S_c, \forall_c \quad (10) \qquad \sum_b z_b = 1 \quad (11)$$

with:

y_c : Production per area of the c-th land area (ton/hectares)

p_c : Price per product (\$/ton)

- d_{cb} : Total of production of the b-th commodity in the c-th land area (ton)
- L : Available land (ton)
- l_{tc} : Percentage of the c-th land in the t-th month (-)
- v_{tc} : Number of farmers needed per area of the c-th land during the t-th month (hour/hectares)
- r^F : Monthly wages for the farmer family (\$/person)
- r^P : Monthly wages for the fixed farmer (\$/person)
- r^T : Hourly wages for the temporary farmer (\$/hour)
- h_t : Total of working hours in the t-th month (hour/person)
- V^F : Number of persons in the farmer family (person)
- W : The volume of water available (litter)
- w_t : Limitation on the water volume usage in the t-th month (liter)
- R_{tc} : Volumetric rate of water needed for the c-th land in the t-th month (litter/hour)
- p^W : Price of water (dollar/litter)
- x_c : Area of the commodity land (hectares)
- V^P : Number of the fixed farmer (person)
- V_t^T : Total working hours for the temporary farmer in the t-th month (hour)
- S_c : Production of the c-th land (ton)
- z_b : Fraction of the b-th commodity consumed (-)

The optimization model by using equations 4 - 11 will be divided into two parts, i.e., production and cost. The basic form of the model is the production deducted by the cost.

C. Genetic Algorithm (GA)

A Genetic Algorithm (GA) is used to search the optimal parameters using the heuristics approach. A strategy to find the solutions to a problem selectively against the most optimal possible solutions and out solutions; others are less than optimal [35]. Heuristic functions are needed to evaluate the states of the individual problem and determine how far they can be used to get the expected solutions [36]. The concept of GA is that there are groups of individuals called populations where one individual states a solution. The initial population will evolve into a new generation through an iteration process. At the end of the iteration, GA returns one of the best population members as the optimal solution to problems [22]. The whole step of GA utilized for optimizing land-use planning is depicted in Figure 3.

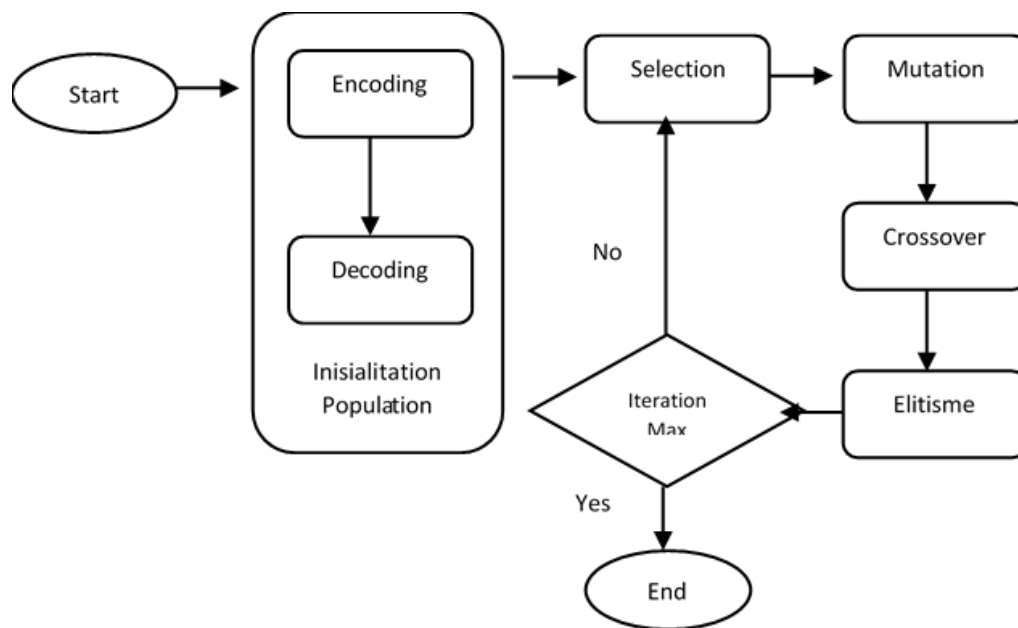


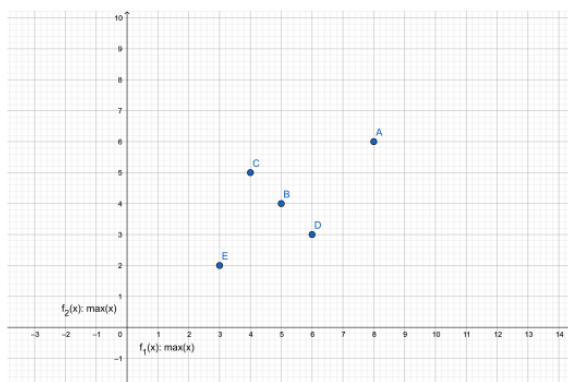
Figure 3. GENETIC ALGORITHM (GA) METHOD

D. Nondominated Sorting Genetic Algorithm (NSGA)

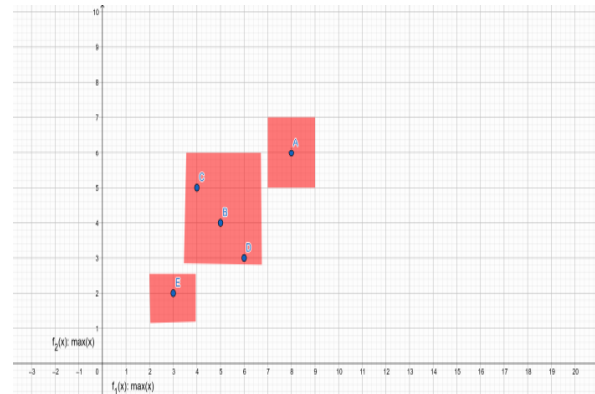
Non-dominated Sorting Genetic Algorithm (NSGA) is an algorithm developed from GA on selection stages used to solve multi-objective problems triggered by a previous study [21]. The advantage of NSGA is that it can avoid the bias that often occurs in GA. In NSGA, the crossover and mutation process is still carried out as in the GA in general. Yet before the selection process is carried out, there is a nondominated sorting process for the individuals in a population. It will be sorted into several nondominated ranks or optimal Pareto solutions. Nondominated rank groups object with no optimal values dominant between all objective functions on a problem [37].

Illustrations on how NSGA is searching for an optimal solution until it has sorted into Pareto optimal can be seen in Figure 3. Figure 3 shows that there are solutions of objects A to E. There are two functions, namely $f_1(x)$ and $f_2(x)$, which have the same objective to maximize the goal. The followings are observations drawn by comparing the values of A to E.

1. Object A has an objective function value in both $f_1(x)$ and $f_2(x)$, which is greater than B, C, and D. So, A is said to be dominant against the other objects and becomes a Pareto group optimal.
2. Object B has an objective function greater than C in C for $f_1(x)$ but smaller than object D. It means that B, C, and D are not dominating in absolute. Those three objects are one group of Pareto optimal.
3. Left is object E, making E as one group of Pareto optimal. Figure 4. b shows the completed Pareto optimal grouping.



a. Solution Value on $f_1(x)$ and $f_2(x)$



b. Pareto Optimal

Figure 4. NSGA IN SEARCHING SOLUTION OPTIMAL

After optimal Pareto grouping is done, the next step is to sort the Optimal Pareto group built earlier by finding Crowding Distance. Crowding Distance is the value used as the second reference after the sequence of the optimal Pareto group. It is an estimated density of solutions around a certain point in the population. It is also obtained by taking an average distance of two points on either side of the i -th point.

NSGA process begins with merging parent and child populations after the selection process. After that, do a non-dominated sort that will result in Pareto optimal groups (as represented in Figure 3. b). After that, initialize the new population with the first sum is zero. Then included

crowding distance value with a population in every Pareto optimal and chosen individual like the sorting of the non-dominated sort until got new population with the number of population maximal. Then the new population was sorted again based on fitness total to get the best individual. The outcome of NSGA is a new population using the best hyperparameters from the crossover, mutation, and elitism process. The step process of NSGA can be seen clearly in Figure 5.

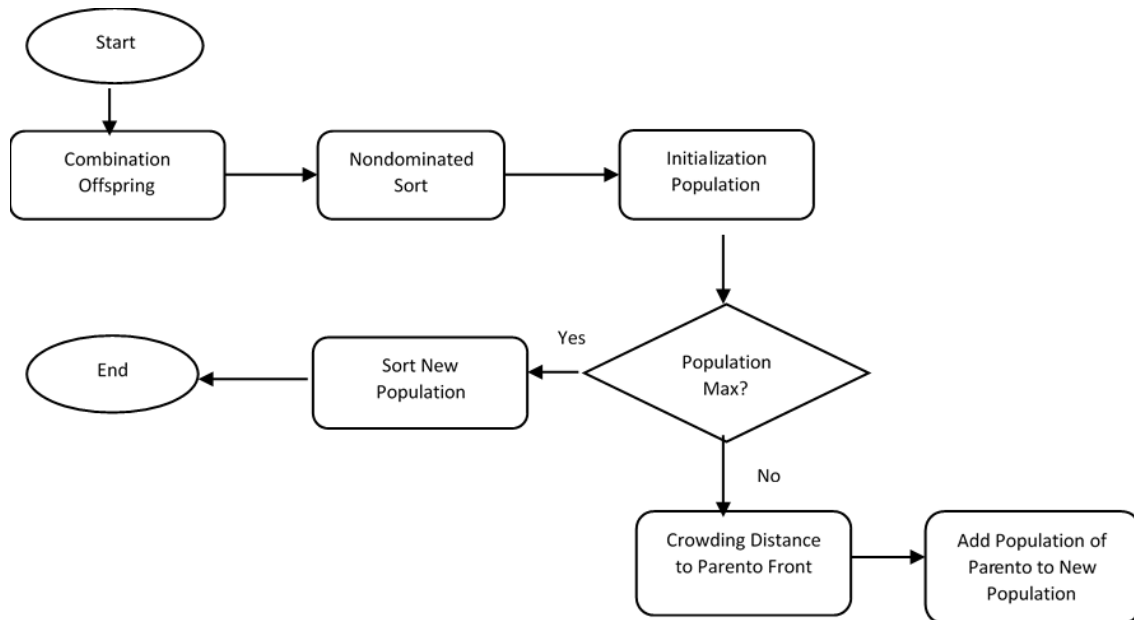


Figure 5. NSGA ALGORITHM METHOD

III. RESULT AND DISCUSSION

The results and discussions in this study will be divided into finding the optimum solution from the multi-objective functions used to cope with the land-use design problem was A. Genetic Algorithm (GA) and studied empirically about the hyperparameters from previous research; B. its expansion called Nondominated Sorting Genetic Algorithm (NSGA) and comparative improvement from another research while using it; Furthermore, at point C. will tell both NSGA and GA can be used to make a planning scheme that is optimal for the farming commodities in West Java. It will continue to discuss the allocation of land-use for other vegetables type in different cities in West Java.

A. Result and Analysis for GA Hyperparameter

In this scenario, testing measures about hyperparameter of GA are described in figure 3. The setting of parameter evolution from [5] [17-18] is an insight to measure in this study.

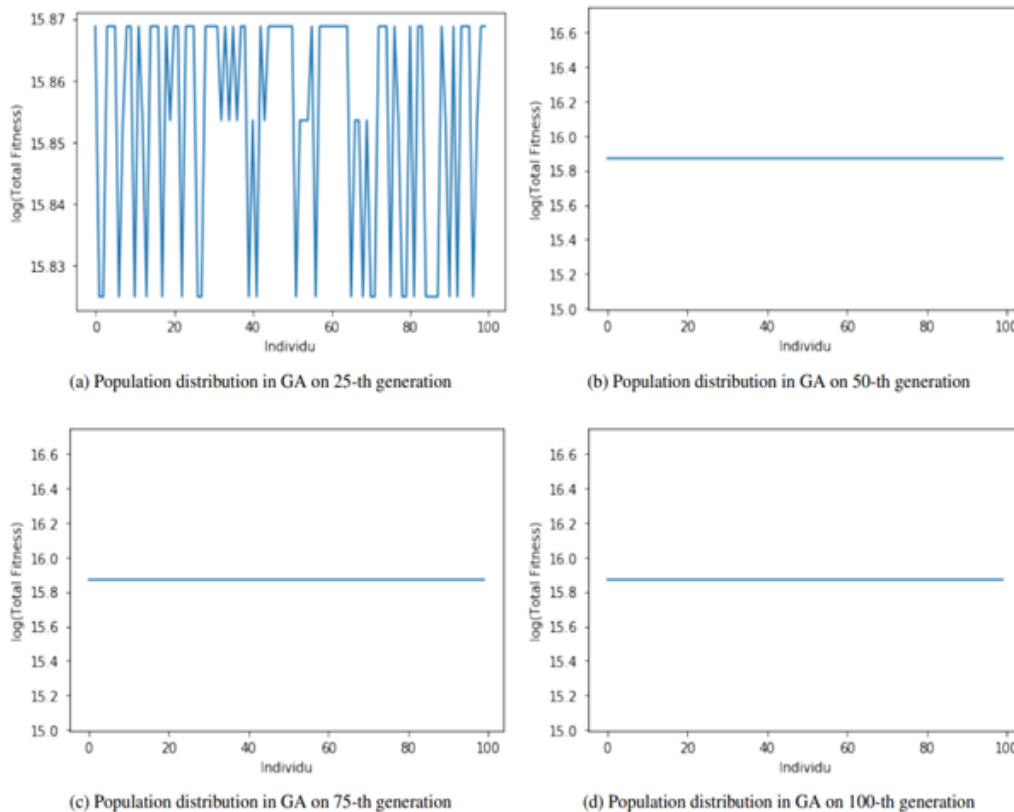


Figure 6. DISTRIBUTION OF GA OBJECTIVE FUNCTION ONE POPULATION

The result of the distribution of objective function value for GA method on 25-th, 50-th, 75-th, and 100-th generation indicates that the dominant fitness value among all individuals is noticed after the 25-th iteration since the elitism process of GA only saves one best individual. At the maximum iteration, the fitness value in all individuals in one generation will be heading to one similar dominant value. The finding of the hyperparameters of GA in each generation illustrates in Figure 6.

Comparative study corresponds to the result in this scenario from several references, such as observations from [17] which described different experiments about GA in optimizing one of the market areas in Singapore, even better than designer measurement. Although that study had a different perspective view in using GA population and distribution, it could still be knowledgeable in this research about GA functionality. Moreover, the study from [18] also explained another gap in using parameter GA to answer the problem about land use planning in an artificial city. The other different studies emerge with consideration about the efficiency of multi-objectives which will constrain GA in measuring the flexibility of the adjustment of evolution parameter. It would lead to another better optimization with huge distinction with this study [10]. GA hyperparameters in their applications have also been reviewed by [3], concluding that different cases and observations would bring different approach optimization than this study.

B. Result and Analysis for NSGA Hyperparameter

This part consists of two sub-sections, i.e., test results and analysis. The test results comprise the distribution of objective function value and the comparison of fitness value from NSGA methods. Figure 7 presents the distribution of objective function values for the NSGA method on the 25-th, 50-th, 75-th, and 100-th generations. That result had the analysis about the distribution of population on NSGA demonstrates different values until the last iteration. It is shown that population 1-th to 50-th shows a marginal change. However, a significant change is observed for the 51-th until 100-th population. It is due to the best hyperparameters at the evolution of the NSGA algorithm, such as selection, crossover, and mutation.

The other analysis came from the elitism process in NSGA that involves best n-individual, which is taken from the nondominated sort process. On the other hand, only one best individual is entailed in the GA elitism process. The population distribution will be dominant on one best value the newer the generation is. The result said similar to previous studies in elaborating NSGA concepts, but of course, in different circumstances. NSGA hyperparameter was systematically analyzed in different countries, such as study from [8] that uses NSGA in Mediterranean Island, whereas another study focuses on the United Nations context [7].

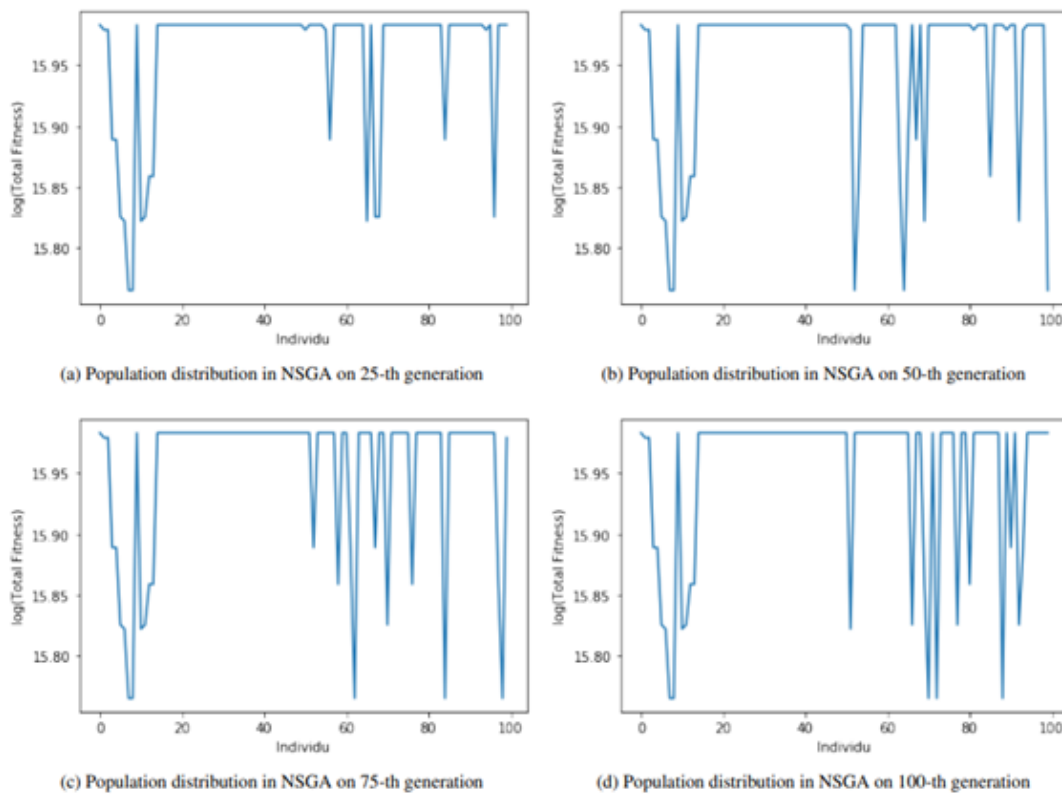


Figure 7. DISTRIBUTION OF NSGA OBJECTIVE FUNCTION ONE POPULATION

C. Result and Analysis for GA and NSGA Scheme

Figure 8 shows the fitness graph for the best and second-best fitness of NSGA and GA. The results emphasize that the difference is only found in individuals who have the worst fitness, with a difference between NSGA and GA. In NSGA, the parameters fitness such as best fitness, second-best fitness, worst fitness, and mean fitness demonstrates the difference of fitness values. In GA, they indicate the values leading to the same dominant as the development of the fitness value in the best population, showing that the better the new generation, the more optimal values will be.

Another finding is that the difference between NSGA and GA comes from individuals with the worst fitness. The reason is that the distribution of fitness values in the NSGA population did not lead to an optimum value until the end of the iteration. Contrasted with the distribution of fitness values in GA, It leads to an optimum value until the end of the iteration.

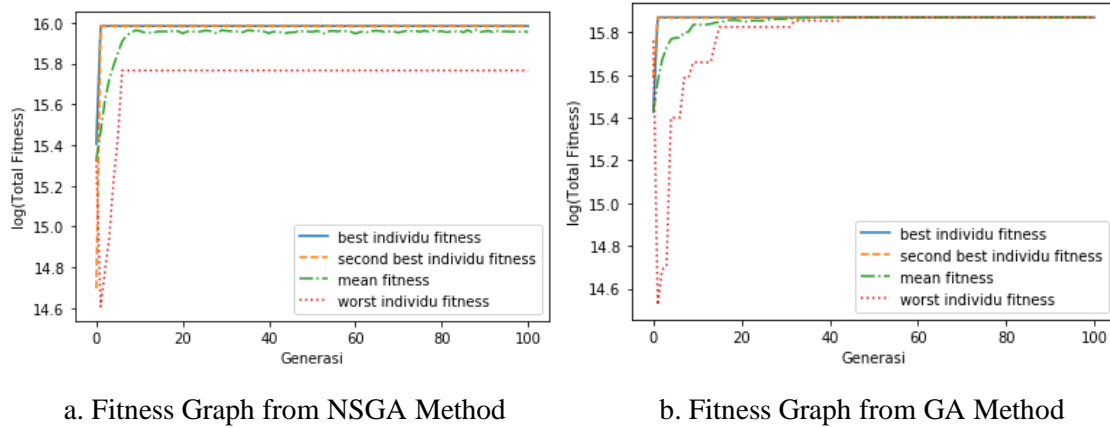


Figure 8. COMPARISON OF HYPERPARAMETER

After the whole hyperparameters both in GA and NSGA have been tested, the scenario will try to find land-Use in planning for farming area in West Java to divide allocation of the vegetable commodity. As indicated in Table 3, the optimum distribution of commodities mainly occurs in the regencies. At the same time, it has a minimum optimal value with a commodity area of 0 in some of the cities. According to the result from Table 3, the distribution of optimum commodities occurs in many regencies. At the same time, in some city areas, it has a minimum optimal value with a commodity area of 0. It can be seen from Table 3 also that the largest area of optimum value was found in large red chilies in Garut Regency at around 8067,39 hectares. Meanwhile, the lowest commodity was 0 hectares and was spread across several commodities in urban areas in West Java. To clarify, the optimal area distribution of commodities to regions can be observed in a heat map diagram, as shown in Figure 9.

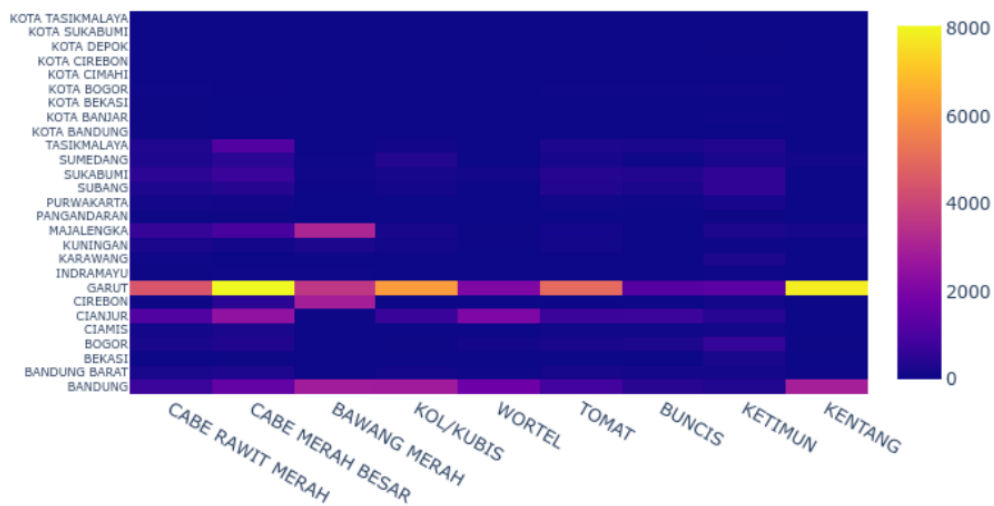


Figure 9. THE OPTIMAL AREA DISTRIBUTION OF COMMODITIES IN WEST JAVA

Table 3. SUMMARY OF OPTIMUM AREA FOR DIFFERENT VEGETABLE COMMODITIES

Commodity Area (ha)	Red Cayenne Pepper	Big Red Chilli	Shallot	Cabbage	Carrot	Tomato	Bean	Cucumber	Potato
Kab. Bandung	726.034	1497.16	2836.51	2794.73	1687.45	848.034	428.327	309.642	2902.15
Kab. Bandung Barat	186.541	247.259	3.657	98.025	24.872	159.109	122.898	122.898	22.311
Kab. Bekasi	4.062	11.17	0.507	0	0	0	0	190.915	0
Kab. Bogor	184.069	296.59	3.057	18.345	114.967	166.335	238.495	632.928	9.172
Kab. Ciamis	79.769	200.123	0	6.997	0	45.715	42.916	81.168	0
Kab. Cianjur	1111.69	2448.39	10.833	670.016	2039.22	712.517	724.184	394.176	0.833
Kab. Cirebon	13.993	446.39	2897.34	0	0	1.399	0	82.561	0
Kab. Garut	4460.56	8067.39	3611.78	6211.54	2077.44	5001.68	1227.67	1309.78	7842.83
Kab. Indramayu	13.713	31.577	31.487	0	0	4.871	0	23.818	0
Kab. Karawang	24.055	4.51	0.5011	0	0	0	0	230.543	0
Kab. Kuningan	200.59	113.12	236.762	84.182	21.045	99.966	7.234	21.703	1.315
Kab. Majalengka	626.128	939.682	3048.59	165.596	17.637	131.301	1.959	237.125	146.978
Kab. Pangandaran	16.538	8.728	0.918	0	0	1.837	1.378	10.566	0
Kab. Purwakarta	96.203	91.585	0	1.924	0	40.79	33.039	177.399	0
Kab. Subang	245.99	364.54	18.77	115.586	0	344.782	196.595	555.207	0
Kab. Sukabumi	499.1	714.23	63.104	159.483	96.951	380.349	347.649	549.584	4.589
Kab. Sumedang	279.987	433.012	35.313	332.957	3.363	177.409	32.791	212.723	79.876
Kab. Tasikmalaya	312.474	1156.9	5.775	92.991	0	258.758	227.569	344.241	0
Kota Bandung	15.842	4.752	0	1.584	0	0.792	0	4.752	0
Kota Banjar	12.604	4.848	0	0	0	7.272	0	26.179	0
Kota Bekasi	10.977	2.993	0	0	0	0	0	4.989	0
Kota Bogor	38.969	19.484	0	0	0	29.227	24.356	49.686	0
Kota Cimahi	1.944	0.486	0	0	0	1.458	0	0.486	0
Kota Cirebon	0	0	4.978	0	0	0	0	1.659	0
Kota Depok	0	0	0	0	0	0	0	12.646	0
Kota Sukabumi	0	1.002	0	0	0	0	0.2505	2.171	0
Kota Tasikmalaya	0.58	2.284	0	0	0	0	0.435	1.341	0

Furthermore, the area distribution using GA and NSGA plotted onto the map of West Java for each commodity is provided in Figure 10. As shown in Figure 10, the distribution of commodities is better to spread in the regencies than in the cities. Due to the limitation of 0 on land-use farming in urban areas, the search is carried out automatically to 0 and stops to develop. Meanwhile, some of the commodity area limitations for many regencies have high value resulting in large search space when determining the optimal land-use scheme.

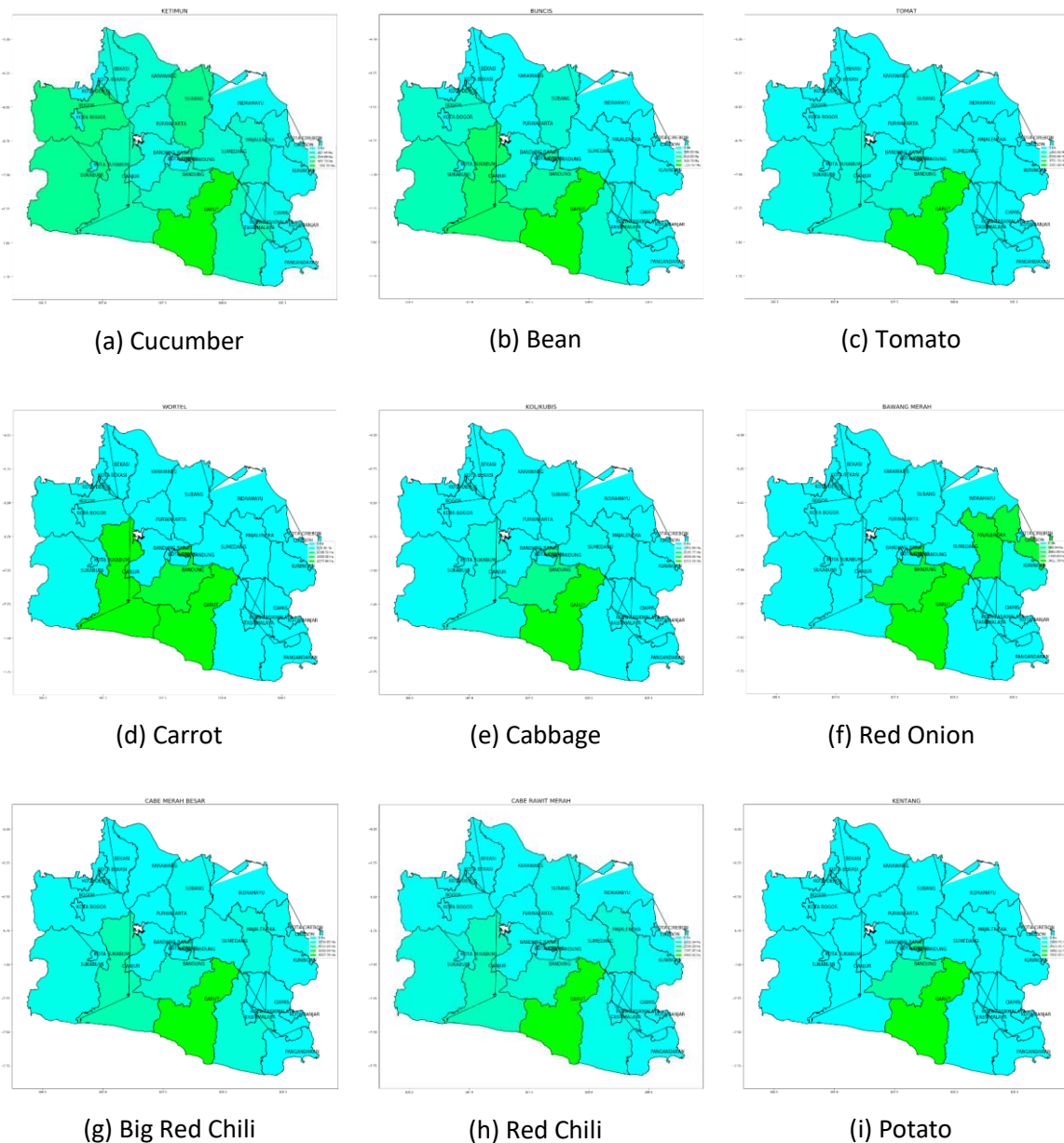


Figure 10. THE DISTRIBUTION OF VEGETABLES USING A GENETIC ALGORITHM

D. Discussion Land-Use Planning for Farming Area in West Java Using GA and NSGA Approach

Based on the goals in this study, the test results indicate the following as are 1) The best total fitness results for NSGA and GA are relatively the same value a represented using in percentage. 2) The distribution of population values in NSGA shows different values until the end of the generation. In contrast, the distribution of values for the entire population in GA leads to the same dominant value after the 25th generation. Those results refer to the primary purpose of this study was to optimize the allocation of agricultural land in West Java using models embedded in

GA and NSGA to meet the vegetable needs the consumption of the people in West Java. As indicated in the fitness chart in Figure 7, the values of the best and second-best fitness for NSGA and GA tend to be the same in the end due to the development of the fitness value in the best population where more optimal values are generated along with the new generation.

The variation adjusts of hyperparameters between NSGA and GA is found only in individuals who have the worst fitness considering the difference of each method in determining the distribution of fitness values until the end of the iteration. The optimal value generated in the distribution of commodities in each region is shown to meet the specified constraints since there was the first check whether the genotype generated has a phenotype value that exceeds the constraints contained in the model during the decoding process.

The optimal fitness values of NSGA and GA were obtained when 25% of the iterations had been run (see Figures 7. a and 7. b). It is because of the search space, which has been limited by the constraints contained in the model. In the distribution of commodities in the distribution map (see Figure 9), the distribution of commodities is more profound in the regencies compared to the cities. The area with the most extensive land-use farming distribution for various commodities is Garut (regency). In West Java, the study shows that cucumber is a vegetable commodity farmed in all regions. Based on the maximum optimum of best fitness value using NSGA, 37.35% of the farmland in West Java is the best fit for the big red chili commodity. The city where the land use for extensive red chili farming is found to have the maximum optimum value is Garut, allocating 98.73% of its total farm area. The results can then be used as an input starting from the planning phase to the decision-making process on optimizing the land use for farming in West Java. Hopefully, this result will support coping with the turmoil for optimization land use then.

IV. CONCLUSION

The GA and NSGA method is vital in farming, especially in the COVID-19 situation, as it determines clearly which procedure needs to be involved for land-use farming optimization. This study has summed up that NSGA and GA show relatively similar cost-optimal values in measuring the optimal land use for the vegetable commodity in West Java. By using 16 schemes, the algorithm has offered optimized land-use planning for farming activities in West Java. However, the distribution of commodities is dominant in regencies rather than urban areas, given that several constraints limited the search space. According to the variables involved to get optimal solution, it can be concluded that both NSGA and GA can be used to create the optimum planning schemes on agricultural commodities vegetables in West Java.

Nonetheless, it is highlighted that the distribution is not evenly spread. As an improvement optimization algorithm, NSGA can give better results both theoretically and practically.

The highest optimum value is found for farming significant red chili commodities in Garut (regency) with 8067.39 hectares. It is also interesting that some commodities are not prioritized for planting in certain areas, e.g., Bekasi (city), as it is not optimal for growing onions, cabbage, carrots, tomatoes, beans, and potatoes according to the study. The city where the land used for extensive red chili farming is found to have the maximum optimum value is Garut, allocating 98.73% of its total farm area. The allocation of land use for other vegetable types in different West Java cities was also discussed in this study.

Concerning the pandemic situation, it is in the Authors' hope that the results of this research can be used in supporting the government to solve the land-use problem. The results can then be used as an input starting from the planning phase to the decision-making process on optimizing the land use for farming in West Java. For a long-term solution, the expectation from this research's outcome is aimed to indirectly support the capital flows of Indonesia's emerging markets and prepare for the post-pandemic era. Suggestions for future research regarding the other heuristic search objects and adding general farming areas as a dataset are welcomed. In addition, using expert judgment from the designer as a comparative study also brings a more empiric result to be learned.

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