

Optuna-Driven Hyperparameter Optimization in Tsukamoto Fuzzy Logic for House Price Estimation

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Abstract—The property sector faces challenges in determining accurate house selling prices due to subjectivity and market uncertainty. The relationship between physical attributes, such as land area and building area, and price is not always linear, making conventional methods often less precise in estimation. This study aims to design a decision support system to objectively estimate house prices in the Plamongan area, Semarang. The method used is Fuzzy Tsukamoto Logic. This preliminary study explores the integration of the Tree-structured Parzen Estimator (TPE) algorithm through the Optuna framework to automatically optimize membership function limits, replacing manual trial and error methods. The dataset was collected via scraping techniques, providing a pilot dataset of 26 data points. Final model performance evaluation showed a Mean Absolute Percentage Error (MAPE) value of 11.39%, which falls into the 'Good Forecast' category. However, given the highly limited sample size, these findings primarily serve as a proof-of-concept that requires further validation with larger, multi-variable datasets. These results prove that integrating the Fuzzy Tsukamoto method with hyperparameter optimization is effective in reducing subjectivity and providing reliable property price estimates. The primary contribution of this research is providing a mathematical proof-of-concept for an automated, objective property valuation system that eliminates human bias in fuzzy parameter configuration, offering a practical baseline tool for localized real estate markets.

Keywords: Fuzzy Tsukamoto; House Price; Optuna; Decision Support System; Hyperparameter Tuning

1. INTRODUCTION

One of the main foundations of the economy is the property sector, which grows stably in line with population growth [1]. A house is not only a basic need but also a long-term investment whose value constantly fluctuates due to the demand for comfortable accommodation that suits personal needs. Determining the selling price of a house is a crucial stage in the buying and selling process. Impartial and accurate valuation methods are urgently needed because prices must reflect the property's intrinsic value while remaining competitive in the market.

Two of the main and most important criteria in determining house selling prices in property valuation practice are Land Area and Building Area [2]. However, there is not always an exact linear relationship between these two physical factors and the selling price. Qualitative or linguistic descriptions such as “Quite large Land Area,” “Medium Building Area,” or “Quite high Price” are frequently used in assessing market situations and interpreting physical data. Rigid traditional pricing techniques (such as linear regression or cost approaches) often fail to accurately depict expert reasoning due to the element of uncertainty inherent in these valuations. The decision-making process can be disrupted by a mismatch between the proposed market price and the property's true value [1]. Fuzzy Logic has proven to be a useful computational framework for dealing with uncertainty and ambiguous data. The Tsukamoto Fuzzy Inference Model, in particular, has been widely used in determining selling prices across various fields. The efficacy of Tsukamoto fuzzy logic has been proven in previous studies, such as in systems for determining the selling price of embossed letter products in the advertising business [3], systems for determining boarding house room rental prices [3], systems for determining used smartphone selling prices [4], systems for determining car selling prices [5], and systems for determining used laptop selling prices [6]. The integrated defuzzification process of the Tsukamoto model, which can produce crisp output values from fuzzy premises visibly and measurably, is its main advantage.

Tsukamoto Fuzzy Logic simulations provide a highly relevant way to simulate the complexities of determining house selling prices, according to literature reviews. By using membership functions, this approach enables the conversion of qualitative evaluations (e.g., “Large Land Area”) into fuzzy sets. This approach maps ambiguous inputs about Land Area and Building Area into objective conclusions about selling prices by creating a rule base that mimics the expertise of property professionals [7]. While non-fuzzy Machine Learning models (such as Random Forest or Artificial Neural Networks) are capable of handling non-linear relationships, Fuzzy Logic provides superior interpretability. It is less prone to 'black-box' assumptions when working with very limited, localized datasets, making it highly suitable for establishing baseline rules. It is estimated that this strategy will reduce subjectivity and improve the precision of market forecasts for house prices.

However, the effectiveness of the Tsukamoto Fuzzy model heavily depends on accurately determining the boundary parameters of the membership functions. In many implementations, these parameters are often determined manually through trial and error, which risks producing suboptimal or biased models [8]. To overcome this, it is necessary to automate the parameter search using the Tree-structured Parzen Estimator (TPE) algorithm through the Optuna framework. TPE is a Bayesian optimization algorithm that works by modeling probability distributions to efficiently explore the search space [9]. The integration of TPE in this study aims to automatically optimize the points on the membership functions so that it can produce a higher level of accuracy and be adaptive to real data [10].

Several recent related studies have been conducted as a foundation for this research. First, a study by Rokhmah et al. [3] applied the Fuzzy Tsukamoto method for product price estimation, but it still relied on manual parameter tuning. Second, S. Pontianak et al. [4] utilized Fuzzy Logic in a similar domain, yet the membership boundaries were subjectively determined by experts. Third, research by Giawa & Marbun [5] implemented machine learning for price prediction but lacked the interpretability offered by fuzzy rule-based systems. Fourth, Pangestu et al. [7] successfully used the Optuna framework for hyperparameter optimization; however, its application was limited to deep learning architectures rather than Fuzzy Inference Systems. Lastly, while previous studies have explored hyperparameter tuning, its application was mostly limited to deep learning architectures rather than Fuzzy Inference Systems for localized property data. Based on the limitations of these previous studies, the explicit research gap addressed in this study is the lack of baseline exploratory models that integrate automated TPE hyperparameter tuning with Tsukamoto Fuzzy Logic specifically for localized, small-scale property data.

Therefore, the main objective of this pilot study is to apply this integration in designing a decision support system that can determine house selling prices using Land Area and Building Area as the primary input variables. By developing this focused model as a mathematical proof-of-concept, this research aims to verify how Optuna can eliminate human subjectivity in setting membership boundaries. The main contribution of this research lies in demonstrating the mathematical feasibility of using Optuna's TPE algorithm to eliminate manual subjectivity in Tsukamoto Fuzzy Logic. This provides an objective, adaptable baseline tool for property market participants and enriches the literature on automated fuzzy systems for asset valuation.

2. RESEARCH METHODOLOGY

2.1 Research Stages

The stages carried out in this research can be seen from the research stage flowchart depicted in Figure 1.

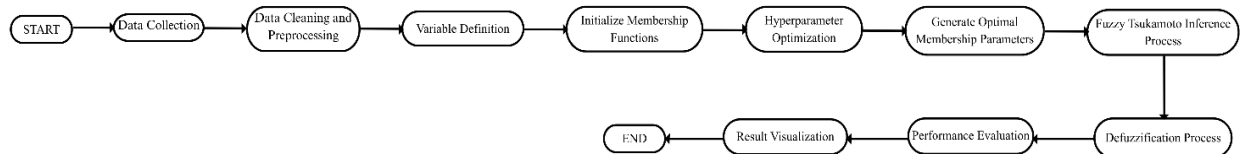


Figure 1. Research Method

The methodology of this research follows a structured and specific flow combining the Optuna framework with Fuzzy Tsukamoto logic, illustrated as follows:

- a. **Data Collection:** The process begins with web scraping from local property websites to gather raw house pricing data.
- b. **Data Cleaning and Preprocessing:** The scraped data undergoes formatting and missing value handling to ensure dataset integrity.
- c. **Variable Definition:** Defining the parameters for the system. This study uses two inputs (Land Area and Building Area) and one output (House Price). This study intentionally limits the variables to land area and building area to establish a baseline model before incorporating more complex determinants.
- d. **Initialize Membership Functions:** Establishing the initial mathematical boundaries using Triangular and Trapezoidal functions.
- e. **Hyperparameter Optimization:** Applying the Optuna framework utilizing the Tree-structured Parzen Estimator (TPE) algorithm to search for the most optimal fuzzy boundaries automatically.
- f. **Generate Optimal Membership Parameters:** The system outputs the best hyperparameter configurations.
- g. **Fuzzy Tsukamoto Inference Process:** Evaluating the rules based on the optimized membership functions to process the inputs.
- h. **Defuzzification Process:** Converting the fuzzy output back into a crisp price prediction value using the Center Average Method.
- i. **Performance Evaluation:** Calculating the error rate of the predictions against actual data using Mean Absolute Percentage Error (MAPE).
- j. **Result Visualization:** Analyzing the final prediction distribution and errors through Scatter Plot Analysis before concluding the research.

The initial step of the research began with preparing the dataset, which was retrieved via data scraping from the house buying and selling website www.brighton.co.id. The dataset collected consists of house data sold in the Plamongan area of Semarang City, with a house price filter ranging from 50 million rupiahs to 3 billion rupiahs. Due to strict constraints in local market listing availability during the scraping period, the successfully collected dataset consists of only 26 records with columns for property location, price, land area, and building area. This research explicitly treats this as a pilot dataset to test the mathematical feasibility of the optimization framework. By geographically restricting the data entirely to the Plamongan area, macro-location factors are held relatively constant. This allows the baseline model to focus strictly on the foundational physical variables: Land Area and Building Area.

The initial stage in pre-processing involved cleaning the data format to standardize price values. Price data that initially had a non-standard string format, such as "Rp1.2 Billion" or "Rp800 Million", were converted into a numeric (float) format in units of Million Rupiah. This text parsing and transformation process utilized Natural Language Processing (NLP) techniques or regular expressions to identify, extract, and convert numerical value patterns and their associated units in the text into a standard numerical format [8].

Subsequently, Missing Values were handled by dropping data rows that contained NaN values in either the input variables (such as Land Area and Building Area) or the target variable (Price), aiming to ensure calculation integrity. Although dropping NaN values further reduced the already minimal dataset, it was deemed analytically necessary to maintain the factual integrity of the physical metrics without introducing synthetic biases from data imputation on such a small sample [9].

In the final stage, variables were defined for analysis. The Input Variables (Antecedent) used are Land Area (in m²) and Building Area (in m²), while the Output Variable (Consequent) serving as the target is House Price (in Million Rupiah). This study intentionally limits the variables to land area and building area to establish a baseline model before incorporating more complex determinants. It should be emphasized that the Building Area, which represents the total floor space of the property, is a crucial factor affecting house prices. Generally, a larger building area indicates more living space, making it a highly desirable feature for buyers, thus tending to increase the price [10].

2.2 Tsukamoto Fuzzy Method

The core method applied to process the data is Fuzzy Tsukamoto. This method was chosen due to its characteristics that can handle monotonic input-output relationships [11]. The computational process begins with the Fuzzification stage, which maps crisp input values into degrees of membership $\mu(x)$ with a range of [0,1] using trapezoidal and triangular curves whose parameters are computationally optimized [12], [13], [14]. After obtaining the membership values, the process continues to the Inference stage. The system uses the AND logical operator, calculated using the MIN function, to connect the input variables in each rule [15], [16], [17], [18]. The rule firing strength or α -predicate (α_i) is calculated using equation 1.

$$\alpha_i = \min(\mu_{Tanah}(x), \mu_{Bangunan}(y)) \quad (1)$$

Tsukamoto's distinctive characteristic lies in the calculation of the output of each rule (z_i) which is done crisply using the inverse of the output membership function [19], [20], [21]. Because price behavior is monotonic, the calculation of z_i is divided into two conditions. For rules with a monotonically increasing consequent set, the value of z is directly proportional to α as in equation 2.

$$z_i = a + \alpha_i(b - a) \quad (2)$$

Meanwhile, for rules with a monotonically decreasing consequent set, the value of z is inversely proportional to α using equation 3 below.

$$z_i = d - \alpha_i(d - c) \quad (3)$$

The final stage of this method is Defuzzification, utilizing the Center Average Defuzzifier method to aggregate all rule outputs into a single final price prediction value (Z_{akhir}) [22], which is calculated using formula 4 below.

$$Z_{akhir} = \frac{\sum_{i=1}^n (\alpha_i \times z_i)}{\sum_{i=1}^n \alpha_i} \quad (4)$$

The novelty offered in this study lies in the mechanism for determining membership function parameters, which are optimized using the Tree-structured Parzen Estimator (TPE) algorithm through the Optuna framework. This approach replaces the manual trial and error method by automatically finding optimal coordinate points (a, b, c, d) to minimize the objective function [23], [24], [25]. As a final step, model performance is evaluated using the Mean Absolute Percentage Error (MAPE) metric to measure the percentage of deviation of the predicted price against the actual price (A_t) [26], [27], [28], with the formula:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{A_t - P_t}{A_t} \right| \quad (5)$$

In addition to numerical evaluation, analysis is also carried out using Scatter Plot visualizations to compare the distribution of predicted prices against actual prices to see their pattern conformity with the ideal regression line [29].

3. RESULTS AND DISCUSSION

This research focuses on implementing and evaluating the performance of the Tsukamoto Fuzzy method optimized using the Tree-structured Parzen Estimator (TPE) algorithm in predicting house prices in the Plamongan area, Semarang. The results analysis begins with the data pre-processing stage on the 26 successfully collected property datasets. This stage is crucial for converting the raw scraped data format into a numerical format ready for



computational processing. The data cleaning process was carried out by converting the price variable from a text string format (e.g., "Rp1.15 Billion") into a float data type in units of Million Rupiah, as well as handling missing values to maintain dataset integrity. An overview of the data samples after going through the standardization and currency conversion process can be seen in Table 1.

Table 1. Data Samples After Pre-processing

No	Property Location	Raw Price	Land (m ²)	Area (m ²)	Building (m ²)	Converted Price (Million Rp)
1	Jasmine Park Plamongan	Rp1,15 Billion	129	98		1.150,0
2	Jasmine Park Plamongan	Rp800 Million	112	130		800,0
3	Jalan Albasia	Rp325 Million	65	65		325,0
4	Jl. Kelapa Sawit	Rp700 Million	65	150		700,0
5	Jl. Plamongan Indah	Rp675 Million	120	120		675,0

After the data was ready, the next step was determining the Membership Function parameters which act as the knowledge base for the fuzzy system. Unlike conventional approaches that determine set boundaries manually, this study utilized the Optuna framework to find the parameter combination that minimizes the Mean Absolute Percentage Error (MAPE) value. Based on 1,000 trials, the algorithm found the best parameter configuration in the 612th trial. The results of this optimization provide set boundaries that are dynamic and adaptive to data patterns, as detailed in Table 2.

Table 2. Membership Function Parameters from Optuna Optimization

Input/Output Variable	Fuzzy Set	Curve Type	Boundary (Coordinate Points)	Parameters
Land Area (m ²)	Narrow	Trapezoidal	[0, 0, 90, 125]	
	Medium	Triangular	[125, 140, 205]	
	Wide	Trapezoidal	[200, 250, 300, 300]	
Building Area (m ²)	Narrow	Trapezoidal	[0, 0, 75, 110]	
	Medium	Triangular	[115, 130, 145]	
	Wide	Trapezoidal	[115, 130, 350, 350]	
Price (Million Rp)	Cheap	Trapezoidal	[0, 0, 300, 1000]	
	Medium	Triangular	[400, 650, 800]	
	Expensive	Trapezoidal	[650, 1400, 2500, 2500]	

An interesting finding from this optimization is that the boundary for the "Cheap" price category stretches up to Rp1 Billion, indicating that the distribution of property prices in this dataset is dominated by the middle-to-upper segment, prompting the system to adjust the definition of "Cheap" to maintain predictive flexibility. It is critically important to acknowledge that this high threshold for the 'Cheap' category is likely an artifact of the very small 26-point dataset, which may be heavily skewed toward middle-to-upper segment listings available during the specific data collection period. It cannot be generalized to the broader Semarang market. Below in Figure 2, the membership function graphs for Land Area, Building Area, and House Price are displayed.

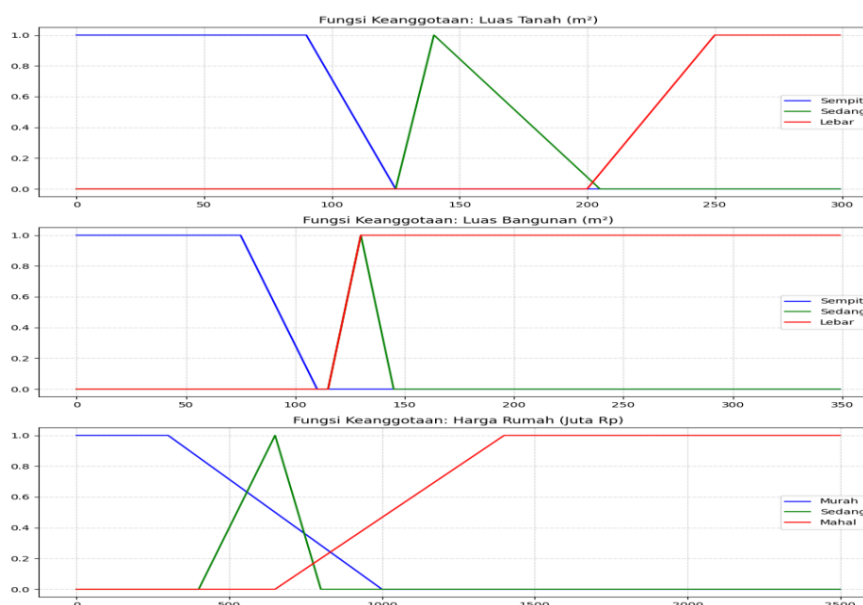


Figure 2. Membership Function Graphs



The parameters that have been formed are then implemented into the Tsukamoto inference system. The calculation process begins with Fuzzification, mapping the input values of land area and building area into degrees of membership (μ) between 0 and 1. Table 3 below shows how each test data is classified into the Narrow, Medium, or Wide categories based on Optuna parameters.

Table 3. Membership Degree Calculation Results (Fuzzification)

No	Land Area (m ²)	μ Narrow	μ Medium	μ Wide	Building Area (m ²)	μ Narrow	μ Medium	μ Wide
1	129	0	0.27	0	98	0.34	0	0
2	112	0.37	0	0	130	0	1	1
3	65	1	0	0	65	1	0	0
4	65	1	0	0	150	0	0	1
5	120	0.14	0	0	120	0	0.33	0.33
6	72	1	0	0	72	1	0	0
7	160	0	0.69	0	160	0	0	1
8	120	0.14	0	0	150	0	0	1
9	97	0.8	0	0	80	0.86	0	0
10	144	0	0.94	0	144	0	0.07	1
11	65	1	0	0	36	1	0	0
12	123	0.06	0	0	100	0.29	0	0
13	77	1	0	0	77	0.94	0	0
14	160	0	0.69	0	140	0	0.33	1
15	123	0.06	0	0	123	0	0.53	0.53
16	66	1	0	0	40	1	0	0
17	140	0	1	0	300	0	0	1
18	97	0.8	0	0	80	0.86	0	0
19	154	0	0.78	0	150	0	0	1
20	108	0.49	0	0	90	0.57	0	0
21	174	0	0.48	0	60	1	0	0
22	130	0	0.33	0	130	0	1	1
23	144	0	0.94	0	200	0	0	1
24	60	1	0	0	60	1	0	0
25	221	0	0	0.42	300	0	0	1
26	77	1	0	0	77	0.94	0	0

It can be seen that several data points have partial membership (for instance, data point 1 has a μ Medium value of 0.27 for Land Area), indicating that the data is in the transition area between sets. These membership degrees are then used to calculate the predicate value (α) or firing strength for each rule. The system utilizes 9 rule bases linking input conditions to price outputs as follows.

- R1: IF Land Area is Narrow AND Building Area is Narrow THEN Price is Cheap
- R2: IF Land Area is Narrow AND Building Area is Medium THEN Price is Cheap
- R3: IF Land Area is Narrow AND Building Area is Wide THEN Price is Medium
- R4: IF Land Area is Medium AND Building Area is Narrow THEN Price is Cheap
- R5: IF Land Area is Medium AND Building Area is Medium THEN Price is Medium
- R6: IF Land Area is Medium AND Building Area is Wide THEN Price is Expensive
- R7: IF Land Area is Wide AND Building Area is Narrow THEN Price is Medium
- R8: IF Land Area is Wide AND Building Area is Medium THEN Price is Expensive
- R9: IF Land Area is Wide AND Building Area is Wide THEN Price is Expensive

For example, in Data point 3, rule R1 (Narrow-Narrow \rightarrow Cheap) is perfectly active with a value of 1.00, while the other rules evaluate to 0. This signifies that the system is highly confident the property falls into the cheap category. Conversely, in complex data like Data point 2, multiple rules activate simultaneously (R2 and R3), which are then combined (accumulated) in the defuzzification stage. Table 4 below presents the rule activation values for each data point.

Table 4. Fuzzy Rule Activation Values (α -predicate)

No	R1	R2	R3	R4	R5	R6	R7	R8	R9
1	0,00	0,00	0,00	0,27	0,00	0,00	0,00	0,00	0,00
2	0,00	0,37	0,37	0,00	0,00	0,00	0,00	0,00	0,00
3	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
4	0,00	0,00	1,00	0,00	0,00	0,00	0,00	0,00	0,00
5	0,00	0,14	0,14	0,00	0,00	0,00	0,00	0,00	0,00
6	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00



No	R1	R2	R3	R4	R5	R6	R7	R8	R9
7	0,00	0,00	0,00	0,00	0,00	0,69	0,00	0,00	0,00
8	0,00	0,00	0,14	0,00	0,00	0,00	0,00	0,00	0,00
9	0,80	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
10	0,00	0,00	0,00	0,00	0,07	0,94	0,00	0,00	0,00
11	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
12	0,06	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
13	0,94	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
14	0,00	0,00	0,00	0,00	0,33	0,69	0,00	0,00	0,00
15	0,00	0,06	0,06	0,00	0,00	0,00	0,00	0,00	0,00
16	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
17	0,00	0,00	0,00	0,00	0,00	1,00	0,00	0,00	0,00
18	0,80	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
19	0,00	0,00	0,00	0,00	0,00	0,78	0,00	0,00	0,00
20	0,49	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
21	0,00	0,00	0,00	0,48	0,00	0,00	0,00	0,00	0,00
22	0,00	0,00	0,00	0,00	0,33	0,33	0,00	0,00	0,00
23	0,00	0,00	0,00	0,00	0,00	0,94	0,00	0,00	0,00
24	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
25	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,42
26	0,94	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

The final stage of the computation process is defuzzification using the center average method to obtain the final price prediction value. A complete comparison between the system's predicted prices and the actual market prices is presented in Table 5.

Table 5. Final House Price Prediction Results and Error Evaluation

No	Location	Land Area (m ²)	Building Area (m ²)	Actual Price (Million Rp)	Predicted Price (Million Rp)	Difference (Million Rp)	Error (%)
1	PERUM JASMINE PARK	129	98	1150	813.33	336.67	29.28%
2	JASMINE PARK PLAMONGAN	112	130	800	616.43	183.57	22.95%
3	JALAN ALBASIA	65	65	325	300	25	7.69%
4	JL. KELAPA SAWIT	65	150	700	650	50	7.14%
5	JL PLAMONGAN INDAH	120	120	675	667.86	7.14	1.06%
6	PLAMONGAN INDAH	72	72	360	300	60	16.67%
7	GARDENIA CLUSTER	160	160	1250	1169.23	80.77	6.46%
8	PLAMONGAN INDAH	120	150	430	435.71	5.71	1.33%
9	PLAMONGAN INDAH SEMARANG	97	80	425	440	15	3.53%
10	JASMINE PARK PLAMONGAN	144	144	1200	1291.69	91.69	7.64%
11	ALBISIA	65	36	400	300	100	25.00%
12	PLAMONGAN INDAH	123	100	850	960	110	12.94%
13	JL. PLAMONGAN INDAH	77	77	385	340	45	11.69%
14	GARDENIA PEDURUNGAN	160	140	895	946.31	51.31	5.73%
15	JL. CEMARA RAYA	123	123	650	687.14	37.14	5.71%
16	PLAMONGAN SEMARANG	66	40	340	300	40	11.76%
17	JL. PLAMONGAN ELOK	140	300	1800	1400	400	22.22%
18	PLAMONGAN INDAH	97	80	460	440	20	4.35%
19	JL PLAMONGAN INDAH	154	150	1300	1238.46	61.54	4.73%
20	PLAMONGAN INDAH	108	90	650	660	10	1.54%
21	PLAMONGAN INDAH	174	60	750	666.15	83.85	11.18%
22	JL CEMARA RAYA	130	130	650	691.67	41.67	6.41%
23	JASMINE PARK	144	200	1050	1353.85	303.85	28.94%
24	PLAMONGAN ASRI	60	60	265	300	35	13.21%
25	JL KELAPA SAWIT	221	300	800	965	165	20.63%
26	PLAMONGAN INDAH	77	77	320	340	20	6.25%
Average							11.39%

Based on Table 5, an in-depth analysis of several interesting prediction patterns was conducted. In Data point 5 (Jl. Plamongan Indah), the model demonstrated highly precise performance with an error of only 1.06%. Input for land and building area, both measuring 120 m², were categorized by the system into the transition area from "Narrow"

to "Medium," resulting in a prediction of Rp667.8 Million, which is very close to the actual price of Rp675 Million. This illustrates Optuna's capability to find accurate intersection points for standard house sizes. However, a rather large deviation was found in Data point 1 (Jasmine Park) with an error of 29.28% (under-prediction). The system predicted a price of Rp813 Million, well below the actual price of Rp1.15 Billion. This error is highly likely caused by latent variables not captured by the model, such as strategic location factors within a cluster or premium building material quality, considering the building area of the data point is relatively small (98 m²). Furthermore, in Data point 23, an anomaly occurred where the system made an over-prediction (28.9% error). With a building area of 200 m², the system estimated a price of Rp1.35 Billion, but the actual price was only Rp1.05 Billion. This condition indicates the possibility that the property was sold below market value (In Need of Cash) or the physical condition of the building was old. Presented in Figure 3 is the comparison graph of actual prices versus Tsukamoto fuzzy predictions.

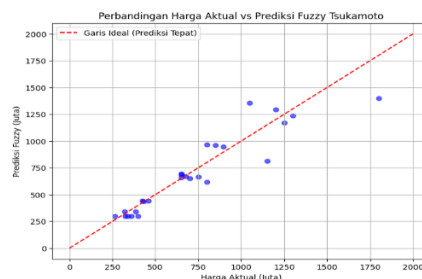


Figure 3. Comparison Graph of Actual Prices vs. Tsukamoto Fuzzy Predictions

The graph above presents a visualization of the Tsukamoto Fuzzy prediction model's performance in estimating prices. The horizontal axis (x) shows Actual Price (Millions), while the vertical axis (y) indicates Fuzzy Prediction (Millions). The red dashed line crossing the graph's diagonal (called the Ideal Line (Exact Prediction)) represents the ideal condition where the predicted value exactly equals the actual value. The blue dots scattered across represent pairs of model prediction data. Overall, the blue dots tend to cluster near the Ideal Line, although a few dots are situated quite far away (both above and below the line), indicating that the Tsukamoto Fuzzy model performs fairly well, though not perfectly, in predicting prices, with the majority of predictions falling within a reasonable range of their actual prices.

From calculations across all test data, an average error (MAPE) of 11.39% was obtained. Referring to forecasting evaluation standards, this value falls into the "Good Forecast" category as it is within the 10-20% range. While this value is categorized as a 'Good Forecast' [26], it must be interpreted with strict caution. Given the extremely small sample size (n=26), this performance metric demonstrates a good mathematical fit for the current training distribution but highlights a high risk of overfitting. It serves strictly as a preliminary feasibility indicator rather than a robust, generalizable performance metric. These results prove that the integration of the Tsukamoto Fuzzy method with automated parameter optimization is capable of recognizing property price patterns in Plamongan, Semarang, quite reliably. The use of Optuna proved significant in improving accuracy compared to intuitive, manual boundary determination. Optuna was able to discover precise intersection points (such as 125 m² or 140 m²) that better reflect the real data distribution. Nevertheless, this study still has limitations, particularly concerning price variations influenced by micro-location factors and legality (SHM/HGB) which have not been included as input variables, presenting an opportunity for further development in future research.

4. CONCLUSION

This pilot study explored the integration of the Tree-structured Parzen Estimator (TPE) via the Optuna framework to optimize Tsukamoto Fuzzy Logic parameters for house price estimation. The system successfully generated dynamic membership boundaries and achieved a MAPE of 11.39%, categorized as a 'Good Forecast'. However, these findings must be interpreted with significant caution due to fundamental limitations: the extremely small dataset size (26 points) and the restriction to only two physical input variables (Land Area and Building Area). While the optimization effectively reduced manual trial-and-error subjectivity for this specific sample, the current model lacks broader generalizability and intrinsically fails to capture crucial latent variables such as exact micro-location, material quality, and temporal market conditions. Future research must aggressively expand the dataset and incorporate these non-physical determinants to build a truly robust, comprehensive, and reliable property valuation system. Ultimately, the primary contribution of this study is the successful development of an objective, automated baseline model that eliminates the need for manual trial-and-error in fuzzy property valuation, serving as a foundational tool for both market practitioners and future academic developments.

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