Received: May 4, 2022. Revised: July 20, 2022.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Optimizing Cost of Sugarcane Logging and Transportation to Milling Using Iterative Fuzzy Inference System

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Abstract: The problem in this research is optimizing logging distribution from three sugarcane plantation locations to three sugar mill locations. In the existing method, each sugar factory location is only supplied by one plantation location, which is located closest to the factory location. This article proposes the Iterative Fuzzy Inference System (IFIS) method to optimize the cost. IFIS used two FIS. The first FIS was carried out iteratively to find the best factory priority as a destination for delivery of logged sugarcane. The second FIS was conducted to find the best log quantity from each plantation to be sent to each mill. This research contributes to optimization. On the plantation side, the harvested products from one plantation are sent to all the mills that need them, and on the mill side, the mill only accepts sugar cane shipments as needed, so no sugar cane has to wait long in the mill.

Keywords: Sugarcane logging cost, Sugarcane transportation cost, Cost optimization, Waiting time optimization, Iterative fuzzy inference system.

1. Introduction

Sugarcane crop logging is a series of activities to log sugarcane ready to be harvested while loading it onto a transport vehicle and transporting it to the sugar mill. Several limitations must be met in the sugarcane crop logging process, making it complex [1]. Some of these limitations are ripe sugarcane that must be logged down immediately, and harvested sugarcane must be milled before 36 hours, mill capacity, queue capacity at the mill, logging and loading costs, transportation costs, distance from the plantation to the mill, and milling costs [2].

The current sugarcane crop logging process is still not optimal. Currently, each sugar factory location is only supplied by one plantation location, which is located closest to the factory location. We call this method an existing method. This non-optimality is indicated by the reduction in sugarcane yield in the sugarcane crop logging process in 2013, which reached 35% [3]. This shrinkage is mainly due to the delay in milling. Milling delays were caused by limited milling capacity and queue capacity at the mill, inaccurate harvesting schedules, and inaccurate delivery destinations. Therefore, this study optimizes the harvesting schedule and determines the destination and quota of sugarcane delivery to the sugar mill.

Several studies have been conducted to optimize the sugarcane crop logging process. In 2000, research conducted by Salassi, Champagne, and Legendre used a linear programming algorithm to maximize profits in agricultural processes [4]. In 2004 Salassi, Garcia, Breaux, and No simulated the sugarcane crop logging process to reduce losses due to the long delivery time of sugarcane from the field to the mill [5]. Thuankaewsing, Pathumnakul, Piewthongngam, 2011, performed schedule optimization based on the estimated yield using an artificial neural network algorithm [6]. Lamsalz, Jones, and Thomas, 2016, tried to reduce the waiting time of trucks at the mill using integer programming [7]. Junqueira and Morabito, 2017, used harvest front programming to

Received: May 4, 2022. Revised: July 20, 2022.

optimize sugarcane harvest scheduling [8]. Florentino, Irawan, Aliano, Jones, Cantane, and Nervis used genetic algorithms and goal programming to schedule sugarcane harvests as close to sugarcane maturity [1]. In addition, Afifah, Alamsyah, and Sugiharti also performed scheduling optimization by minimizing sugarcane transport trucks from the land to the mill using the simulated annealing algorithm [9]. Caixeta-Filho and Miyashita optimized the sugarcane harvest scheduling with processing capacity limits and the minimum proportion of land harvested using mixed-integer linear programming [10]. In 2019 Junqueira and Morabito tried to optimize sugarcane harvest scheduling using mixed-integer programming [11]. In 2020 Masoud, Kozan, Liu, Elhenawy, Corry, Burdett, and D'ariano scheduled a sugarcane hauling truck to minimize transportation costs using constraint programming and mixed-integer programming [12].

Meanwhile, Jarumaneeroj, Laosareewatthanakul, and Akkerman, in 2021, carried out an optimization of year-round scheduling using an evolutionary genetic algorithm [13]. Optimization of the multi-stage distribution process using an Improved Genetic Algorithm was also carried out by Wayan Firdaus Mahmudy, Mohammad Zoqi Sarwan, Asyrofa Rahmi, and Agus Wahyu Widodo in 2020. The result proves the robustness of the improved GA for solving big-size problems [14]. In 2020, Florentino, Jones, Irawan, Ouelhadj, Khosravi, and Cantane used a new integrated mathematical programming model to deal with the sugarcane varieties selection to be planted and determine the optimal planting and harvesting periods to increase production in the sugarcane industry. This study provides sugarcane company managers with decision support in selecting the most suitable varieties and in determining the best period to plant and harvest their sugarcane [15]. In 2017, Aziz Fajar and Riyanarto Sarno used an agent-based simulation method to reduce the AWT by parallelizing the agents of an organization and simulating the parallelized agents [16]. Aziz Fajar and Riyanarto Sarno also performed an optimization process using Stochastic Multicriteria Adaptability Analysis 2 (SMAA-2). This study result shows that parallelization can reduce the AWT of the current system. The optimization process using SMAA-2 shows the most optimal number of multiple tasks an agent can do simultaneously [17]. In 2019, Gita Intani Budiawati and Riyanarto Sarno used PERT and goal programming for time and cost optimization of business process RMA. This study shows that the processing time is reduced by 50%, and the cost is reduced by almost 55% [18].

In previous studies, optimization was only carried out on the schedule for logging and transporting sugarcane. In this study, the purpose and quantity of sugarcane delivery were also determined. The optimization algorithm used in this research is Iterative Fuzzy Inference System (IFIS). With this method, there will be a distribution of logging results from each plantation for each sugar mill. Using IFIS, it is hoped to optimize logging and transportation costs and decrease the amount of sugarcane waiting to be milled.

This study will compare the optimization results using the IFIS method with the optimization using the existing and FIS methods.

2. Theory

The sugarcane crop logging scheduling, transportation cost, waiting time, optimization, and fuzzy inference system in sugarcane milling can be explained.

2.1 Sugarcane crop logging schedule

Sugarcane crop logging schedule is made based on the determining factors that must be considered: incidence of pests and diseases, planting time, the ripeness of the sugarcane, sugarcane varieties, and difficulty level of transportation, especially during the rainy season [19].

Ripe sugarcane cannot just be logged down and brought to the mill. The logging carried out must have regulations so that it is not logged too much and can also be adjusted to the mill's capacity. Sugarcane is harvested through logging and transporting activities. There is a time from logging in the plantation to milling at the mill. Metabolism in sugarcane can cause the decomposition of polysaccharides into disaccharides or monosaccharides, so that the sugar level in sugarcane is reduced. Therefore, appropriate and efficient logging and transport activities play a critical role in saving the production potential that already exists in plants [20].

The flow of sugarcane crop logging and transport from the plantation to the sugar mill is shown in Fig. 1.

2.2 Transportation cost

Transportation costs are part of sugarcane's logging, loading, and transporting costs in a sugar mill and have the largest share of these costs.

Various efforts and strategies were made to reduce transportation costs. In cost, the main components of costs are volume and price. Volume can be in product units, activities, distances, orders,

Received: May 4, 2022. Revised: July 20, 2022.

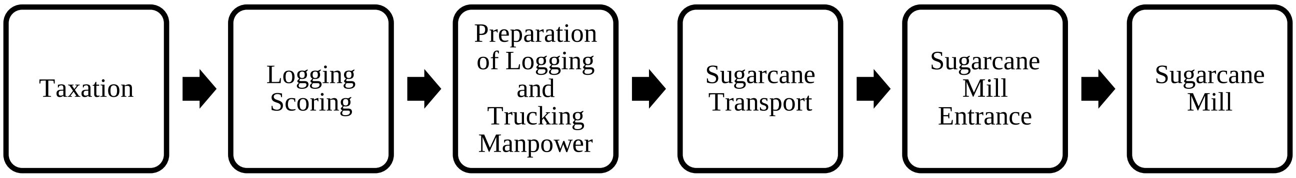

Figure. 1 Flow of sugarcane crop logging and transport

customers, area, number of machine-hours worked, direct labor hours, and others that affect costs. Meanwhile, prices can be fuel prices, wage rates, electricity rates, depreciation, vehicle rentals, and warehouse rentals, calculated in the price per unit of measurement.Cost reduction is made by reducing the volume or lowering the cost per unit. Activity-based management can help companies reduce logistics costs by reducing activities that do not provide added value and lowering the cost per unit of logistics activities [21].

In 2010, A.L. Gómez P., D.F. Cobo B., P.W. Castro F., and C.H. Isaacs E. conducted a comprehensive study of the cane transport system covering topics from system logistics to cane bin design. Among the total sugar and ethanol production system costs, activities involving harvesting (manual and mechanical), road transportation, and unloading are the most expensive operating categories. A comprehensive study of sugarcane transportation systems, covering topics from logistics systems to garbage bin design, is being carried out for the Colombian sugar industry. Models for predicting fuel have been developed and tested using GPS, tensile load, and direct fuel flow measurement for a complete operational cycle. Sensitivity tests have also been carried out to analyze the effect of weight on fuel consumption in a complete cycle. FEA modeling has been applied to the design and construction of new equipment. The results show that a 5% reduction in fuel costs is achieved with a 10% reduction in construction weight [22].

This study carried out cost reduction by implementing a sugarcane distribution strategy.

2.3 Waiting time

The logging and transporting of sugarcane are complex because many factors influence this activity, so the solution requires an appropriate scheduling system to obtain optimum work efficiency.

Various reasons can be put forward to explain the long delays in milling harvested sugarcane in sugarcane agroindustry units: mill downtime, tractor failures in queues, accidents due to tractor crowding in the yard, and shift changes that create long queues. The application of queuing theory to this problem aims to: (1) obtain a queuing system for the supply of sugarcane, (2) obtain the right queuing system in the supply of sugarcane, (3) to obtain a minimal cost for the queuing system in the procurement of sugarcane. The research was conducted in the sugarcane agroindustry in Khuzestan province. Required data related to arrival time and tractor service were collected in 2016. Data analysis was carried out according to the queuing model in the agroindustry unit. Based on initial observations, the queuing system of the agroindustry unit is a single channel model with one server, so this research was carried out with the M/M/1 model. Long queues in the queuing system can be improved by increasing the level of service, including following preventive maintenance rather than corrective maintenance, using hidden factories, using spare parts, and expanding the area for queuing [23].

Determining the number of transportation fleets and the right workforce will reduce lost time. Loss of operating time causes delays in milling time due to queues handling will reduce the quality of sugarcane and the quantity of juice produced. Sugarcane distribution strategy is one of the variables considered in minimizing transportation costs [2].

2.4 Optimization

The mathematical optimization techniques practiced are integer programming, dynamic programming, branch and bound, and simplex algorithm. Other optimization techniques that are also being developed are natural/bio-inspired (also referred to as metaheuristics) such as Evolutionary Algorithms (EA) and Swarm Intelligence (SI) [24].

In this study, the optimization is done using the fuzzy inference method. There are several reasons why people use fuzzy logic. Among others, namely, the concept of fuzzy logic is easy to understand, fuzzy logic is very flexible, fuzzy logic has tolerance for inaccurate data, fuzzy logic can model very complex nonlinear functions, fuzzy logic can build and apply the experiences of experts directly without having to go through the training process, fuzzy logic can work with conventional control techniques, and fuzzy logic is also based on natural language [25].

2.5 Fuzzy inference system

Several parameters determine how plantations are ready to be harvested to assess logging priorities: incidence of sugarcane pests and diseases, planting age, maturity factor, and sugarcane varieties cultivated. Meanwhile, the location of the plantations that are logged down is the plantations that are closest to the mill [26].

Fuzzy Inference System (FIS) can do logging scheduling optimization. In addition to considering these parameters to obtain priority for plantations that are ready to be harvested, FIS also considers logging costs, loading costs, transportation costs, mill capacity, and mill queue capacity to select the location of the plantations to be harvested [27]. FIS was chosen for this optimization case because it can make high input and output data predictions [28, 29].

3. The proposed method

The optimization method proposed in this research is the Iterative Fuzzy Inference System (IFIS). In IFIS, the method is based on how to prevent the accumulation of logging results in a mill. IFIS can divide the harvested yield of each plantation by all existing mills with the optimal amount calculated through iterations of dividing the percentage of the total harvested area of each plantation.

This method is used by utilizing the advantages of the fuzzy inference approach to get better results than the methods that have been used to solve the problem of optimizing logging scheduling in sugarcane plantations [28].

The advantages of the fuzzy inference system used in this study are:

- The ability to present quantitative values in qualitative values.
- The rules used can be represented in everyday language to facilitate reasoning in understanding the problem.

3.1 Data

The data used in this study is data obtained from a sugar mill located in Jember, East Java, Indonesia. The data includes plantation area, ready-to-logged plantation data, logging costs, sugarcane transportation costs from the plantation to the sugar mill, and milling capacity of the sugar mill.

There were three plantations with ready-to-logged status, namely Kaliketepak (KKT), Kalikempit (KKP), and Kalirejo (KRJ). Each plantation is divided into blocks with a maximum logging capacity of 3,000 tons, as shown in Table 1.

Table 1. Plantation logging capacities and cost

Plantation	Production quantity (Tons)	Number of blocks	Logging cost (Rupiah)
KKT	12,168	4	58,500
KKP	194,004	65	74,100
KRJ	289,719	97	88,400

Table 2. Logging potential of KKT plantation

No.	Block Name	Logging potential (tons)
1	KKT-1	2,500
2	KKT-2	1,000
3	KKT-3	2,000
4	KKT-4	2,000

Table 3. Logging potential of KKP plantation

No.	Block Name	Logging potential (tons)
1	KKP-1	3,000
2	KKP-2	3,000
3	KKP-3	2,000
4	KKP-4	2,811
5	KKP-5	2,853
6	KKP-6	2,925
7	KKP-7	2,420
8	KKP-8	2,189
9	KKP-9	2,357
10	KKP-10	2,254
.	.	.
.	.	.
.	.	.
63	KKP-63	2,102
64	KKP-64	2,332
65	KKP-65	2,550

The following is a sequence of blocks in each plantation according to the priority of logging potential, calculated based on the determining factors. The logging potential of each block from each plantation is shown in Table 2 to 4.

There are three sugar mills used in this paper, as shown in Table 5. The priority value of the factory as the destination for the delivery of logged sugarcane from each plantation is calculated based on the logging cost, milling capacity, queue capacity, the distance from the plantation, and the rest of the mill.

The transportation costs from the plantations to the mills are grouped into three groups, as shown in Table 6.

Table 4. Logging potential of KRJ plantation

No.	Block Name	Logging potential (tons)
1	KRJ-1	3,000
2	KRJ-2	2,000
3	KRJ-3	2,500
4	KRJ-4	2,888
5	KRJ-5	2,148
6	KRJ-6	2,067
7	KRJ-7	2,271
8	KRJ-8	2,553
9	KRJ-9	2,410
10	KRJ-10	2,304
.	.	.
.	.	.
.	.	.
95	KRJ-95	2,064
96	KRJ-96	2,760
97	KRJ-97	2,100

Table 5. Sugar mills

Mill	Milling capacity (tons)	Queue capacity (tons)	Distance from plantation (kms)		
			KKT	KKP	KRJ
IG-1	8,000	2,400	25	10	2
IG-2	1,900	570	113	110	117
IG-3	650	195	97	93	104

Table 6. Transportation costs

Distance (kms)	Cost (rupiah/tons)
0 – 40	74,360.00
41 – 80	87,360.00
81 – 120	100,360.00

3.2 Iterative fuzzy inference system (IFIS) procedure

In IFIS, optimization calculations are performed using two FIS. The first FIS is used to calculate mill priority values for each plantation. Furthermore, based on the order of priority, a second FIS iteration will be carried out to calculate the percentage of the number of logged sugarcane sent to each mill. The iteration will stop when the number of deliveries has reached the milling capacity.

3.2.1. Finding plantation priorities for each mill

First FIS, performed to determine the priority of the plantation to be logged down, uses five input variables and one output variable. Input variables include logging cost, distance to mill, milling capacity, queue capacity, and rest of the mill. Meanwhile, the output variable is the priority value of the plantation block selected for logging. The smaller the priority value, the higher priority the plantation block will be chosen as the plantation block to be logged down to meet the needs of a mill.

The fuzzy sets of each variable are presented in Table 7.

The next step is to determine the implication function by selecting the fuzzy logic rules. A Fuzzy Inference System will seek/find a conclusion (output) based on the data/facts provided (input) and fuzzy rule-based. The fuzzy logic rules to determine the priority used in this step are shown in Table 8.

3.2.2. Finding the percentage of the number of logging sent to each mill

The second FIS, used to determine the percentage of harvest for each plantation to meet the mill's needs, uses seven input variables and one output variable. Input variables include the number of harvests per block, logging cost, distance to mills, milling capacity, queue capacity, rest of the mill, and plantation priority. Meanwhile, the output variable is the percentage of the logging capacity of a plantation block to meet the sugarcane needs of a mill.

The fuzzy sets of each variable are presented in Table 9 as follows.

The fuzzy logic rules used in this step are as shown in the Table 10 as follows.

Table 7. Fuzzy set of FIS 1 variables

Variable	Fuzzy set 1	Fuzzy set 2	Fuzzy set 3
Logging cost (rupiah)	Inexpensive (30,000 –50,000)	Moderate (40,000 – 70,000)	Expensive (60,000 – 90,000)
Distance to mill (kilometres)	Close (0 – 50)	Medium (40 – 60)	Far (50 – 120)
Milling capacity (tons)	Small (0 – 5,000)	Medium (3,000 – 7,000)	Large (5,000 – 10,000)
Queue capacity (tons)	Small (0 – 3,000)	Medium (2,000 – 4,000)	Large (3,000 – 5,000)
Rest of the mill (tons)	little (0 – 50)	Medium (30 – 70)	Many (50 – 100)
Priority	Beginning (0 – 0.5)	Middle (0.3 – 0.7)	End (0.5 – 1)

Tabel 8. Fuzzy logic rules to determine priority

Logging cost	Distance to mill	Milling capacity	Queue capacity	Rest of the mill	Priority
inexpensive	close	large	small	little	beginning
moderate	medium	medium	medium	medium	middle
expensive	far	small	large	many	end

Table 9. Fuzzy set of FIS 2 variables

Variable	Fuzzy set 1	Fuzzy set 2	Fuzzy set 3
Block capacity (tons)	Slight (0 – 1,500)	Medium (1,000 – 2,500)	Considerable (2,000 – 3,000)
Logging cost (rupiah)	Inexpensive (30,000 –50,000)	Moderate (40,000 – 70,000)	Expensive (60,000 – 90,000)
Distance to mill (kilometres)	Close (0 – 50)	Medium (40 – 60)	Far (50 – 120)
Milling capacity (tons)	Small (0 – 5,000)	Medium (3,000 – 7,000)	Large (5,000 – 10,000)
Queue capacity (tons)	Small (0 – 3,000)	Medium (2,000 – 4,000)	Large (3,000 – 5,000)
Rest of the mill (tons)	little (0 – 50)	Medium (30 – 70)	Many (50 – 100)
Priority	Beginning (0 – 0.5)	Middle (0.3 – 0.7)	End (0.5 – 1)
Percentage (%)	Small (0 – 0.5)	Medium (0.3 – 0.7)	Large (0.5 – 1)

Table 10. Fuzzy logic rules to calculate logging percentage

Block capacity	Logging cost	Distance to mill	Milling capacity	Queue capacity	Rest of the mill	Priority	Percentage
slight	inexpensive	close	large	small	little	beginning	small
medium	moderate	medium	medium	medium	medium	middle	medium
considerable	expensive	far	small	large	many	end	large

3.2.3. Rule evaluation

The inference process or Rule Evaluation takes the input values fuzzified and applied them to the rule base rules. The number of outputs from the rule evaluation process depends on the number of rules made in the rule base.

According to Chen & Pham, 2001, if the fuzzy rules using AND rules have the form as shown in Eq. (1), the rule used is C1=MIN(A1, B1), which means that the output is the output value of C1 takes the smallest value between A1 and B1 [29].

$$IF\ (X\ is\ A_1)\ AND\ (Y\ is\ B_1)\ THEN\ (Z\ is\ C_1) \quad (1)$$

If the rules use the OR rules, as shown in Eq. (2), the rule used is C1=MAX(A1, B1), which means that the output is the output value of C1 takes the largest value between A1 and B1.

$$IF\ (X\ is\ A_1)\ OR\ (Y\ is\ B_1)\ THEN\ (Z\ is\ C_1) \quad (2)$$

In concluding, the method used is clipping (alpha cut), cutting the top of the curve according to the maximum/minimum value when applying the rules.

3.2.4. Defuzzification

The last stage of the Mamdani Fuzzy Method procedure is the defuzzification process. The defuzzification process interprets fuzzy membership values into certain decisions or real numbers [30]. This stage returns the fuzzy value to a crisp value (actual number) and changes the fuzzy output to a crisp value based on a predetermined membership function. This defuzzification process needs to be done because the fuzzy decision or output is a fixed linguistic variable, and this linguistic variable needs to be converted into a crisp variable.

The input of the defuzzification step is a fuzzy set obtained from the composition of fuzzy rules, while the output is a number in the domain of the fuzzy set. Therefore, if a fuzzy set is known within a specific range, it must be able to obtain a particular crisp value (actual number) as the output or the result of the decision. The method used in this defuzzification process is defuzzification with the Centroid Method (center point). This method pays attention to the condition of each fuzzy area, resulting in more

Received: May 4, 2022. Revised: July 20, 2022.

accurate results [31]. The centroid method is a method in which all fuzzy areas from the results of the composition of the rules are combined to form optimal results and take the center point of the fuzzy area. The defuzzification procedure uses the Centroid Method to determine the moment (the integral of each membership function from the composition of the rules), specify the area, and select the center point.

3.2.5. Inference correction

The number of logging percentages resulting from fuzzy inference is not the same as the amount of sugarcane needed by the sugar mill, so a correction rule is required. The correction steps are as follows:

- Add up the percentage of harvested yields for each plantation.
- Calculate the difference between the total number of loggings and the need for sugarcane in each sugar mill. This difference is referred to as mill residue.
- The rest of the mill is divided again among the existing plantations as a reduction in the number of logging requirements.
- Make the inference again to get a new number of logs.
- The result of the logging percentage is added to the previous harvest.
- Calculate the difference between the total logging and the need for sugarcane at the sugar mill.
- Repeat until the total logging>= sugarcane needs at the sugar mill.

3.3 Experimental design

In this chapter, two experiments will be carried out. The first experiment determines the values of a, b, and c used for each membership function in the FIS. The following experiment is to determine the load of the garden to be logged, whether it is dense at the beginning, in the middle of the season, at the end of the season, randomly, or gently.

The first experiment to analyze fuzzy parameters on logging and transportation costs is as follows. The fuzzy inference system consists of three membership functions: two membership functions located at the edges (mf1 and mf3) and one membership function in the middle (mf2). The membership function can be seen in Fig. 2 below.

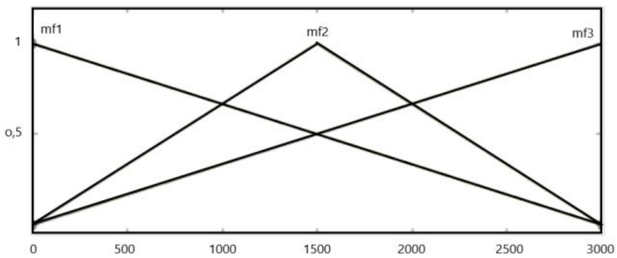

Figure. 2 Fuzzy membership function

Table 11. Parameters used for testing

Experi-ment	mf2		
	a	b	c
1	min	(min+max)/2	max
2	min + (10% max)	(min+max)/2	max - (10% max)
3	min + (20% max)	(min+max)/2	max - (20% max)
4	min + (30% max)	(min+max)/2	max - (30% max)
5	min + (40% max)	(min+max)/2	max - (40% max)

In this analysis, two tests are carried out using Matlab: testing the fuzzy parameters in the middle and the fuzzy parameters at the edges.

In testing the fuzzy parameters in the middle, the parameters a and c are shifted so that the mf2 triangle becomes narrower, as shown in Table 11.

The results of this experiment are shown in Table 12 and Fig. 3 as follows. It can be seen in the table that the lowest cost was obtained in the first experiment where the values a=min, b=(min+max)/2, and c=max.

The following experiment is to find fuzzy parameters on edge to get the lowest cost. The parameters used are shown in Table 13.

The results of this trial are shown in Table 13 as follows. It can be seen in the table that the lowest cost was obtained in the sixth trial, where in mf1, the values a=0, b=0, and c=max-(50%.max), and in mf3, the value a=min+(50%.max), b=0, and c=max as shown in Table 14 and Fig. 4 below.

Table 12. The most optimal of the mf2 finding result

Experiment	Sugarcane Logging and Transportation Costs (Rupiah)
1	50,529,489,258.04
2	53,191,791,029.52
3	53,191,791,029.52
4	53,191,791,029.52
5	53,191,791,029.52

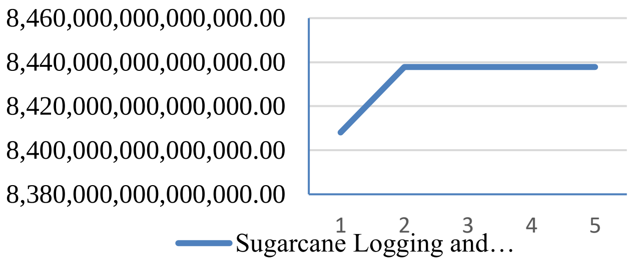

Figure. 3 Sugarcane logging and transportation cost

 DOI: 10.22266/ijies2022.1031.49

Table 13. Hasil ujicoba

Ujicoba ke	mf1			mf3		
	a	b	c	a	b	c
1	0	0	max	Min	0	max
2	0	0	max-(10% max)	min+(10% max)	0	max
3	0	0	max-(20% max)	min+(20% max)	0	max
4	0	0	max-(30% max)	min+(30% max)	0	max
5	0	0	max-(40% max)	min+(40% max)	0	max
6	0	0	max-(50% max)	min+(50% max)	0	max
7	0	0	max-(60% max)	min+(60% max)	0	max

Table 14. Experiment result

Experiment	Sugarcane Logging and Transportation Costs (Rupiah)
1	50,529,489,258.04
2	52,884,113,974.77
3	54,123,036,830.33
4	49,300,054,283.87
5	49,282,179,723.53
6	49,505,258,507.64
7	49,560,283,880.51

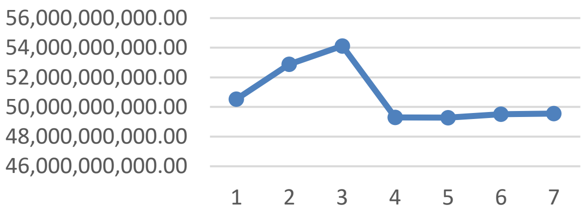

Figure. 4 Experiment results chart

Thus, to get the most optimal logging and transportation cost value, the parameters used are presented in Table 15 as follows.

The membership function using these parameters can be seen in Fig. 5 below.

Table 15. Optimal parameter of fuzzy variables

	a	b	c
mf1	0	0	max-50% max
mf2	min	(min+max)/2	max
mf3	min+50% max	0	max

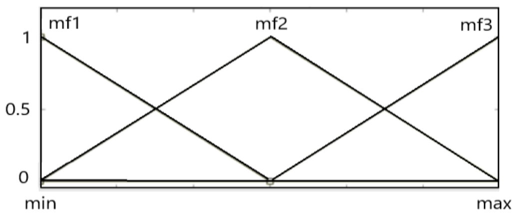

Figure. 5 Optimal fuzzy membership function

3.4 Experiment

Using Matlab, and based on the fuzzy parameters set, the first FIS is run to determine the milling priority, and the second FIS determines the amount of sugarcane to be logged. This process is iterated until the amount of sugarcane in all the plantations shown in Table 2 to 4 has been logged down. The iteration results in this experiment are shown in Table 16.

The total costs of logging and transportation are obtained from the iterations carried out above, as shown in Table 17. From Table 17, it can be seen that the total logging and transportation cost using IFIS method is 49,282,179,723.53 rupiahs.

3.5 Comparison with other methods

As a comparison, the optimization with the IFIS method above was compared with the existing and

Table 16. Iteration result

Day	Mill	Plantation	Iteration	Logged (tons)
1	IG-1	KRJ	1	1,151.00
1	IG-1	KRJ	2	575.50
1	IG-1	KRJ	3	287.75
1	IG-1	KRJ	4	143.88
1	IG-1	KRJ	5	71.94
1	IG-1	KKT	1	1,250.00
1	IG-1	KKT	2	625.00
1	IG-1	KKT	3	312.50
1	IG-1	KKT	4	156.25
1	IG-1	KKT	5	78.13
1	IG-1	KKP	1	1,770.00
1	IG-1	KKP	2	885.00
1	IG-1	KKP	3	442.50
1	IG-1	KKP	4	221.25
1	IG-1	KKP	5	110.63
1	IG-2	KRJ	1	1,956.97
1	IG-3	KRJ	1	2,440.48
2	IG-1	KRJ	1	1,220.24
2	IG-1	KRJ	2	610.12
2	IG-1	KKT	1	2,039.06
2	IG-1	KKT	2	1,019.53
2	IG-1	KKP	1	2,111.31
2	IG-1	KKP	2	1,055.66
2	IG-2	KRJ	1	1,726.56
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50	IG-3	KKP	7	4.86
50	IG-3	KKP	8	2.43
50	IG-3	KKP	9	1.22
50	IG-3	KKP	10	0.61
50	IG-3	KKP	11	0.30

Table 17. Total cost using IFIS

KRJ	Logged	Logging and Transportation Cost (Rp)
IG-1	50,829.60	4.101.001.130,79
IG-2	52,168.15	7.894.614.058,21
IG-3	109,938.67	11.688.226.985,63
Total A		23,683,842,174.63
KKP	**Logged**	**Logging and Transportation Cost (Rp)**
IG-1	51,294.08	10.628.614.812,07
IG-2	4,040.65	6.527.613.681,28
IG-3	4,040.65	2.426.612.550,49
Total B		19,582,841,043.84
KKT	**Logged**	**Logging and Transportation Cost (Rp)**
IG-1	548.98	4,101,001,130.79
IG-2	0.00	0,00
IG-3	5,606.66	0,00
Total C		4,101,001,130.79
Total A+B+C		**49,282,179,723.53**

FIS method. The existing method is the method that is currently used to select plantations to be logged, where logging and transportation costs and sugarcane waiting time in sugar mills are still very high. While the optimization using the FIS method shows that the waiting time for sugarcane waiting to be milled at the sugarcane factory is still high, resulting in sugarcane quality reduction. The results of the two methods are as follows.

3.5.1. Comparison with existing methods

In the optimization carried out using the existing method, the sugarcane needs of each sugar mill are met from the plantations that are located closest to the mill so that the sugarcane needs of sugar mill IG-1 are met from KRJ plantation, IG-2 from KKP, and IG-3 from KKT. The fulfilment of sugarcane needs of each mill can be seen in Table 18 to 20.

Table 18. Fulfilment of sugarcane needs of IG-1

Day	Number of blocks	Logged
1	4	10,388.00
2	3	6,486.00
3	4	9,674.00
4	3	7,305.00
5	3	7,661.00
6	3	6,934.00
7	4	8,899.00
8	3	7,259.00
9	4	9,851.00
10	3	7,476.00
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47	4	9,347.00
48	3	8,606.00
49	4	10,457.00

Table 19. Fulfilment of sugarcane needs of IG-2

Day	Number of blocks	Logged
1	1	3,000.00
2	1	3,200.00
3	1	3,735.00
4	0	-
5	1	2,946.00
6	1	3,999.00
7	0	-
8	1	3,324.00
9	1	3,944.00
10	1	-
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47	1	3,000.00
48	1	3,200.00
49	1	3,735.00

Table 20. Fulfilment of sugarcane needs of IG-3

Day	Number of blocks	Logged
1	1	2500.00
2	1	-
3	1	-
4	0	1000.00
5	1	-
6	1	1000.00
7	0	-
8	1	-
9	1	-
10	1	-
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47	1	3,347.00
48	0	-
49	0	-

From Table 18 to 20, it can be calculated that the logging and transportation cost using the existing method is 74,893,222,735.50 rupiah.

3.5.2. Comparison with FIS methods

The following optimization experiment using the FIS method is as follows. In this method, FIS is carried out once a day, choosing which plantations are the most optimal based on considerations of harvest costs, transportation costs, and the distance from the plantations to the mills. The fulfilment of sugarcane needs of each mill using the FIS method for ten days can be seen in Table 21 to 23.

From Table 21 to 23, it can be calculated that the logging and transportation cost using FIS method are

28,861,868,425.39 rupiah for IG-1, 33,532,416,871.59 rupiah for IG-2, and 2,367,409,650.06 rupiah for IG-3. So the total logging and transportation cost using the FIS method is 64,761,694,947.04 rupiah.

3.6 Determining the best seasonal density when using the IFIS method

The following experiment is to determine the load on the garden to be felled. Experiments were carried out by giving different inputs for the plantations to be harvested, namely dense at the beginning of the season, in the middle of the season, at the end of the season, random, or gently as shown in Fig. 6.

The results obtained from this experiment are shown in Table 24.

This experiment shows that the IFIS method is best used for scheduling sugarcane logging with random densities throughout the season as shown in Fig. 7.

Table 21. Fulfilment of sugarcane needs of IG-1

Day	**Plantation name**	**Number of blocks**	**Logging ammount plus the remaining milling of the previous day (tons)**	**Remaining milling of the previous day (tons)**
1	KKT	4	8,500	500
2	KKP	3	7,627	127
3	KKP	4	9,827	1,954
4	KKP	3	8,083	3,781
5	KKP	3	6,437	2,218
6	KKP	3	7,873	2,091
7	KKP	3	7,017	1,108
8	KKP	3	6,986	94
9	KRJ	4	10,210	2,304
10	KRJ	3	7,718	2,022
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48	KKP	3	6,986	94
49	KRJ	4	10,210	2,304
50	KRJ	3	7,718	2,022

Table 22. Fulfilment of sugarcane needs of IG-2

Day	**Plantation name**	**Number of blocks**	**Logging ammount plus the remaining milling of the previous day (tons)**	**Remaining milling of the previous day (tons)**
1	KKP	1	3,000	1,200
2	KKP	1	2,965	2,365
3	no logging	0	2,365	565
4	KKP	1	2,171	1,135
5	KKP	1	2,760	2,095
6	no logging	0	2,095	295
7	KRJ	1	3,000	1,495
8	KKP	1	2,709	2,404
9	no logging	0	2,404	604
10	KKP	1	2,051	855
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48	KKP	1	2,604	2,404
49	no logging	0	2,404	1.604
50	KKP	1	1,604	804

Received: May 4, 2022. Revised: July 20, 2022.

Table 23. Fulfilment of sugarcane needs of IG-3

Day	Plantation name	Number of blocks	Logging ammount plus the remaining milling of the previous day (tons)	Remaining milling of the previous day (tons)
1	KKP	1	2,000	1,350
2	no logging	0	1,350	700
3	no logging	0	700	50
4	KKP	1	2,867	2,267
5	no logging	0	2,267	1,617
6	no logging	0	1,617	967
7	no logging	0	967	317
8	KRJ	1	2,000	1,667
9	no logging	0	1,667	1,017
10	no logging	0	1,017	367
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48	KKP	1	3,000	2,350
49	no logging	0	2,350	1.700
50	no logging	0	1.700	1.050

Table 24. Seasonal density experiment results

Input density	Sugarcane Logging and Transportation Costs (Rupiah)
Randomly	51,513,642,431.55
End	51,673,337,581.32
Beginning	51,918,445,528.30
Sloping	50,429,336,050.34
Middle	53,438,623,825.73

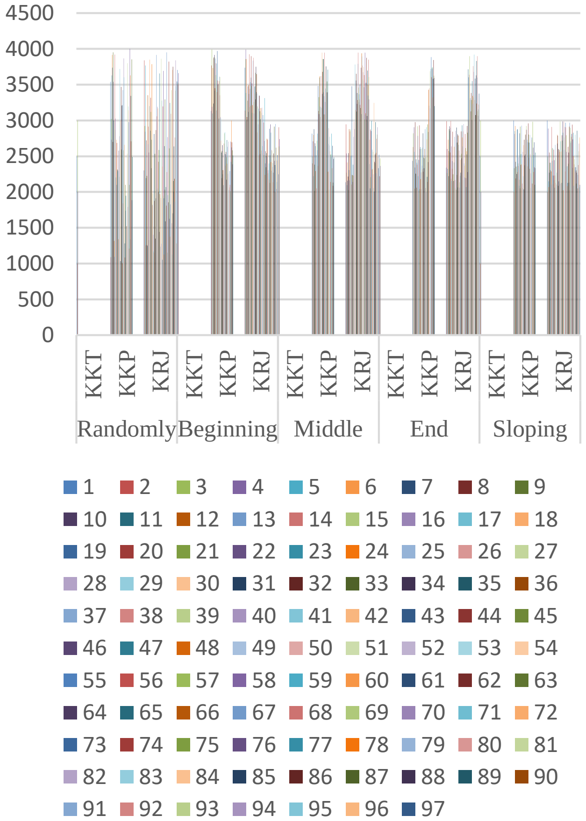

Figure. 6 Variation of input data

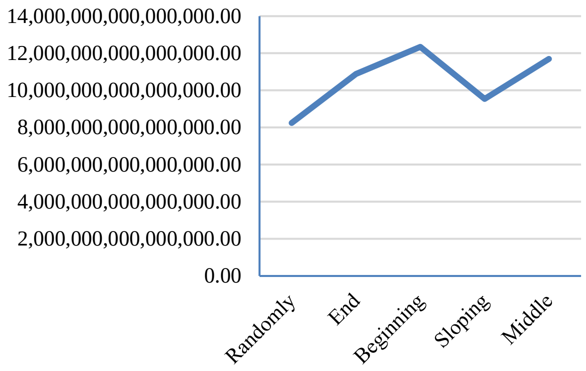

Figure. 7 Seasonal density experiment chart

3.7 Discussion of experimental result

3.7.1. Comparison of logging and transportation costs

The comparison of the optimization results using the three methods can be seen in Table. 25.

The table shows that the IFIS method can reduce logging and transportation costs by 20.22% compared to the existing method and 16.17% compared to the non-iterative FIS method.

3.7.2. Comparison of sugarcane waiting time in sugar mill

In the optimization carried out using the existing method, the waiting time for sugarcane in the sugar

Table 25. Total cost comparation

Method	Total cost (Rupiahs)
Existing	74,893,222,735.50
FIS	64,761,694,947.04
IFIS	49,282,179,723.53

mill is very high, especially for mills that have small milling capacities. This waiting time is because all of the logged sugarcane from one block of plantations must be sent to a sugar mill.

In the optimization carried out using the FIS method, the waiting time is smaller than existing because the selection of the plantations to be logged has taken into account the milling capacity of the sugar mill.

Meanwhile, in the optimization carried out using the IFIS method, the waiting time is shorter than the existing and FIS methods because one log in a plantation block is not sent to one mill but is distributed to all existing mills.

4. Conclusion

Based on the discussion above, we can conclude that the IFIS method used in this case can overcome the problem of optimizing the cost of logging and transporting sugar cane to the mill. Compared to existing methods and FIS, optimization of sugarcane harvesting using IFIS results in significantly lower sugarcane felling and transportation costs. The parameters used by the fuzzy system in IFIS to get the most optimal logging and transportation cost are: mf1: a=0, b=0, and c=max-(50% max), mf2: a=min, b=(min +max) /2, and c=max, mf3, a=min+(50%.max), b=0, and c=max. In addition, IFIS method is best used for scheduling sugarcane logging with random densities throughout the season.

The IFIS method also results in shorter sugarcane waiting times because one log in the plantation block is not sent to one mill but is distributed to all existing mills so that the decline in sugarcane quality can be reduced.

Conflicts of Interest

The authors (Adi Heru Utomo, Riyanarto Sarno, R.V. Hari Ginardi, Muhammad Ainul Yaqin) declare no conflict of interest.

Author Contributions

Conceptualization, Adi Heru Utomo; Methodology, Adi Heru Utomo; Validation, Adi Heru Utomo; Formal analysis, Adi Heru Utomo; Investigation, Adi Heru Utomo; Resources, Adi Heru Utomo; Data curation, Adi Heru Utomo; Writing—original draft preparation, Adi Heru Utomo and Muhammad Ainul Yaqin; Writing—review and editing, Riyanarto Sarno, R.V. Hari Ginardi, and Muhammad Ainul Yaqin; Visualization, Adi Heru Utomo; Supervision, Riyanarto Sarno and Hari Ginardi; project administration, Adi Heru Utomo.

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