Jurnal Sains Matematika dan Statistika
p-ISSN: 2460-4542
e-ISSN: 2615-8663

Application of the Mamdani Fuzzy Inference System in Evaluating Traffic Accident Risk for Four-Wheeled Vehicles

Fahrul Purnama[1], Indra Budiman[2], Nur Azizah[3]

[1,2,3] Mathematics Education Study Program, Universitas Singaperbangsa Karawang
Jl. HS.Ronggo Waluyo, Puseurjaya, Telukjambe Timur, Karawang, Jawa Barat 41361, Indonesia
Email: 2210631050012@student.unsika.ac.id[1], indra.budiman@fkip.unsika.ac.id[2], nur.azizah@fkip.unsika.ac.id[3],
Corresponding author : 2210631050012@student.unsika.ac.id

Submitted : 20 Oktober 2025 Accepted : 3 Ferbruari 2026 Published : 11 Februari 2026

Abstract

Traffic accidents involving four-wheeled vehicles constitute a complex problem influenced by multiple factors, including vehicle speed and traffic density. Accurate accident-risk assessment is essential to support preventive and control efforts on road networks. This study aims to design and implement an accident-risk evaluation model based on a Mamdani-type Fuzzy Inference System (FIS) to accommodate uncertainty in decision-making. The research procedure includes identifying input and output variables, constructing membership functions, fuzzification, formulating fuzzy rules, and performing inference and defuzzification. Testing results indicate that, for a combination of 80 km/h speed and 70 vehicles/km density, the centroid defuzzification method yields a risk value of 25.31%. This value falls within the low-to-moderate risk category. These findings suggest that the developed Mamdani FIS model is effective as a methodological approach for accident-risk evaluation.

Keywords: traffic accident risk evaluation; fuzzy inference system; Mamdani method

1. Introduction

Traffic accidents are unexpected and unintentional events involving vehicles, with or without other road users, and may result in injuries, loss of life, and property damage [1][2]. One of the major causes of accidents is human error. [3]. In Indonesia, the number of traffic accidents has shown an increasing trend; Statistics Indonesia (BPS) recorded 103,645 incidents in 2021 [4][5].

Excessive vehicle speed is a major risk factor in traffic accidents [6]. Increased vehicle speed is directly proportional to increased risk and severity of accidents, thus forming the basis for setting speed limits as a measure to reduce traffic accident rates [7]. However, in real traffic conditions, the assessment of accident risk levels is influenced by various conditions that are uncertain.

One approach that can be employed is the Fuzzy Inference System (FIS), which enables linguistic modelling of variables and reflects human decision-making patterns [8][9]. Previous studies indicate that fuzzy approaches can provide more adaptive performance than conventional methods in traffic management, particularly in controlling waiting time and improving vehicle flow [10]. Consistently, other research reports that a reduced fuzzy rule base can improve performance—evidenced by reductions in average vehicle delay, estimated fuel consumption, and CO_2 emissions—while also enhancing computational efficiency due to shorter execution time and lower computational cost [11]. Further experiments show that the proposed methods can increase throughput while reducing delay, queue length, and vehicle stopping rates [12].

Nevertheless, most prior research has focused on traffic control aspects, whereas studies that specifically use FIS for accident-risk evaluation remain relatively limited Accordingly, this study proposes the application of a Mamdani-type FIS to evaluate the accident risk of four-wheeled vehicles based on two main variables: vehicle speed and traffic density. The objective is to develop a Mamdani FIS model that classifies accident risk into low, moderate, and high categories to support an early-warning system for traffic safety.

2. Research Method

In this study, a Mamdani-type Fuzzy Inference System (FIS) is applied as an analytical tool to evaluate the risk of traffic accidents involving four-wheeled vehicles using two input variables—vehicle speed (km/h) and traffic density (vehicles/km)—and one output variable, namely the accident risk level. The novelty of this research lies in using Mamdani FIS as a risk-evaluation tool based on traffic parameters rather than as a control system, thereby positioning it as a safety-oriented decision-support approach.

The data are simulation-based and assumed according to value ranges commonly used in traffic studies and related literature [13][14]. The methodological stages are implemented through several steps illustrated in the following flowchart:

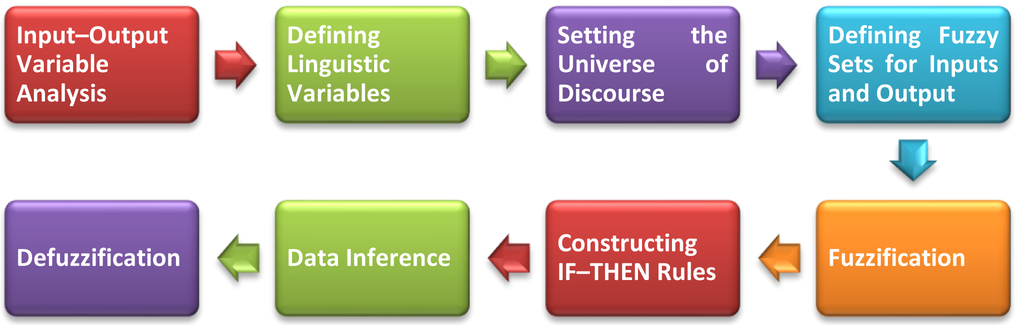


Figure 1. Research method flowchart using a Mamdani-type Fuzzy Inference System (FIS) model

The universe-of-discourse intervals and the shapes of membership functions are determined based on theoretical considerations and the researchers' assumptions adjusted to traffic-condition characteristics, enabling gradual representation of changes in risk. System validation is conducted by testing multiple scenarios of speed–density combinations and analysing the consistency of the risk outputs produced by the fuzzy system.

3. Results and Discussion

After completing all stages of designing the Mamdani-type fuzzy inference system, the next step is to use the constructed model to evaluate accident risk for four-wheeled vehicles. This evaluation is carried out by selecting combinations of speed and traffic density that correspond to the fuzzification results expressed as linguistic sets. This process is important to assess how well the system can provide decisions based on the predefined fuzzy rules.

The transformation from crisp values to fuzzy values is performed through fuzzification to obtain membership degrees for each input variable. These membership degrees are then processed using IF–THEN rules under the Mamdani method to produce an output accident risk level according to the combination of vehicle speed and traffic density. In the Mamdani method, fuzzification assigns a membership degree to each fuzzy rule [15].

A. Input Output Variable Analysis

The developed system aims to evaluate the accident risk level for four-wheeled vehicles on a toll-road segment based on two key variables: vehicle speed (km/h) and traffic density (vehicles/km). Based on empirical information and a report from Kompas.com (16 March 2023), a 15% increase in accidents on the Jakarta–Surabaya toll road in 2022 was associated with peak-hour traffic densities exceeding 120 vehicles/km, particularly when average speeds exceeded 80 km/h. This combination significantly reduces driver reaction time and increases the likelihood of multi-vehicle collisions. Therefore, in this fuzzy model, speed and density are used as input variables, while accident risk is specified as the output variable with three linguistic categories: low, moderate, and high.

A system is intended to evaluate the accident risk of four-wheeled vehicles (cars) on a road segment based on vehicle speed (km/h) and traffic density (vehicles/km). Accident risk is classified as low, moderate, or high.

Data used::

Input = Vehicle Speed; Traffic Density

Output = Accident Risk

" Traffic Density as the Main Cause of Accidents on Toll Roads "

(Kompas.com, 16 March 2023)

Content: The report states that accidents on the Jakarta–Surabaya toll road increased by 15% in 2022. The primary cause was traffic density exceeding 120 vehicles/km during peak hours, especially when the average speed exceeded 80 km/h. The combination of high density and high speed reduces driver reaction time and increases the potential for chain-reaction collisions.

B. Defining Linguistic Variables

To build a fuzzy inference system that represents human reasoning, the input and output variables are classified into linguistic sets. Vehicle speed is divided into three categories: slow, medium, and fast. Traffic density is also classified into three categories: light, moderate, and congested. The output variable (accident risk) is categorised into three levels: low, moderate, and high. These categories are designed to accommodate ambiguity in numerical values and represent human reasoning more realistically.

Linguistic variables
Speed = (Slow, Medium, Fast)
Density = (Light, Moderate, Congested)
Accident Risk = (Low, Moderate, High).

C. Establishing the universe interval

The universe of discourse defines the value boundaries for each variable in the system. For vehicle speed, the range is set from 0 to 180 km/h. Traffic density ranges from 10 to 200 vehicles/km. Accident risk as the output variable is defined on a percentage scale from 0% to 100%, which facilitates the defuzzification process.

Vehicle Speed (0–180 km/h)
Traffic Density (10–200 vehicles/km)
Accident Risk (0%–100%).

D. Defining Fuzzy Sets for Inputs and Output

Each linguistic category is defined mathematically using triangular membership functions. For example, the "slow" speed membership function reaches its maximum value in the 0–30 km/h range and decreases to zero at 60 km/h. A similar approach is used for the "medium" and "fast" categories. For traffic density, the "light" category applies to 10–80 vehicles/km, "moderate" to 40–160 vehicles/km, and "congested" to 120–200 vehicles/km. The output accident risk is defined over 0–100% using membership functions representing each risk category.

Table 1. Input fuzzy sets

Variable	Input Fuzzy Sets	Graph
Vehicle Speed	$\mu_{kcSLOW}(x_1) = \begin{cases} \frac{x_1 - 0}{30 - 0} & if\ 0 \le x_1 \le 30 \\ \frac{60 - x_1}{60 - 30} & if\ 30 \le x_1 \le 60 \\ 0 & for\ other\ x \end{cases}$ $\mu_{kcMEDIUM}(x_1) = \begin{cases} \frac{x_1 - 30}{90 - 30} & if\ 30 \le x_1 \le 90 \\ \frac{150 - x_1}{150 - 90} & if\ 90 \le x_1 \le 150 \\ 0 & for\ other\ x \end{cases}$	

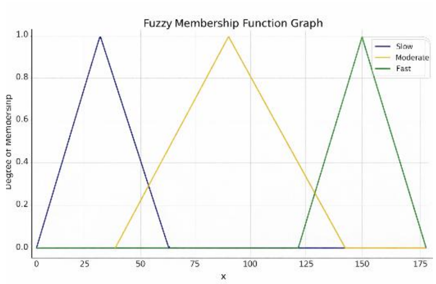
<table>
<tr>
<td></td>
<td>$\mu_{kcFAST}(x_1) = \begin{cases} \frac{x_1-120}{150-120} & if\ 120 \le x_1 \le 150 \\ \frac{180-x_1}{180-150} & if\ 150 \le x_1 \le 180 \\ 0 & for\ other\ x \end{cases}$</td>
<td>

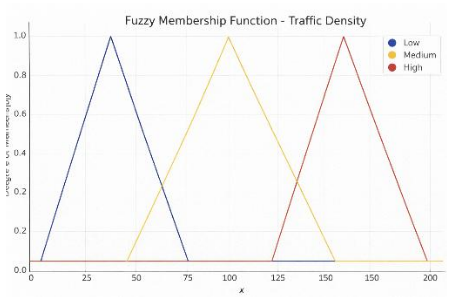
Figure 2. Graph of the Fuzzy Membership Function of Vehicle Speed</td>
</tr>
<tr>
<td>Traffic Density</td>
<td>$\mu_{kpQUIET}(x_2) = \begin{cases} \frac{x_2-10}{45-10} & if\ 10 \le x_2 \le 45 \\ \frac{80-x_2}{80-45} & if\ 45 \le x_2 \le 80 \\ 0 & for\ other\ x \end{cases}$
$\mu_{kpMEDIUM}(x_2) = \begin{cases} \frac{x_2-40}{100-40} & if\ 40 \le x_2 \le 100 \\ \frac{160-x_2}{160-100} & if\ 100 \le x_2 \le 160 \\ 0 & for\ other\ x \end{cases}$
$\mu_{kpDENSITY}(x_2) = \begin{cases} \frac{x_2-120}{160-120} & if\ 120 \le x_2 \le 160 \\ \frac{200-x_2}{200-160} & if\ 160 \le x_2 \le 200 \\ 0 & for\ other\ x \end{cases}$</td>
<td>

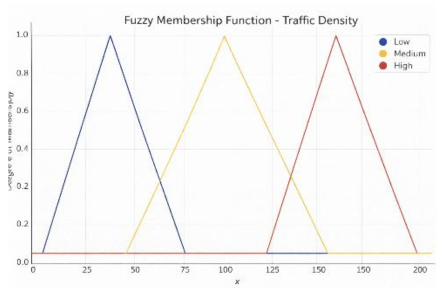
Figure 3. Traffic Density Fuzzy Membership Function Graph</td>
</tr>
<tr>
<td>Risk of Accidents</td>
<td>$\mu_{rLOW}(y_1) = \begin{cases} \frac{y_1-0}{20-0} & if\ 0 \le y_1 \le 20 \\ \frac{40-y_1}{40-20} & if\ 20 \le y_1 \le 40 \\ 0 & for\ other\ x \end{cases}$
$\mu_{rMEDIUM}(y_1) = \begin{cases} \frac{y_1-20}{50-20} & if\ 20 \le y_1 \le 50 \\ \frac{80-y_1}{80-50} & if\ 50 \le y_1 \le 80 \\ 0 & for\ other\ x \end{cases}$
$\mu_{rHIGH}(y_1) = \begin{cases} \frac{y_1-60}{80-60} & if\ 60 \le y_1 \le 80 \\ \frac{100-y_1}{100-80} & if\ 80 \le y_1 \le 100 \\ 0 & for\ other\ x \end{cases}$</td>
<td>

Figure 4. Fuzzy Membership Function Graph of Accident Risk</td>
</tr>
</table>

E. Fuzzification

Fuzzification is the process of converting crisp input values into fuzzy membership degrees. For example, if vehicle speed is 80 km/h and traffic density is 70 vehicles/km, then the membership degree for the “medium” speed category is 0.83, while the membership degrees for the “light” and “moderate” density categories are 0.68 and 0.50, respectively. These values form the basis for determining the risk level through fuzzy inference

Example problem: “Suppose that, under certain conditions, vehicle speed is 80 km/h and traffic density is 70 vehicles/km. What is the accident risk level?”

Input (X1,X2):

Speed (Input 1):

μ_1Slow (80km/h) = 0

μ_1Medium (80km/h) = $\frac{80-30}{60}$ = 0,83

$\mu_1$fast (80km/h) = 0

Density (Input 2):

$\mu_2$light (70 vehicles/km) = $\frac{80-70}{35}$ =0,68

$\mu_2$moderate (70 vehicles/km) = $\frac{70-40}{60}$ =0,5

$\mu_2$congested (70 vehicles/km) = 0

F. Constructing IF–THEN Rules

Fuzzy rules are a set of statements that define the relationship between inputs and output in the form of IF–THEN expressions. Each rule contains an IF condition (based on the received inputs) and a THEN consequence (the output to be produced). Rules can be developed with the involvement of experts in relevant domains [17]. In this study, nine rules are formulated based on combinations of the three speed categories and the three density categories. For instance, Rule R1 states: IF speed is slow AND density is light THEN accident risk is low. These rules model human reasoning in qualitatively assessing traffic situations.

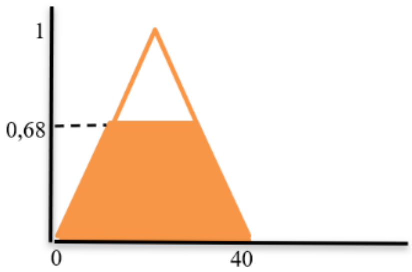
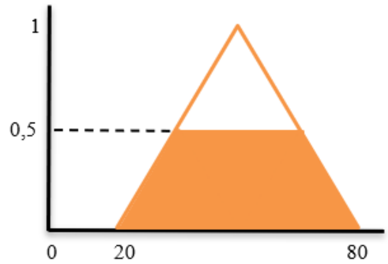
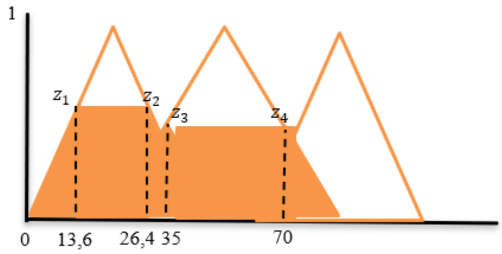
[R1] IF speed is SLOW AND density is LIGHT THEN accident risk is LOW.
[R2] IF speed is SLOW AND density is MODERATE THEN accident risk is LOW.
[R3] IF speed is SLOW AND density is CONGESTED THEN accident risk is MODERATE.
[R4] IF speed is MEDIUM AND density is LIGHT THEN accident risk is LOW.
[R5] IF speed is MEDIUM AND density is MODERATE THEN accident risk is MODERATE.
[R6] IF speed is MEDIUM AND density is CONGESTED THEN accident risk is MODERATE.
[R7] IF speed is FAST AND density is LIGHT THEN accident risk is MODERATE.
[R8] IF speed is FAST AND density is MODERATE THEN accident risk is HIGH.
[R9] IF speed is FAST AND density is CONGESTED THEN accident risk is HIGH.

G. Data Inference

The fuzzy inference system receives crisp inputs, which are then processed by the knowledge base containing IF–THEN rules [18]. Inference is performed using fuzzy logic operators, such as the minimum operator to represent AND. Based on the fuzzification membership degrees, several rules are activated—for example, R4 and R5—producing low and moderate risk outputs with activation levels of 0.68 and 0.50, respectively. These activation levels are used in the next stage to determine a numerical output through defuzzification.

DOI : https://dx.doi.org/10.24014/jsms.v12i1.38351

Table 2. Defuzzifiction

Membership Function	Degree of Membership
[R1] = Logical Operation -----> Min (Slow, Quiet) = (0 , 0.68) = (0) [R2] = Logical Operation -----> Min (Slow, Medium) = (0 , 0.5) = (0) [R3] = Logical Operation -----> Min (Slow, Dense) = (0 , 0) = (0) [R4] = Logical Operation -----> Min (Moderate, Quiet) = (0.83 , 0.68) = (0.68)	 **Figure 5a. Degree of membership on Defuzzification**
R5] = IF Speed is MEDIUM AND Density is MEDIUM THEN Accident Risk is MEDIUM Logical Operation-----> Min (Medium, Medium) = (0.83 , 0.5) = (0.5)	 **Figure 5b. Degree of membership on Defuzzification** Finding the Intersection Point for Each Region: a) Z1=13,6 *b)* Z2 = 26,4 *c)* Z3 = 35 d) Z4 = 70
R6 = Logical Operation -----> Min (Medium, Medium) = (0.83 , 0) = (0) R7 = Logical Operation -----> Min (Medium, Medium) = (0 , 0) = (0) R8 = Logical Operation -----> Min (Medium, Medium) = (0 , 0.5) = (0) R9 = Logical Operation -----> Min (Medium, Medium) = (0 , 0) = (0)	Combine the membership graphs of each linguistic variable, resulting in:  **Figure 6. Combine the membership graphs of each linguistic variable** $M_{(z)} = \begin{cases} \frac{z}{2} & 0 \le z \le 13{,}6 \\ 0{,}6 & 13{,}6 \le z \le 26{,}4 \\ \frac{40-z}{20} & 26{,}4 \le z \le 35 \\ 0{,}5 & 35 \le z \le 70 \\ \frac{80-z}{30} & 70 \le z \le 100 \end{cases}$

H. Defuzzification

The input to defuzzification is a fuzzy set obtained from the composition of fuzzy rules, whereas the output is a crisp number within the domain of that fuzzy set. Thus, given a fuzzy set in a certain range, a specific crisp value must be derived as the final output [19]. In this study, the fuzzy output from the inference stage is converted back into a crisp value using the centroid (centre-of-gravity) method commonly used in Mamdani systems [20]. Based on the computed moments and areas of the membership-function segments, the final value is z* = 25.31. This indicates that when a vehicle travels at 80 km/h under a traffic density of 70 vehicles/km, the estimated accident risk is 25.31%, which lies within the low-to-moderate risk category.

Calculating the Moment (M)

$$M_1 = \int_0^{13,6} \frac{z}{20} z\, dz$$

This is the integral of $\frac{z^2}{20}$:

$$M_1 = \int_0^{13,6} \frac{z}{20} z\, dz = \frac{1}{20} \cdot \left[\frac{z^3}{3}\right]_0^{13,6}$$

$$M_1 = \int_0^{13,6} \frac{z}{20} z\, dz = 41,924$$

$$M_2 = \int_{13,6}^{26,4} 0,68\, z\, dz = 174,08$$

$$M_3 = \int_{26,4}^{35} \frac{40-z}{20} z\, dz = 120,119$$

$$M_4 = 0,5 \int_{35}^{70} z\, dz = 918,75$$

$$M_5 = \int_{70}^{100} \frac{80-z}{30} z\, dz = -500$$

Calculating the Area (A)

1. $A_1 = \int_0^{13,6} \frac{z}{20} z\, dz = 4,624$
2. $A_2 = \int_{13,6}^{26,4} 0,68\, z\, dz = 8,704$
3. $A_3 = \int_{26,4}^{35} \frac{40-z}{20} z\, dz \approx 3,999$
4. $A_4 = \int_{35}^{70} 0,5\, dz = 17,5$
5. $A_5 = \int_{70}^{100} \frac{80-z}{30} dz = -5$

Calculating Z using the centroid method :

$$z^* = \frac{M_1+M_2+M_3+M_4+M_5}{A_1+A_2+A_3+A_4+A_5}$$

$$= \frac{41,924+174,08+120,119+918,75+(-500)}{4,624+8,708+3,999+17,5+(-5)}$$

$$z^* = 25,31$$

If you drive at a speed of 80 km/h under a traffic density of 70 vehicles/km, then the accident risk is 25.31%.

Based on the evaluation and analysis, the fuzzy inference system is able to categorise the accident risk level for four-wheeled vehicles by considering vehicle speed and traffic density. The system output indicates that the combination of high speed and congested traffic density consistently produces a high risk level, consistent with real-world conditions.

A risk value of 25.31% for a combination of 80 km/h speed and 70 vehicles/km density indicates that these conditions fall into the low to moderate risk category.

Empirically, this condition can be justified because at moderate density levels, drivers still have sufficient distance between vehicles to maneuver and brake, so the potential for accidents is not yet at a critical level. This finding is in line with research [21] which shows that the relationship between traffic density and accident rates can be modeled accurately, where accident rates tend to be relatively stable at low to moderate densities, and confirms the importance of managing traffic speed and density in improving safety in Indonesia. In addition, several studies also show that low density is often correlated with increased vehicle speed, which under certain conditions can increase the risk of accidents. Thus, the results of the fuzzy model developed are still consistent with actual conditions in the field, where accidents with a high severity level generally occur in a combination of high density and high speed. However, this model has limitations because it only considers two input variables, so it is not yet able to represent other factors such as weather conditions, road geometry, and driver behavior that could potentially affect the sensitivity of the risk assessment results.

4. Conclusion

This study demonstrates that a Mamdani-type Fuzzy Inference System (FIS) is effective for evaluating the traffic accident risk of four-wheeled vehicles using speed and density as the primary parameters. The system can adaptively classify risk into low, moderate, and high levels based on linguistic data and uncertainty. Using centroid defuzzification for a speed of 80 km/h and a density of 70 vehicles/km, the resulting risk value is 25.31%, indicating a low-to-moderate risk level.

For future research, it is recommended to incorporate additional variables such as weather, time, visibility, and driver behaviour, and to integrate real-time data and field testing to improve validity, reliability, and applicability for Intelligent Transportation Systems.

References

[1] A. D. Saputra, "Studi Tingkat Kecelakaan Lalu Lintas Jalan di Indonesia Berdasarkan Data KNKT (Komite Nasional Keselamatan Transportasi) dari Tahun 2007-2016," *Warta Penelitian Perhubungan*, vol. 29, no. 2, pp. 179–190, 2018.

[2] G. U. Agbeboh and O. Osarumwense, "Empirical analysis of road traffic accidents: A case study of Kogi State, North-Central Nigeria," *International Journal of Physical Sciences*, vol. 8, no. 40, pp. 1923–1933, 2013, doi: 10.5897/IJPS2013.3978.

[3] S. F. E. Mubalus, "Analisis Faktor-Faktor Penyebab Kecelakaan Lalu Lintas Di Kabupaten Sorong Dan Penanggulangannya," *Soscied*, vol. 6, no. 1, pp. 182–197, 2023.

[4] R. Rahmadeni and S. Raudi, "Analisis Tingkat Kerugian Material Akibat Kecelakaan Lalu Lintas Dengan Menggunakan Dummy Variable Di Provinsi Riau Tahun 2013-2017," *Jurnal Sains Matematika dan Statistika*, vol. 6, no. 1, p. 58, 2020, doi: 10.24014/jsms.v6i1.9253.

[5] M. B. Santoso, “Keamanan Manusia: Pergeseran Paradigma Keamanan Nasional (Studi Literatur Pada Kecelakaan Lalu Lintas Dalam Perspektif Kesejahteraan Sosial),” *Share : Social Work Journal*, vol. 13, no. 2, pp. 175–185, 2024, doi: 10.24198/share.v13i2.51546.
[6] F. Sholahudin, Y. M. Muna, and M. A. Istianti, “Manajemen Kecepatan Kendaraan di Ruas Jalan MT Haryono, Kota Semarang, Jawa Tengah,” *Praxis : Jurnal Sains, Teknologi, Masyarakat dan Jejaring*, vol. 7, no. 2, pp. 139–149, 2025, doi: 10.24167/praxis.v7i2.12786.
[7] A. Hidayati and L. Y. Hendrati, “Analisis Risiko Kecelakaan Lalu Lintas Berdasar Pengetahuan, Penggunaan Jalur, dan Kecepatan Berkendara Traffic Accident Risk Analysis by Knowledge, the Use of Traffic Lane, and Speed,” *Jurnal Berkala Epidemiologi*, vol. 4, no. 2, pp. 275–287, 2017, doi: 10.20473/jbe.v4i2.2016.275.
[8] A. S. Mugirahayu, L. Linawati, and A. Setiawan, “Penentuan Status Kewaspadaan COVID-19 Pada Suatu Wilayah Menggunakan Metode Fuzzy Inference System (FIS) Mamdani,” *Jurnal Sains dan Edukasi Sains*, vol. 4, no. 1, pp. 28–39, 2021, doi: 10.24246/juses.v4i1p28-39.
[9] Tomi Tamara, “Sistem Pendukung Keputusan Dalam Skema Pengusulan Awal Jabatan Fungsional Dosen Menggunakan Sistem Inferensi Fuzzy Tipe Mamdani (Studi Kasus : Di Bagian Kepegawaian – Kopertis Wilayah X),” *Menara Ilmu*, vol. XIII, no. 2, pp. 146–157, 2019, [Online]. Available: http://jurnal.umsb.ac.id/index.php/menarailmu/article/view/1189
[10] S. Setianto, L. K. Men, B. M. Wibawa, and D. Hidayat, “Pengaturan Lampu Lalulintas Berbasis Fuzzy Logic,” *JIIF (Jurnal Ilmu dan Inovasi Fisika)*, vol. 1, no. 2, pp. 94–98, 2017.
[11] T. D. Chala and L. T. Kóczy, “Intelligent Fuzzy Traffic Signal Control System for Complex Intersections Using Fuzzy Rule Base Reduction,” *Symmetry (Basel).*, vol. 16, no. 9, pp. 1–24, 2024, doi: 10.3390/sym16091177.
[12] Y. Bi, D. Srinivasan, X. Lu, Z. Sun, and W. Zeng, “Type-2 fuzzy multi-intersection traffic signal control with differential evolution optimization,” *Expert Syst. Appl.*, vol. 41, no. 16, pp. 7338–7349, 2014, doi: 10.1016/j.eswa.2014.06.022.
[13] F. Andika, N. Nurviana, and R. P. Sari, “Perbandingan Model Chen dan Lee pada Metode Fuzzy Time Series untuk Peramalan Nilai Tukar Petani (NTP) di Provinsi Aceh,” *Jurnal Sains Matematika dan Statistika*, vol. 10, no. 1, p. 71, 2024, doi: 10.24014/jsms.v10i1.23463.
[14] I. Wahyuni, W. F. Mahmudy, and A. Iriany, “Rainfall prediction in Tengger region Indonesia using Tsukamoto fuzzy inference system,” *Proceedings - 2016 1st International Conference on Information Technology, Information Systems and Electrical Engineering, ICITISEE 2016*, pp. 130–135, 2016, doi: 10.1109/ICITISEE.2016.7803061.
[15] MZ Haqqul Barir, “Analisa Permodelan Penjadwalan Yang Optimal Dengan Logika Fuzzy Mamdani-Algoritma Genetika Dan Logika Fuzzy Sugeno-Algoritma Genetika Thesis Oleh : Much . Zuyyinal Haqqul Barir,” 2024.
[16] B. A. Restuputri, “Optimasi Fungsi Keanggotaan Fuzzy Tsukamoto Dua Tahap Menggunakan Algoritma Genetika Pada Pemilihan Calon Penerima Beasiswa PPA Dan BBP-PPA,” Malang, 2015.

[17] A. Burhanuddin, “Analisis Komparatif Inferensi Fuzzy Tsukamoto, mamdani dan Sugeno Terhadap Produktivitas Padi di Indonesia,” *Journal Informatic and Informtion Technology*, vol. 2, no. 1, pp. 49–57, 2023.

[18] P. Harliana, M. Mardiana, and Y. A. Nainggolan, “Analisa Perbandingan Tingkat Akurasi dalam Memprediksi Laju Inflasi Kota Medan Menggunakan Model Fuzzy Inference System Sugeno dan Mamdani,” *Hello World Jurnal Ilmu Komputer*, vol. 1, no. 3, pp. 145–52, 2022, doi: 10.56211/helloworld.v1i3.130.

[19] D. A. Puryono, “Metode Fuzzy Inferensi System Mamdani Untuk Menentukan Bantuan Modal Usaha Bagi UMKM Ramah Lingkungan,” *Jurnal STIMIKA*, vol. 1, no. 1, pp. 1–6, 2014.

[20] T. M. Purba and P. Gultom, “Analisis Perbandingan Fuzzy Inference System Metode Mamdani dan Sugeno dalam Optimisasi Produksi Barang,” *INNOVATIVE: Journal Of Social Science Research*, vol. 4, pp. 4076–4088, 2024.

[21] W. Kriswardhana, S. Sulistyono, W. Yunarni Widiarti, and T. A. Rahmawaty, “Speed, Density, and Crash Relationship in Urban Arterial Roads,” *Civil and Environmental Science*, vol. 6, no. 2, pp. 100–107, 2023, doi: 10.21776/civense.v6i2.401.