Enhancing the fuzzy inference system using genetic algorithm for predicting the optimum production of a scientific publishing house

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ABSTRACT

As a scientific publishing house, Indonesian Institute of Sciences (LIPI) Press' encountered some problems in publication planning, mainly predicting the optimum production of publications. This study aimed to enhance a fuzzy inference system (FIS) parameters using the genetic algorithm (GA). The enhancements led to optimally predict the number of LIPI Press publications for the following year. The predictors used were the number of work units, the number of workers, and the publishing process duration. The dataset covered a five years range of total production of LIPI Press. Firstly, an expert set up the parameters of the fuzzy inference system denoted as a FIS expert. Next, we performed a FIS GA by applying the genetic algorithm and K-fold validation in splitting the training data and testing data. The FIS GA revealed optimum prediction with parameters that were composed of both population size (30), the probability of crossover (0.75), the probability of mutation (0.01), and the number of generations (150). The experiment results show that our enhanced FIS GA outperformed FIS expert approach.

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1. INTRODUCTION

In the current era, an increase in the number of scientific publications always accompanies the development of science and technology. Scientific publications that include publishing journals and books are carried out by many publishers, including private publishers and government publishers. LIPI Press as a national publisher managed by the Indonesian Institute of Sciences (LIPI), strives to continue to increase its production capacity and capability. LIPI Press is a technical unit in the scientific publication of LIPI. The mission of the LIPI Press establishment is to become a professional and integrated publisher to maintain all LIPI's scientific work results by specializing in the characterization of LIPI's publication and dissemination of information [1].

Focusing on one of LIPI Press' tasks, planning for publishing the scientific works of LIPI, there is the main problem found, especially in predicting the number of book publications for the following years. This plan is necessary for administrative staff to propose the budget needed, determine the resources required in the production process, and arrange annual work plans in LIPI Press. So far, such a planning program in LIPI Press is always to complete based on self-estimation only without specific knowledge or model, so it is essential to highlight this issue in this study. This study predicts the number of publications in the coming year by applying a fuzzy inference system (FIS).

Prior work on FIS has been conducted. The inference system is no longer get the linguistic information from an expert only but also adapting fuzzy system using numerical data (input/output pairs) to get better performance, in this case, the accuracy of the data analysis results [2]. The development of fuzzy logic shows that fuzzy logic can model various systems, map an input into an output without losing sight of the factors, be very flexible, and have a tolerance to the existing data [3]. One article in a journal mentions two steps of synthesizing a fuzzy system that is commonly used, namely identifying structural and parameter optimization [4]. Furthermore, there is an optimization of membership function in FIS rules using genetic algorithms (GA) applied to the automatic classification of corporate bonds (bond rating) in Japanese companies [5]. While to determine the type of curve and parameters of the fuzzy set, the GA were conducted to optimize [6].

This research aims to perform the parameter optimization of FIS using a GA to predict the number of publications published by LIPI Press for years to come optimally. The study is limited to predicting the number of publications published by LIPI Press using a FIS. The variables used are the variables that affect the number of publications, the number of work units, the number of employees, and the length of the productive process of publication. The data used are secondary data output from LIPI Press from 2006 to 2010. The main contribution of our paper is to describe the enhancement of the FIS using a GA for Predicting the optimum production of a scientific publishing house.

The remainder of this paper is organized: in section 2, we review work related to optimation of fuzzy inference system using genetic algorithm. In section 3, we outline our research methodology. Then we discuss the results of our experiments in section 4. Finally, we present our conclusions and future directions in section 5.

2. RELATED WORK

Some works studied are the application of the GA in performing fuzzy optimization. Huang *et.al.*, comparing FIS-based information granulation developed using space optimization algorithm (SOA) and GA, with the result that SOA is more computationally effective than using GA [7]. Chen *et.al.* made a water-saving irrigation decision-making model for greenhouse tomatoes by optimizing the genetic Takagi-Sugeno (T-S) fuzzy network using genetic algorithms. Chen *et.al.* succeeded in proving that the GA improved T-S fuzzy neural network (GA-TSFNN) can be used to predict the volume of water-saving greenhouse tomato irrigation with better aquation than backpropagation (BP) neural network (BPNN) and GA-BPNN [8]. Sakalli optimized production-distribution planning (PDP) in supply chain systems - supply chain systems (SCS) using ant colony optimization (ACO) and GA. The results of ACO and GA were able to solve non-deterministic polynomial-time hardness (NP-hard) PDP for SCS sizes big. However, GA produces a better solution than ACO [9]. Hashim *et.al.*, solving sustainable strategic supplier selection (SSSS) based on multi-object fuzzy optimization using GA. Hashim *et.al.* successfully developed a multi-objective programming model based on a GA to select a SSSS under a fuzzy environment [10]. Wang and Yin developed a method to ensure that fresh food can be delivered on time and with minimum total cost while maintaining the quality of fresh food using the fuzzy genetic algorithm (FGA). The result showed that the FGA performed better than traditional GA [11]. Jamwal *et.al.* assists users in selecting the final solution from a set of Pareto optimal solutions using an equitable fuzzy sorting genetic algorithm (EFSGA) [12].

Furthermore, Lazli and Boukadoum performed increased segmentation of cerebrospinal fluid (CSF), white matter (WM), and gray matter (GM) networks in a case study of brain tissue in Alzheimer's disease patients using a hybrid fuzzy - possibilistic clustering model with genetic optimization [13]. Mounche *et.al.*, developing urban flood impact mitigation by optimizing the sewer system using a GA. The result revealed that the optimized GA could predict flood volume reduction by 25% better than expert predictions, but this only applies to specific urban drainage systems and variable rainfall [14]. Civelek optimized fuzzy logic on wind turbine pitch angle controllers using genetic algorithms. The simulation results showed that the optimization made the output power better [15]. Luy *et.al.* proposed a short-term electrical load prediction/experience model using genetic-fuzzy and ant colony-fuzzy knowledge base optimization. The results showed that the proposed model was more successful than the standard fuzzy logic approach usually seen in the literature and proved that the method was based on nature-inspired (NI) helps when working in a more flexible estimation environment. Due to the limitations of the method proposed by Luy *et..al.*, some cases are not active in the optimization process, such as a period of high-temperature time. The results in an unnecessary increase in optimization errors and a decrease in optimization performance [16].

Next, a few papers reported the absence of updating of methods in fuzzy logic optimization. Vannucci *et.al.* fixed industrial optimization problem solutions using fuzzy adaptive genetic algorithm [17]. Sánchez *et.al.* optimized the FIS applied to response integration for pattern recognition using a hierarchical GA [18]. Costaner *et.al.* predicted the optimum amount of bread production per day by optimizing the fuzzy logic on the demand and supply input variables and the bread production output variables. The results were obtained by predicting the amount of bread production per day based on existing input variables [19]. Nasution and Prakarsa developed an application for predicting the number of production goods based on the demand and supply of goods in the company using Mamdani fuzzy logic [20]. Beklaryan *et.al.* optimized the new real-code GA with fuzzy control for real-coded genetic algorithms (F-RCGA). The algorithm aggregated with the system dynamics (SD-model) model and resulted in greater time efficiency of F-RCGA than RCGA others and the Monte-Carlo method [21].

Meanwhile, Kangrong and Tokinaga optimized the membership function in the rules of the FIS using a GA and applying it to the classification of corporate bonds. The result is about 5% of the bond rating compared to the conventional FIS [5]. Patel and Marwala developed self-service applications in the classification system feature for payment recipient applications through the optimized FIS classifier using GA and simulated annealing (SA) [22]. Veerababu *et.al.* analyzed and optimized fuzzy inference with a GA-based approach that reduced rules and computation time and complexity. The result is that Mamdani-based FIS has been optimized using GA for control system applications [23]. Lipiński *et.al.* optimized the sequential grinding process of ceramic elements to define the purpose and limitations imposed on the machining process by applying fuzzy logic, resulting in the highest process efficiency in sequential grinding of small ceramic elements [24]. Djunaidi *et.al.* predicted the amount of production based on the fuzzy Mamdani logic (Min-Max) by observing the variables of the amount of demand and the amount of supply. The results were successful in predicting based on the input variables [3].

The rest papers are generally used to implement adaptive-network-based fuzzy inference system (ANFIS). Khosbin *et.al.* modeled coefficient by optimizing multi-object ANFIS using GA/ singular value decomposition (SVD). The result is that the model designed by GA/SVD-ANFIS can predict the discharge coefficient with a reasonable degree of accuracy. Furthermore, compared to the GA/SDV-ANFIS method with the existing equations and the multi-layer perceptron-artificial neural network (MLP-ANN), the results show that the GA/SVD-ANFIS method has superior performance in simulating the side weir removal coefficient [25]. Ishola *et.al.* optimized the iron-sulfate catalyzed esterification of palm kernel oil using ANFIS GA, which then compared this method with the response surface method (RSM). ANFIS predictions were better than RSM, while GA outperformed RSM in optimizing the esterification process [26]. Yaghoobi *et.al.* optimized the pressure pathway in the sheet hydroforming process using an ANFIS-GA. As a result, the combination of the ANFIS approach and the optimization algorithm is a good scheme for predicting the path of the increased loading pressure minimizing depletion in the critical region of the section, and avoiding various simulations or trial and error experiments [27]. Ponticell *et.al.* modeled and optimized the shear strength of hybrid composite polymer joints obtained by a two-step laser splicing process by combining fuzzy and GAs. Also, use analysis of variance (ANOVA) to detect the statistical effect of process parameters. Ponticell *et.al.* can provide information about how much the precision of models and processes varies by changing process parameters [28].

Next, Khosravi *et.al.* applied the ANFIS-genetic algorithm and teaching-learning-based optimization algorithm (ANFIS-GATLBO) to determine the optimal parameters of the thermo-economic model. As a result, it was able to predict targets with correlation coefficients close to 1. Torkzadeh optimized the layout of the double-layer grids using GA FIS [29]. Seghier *et.al.* developed a new framework for stress intensity factor (SIF) prediction using artificial intelligence (AI) via ANFIS-GA and ANFIS-particle swarm optimization (ANFIS-PSO), succeeded in providing a hybrid AI framework that can serve as an efficient numerical tool for SIF prediction and analysis [30]. Ighose *et.al.* predicted the production of fatty acid methyl esters (FAME) from yellow oleander seed oil (Thevetia peruviana) for biodiesel fuel by applying the ANFIS and RSM. The input variable for the transesterification process is optimized using a GA coupled with the ANFIS model and the RSM optimization tool. As a result, ANFIS's ability is superior to that of RSM [31]. Elbaz *et.al.*, predicting the performance of earth pressure balance (EPB) using ANFIS GA, the results using the multi-objective ANFIS-GA are more successful than the ANFIS results [32]. Armanda and Mahmudy optimized the Tsukamoto fuzzy system to determine the appropriate membership function boundaries. Using GA to improve the fuzzy membership function limitations, the result is that the optimized FIS can provide more accurate results [33].

3. RESEARCH METHOD

3.1. Research flowchart

We performed the FIS parameter optimization using GA to predict the optimal number of publishing books. To design the FIS, we applied the Mamdani method known as the Max-Min method. Figure 1 illustrates the research flowchart represented within the methodological framework.

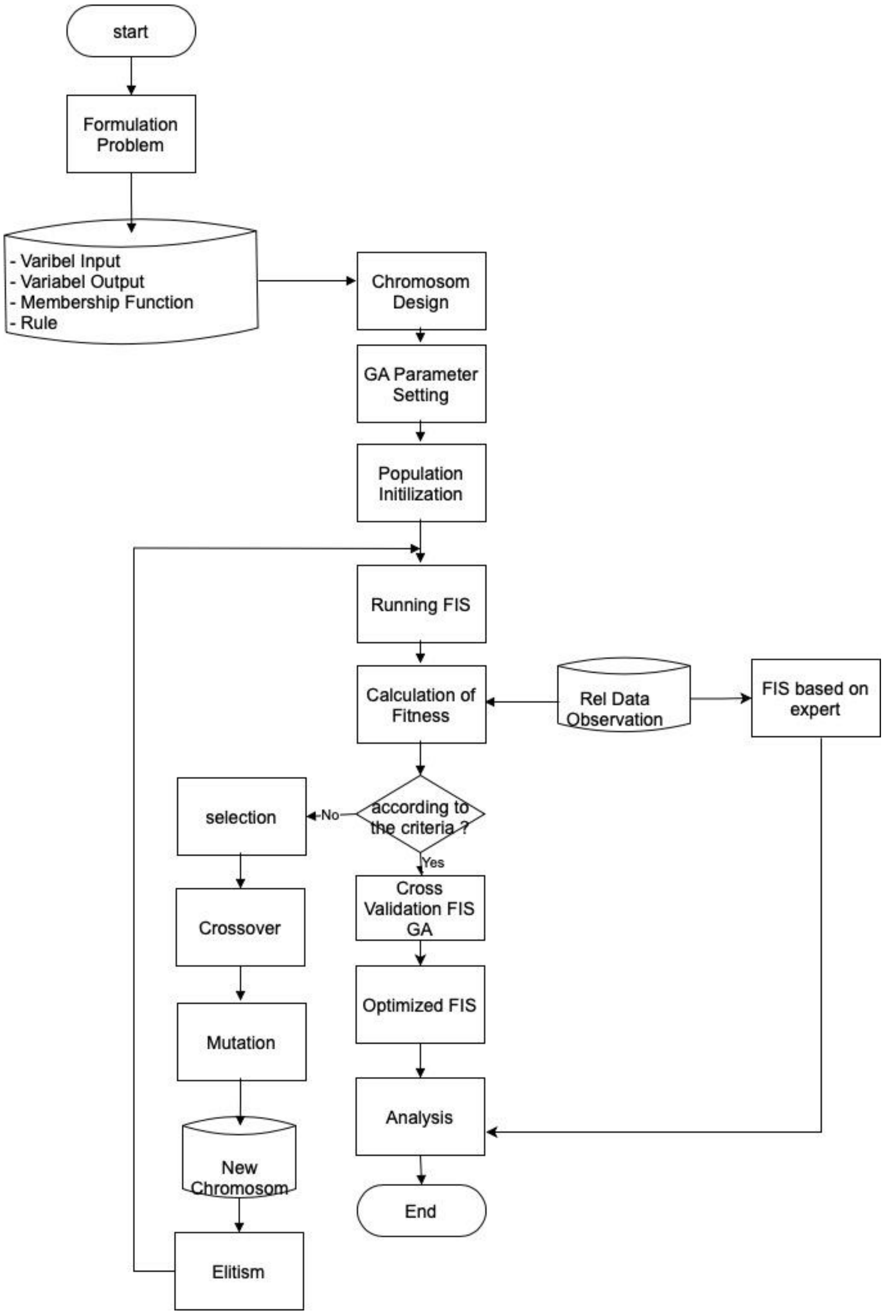

Figure 1. Research method flowchart diagram

At problem formulation phase, we identified the underlying problem in predicting the number of book publications for years to come. Next, we designated some specified input variables that will affect the number of publications, the number of publications output. The input variables were the number of work units, the workforce, and the duration of the publishing process.

Membership functions used in the FIS based on expert is a trapezoid, while the membership functions which will be used in optimizing the FIS with GA were:

– S-shaped curve to set a little shrinkage. This curve will move from the far-right side (membership value = 1) to the far left (membership value = 0).
– S-shaped growth curve for plenty of sets. This curve moves from the far-left side (membership value zero) to the far right (membership value = 1). Membership functions will be concentrated in 50% of the value of membership; it is often referred to as the point of inflection.
– PI curve to moderate set. This curve consists of two parameters: γ and β with membership degree 1 where γ indicates the domain value on the center of the curve, while β is the half-width of the curve.

Figure 2 shows some example curve membership functions that were used in this study.

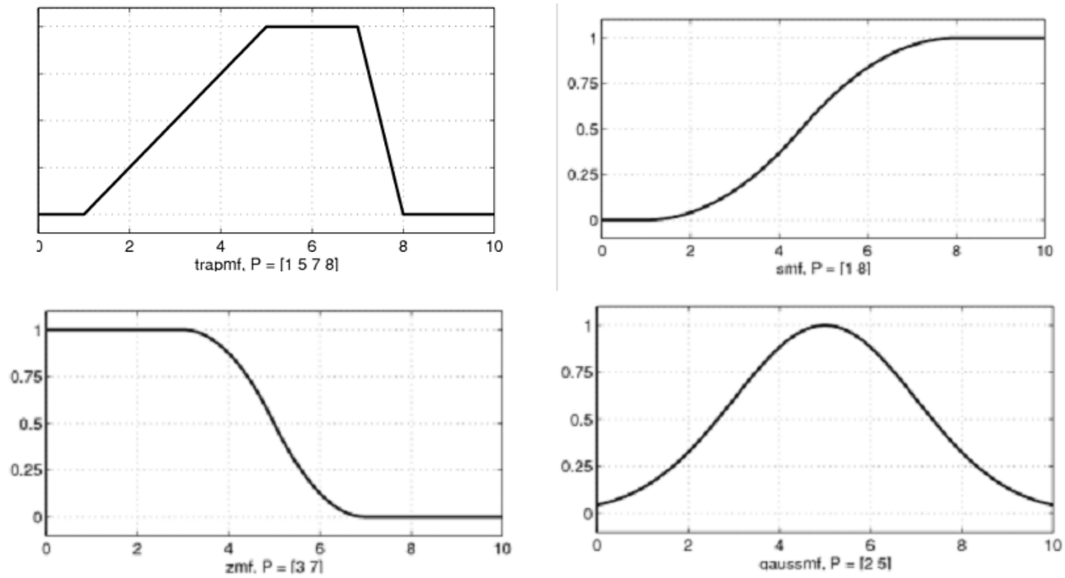

Figure 2. Example curve membership functions used

At the flowchart in Figure 1 we generated the rule that consists of 27 rule combinations. Then, the expert appointed 14 rules to be included in the FIS. In this study, we represented the parameters of membership functions in chromosomes. The chromosome was represented in binary form, where every single chromosome consists of four variables: the number of work units (x), the amount of workforce (y), duration of the process (z), and the total number of production (w). Each variable has two parameters, namely α and β, with the length of chromosomes (genes) under the range of each variable. Table 1 summarizes the variables and length range of each chromosome. Thus, the design of chromosomes can be represented in Figure 3.

Table 1. Variables and length range of each chromosome

Variable	Range	Length of Chromosome
X	[0 60]	25
Y	[0 20]	20
Z	[0 220]	35
W	[0 100]	30

<table>
<tr><td>αXlittle</td><td>βXlittle</td><td>αXmoderate</td><td>βXmoderate</td><td>αXlots</td><td>βXlots</td><td>…</td><td>αWlots</td><td>βWlots</td></tr>
<tr><td colspan="2">5 bits</td><td colspan="2">9 bits</td><td colspan="2">11 bits</td><td>…</td><td colspan="2">13 bits</td></tr>
<tr><td colspan="9">110 bits</td></tr>
</table>

Figure 3. Design of the chromosome’s representation

In this research, GA parameters setting used are: i) size of population (UkPop): 30, 50 and 80; ii) probability of crossover (Pc): 0,75; 0,85 and 0,95; iii) probability of mutation (Pmutasi): 0,01 and 0,001; and iv) number of generations: 50, 100 and 150. The initialization of the population process is forming the initial population in the form of binary code generated randomly within a range of values according to the determining population size. We implemented the population size is: 30, 50, and 80. The fitness value was denoted as the value of error. The calculation was accomplished on the fitness value of each chromosome by testing or running Mamdani FIS to obtain a small error. However, the calculation of fitness value is 1/error. Thus, the best fitness is the maximum error.

The selection was made if the individual does not meet the criteria. The method used in this selection was the roulette wheel, which rotated as many as the number of chromosomes. This method allows the chromosomes with higher fitness values to have a greater chance of election than the chromosomes with low fitness values. Nevertheless, this also allowed a chromosome to be selected more than once.

Crossover aimed to increase the diversity of individuals in the population by the mating of individuals to produce offspring in a new individual. The crossover was achieved by exchanging genes from two parents at random and the crossover performed on each individual with a specified probability crossover. The crossover and mutation process can be seen in Figure 4.

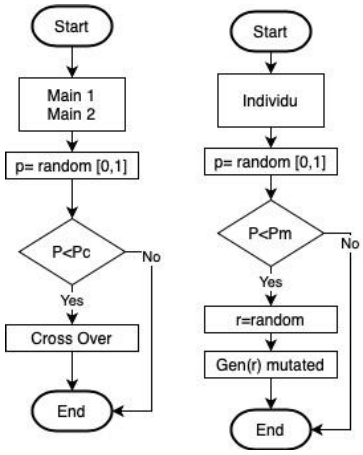

Figure 4. Crossover and mutation process

The mutation process was executed in binary code as in representing chromosomes in binary form, so the mutation is a change in a single bit (bit 0 to 1 and vice versa) of the elected members of the population. An individual who has a gene mutation is based on the probability of determining mutation. This mutation process can be spotted in Figure 4.

Then, we applied k-fold cross-validation, with a k value are 5 (5-fold), to divide the data train and test data. The training data consisted of 4 data of publications, while the test data is 1 datum. In other words, this strategy used in cross-validation is a leave one out strategy. Table 2 shows the validation cross method using leave one out. We use operating system to support the development of our system. Our machine environment is: OS Windows 7 Starter (32-bit), Matlab 2008, Microsoft Office Excel 2007, AMD Dual-Core E-450, 2GB memory, 320GB hard disk drive.

Table 2. Validation cross method using leave one out

Trial	Data training	Data testing
1	2,3,4,5	1
2	1,3,4,5	2
3	1,2,4,5	3
4	1,2,3,5	4
5	1,2,3,4	5

4. RESULTS AND DISCUSSION

4.1. FIS expert

A fuzzy set was used on each of the variables, as shown in Table 3, where the experts obtained the parameters. Of parameters and rules that experts have defined, the prediction of complete book publication can be observed in Table 4. The predicted results by experts have different values from the data's publication number.

4.2. FIS GA

The entire experiment conducted from GA parameters specified was 54 trials. The data distribution using the leave one out cross-validation resulted in 4 data, and 1 trained data with some experimental test data as *k* is 5 trials. Therefore, the amount of combination obtained was 270. The experimental results can be observed in Table 5. From the experiment results, it can be examined that the fifth experiment has a smaller margin than other experiments do. Thus, it can be said that the fifth trial produced optimal GA parameters. Table 6 compares the predicted result of book publication using the FIS experts and using GA FIS or optimized FIS. Figure 5 shows that the optimized prediction of book publication gives a better result than the expert's prediction.

Table 3. Fuzzy set book on outlook publication

Variable	Fuzzy association name	Parameter
number of work units (x)	Little	[0;0;8;15]
	Moderate	[12;24;30;42]
	Lots	[36;48;60;60]
Number of Worker (y)	Little	[0;0;2;5]
	Moderate	[3;6;8;12]
	Lots	[10;15;20;20]
Process Time (Number of days) (z)	Short	[0;0;18;55]
	Moderate	[40;80;100;125]
	Long	[110;150;220;220]
number of book publications (w)	Little	[0;0;15;30]
	Moderate	[25;40;50;70]
	Lots	[60;80;100;100]

Table 4. Prediction of book publication by expert

Year	Number of book publication based on observational Data	Number of book publication based on expert of FIS	Difference
2006	65	50	15
2007	60	50	10
2008	19	47	28
2009	40	47	7
2010	27	47	20

Table 5. Results of experiment using cross-validation

Observation	Optimal GA Parameter				Observational data	Predicted result	Difference
	UkPop	Pc	Pm	MaxGen			
1	30	0.85	0.01	150	65	62	3
2	30	0.85	0.01	100	60	50	10
3	30	0.75	0.01	50	19	28	9
4	30	0.85	0.01	100	40	37	3
5	30	0.75	0.01	150	27	28	1

Table 6. Comparison of forecasts

Data Observation	Expert of FIS		GA FIS	
	Result of prediction	Difference	Result of prediction	Difference
65	50	15	62	3
60	50	10	50	10
19	47	28	28	9
40	47	7	37	3
27	47	20	28	1

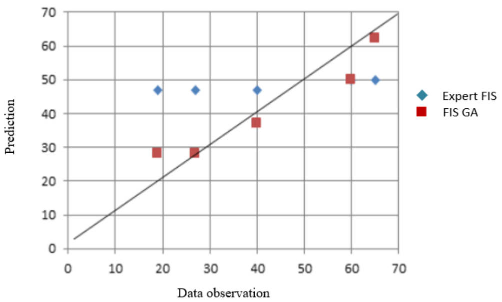

Figure 5. Visualization experts FIS and FIS GA

4.3. User interface (UI)

To achieve the optimization process of a fuzzy inference system using genetic algorithms, we built a simple application using Matlab 7.7.0. The graphic user interface (GUI) of the application can be noticed in Figure 6.

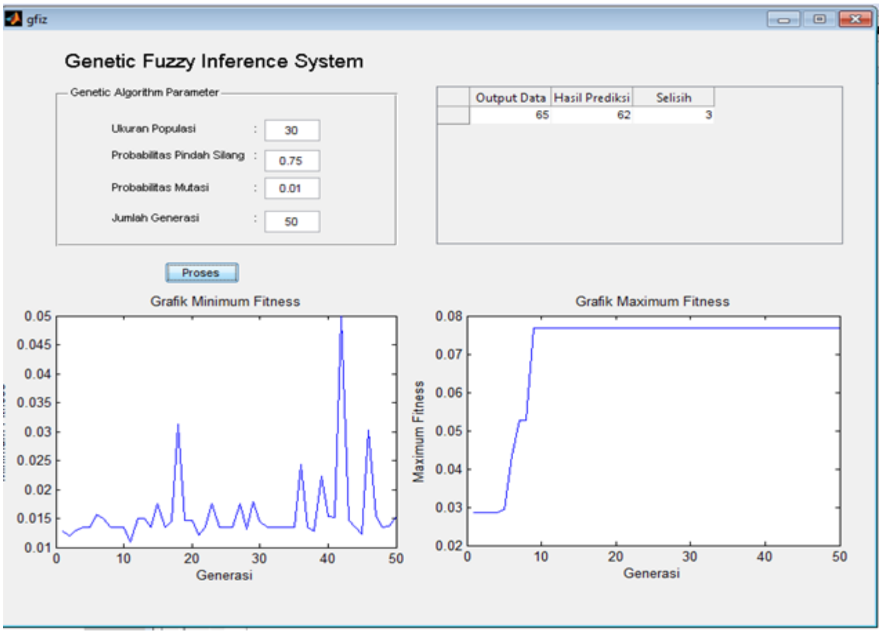

Figure 6. User interface of the application of genetic fuzzy inference system

5. CONCLUSION

In this paper, we have described the optimization of the FIS by applying a GA. We also compare the optimization results by an expert (FIS Expert) with a genetic algorithm (FIS GA). From the various experiments that have been carried out in this study, the results show that GAs can optimize the set of FIS on the size of 30 population, crossover probability of 0.75, mutation probability 0.01, and the number of generations of 150. By obtaining the GA parameters, membership functions used in the FIS to predict the number of publications were generated. The predicted result produced has a minor difference with observational data than the prediction results using the expert's membership function. We can conclude that our enhanced FIS GA outperformed FIS Expert approach. Given the limitations of the datasets and publishers analyzed in this study, in the future, we will consider comparing the optimization of the FIS with the GAs that apply to various publishing institutions. To expand our study, we consider to compare the results with other machine learning methods.

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