The Indonesian Journal of Computer Science
www.ijcs.net
Volume 14, Issue 4, August 2025
https://doi.org/10.33022/ijcs.v14i4.4954

Optimization of Corn Crop Nitrogen Percentage Using Genetic Algorithm

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Article Information

Received : 14 Jul 2025
Revised : 4 Aug 2025
Accepted : 27 Aug 2025

Keywords

Yield, Nitrogen, Genetic algorithm.

Abstract

Corn is one of the strategic commodities in food fulfillment in Indonesia. Despite being one of the strategic commodities for food security, corn production is still far from meeting total consumption. One of the main factors for increasing yield is the availability of nutrients, especially nitrogen. This research aims to determine the optimal nitrogen percentage to maximise corn production using genetic algorithm. Simulations were conducted using the genetic algorithm method with parameters such as population size, maximum number of generations, mutation rate, as well as Bayesian approach for the crossover method and a Gaussian distribution for mutation. The results showed that the more generations used, the better the accuracy of the curve approach to the actual data, with an optimal nitrogen value of 1.506% in the 500th generation and a production yield of 227,718 bu/ac or 15.325 ton/ha.

A. Introduction

Corn is one of the strategic commodities in food fulfillment in Indonesia. Corn is a source of carbohydrates that has great potential to replace rice. Corn is used for various purposes, ranging from animal feed, staple food, snacks, industrial raw materials, and alternative energy. Despite being one of the strategic commodities for food security, corn production is still inversely proportional to total consumption. According to[1], corn consumption in Indonesia is increasing by 11.52% per year, but the average production of corn per year is only 6.11%.

One of the factors that supports increased production is corn growth. Corn growth is influenced by several factors, ranging from soil conditions, water availability, fertilisation, soil acidity, and nutrient availability. Nutrient availability in the soil can be supported by fertilising with the addition of nitrogen, phosphorus, and potassium elements to plants. The presence of these elements helps to increase photosynthetic efficiency in plants, so that productivity and plant growth increase. Therefore, optimizing the composition of fertilisers is a step towards obtaining corn production yields.

Optimization of fertilizer composition can be modeled mathematically to obtain maximum corn production. One approach used to optimize this problem is the genetic algorithm. Genetic algorithms are heuristic search and optimization techniques that mimic the natural evolutionary process. The evolutionary process imitated by genetic algorithms goes through the process of selection, crossover, and mutation. After going through the process, the solution of this process is one of the methods to get the optimal solution, so that the best fertilizer composition is obtained.

The optimization involving genetic algorithms can be seen in the following studies. [2], [3] used genetic algorithms to determine the type of plants suitable for planting in a particular season, with the difference that [3] used genetic algorithms to determine rainfall predictions, while [2] to determine phenotypical traits.. Other related research was conducted by [4], where genetic algorithms with the binary tournament selection method were used to optimize the composition of fertilizers in corn plants. In addition, [5] used genetic algorithms to optimize plant response (ratio of the canopy and stem diameter).

Genetic algorithms can also be used to increase the production yield of plants by optimizing the factors that affect them. These studies can be seen in [6], [7], [8] . The difference between these three studies is that [6] uses genetic algorithms to optimize irrigation systems, [7] to optimize soil fertility, and [8] to optimize soil fertility.

In addition to plants, genetic algorithms can be used in other problems, as done by [9], [10], [11]. [9] used genetic algorithms to optimize broiler feed ingredients with the roulette wheel selection method. Meanwhile, [10] optimized the composition of food for people with cholesterol using genetic algorithms with the elitism selection method, and [11] optimized the nutritional intake of pregnant women to be balanced as needed and at minimum cost using genetic algorithms with the elitism selection method.

Meanwhile, other research related to optimising fertiliser composition using different optimization methods can be seen in the following studies. [12] optimized nitrogen application using deep reinforcement learning (RL) and crop simulations with Decision Support System for Agrotechnology Transfer (DSSAT). [13] performed fertiliser yield efficiency using Optimised Artificial Neural Network (OANN). [14] Optimizing fertilisation on hydroponic lettuce using the Grey Wolf Optimisation (GWO) method. [15] Determining the amount of nitrogen and organic matter in organic fertiliser using Vis-NIR (Visible Near-Infrared Spectroscopy) spectroscopy. And [16]using MILP (Mixed Integer Linear Programming) method, a qualitative model with AHP (Analytic Hierarchy Process), and an integration model with the weighted sum method to optimize the corn planting schedule.

In this research, we will discuss the process of nitrogen composition optimization using a genetic algorithm to obtain optimal corn production. In addition, this study uses a selection method in the form of rank selection because it is a more stable approach and provides more even coverage in the individual selection process than binary tournament selection, roulette wheel, or elitism selection. Another reason is that rank selection provides selection opportunities based on rank order, not absolute fitness value.

B. Research Method

This chapter will present the steps in the genetic algorithm based on [17]and [18]. in addition, the research data used will be presented.

Research Data

In this study, the data used is research data from [19]. The parameters used are yield and percentage of nitrogen content in corn seeds. Table 1 presents 17 out of 645 samples in [19].

Table 1. Nitrogen Percentage Survey of Field Corps

Year	Locate	Yield	N(%)
2014	Adams	210	1,29
2014	Adams	198	1,34
2014	Adams	220	1,34
2015	Bond	180	1,03
2015	Bond	212	1,15
2015	Bond	183	1,18
2014	Boone	210	1,28
2014	Boone	210	1,21
2015	Boone	196	1,06
2015	Boone	190	1,11
2014	Bureau	255	1,18
2014	Bureau	191	1,25
2014	Bureau	279	1,27
2014	Carroll	190	1,45
2014	Carroll	200	1,45
2015	Carroll	220	1,22
⋮	⋮	⋮	⋮
2015	Woodford	203	1,18

Genetic Algorithm

Genetic algorithms are heuristic search and optimization techniques that mimic the process of natural evolution. This process starts with an initial population consisting of individuals with various characteristics. This population then faces natural selection for survival. Individuals that pass the selection will be combined and modified through a process called crossover and mutation, resulting in a new generation that carries the superior traits of its predecessors. Figure 1 is a flowchart of the genetic algorithm following such evolution.

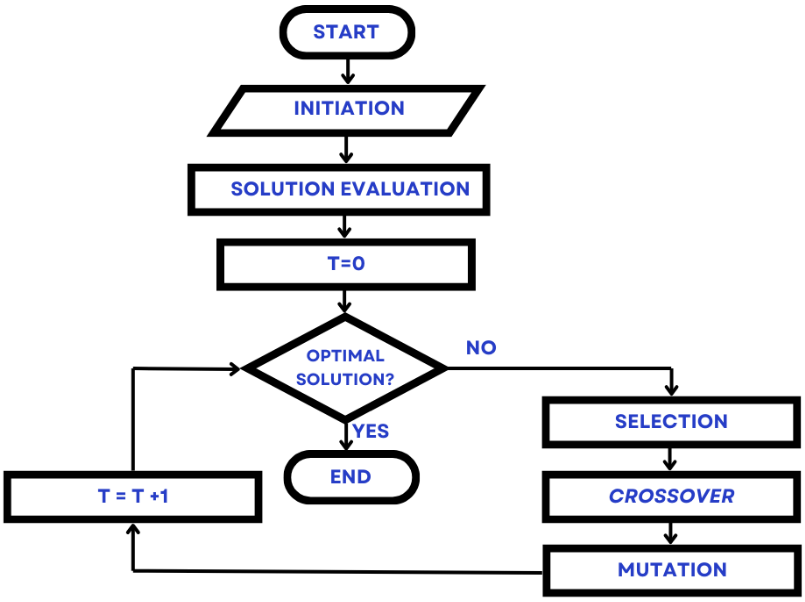

Figure1. Flowchart of Genetic Algorithm

(a) Initiation

Parameter initiation is the first step of the genetic algorithm during the evolutionary process. The parameters used in this research are nitrogen percentage and corn production.

(b) Chromosome Representation

Chromosome representation is the process of presenting a solution in the form of a string that contains the necessary information. In a chromosome, each gene controls a particular characteristic of an individual, similarly each bit in the string represents a characteristic of a solution.

(c) Fitness Value

Solutions in the population are evaluated using a fitness function to measure how good the solution is. Based on [19] the data from Nitrogen on production is normally distributed, so this study utilizes a fitness function in the form of a bell-function, as shown in the equation (1). Furthermore, the penalty is imposed as denoted in the equation (2).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{1}$$

With penalty :

$$\varepsilon_i = f(x_i) - y_i \tag{2}$$

(d) Selection

Selection in genetic algorithms is the process of determining which solutions will be retained and developed and which will be eliminated. Figure 2 presents the selection steps in this research

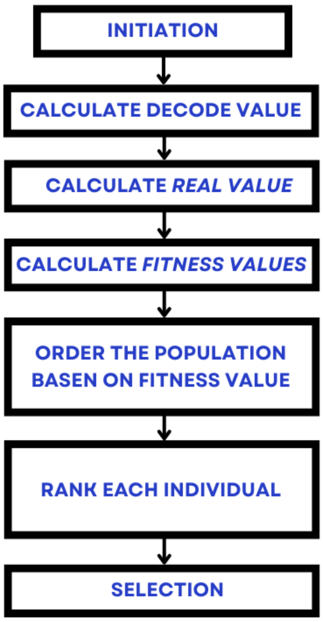

Figure2. Flowchart of Selection

(e) Crossover

Crossover is used to create new solutions from existing solutions in the mating pool after selection. Crossover aims to exchange genetic information between solutions in the mating pool.

(f) Mutation

In this research, the mutation method is applied by using fitness values that have been convolved with Gaussian functions. The approach in this study combines individual fitness values with Gaussian functions to produce new values that are smoother and normally distributed.

C. Result and Discussion

This section contains the results of research and discussion, as well as the parameter simulation.

Parameter Simulation

Parameter simulation in this study was carried out using several parameters that have been determined by the optimization objectives. Table 2 provides the parameter simulation used in this study:

Table 2. Parameter Simulation

Parameter	Value
Number of Population	50
Maximum Number of Generations	500
Mutation Rate	20%
Elitism	0 (Disabled)
Selection Method	Rank
Number of Gene	1
Fitness Function	Normal Distribution
Crossover Method	Bayesian

Main Result

In this section, the main results of the genetic algorithm based on the parameters used will be given using the Python programming language. Figure 3-Figure 5 present the best fit of the genetic algorithm with different numbers of generations, with the blue dots on the graph being the actual data from the observations, while the red curves represent the best approximation results obtained by the genetic algorithm.

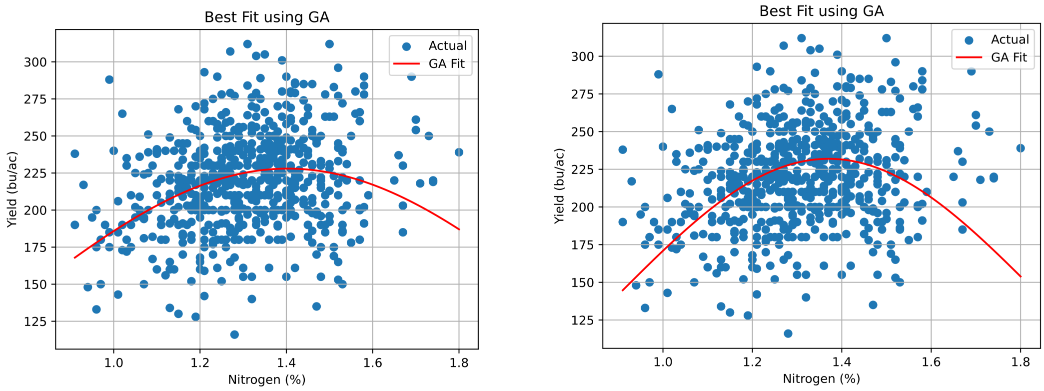

Figure 3. Best fit with number of generations 100 and 200

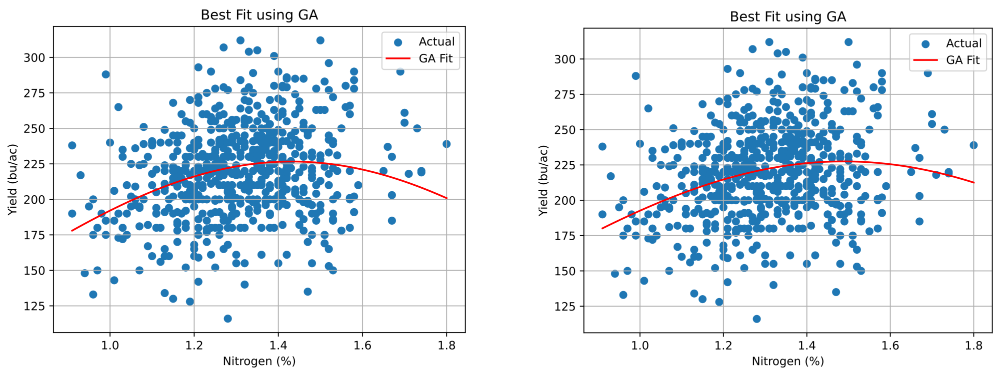

Figure 4. Best fit with number of generations 300 and 400

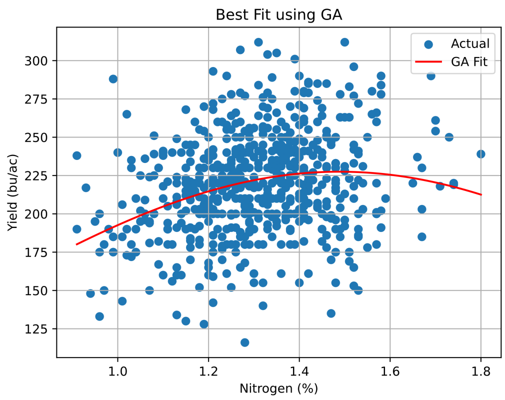

Figure 5. Best fit with number of generations 500

Based on Figure 3 - Figure 5, in generations 100 and 200, the resulting fit curve is still not close to the actual data. Whereas in the 300 and 400 generations, the fit curve has started to approach the actual data. The peak of the parabola begins to move closer to the optimal point with a smoother parabolic pattern. The best results were obtained at generation 500, with the approach curve obtained showing the best fit to the actual data.

Next, Table 3 presents the optimal values obtained from the genetic algorithm using the simulated parameters used.

Table 3. Optimum values of different number of generation

Nitrogen (%)	Yield (bu/ac)	Yield (ton/ha)	Generations
1.379	225.972	15.208	100
1.410	227.359	15.270	200
1.430	227.648	15.320	300
1.485	227.418	15.305	400
1.506	227.718	15.325	500

Based on Table 3, it can be concluded that increasing the number of generations in the genetic algorithm has a positive impact on the approach of more optimal nitrogen values and corn yields. As the generations increase from 100 to 500, there is an increasing trend in the recommended optimal nitrogen value, from 1.379% to 1.506%.

Furthermore, Figure 6 gives the penalty of the genetic algorithm with different generations

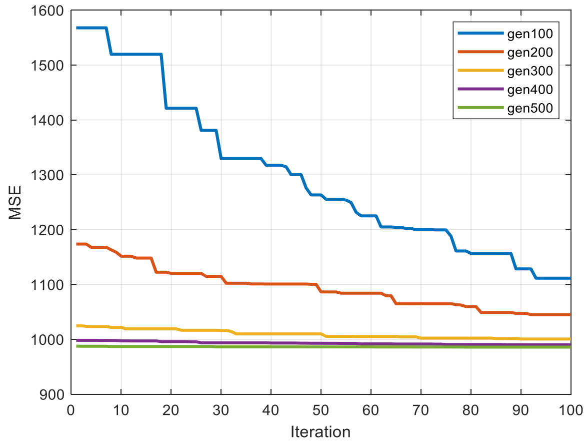

Figure 6. Penalty in Genetic Algorithm

Figure 6 shows that the greater the number of generations used in the genetic algorithm, the smaller the penalty or error value produced, which is indicated by a decrease in the Mean Squared Error (MSE) value at each iteration.

D. Conclusion

In this study, it can be seen that the genetic algorithm can optimize the percentage of nitrogen use to increase corn production. Genetic algorithms in this study provide an approach to the actual data as the number of generations increases. This can be seen with the best fit curve that is getting closer to the actual data value, and the penalty value (MSE) is getting smaller. The optimal percentage of nitrogen obtained also increased as the number of generations increased, with corn production also increasing. The optimal nitrogen value obtained increased from 1.379% in the 100th generation to 1.506% in the 500th generation, with the highest production reaching 227,718 bu/ac, or equivalent to 15.325 tons/ha. This finding confirms that the number of generations plays an important role in the process of convergence to the optimal solution.

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