Genetic Algorithms for Holt Winter Exponential Smoothing Parameter Optimization in Indonesian Car Sales Forecasting

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Abstract. The Indonesian automotive industry contributed significantly to the economy. Indonesia has 22 automotive companies that have been operating and have helped absorb many employees. Sales forecasting is considered as future market demand. So that accurate sales forecasting can be used as one of the decision supports for production planning. This study proposes an integration of a genetic algorithm with Holt-Winters exponential smoothing (GA-HW) in Indonesian Car Sales Forecasting. The proposed method can provide Highly Accurate forecasting results for the Toyota, Daihatsu, and Suzuki brands using both GA-MHW and GA-AHW models. Meanwhile, the proposed method on Honda brand provides good forecasting results. MAPE Comparison between the proposed method and golden section – HW gave the conclusion that the proposed method outperformed the golden section – HW.

Keywords: Forecasting, Hybrid Method, Genetic Algorithm, Holt-Winter Exponential Smoothing, Regression

1 Introduction

Economic development is essential for a country. In Indonesia, one of the main sectors of the national economy is the Automotive Industry. The Indonesian automotive industry is rising, as evidenced by the number of Indonesian car production which has increased to 62.4% percent [1]. This sector has contributed significantly to the economy in Indonesia. Indonesia has 22 automotive companies that have been operating and have helped absorb many employees [2]. Because of this, the sustainability of the automotive industry is crucial. Companies must be able to determine the planning in production to adjust to market demand. Improper production planning becomes risky because it can cause losses. Sales forecasting is considered future market demand [3]. So that accurate sales forecasting can be used as one of the decision support for production planning.

Sales forecasting uses time series data such as historical sales data. This historical data can be processed using statistical methods [4], [5] or artificial intelligence methods [6],[7] to get sales forecasting results. If only one statistical method or one artificial

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intelligence method is used, it is called a stand-alone method. Integration of several models, either statistical-statistical, artificial intelligence-artificial intelligence, or statistical-artificial intelligence is called a hybrid method. Hybrid methods can provide better accuracy when compared to stand-alone methods [8].

The study of [9] uses stand-alone methods to forecast Indonesian Car Sales. [9] uses the Holt-Winters exponential smoothing method as the forecasting method. The Holt-Winters exponential smoothing method requires parameters α, β, γ where the values of α, β, γ are in the range 0-1. Research [9] conducted a parameter search with a trial and error approach. This process takes a long time because it has to try hundreds of combinations to get the optimal parameters α, β, and γ.

[10] uses a hybrid method by integrating the Holt-Winters exponential smoothing method with the golden section. Both methods are statistical methods. The golden section method is used to optimize the Holt-Winters exponential smoothing parameter. the golden section can only produce one parameter so that in [10] the value of α is obtained from optimization of single exponential smoothing, and the value of β is obtained from optimization of double exponential smoothing. While the value of γ is obtained from the Holt-Winters exponential smoothing optimization after getting the value of α, β from the previous process. Although the method proposed by [10] can reduce running time, it has not been able to produce accurate forecasting.

Parameter optimization for statistical-based forecasting methods can also be done using artificial intelligence algorithms such as optimization algorithms. A genetic algorithm is one of the optimization algorithms that provide reliable performance [11]. The study [11] compared Genetic Algorithms, Particle Swarm Optimization, and Simulated Annealing for optimization of the ProfARIMA method. Genetic Algorithms outperform other optimization methods in sales forecasting using Coca-Cola Company data.

This study proposes a hybrid model which is an integration of a genetic algorithm with Holt-Winters exponential smoothing (GA-HW) in Indonesian Car Sales Forecasting. The genetic algorithm can generate multiple parameters as needed from Holt-Winters exponential smoothing. Forecasting results from GA-HW will be compared with the golden section-HW to determine the performance of GA-HW.

2 Research Methods

This section discusses in detail the research method. In this study, the data refer to [10]. The data consist of car sales data on four popular brands Toyota, Honda, Daihatsu, and Mitsubishi. The data is a sales history from 2011 to 2019. The details of the proposed method can be seen in Figure 1. The input data is sales history data. The data divide into testing data and training data. The training data used is data from 2011 to 2018. Then the data in 2019 is used as testing data to evaluate the model. The genetic algorithm is very dependent on the control parameters so in the second stage, the control parameters setting is carried out. In this study, getting the optimal control parameters is done by experiment using several different parameters to get the optimal solution. The next stage is the integration of the genetic algorithm with Holt-Winters exponential smoothing (GA-HW). this integration produces optimized parameters to get a forecast with the minimum MAPE value.

2.1 Holt-Winter Exponential Smoothing

The Holt-Winters method is one of the popular methods for forecasting problems in time series data. This method has two types of models [12].

2.1.1 Multiplicative Holt-Winters

If the time series level increases, the Multiplicative Holt-Winters method will increase the seasonal effect. Calculation of Multiplicative Holt-Winters using equation (1a) until (1b).

Level: $\ell_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1})$ (1a)

Growth: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ (1b)

Seasonal: $s_t = \frac{\gamma y_t}{\ell_{t-1}+b_{t-1}} + (1-\gamma)s_{t-m}$ (1c)

Forecast : $\hat{y}_{t+h|t} = (\ell_t + b_t h)s_{t-m+h_m^+}$ (1d)

2.1.2 Additive Holt-Winters

This method does not depend on the time series level, equation (2a) until (2b) is the equation for calculating Additive Holt-Winters.

Level $\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ (2a)

Growth: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ (2b)

Seasonal: $s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$ (2c)

Forecast : $\hat{y}_{t+h|t} = \ell_t + b_t h + s_{t-m+h_m^+}$ (2d)

In (1a) and (2a) α is seasonal smoothing level, In (1b) and (2c) β is smoothing trend, meanwhile γ in (1c) and (2c) is smoothing seasonal.

2.2 Genetic Algorithm

A genetic Algorithm is an optimization algorithm that can be used to find the optimal solution. Genetic algorithms are inspired by finding solutions with an evolutionary theory approach. This technique is an algorithm that looks for a solution based on the population by looking for individuals who can survive based on the value of the fitness function. These individuals will produce a new population. This process will continue to repeat through the process of crossover and mutation in individuals in the population.

Chromosomal representation, selection, crossover, mutation, and fitness function are the key elements of GA [13].

2.3 Integration of Genetic Algorithm with Holt-Winters (GA-HW)

The integration process of the Genetic Algorithm with Holt-Winters aims to produce optimized parameters α, β, and γ. The following are the steps to find the optimal parameters:

2.3.1 Initialize control parameters: The first process is population initialization to determine the number of chromosomes/individuals that are raised. Each individual will have three genes according to the number of parameters to be optimized. Initialize the maximum number of generations to determine how many iterations to complete the genetic algorithm. Initialization of crossover and mutation probability to avoid premature convergence.

2.3.2 Fitness Function: Defines the fitness value where the fitness value is obtained from the forecasting process with Holt-winter exponential smoothing. Calculating forecasting errors using MAPE. So that MAPE is used as a fitness function in this study. Calculation of MAPE using equation (3) [14]. MAPE is calculated by finding the average difference from actual sales data with forecasting results.

$$MAPE = \frac{1}{n}\sum\frac{|actual - prediction|}{actual} \quad (3)$$

2.3.3 Selection: Selection is the process of getting new individuals based on their fitness function.
2.3.4 Crossover: The crossover process aims to exchange genes from two parents at random
2.3.5 Mutation: Mutation is done by giving shifting the value of the gene to be mutated.
2.3.6 Repeat the process: return to Step b until the maximum number of generations is met and the optimal parameters α, β, and γ are obtained.

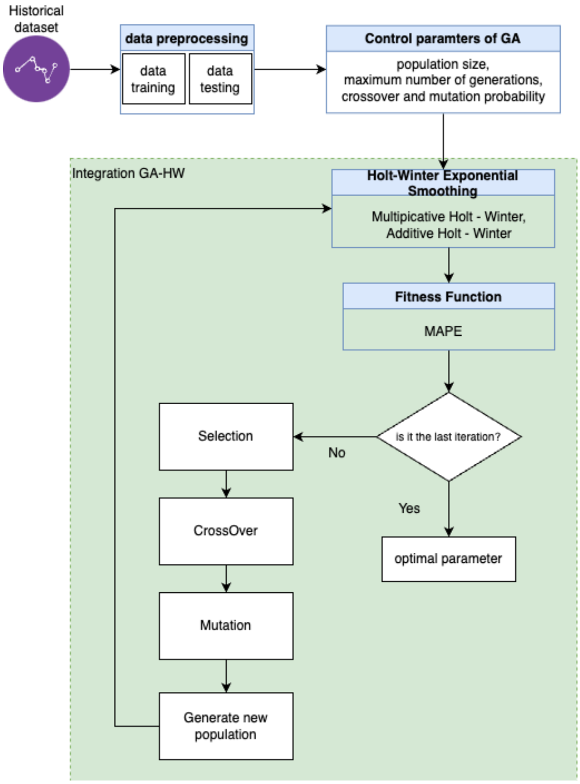


Fig. 1. Details of the proposed method

Table 1. Mape Interpretation.

MAPE	Interpretartion
< 10	Highly Accurate forecasting
10 – 20	Good forecasting
20 – 50	Reasonable forecasting
> 50	Inaccurate forecasting

The parameters obtained from the integration of GA-HW are used to forecast car sales on the testing data. We use 12 months of data testing to test the performance of the proposed method. Testing the performance of the proposed method using MAPE in equation (3). The result of the MAPE value needs to be classified into several categories based on the range of values to determine the quality of the proposed method. The MAPE interpretation values can be seen in table I [15].

3 Result and Discussion

In this study, the parameter optimization of the Holt-winters exponential smoothing (GA-HW) method has been carried out using a genetic algorithm. This study uses 108 months of data on car sales from four car brands in Indonesia. The Experiment was conducted using 96 months of data as training data and 12 months of data as testing data. Furthermore, this data is used to test the performance of the proposed method. Holt-winter multiplicative and additive methods require parameters α, β, and γ to make predictions. This parameter is optimized using a genetic algorithm. GA-MHW as a representation of Holt-Winters multiplicative parameter optimization using a genetic algorithm, while the optimization of the Holt-Winters additive is called GA-AHW.

The genetic algorithm requires several control parameters. These parameters are population size, a maximum number of generations, and genetic operators such as crossover (cr) and mutation (mt) probability selected randomly. Giving the proper parameters to the genetic algorithm can deliver optimal results. Otherwise, if the control parameters of the genetic algorithm are incorrect, it will result in premature and immature convergence [13], [16]. This study experimented to find the control parameters of the Genetic Algorithm for each car brand. This is because each car brand has different data patterns so it may have different control parameters value.

Population size aims to form random individuals which will produce an optimal pair of chromosomes based on the fitness value. The result is the optimal solution for the parameters of the Holt-Winters method. Population parameter experiments are to find the optimal population. If the population is too large, it will require high computational time. Otherwise, if the population is too small, it will result in immature convergence. Experiments used a population size of 5,10,15,20,25,30 with a maximum number of generations is 25, crossover(cr) and mutation(mt) probability refer to [17]. Crossover and mutation are 0.3 and 0.4 respectively. The results of the Population size experiment for the Toyota brand using the MHW method can be seen in Figure 2. In Figure 2 it can be seen that a population size of 30 has the best fitness value so the maximum number of generations test will use a population of 30.

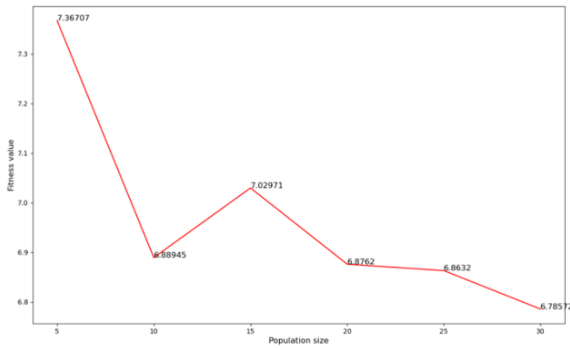


Fig. 2. Population size of Toyota brand

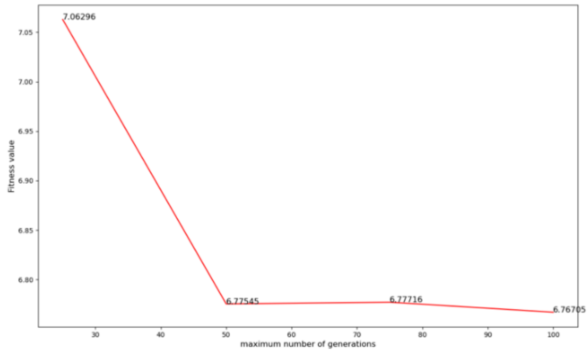


Fig. 3. Maximum number of generations of Toyota brand

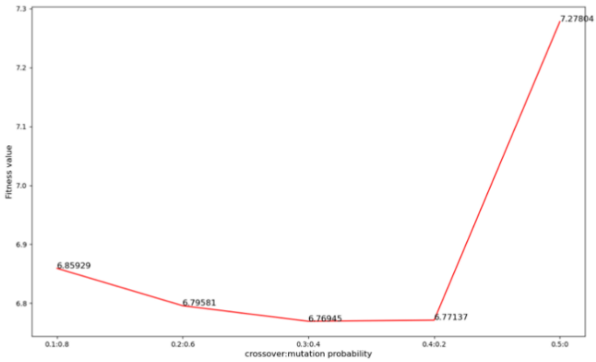


Fig. 4. Crossover and mutation probability of Toyota brand

Testing the maximum number of generations will use the optimal population from the previous experiments. Experiments with the maximum number of generations were carried out four times with each experiment being 25,50,75,100. The experimental results for the maximum number of generations of the Toyota brand using the MHW method can be seen in Figure 3. The maximum number of generations of 100 has an optimal fitness value. These results are used to search for crossover and mutation probability parameters.

Table 2. Controls parameters of GA.

Brand	Model	Population Size	Maximum number of generations	crossover	mutation
Toyota	GA-MHW	30	100	0.3	0.4
	GA-AHW	30	100	0.3	0.4
Honda	GA-MHW	30	100	0.3	0.4
	GA-AHW	25	75	0.4	0.2
Daihatsu	GA-MHW	20	75	0.3	0.4

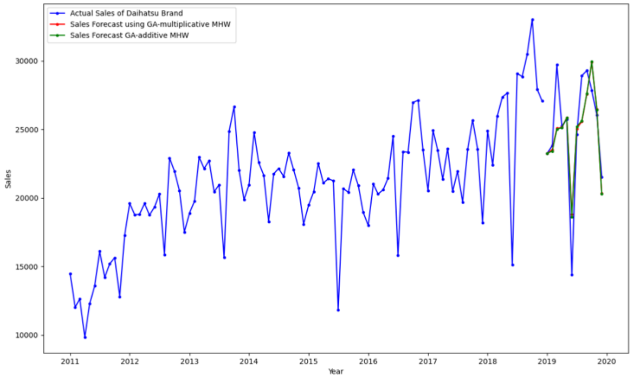
	GA-AHW	30	75	0.1	0.8
Suzuki	GA-MHW	20	75	0.3	0.4
	GA-AHW	20	100	0.4	0.2

Crossover and mutation probability experiments used the results of population size and the maximum number of generations from previous experiments. The results of the population size and the maximum number of generations for each brand give different fitness values. So, crossover and mutation probability are also tested on each brand for both the MHW and the AHW method. The crossover and mutation probability testing scenarios refer to the study [17] where the value of cr*2+mt=1. Furthermore, the values of cr:mt are 0.1:0.8, 0.2:0.6, 0.3:0.4, 0.4:0.2, and 0.5:0. Figure 4 is an experiment of crossover and mutation probability on the Toyota brand using the MHW method, it can be seen in the test that the best cr: mt is obtained at a value of 0.3:0.4.

Control parameters experiments of GA continued for all brands. In addition, experiments were also continued for the MHW and AHW methods. This is done to get the optimal MHW and AHW parameters. The overall test results of the Genetic Algorithm control parameters can be seen in table II. It can be seen in the table that each brand has different parameters. The next experiment is to find the optimal parameters for the MHW and AHW methods. The optimal parameters generated by GA-MHW and GA-AHW are used to forecast car sales.

The forecasting results are presented in a graph that can be seen in Figure 5. The figure is the result of forecasting sales for four car brands in Indonesia using the proposed method. The blue line is the actual car sales data obtained from the Gaikindo website. The green line is the result of forecasting using GA-MHW. While the green line is the result of forecasting using GA-AHW. The results of GA-MHW and GA-AHW are close to each other, which means that GA-MHW and GA-AHW do not have many different performances.

The optimal parameters along with the MAPE values generated by each model for each brand can be seen in table III. MAPE in bold is the best MAPE for each model. Based on the MAPE interpretation in table I, the proposed method can provide Highly Accurate forecasting results for the Toyota, Daihatsu, and Suzuki brands using both GA-MHW and GA-AHW with a MAPE value of less than 10. Meanwhile, the proposed Honda model provides good forecasting results because forecasting results are in the MAPE 10-20 range.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Sales Forecast using GA-multiplicative MHW
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Sales
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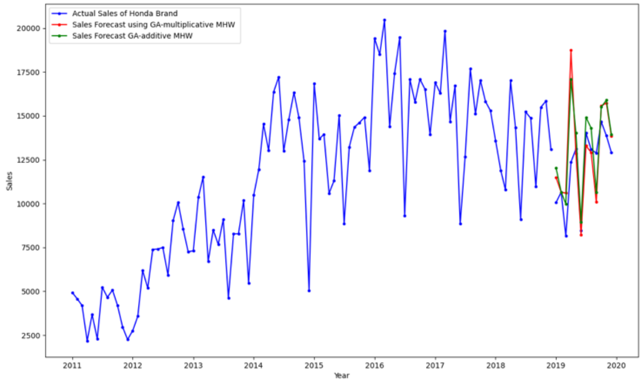
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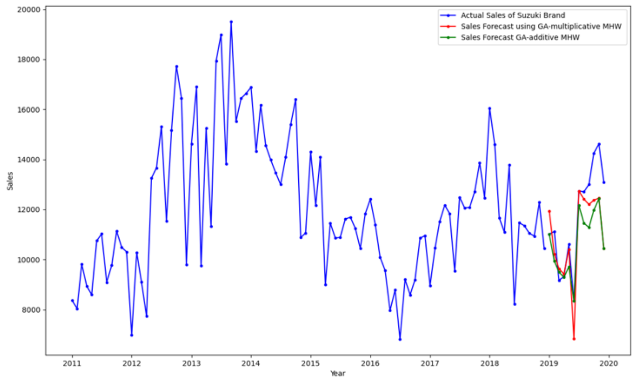
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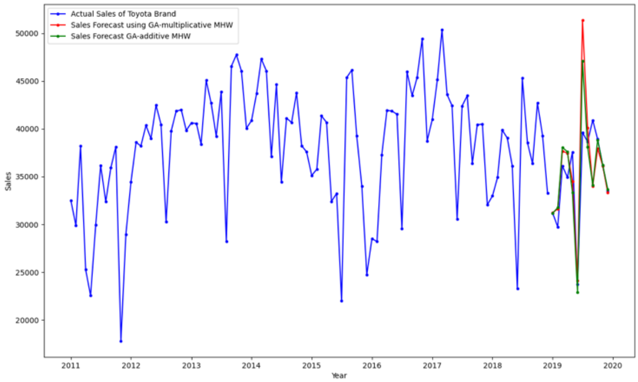
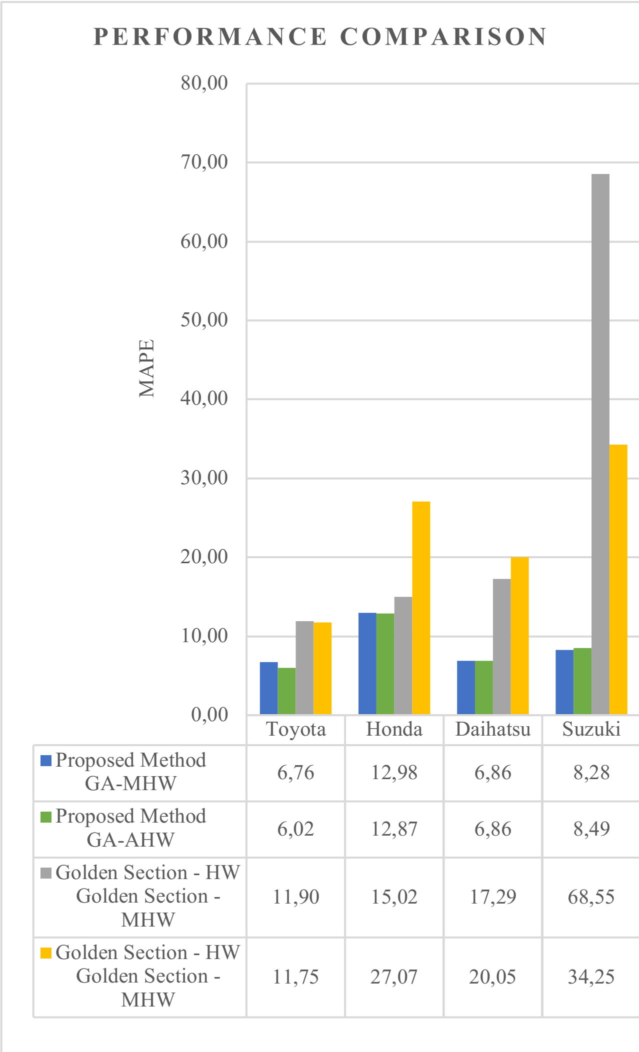


Fig. 5. Forecasting result

Furthermore, to determine the performance of the proposed method, the MAPE generated from the proposed method is compared with the MAPE produced by [10]. The Study [10] performed the Holt-Winters parameter optimization using the golden section method (golden section – HW). The comparison results are represented in graphical form which can be seen in Figure 6. For all brands, the proposed method outperforms the golden section – HW method. It is proven by the MAPE value from the proposed method has a smaller value than the MAPE from the study [10].

Table 3. Parameter optimization GA-MHW and GA-AHW

Brand	Model	GA-MHW			MAPE
		Alpa (α)	Beta (β)	Gamma (γ)	
Toyota	GA-MHW	0.50467	0.06322	0.96087	6,76
	GA-AHW	0.47354	0.65647	0.96004	**6,02**
Honda	GA-MHW	0.42718	0.56495	0.94311	12,98
	GA-AHW	0.10301	0.52046	0.99917	**12,87**
Daihatsu	GA-MHW	0.01263	0.53889	0.52163	**6,86**
	GA-AHW	0.01131	0.61947	0.54509	**6,86**
Suzuki	GA-MHW	0.99992	0.32185	0.57043	**8,28**
	GA-AHW	0.99608	0.16173	0.24307	8,49



	Toyota	Honda	Daihatsu	Suzuki
Proposed Method GA-MHW	6,76	12,98	6,86	8,28
Proposed Method GA-AHW	6,02	12,87	6,86	8,49
Golden Section - HW Golden Section - MHW	11,90	15,02	17,29	68,55
Golden Section - HW Golden Section - MHW	11,75	27,07	20,05	34,25

Fig. 6. Performance comparison

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