FUZZY MULTI-CRITERIA DECISION-MAKING APPROAHCES FOR OPTIMAL SELECTION OF EMBEDDED SYSTEMS FOR AUTONOMOUS NAVIGATED LIGHT VEHICLES

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ABSTRACT

Selecting the best type of embedded system for an autonomous navigated light vehicle is complicated. The complexity arises from the need to consider criteria such as navigation accuracy, processing speed, power consumption, compatibility, and reliability when building an autonomous navigated light vehicle. This study evaluates three types of embedded systems: Arduino, Raspberry Pi, and NVIDIA Jetson. Therefore, this study aims to evaluate and select the best embedded system for an autonomous navigated light vehicle. The Fuzzy Analytic Hierarchy Process (FAHP), the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS), and the Fuzzy Simple Additive

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Weighting (FSAW) methods were used to test and choose from between the three types of embedded systems. Each method has its advantages. The FAHP has the advantage of determining the weight of the criteria hierarchically. The F-TOPSIS and FSAW methods were used to sort and evaluate alternatives based on the set criteria. The study's results showed that of the three methods used, Raspberry Pi is the best alternative, followed by NVIDIA Jetson and Arduino. The findings showed that Raspberry Pi excelled in navigation accuracy and processing speed, NVIDIA Jetson excelled in reliability, and Arduino excelled in power consumption and compatibility. Fuzzy MCDM is an appropriate method to use to select embedded systems for autonomous navigated light vehicles.

Keywords: autonomous navigating light vehicle; fuzzy multi-criteria decision making; navigation accuracy; processing speed, power consumption; compatibility; reliability

1. Introduction

The development of the electronic equipment sector has proliferated. Embedded systems are a series of electronic devices used to control a system, which apply to the Internet of Things (IoT), robotics, automatic control systems, consumer devices, industry, autonomous vehicles, and artificial intelligence (AI). Arduino, Raspberry Pi, and NVIDIA Jetson are embedded systems that are widely utilized in various applications. These three embedded system platforms have a strong developer community and diverse technical capabilities. Arduino is an embedded system platform that excels by being low cost and simple in terms of programming, so it is widely used in simple IoT projects (Sethi & Sarangi, 2017). The Raspberry Pi-type embedded system has advantages in computing capabilities and supports multimedia use. Therefore, this platform suits complex data processing applications (Massimo et al., 2020). The NVIDIA Jetson-type embedded system has powerful GPU capabilities and fast computing advantages. Therefore, this platform is suitable for developing AI and machine learning applications (Li & Zheng, 2020).

In autonomous vehicles, embedded systems are necessary, especially in the development of autonomous navigated light vehicles that require a combination of hardware and software to become efficient and optimal in performance. In order for autonomous light vehicles to work, the embedded systems that include both hardware and software must meet certain requirements, including being able to navigate accurately, process quickly, use little power, be compatible with other systems, and be reliable (Hamadneh et al., 2022). For this reason, selecting an embedded system platform that suits these needs is necessary. The selection is challenging because the various platforms offer different advantages and disadvantages (Shahedi et al., 2023). Therefore, an appropriate method is needed to evaluate the criteria correctly and determine the best alternative for an embedded system platform.

Multi-criteria decision-making (MCDM) methods are used for decision-making by processing criteria weights based on expert input (Shahedi et al., 2023). To determine the best alternative in the selection of the best type of embedded system, the use of MCDM is required. Using subjective expert assessments requires a method that can translate these subjective assessments to fuzzy sets that are suitable for assessing subjective preferences

(Fodor, 2008). Therefore, combining the fuzzy method with MCDM can help select the best choice of embedded system. Some types of fuzzy MCDM include FAHP, F-TOPSIS, and FSAW. Each method provides a different way to determine the best alternative (Afrane et al., 2022). FAHP determines the best choice by using criteria weights based on the level of importance for evaluating the decision (Peng et al., 2021). F-TOPSIS uses ideal solution parameters, which are then calculated for the shortest distance to determine the best choice (al-Sulbi et al., 2023). FSAW aggregates the weights of all its criteria to determine the best choice (Roszkowska & Kacprzak, 2016). This study fills a research gap by providing a method to determine the best-embedded systems for autonomous navigation light vehicles using fuzzy multi-criteria decision-making. Several studies have conducted research related to fuzzy MCDM. Patil & Kant (2014) used fuzzy AHP-TOPSIS to solve problems in the supply chain process. Afrane et al. (2022) used fuzzy MCDM for energy selection with the AHP-TOPSIS integration method. Chen (2012) compared SAW and TOPSIS on interval-valued fuzzy sets in multiple-criteria decision analysis (MCDA) problems. Chou et al. (2008) used FSAW to determine the best facility location. From these studies, few compare FAHP, F-TOPSIS, and FSAW for embedded system selection in the context of autonomous navigation light vehicles. Multi-criteria assessment has a subjective and uncertain nature because it involves expert judgment. The fuzzy method was chosen because it can approach subjective and uncertain assessments. Therefore, this study aims to determine the best type of embedded system with subjective multi-criteria assessment for autonomous navigated light vehicles.

1.1 Problem statement

Even though autonomous navigated light vehicles are becoming more and more popular, it's still unclear which embedded system platforms, such as Arduino, Raspberry Pi, and NVIDIA Jetson, will work best to enable their operation. A major challenge of the study is making sure the selected embedded system platform can easily integrate with the current autonomous navigated light vehicles systems and technologies, including navigation accuracy, processing speed, power consumption, compatibility, and dependability.

1.2 Purpose of the study

Based on the description above, the primary aim of this study is to evaluate and select the best-embedded system for autonomous navigated light vehicles using fuzzy multi-criteria decision-making.

1.3 Research question

The research question is, How can fuzzy multi-criteria decision-making methods be utilized to evaluate and select the most suitable embedded system platform?

2. Literature review

The development of autonomous navigated light vehicles requires essential criteria. Some criteria that must be considered include navigation accuracy, processing speed, power consumption, compatibility, and reliability (Hamadneh et al., 2022). Navigation accuracy criteria are needed to accurately determine the movement of autonomous vehicles from

departure to the destination. This criterion can be enhanced by gear equipped with GPS and visual sensors to ascertain the precise route (Giannaros et al., 2023). Criteria for processing speed are essential for the immediate execution of information acquired from sensors by the embedded system in autonomous vehicles (Adnan Yusuf et al., 2024). Criteria for power consumption are essential for ensuring that autonomous cars operate with energy efficiency and are able to function for extended distances (Brown et al., 2022). Compatibility criteria are essential to ensure that autonomous vehicle components are user-friendly and interoperable with other components (Chaudhary et al., 2024). These components can be hardware and software. Reliability criteria are needed to use autonomous vehicles in road conditions that follow industry standards organizations' specifications (Adnan Yusuf et al., 2024). All of these criteria are needed for autonomous vehicles to function using an embedded system. Commonly applied types of embedded systems are Arduino, Raspberry Pi, and NVIDIA Jetson. Each type of embedded system has its advantages and disadvantages.

Arduino is a simple and inexpensive embedded system, which makes it attractive for many beginners or designers. According to Veeramanickam et al. (2022), Arduino has the advantage of low power consumption and is easy to integrate with other components. Arduino is mainly used for autonomous vehicles as mobile robots (Oltean, 2019). According to Kondaveeti et al. (2021a), one disadvantage of Arduino is its slow data processing. Raspberry Pi has higher processing power specifications, so it has better computing performance when integrated with sensors, cameras, and actuators (Singh et al., 2020). Therefore, Raspberry Pi processing is known to be fast and accurate. Raspberry Pi works on Python language programming, so it has become popular and a popular choice for embedded systems. Due to these benefits, Raspberry Pi has been extensively utilized in robotics, autonomous vehicles, and industrial automation (Hosny et al., 2013). Raspberry Pi can be connected to a camera in autonomous vehicles to detect and track other vehicles (Anandhalli & Baligar, 2018). Another advantage of Raspberry Pi is that it is relatively cheap and competitive with other embedded systems. Lam Loong Man et al. (2018) used Raspberry Pi as the embedded system of choice for building low-cost autonomous vehicles. NVIDIA Jetson is an embedded system that benefits from object detection and deep learning-based decision-making because it uses GPU-based computing (Kortli et al., 2022). Industrial and robotic applications need advanced machine vision that requires object recognition; hence, NVIDIA Jetson is appropriate for this purpose. Likewise, for autonomous vehicles that prioritize road tracking and vehicle detection using object recognition and decision-making using deep learning, NVIDIA Jetson is more appropriate (Li & Zheng, 2020).

Several studies have been conducted on these three embedded systems, but only a few discuss the criteria that support their use. The criteria used for the three embedded systems do not stand alone but consist of several criteria, so the studies use the MCDM method. These multiple criteria are generally uncertain and subjective (Hamadneh et al., 2022). This problem can be solved through a fuzzy logic approach. The combination of fuzzy and MCDM is known as fuzzy MCDM. The fuzzy MCDM method can overcome complex problems when evaluating a system (Hsieh et al., 2004). According to Afrane et al. (2022), fuzzy MCDM can make flexible and accurate assessments when selecting alternatives based on criteria whose weights are uncertain and subjective. Several studies have utilized fuzzy MCDM methods to assist decision-makers in selecting optimal

embedded systems. Some fuzzy MCDMs, including FAHP, F-TOPSIS, and FSAW, are often used.

Tran et al. (2024) show that the FAHP effectively evaluates embedded systems platforms in the IoT applications, where power consumption and compatibility are vital criteria. In the context of autonomous vehicles, this study underlines the importance of using a fuzzy approach to handle uncertainties and variations in criteria that may arise during system development. The FAHP is the most appropriate method when faced with the problem of selecting alternatives that involve experts in determining the weight of the criteria. Peng et al. (2021) state that if the problem involves multiple interrelated criteria and subjective preferences in decision-making, then using FAHP is the right choice. Furthermore, the F-TOPSIS method evaluates alternatives from each criterion by calculating the ideal solution distance; this distance is in the form of PIS (Positive Ideal Solution) and NIS (Negative Ideal Solution). According to Dogan et al. (2020), F-TOPSIS can be used to evaluate the selection of embedded system types based on computing performance, energy efficiency, and hardware compatibility criteria. The FSAW method has the advantage of ease and simplicity in evaluating an alternative. FSAW calculates choices based on the final score of each alternative based on the weight of its criteria (Kabassi et al., 2020). The weight of this criterion comes from expert judgment preference, so it is subjective.

3. Research methods

This study used a quantitative research design with a comparative case study approach. This research design was chosen to allow for in-depth analysis of various platform alternatives based on predetermined criteria. This research was based on the assessment of one expert who has more than 10 years of experience in developing embedded systems for mobile and autonomous robots. This expertise provided in-depth and accurate insights into the criteria being evaluated. In the context of this research, focusing on one expert allowed for a more detailed and in-depth analysis of the relevant criteria, given the complexity and technical specifications of the evaluated platforms.

This research evaluated three fuzzy MCDM methods: FAHP, F-TOPSIS, and FSAW. These three methods were applied to evaluate and decide the best-embedded system among Arduino, Raspberry Pi, and NVIDIA Jetson. The selection of alternative types of embedded systems was based on the following five criteria: navigation accuracy, processing speed, power consumption, compatibility, and reliability. Figure 1 shows the research block diagram.

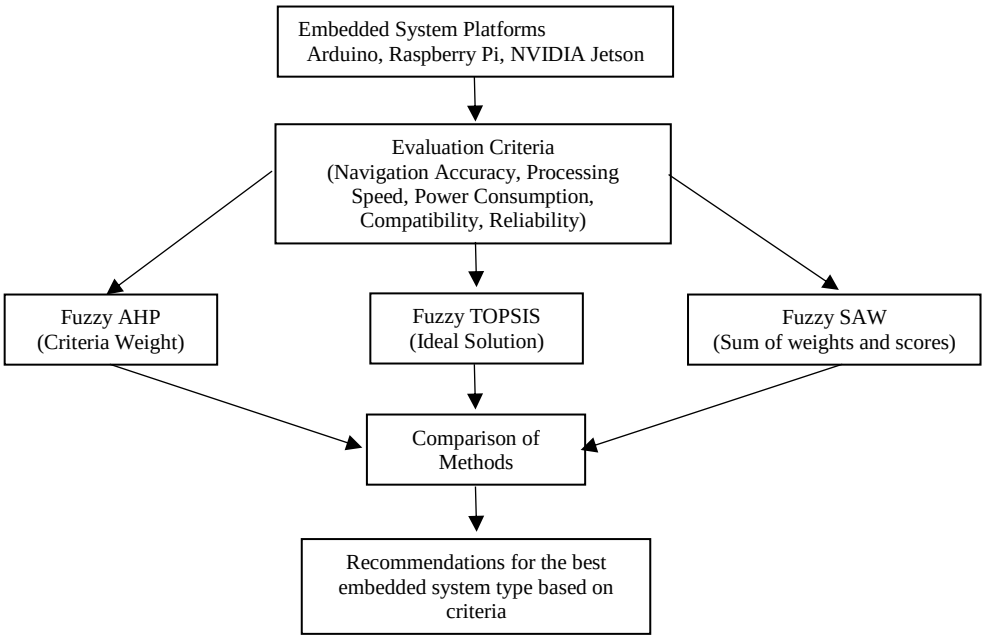

Figure 1 Research block diagram

3.1 Fuzzy AHP

Steps of the FAHP method:

1. Build a hierarchical structure: The hierarchical structure consists of criteria, sub-criteria, and alternatives as shown in Figure 2.

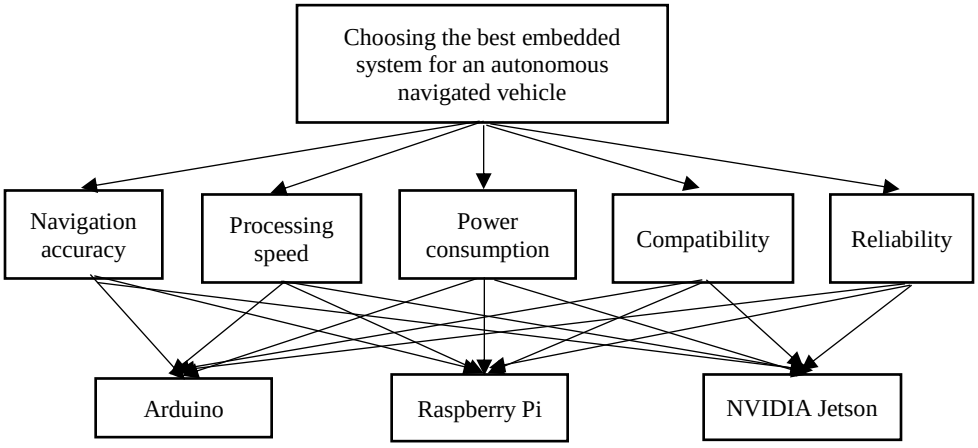

Figure 2 Hierarchical structure

Level 1: The main objective is selecting the best embedded system alternative for autonomous navigated light vehicles.

Level 2: Criteria: navigation accuracy, processing speed, power consumption, compatibility, reliability.

Level 3: Alternatives: Arduino (A1), Raspberry Pi (A2), and NVIDIA Jetson (A3).

2. Create a Pairwise Comparison Matrix (PCM): A PCM is arranged based on comparing each criterion or alternative using a preference scale. Fuzzy numbers are used to handle uncertainty. The fuzzy numbers used in this study are triangular fuzzy numbers (l, m, u), with:
   l = minimum value
   m = medium value
   u = maximum value

3. Normalize the comparison matrix: Normalization is done by dividing each element in a column by the total number of elements in that column. This gives each criterion or alternative a fuzzy weight.

4. Calculate Fuzzy Synthetic Extent (FSE): FSE is calculated using the following formula:

$$S_i = \frac{\sum_{j=1}^{n} M_{ij}}{\sum_{i=1}^{n} M_{ij}}$$

   where M_{ij} is the pairwise comparison fuzzy value, and n is the number of criteria.

5. Determine the degree of possibility: Calculate the degree of possibility $V(M_1 \geq M_2)$ between two fuzzy numbers M_1 and M_2. The formula for the degree of probability is:

$$V(M_1 \geq M_2) = \min(\max\left(\frac{l_2 - u_1}{m_1 - u_1}, 0\right), 1)$$

   l_1, m_1, u_1 are fuzzy values for M_1, and l_2, m_2, u_2 for M_2.

6. Calculate fuzzy weight: The fuzzy weight for each criterion or alternative is calculated by summing the degree of possibility for each alternative compared to the other alternatives.

7. Determine the defuzzification weight: After the fuzzy weights are calculated, defuzzification is performed to change the fuzzy numbers into single values. One of the defuzzification methods is Centre of Area (CoA) or Mean of Maxima (MoM), which is stated as:

$$W = \frac{l + m + u}{3}$$

8. Rank alternatives: After the defuzzification weights for each alternative are calculated, the alternatives are ranked based on these weights. The alternative with the highest weight is considered the best choice.

3.2 Fuzzy TOPSIS

Steps of the F-TOPSIS method:

1. Construct a decision matrix: Each alternative is evaluated based on criteria using fuzzy values. A decision matrix X is formed, where $X_{ij}$is the value of alternative A_i against criterion C_i.

2. Normalize decision matrix: The decision matrix is normalized to eliminate the influence of different scales between criteria. Normalization is done using the following formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

where x_{ij} is the value of alternative A_i against criterion C_j, and m is the number of alternatives.

3. Weight decision matrix: After normalization, the weighted decision matrix v is calculated by multiplying the normalized values by the weights w_j of each criterion:

$$v_{ij} = w_j \times r_{ij}$$

where w_j is the weight of the criterion C_j.

4. Determine the Positive Ideal Solutions (PIS) and Negative Ideal Solutions (NIS): The positive ideal solution A^+ and the negative ideal solution $A^-$are defined as follows:

$$A^+ = (\max(v_{ij}) | \, j \in J, \min(v_{ij}) | \, j \in J')$$
$$A^- = (\min(v_{ij}) | \, j \in J, \max(v_{ij}) | \, j \in J')$$

J J is the benefit criteria, and J' J′ is the cost criteria.

5. Calculate the distance from PIS and NIS: The distance between each alternative and the positive and negative ideal solutions is calculated using the Euclidean formula.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^-)^2}$$

$_{Di}^{+}$ is the distance of alternative A_i from the positive ideal solution, and d_i^- is the distance of alternative A_i from the negative ideal solution.

6. Calculate relative proximity to the Ideal Solution
   The relative closeness C_i^* for each alternative is calculated as follows:

$$C_i^* = \frac{d_i^-}{d_i^+ + d_i^-}$$

   The C_i^* value ranges between 0 and 1. The closer the C_i^* value is to 1, the better the alternative.

7. Rank alternatives: Alternatives are sorted by C_i^* value, and the highest value is considered as the best alternative.

3.3 Fuzzy Simple Additive Weighting (FSAW)

Steps of the FSAW method:

1. Construct a decision matrix: Each alternative is evaluated against the criteria, and fuzzy values are used to handle the uncertainty in the data. A decision matrix X is formed where X_{ij} is the value of alternative A_i against the criterion C_j.

2. Normalize decision matrix: Normalization is done to eliminate the influence of different scales between criteria. The decision matrix is normalized using the formula:

3. For benefit criteria

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})}$$

   For cost criteria

$$r_{ij} = \frac{\min(x_{ij})}{x_{ij}}$$

   where x_{ij} is the value of alternative A_i against criterion C_j, and r_{ij} is the normalization value.

4. Weight decision matrix: After normalization, the weighted decision matrix is calculated by multiplying the normalized values by the criterion weights w_j:

$$v_{ij} = w_j \times r_{ij}$$

where w_j is the weight of the criterion C_j.

5. Calculate the total score for each alternative: After weighting, the total score for each alternative is calculated by summing all the weighted values for that alternative.:

$$S_i = \sum_{j=1}^{n} v_{ij}$$

S_i is the total score for alternative A_i, and n is the number of criteria.

6. Rank alternatives: Each alternative is ranked based on its total score, with the highest score considered the best.

The study provides a comprehensive and in-depth analysis of selecting the best embedded system based on predetermined criteria using these three methods. Each method has a unique approach that can complement each other in the decision-making process.

4. Research results

This study aims to determine the best alternative for embedded systems among the following three candidates: Arduino, Raspberry Pi, and NVIDIA Jetson. To achieve this goal, three multi-criteria decision-making methods, namely the FAHP, F-TOPSIS, and FSAW, were used. Saaty's scale, which is defined as a fuzzy triangular scale, was used as an assessment scale. Table 1 shows the fuzzy triangular scale.

Table 1
Saaty's scale with definitions for the fuzzy triangular scale

Linguistic preferences	**Fuzzy triangular scale**	**Linguistic preferences**	**Fuzzy triangular scale**
Equally important	(1,1,1)		
		Intermediate value	(1,2,3)
Weakly important	(2,3,4)		
		Intermediate value	(3,4,5)
Fairly important	(4,5,6)		
		Intermediate value	(5,6,7)
Strongly important	(6,7,8)		
		Intermediate value	(7,8,9)
Absolutely important	(9,9,9)		

Furthermore, an expert in autonomous vehicles provided expert judgments on the weight of the selection criteria in the form of a paired matrix. Table 2 shows a paired matrix using triangular-type fuzzy membership.

Table 2
Paired matrix

	Navigation accuracy			**Processing speed**			**Power consumption**			**Compatibility**			**Reliability**		
Navigation accuracy	1	1	1	4	5	6	9	9	9	0,25	0,2	0,167	4	5	6
Processing speed	0,167	0,2	0,25	1	1	1	6	7	8	6	7	8	0,25	0,2	0,167
Power consumption	0,111	0,111	0,111	0,125	0,143	0,167	1	1	1	0,167	0,143	0,125	0,167	0,143	0,125
Compatibility	6	5	4	0,125	0,143	0,167	8	7	6	1	1	1	0,167	0,143	0,125
Reliability	0,167	0,2	0,25	6	5	4	8	7	6	8	7	6	1	1	1

The three methods used five criteria: navigation accuracy, processing speed, power consumption, compatibility, and reliability. An expert in the field of autonomous vehicles was also asked for their expert judgments to provide criteria weights. The criteria weights are as follows: navigation accuracy (0.3), processing speed (0.25), reliability (0.2), compatibility (0.15), and power consumption (0.1).

4.1 Fuzzy AHP

The final results of the alternative ranking based on FAHP are shown in Table 3.

Table 3
Fuzzy AHP ranking results

	Arduino	**Raspberry Pi**	**NVIDIA Jetson**
Navigation accuracy	0.013473	**0.252218**	0.058293
Processing speed	0.013677	**0.119898**	0.040589
Power Consumption	**0.023766**	0.005493	0.001269
Compatibility	**0.110346**	0.025503	0.005894
Reliability	0.015273	0.080642	**0.233667**
Sum	0.176534	**0.483754**	0.339712

Table 3 shows that Raspberry Pi (A2), with the highest weight of 0.483754, ranks first. NVIDIA Jetson (A3) ranks second with a weight of 0.339712. Arduino (A1) ranks third with a weight of 0.176534. The results also show that Raspberry Pi is superior in the navigation accuracy and processing speed criteria, Arduino is superior in the power consumption and compatibility criteria, and NVIDIA Jetson is superior in the reliability criterion.

4.2 Fuzzy TOPSIS method results

In the F-TOPSIS method, the PIS and the NIS are calculated based on each criterion's maximum and minimum values. The distance between the alternatives with the PIS and NIS is calculated using the Euclidean formula, and the relative proximity of each alternative to the ideal solution is calculated. The ranking results are shown in Table 4.

Table 4
Fuzzy TOPSIS ranking results

	Distance from FPIS (di^*)	**Distance from FNIS (di^-)**	**Relative closeness (CC_i)**
Arduino	17.976	7.267	0.287878
Raspberry Pi	7.168	18.280	0.718333
NVIDIA Jetson	12.900	12.597	0.494067

The results of the F-TOPSIS calculations show that Raspberry Pi (A2) obtains the highest relative proximity value, 0.718333, thus ranking first. NVIDIA Jetson (A3) has a relative proximity value of 0.494067, ranking second, Arduino (A1) ranks third with a relative proximity value of 0.287878. These results are consistent with FAHP, where Raspberry Pi remains in the first place.

4.3 Fuzzy SAW method results

In the FSAW method, the value of each alternative is normalized by dividing each element in the column by the maximum value of the column (for the benefit criterion). The exact weights, as in FAHP, are used to calculate the weighted value. The total score is calculated by adding the weighted values for each alternative. The final result of the FSAW calculation is shown in Table 5.

Table 5
Fuzzy SAW ranking results

Arduino	Fuzzy numbers	0.072	0.078	0.083
	Defuzzified value	0.078		
Raspberry Pi	Fuzzy numbers	0.144	0.153	0.162
	Defuzzified value	0.153		
NVIDIA Jetson	Fuzzy numbers	0.106	0.118	0.130
	Defuzzified value	0.118		

The results of the FSAW calculation show that Raspberry Pi (A2) obtained the highest score, 0.153, thus ranking first. NVIDIA Jetson (A3) ranked second with a score of 0.118, and Arduino (A1) ranked third with a score of 0.078. The consistency of the results from these three methods strengthens the conclusion that Raspberry Pi is the best choice based on the five criteria evaluated in developing an autonomous navigated light vehicle.

5. Discussion

The study showed that using the FAHP, F-TOPSIS, and FSAW produced consistent results, namely, that Raspberry Pi is the best embedded system for autonomous navigated light vehicles based on expert judgments with the five selected criteria. Raspberry Pi has advantages in the criteria of navigation accuracy and processing speed, as shown by the results of FSAW. These results align with Lewis et al. (2016), who state that the Raspberry Pi performs well, requires real-time data processing applications, and can handle various sensor interfaces simultaneously. The study results also showed that Raspberry Pi is superior to NVIDIA Jetson with regard to power efficiency. The result is related to the superiority of NVIDIA Jetson in reliability, resulting in higher power consumption and greater complexity compared to Raspberry Pi and Arduino. These results are supported by Suder et al. (2023) who stated that Raspberry Pi is preferred for applications where energy efficiency is a priority. This is also supported by Mudaliar and Sivakumar (2020), who state that with efficient power usage, Raspberry Pi is widely used in applications in the fields of robotics and the IoT. In terms of lower power usage, Arduino exceeds Raspberry Pi. Arduino excels in adaptability with diverse hardware. Kondaveeti et al. (2021b) indicate that Arduino is appropriate and effective for simple tasks, but it has limits in more sophisticated applications. Conversely, Raspberry Pi surpasses Arduino in processing speed and navigational precision.

6. Conclusion

This study shows that three types of fuzzy MCDM, FAHP, F-TOPSIS, and FSAW, can select and evaluate the best embedded system for developing an autonomous navigated light vehicle. The calculated weights of the criteria show that Raspberry Pi is the best embedded system, followed by NVIDIA Jetson and then Arduino. The superiority of Raspberry Pi is demonstrated by its highest ranking for the navigation accuracy and processing speed criteria, which are very important for embedded system applications in autonomous navigating light vehicles. In terms of power consumption criteria, Raspberry Pi was superior to NVIDIA Jetson but not Arduino. The results of this study indicate that the FAHP, F-TOPSIS, and FSAW can be relied on to assist decision-makers to determine the best embedded systems for optimal autonomous navigated light vehicles based on the relevant criteria. Further research can utilize several experts in making decisions related to determining the criteria, the weight of expert assessments of these criteria, and evaluation using the appropriate group decision-making method.

7. Recommendations

This research only consulted a single expert which can limit the variety of opinions and add potential bias in the assessment. However, the authors believe that the expert's expertise and experience provide significant added value. The authors recommend further research involving multiple experts to broaden the analysis and reduce potential bias; they plan to conduct further studies involving more experts to validate the results and provide a more comprehensive perspective.

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