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ANFIS-Driven Optimization of Indoor Navigation Systems for Automated Guided Vehicles Utilizing UWB Signals

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ABSTRACT

This paper chronicles the fusion of the Adaptive Neural Fuzzy Inference System (ANFIS) and Ultra Wideband (UWB) technology for navigation system optimization in Indoor Autonomous Guided Vehicles (AGVs). In the Industry 4.0 era, the significance of accurate, effective and flexible AGV systems cannot be overemphasized in the industrial applications of today. UWB has centimeter-level location accuracy because of its low power consumption and large bandwidth, and is therefore very suitable for challenging indoor environments. In response to the challenge of high installation costs and environmental sensitivity, the ANFIS model is utilized to integrate the learning ability of artificial neural networks with the inference ability of fuzzy logic in order to increase the accuracy and effectiveness of UWB signal data processing. The real-time adaptive navigation of the system is also supported by dynamically adjusting the motor control according to the vehicle position using Pulse Width Modulation (PWM). The approach enables AGVs to adapt to environmental changes in a flexible manner, improving their performance in dynamic industrial environments. Future work can involve the investigation of UWB integration with other sensors or sensor technologies or application in cluster robotics to enable coordination and navigation in dynamic environments to be improved.

Keywords: UWB Signals, ANFIS, Automatic Guided Vehicle (AGV), Indoor Navigation, Positioning Optimization

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Introduction

Automated Guided Vehicles (AGVs) play a critical role in modern industrial automation and the autonomous management of material handling operations in factory and warehouse environments. They exhibit efficiency and precision by following paths determined by sensors, magnetic strips and other advanced guidance mechanisms. In the context of Industry 4.0, AGV systems are shifting from rigid centralized structures to flexible and decentralized structures, prioritizing features such as flexibility, durability and scalability, adapting to dynamic industrial environments and increasing the resilience of systems[1]. In contexts of smart factories, the tools have now evolved as an integral part of next-generation manufacturing system design. When combined with technologies like machine learning, data analytics and artificial intelligence, the tools enhance efficiency and performance in systems[2]. The self-driving car capability of dealing with sensing, decision-making, and control processes in real-time is enhanced through advancements in computer vision, wireless communications, machine learning, and sensor technologies. But there are challenges for them to make reliable decisions in complex traffic environments[3]. Proper sensing and navigation of positions is of paramount significance for the reliable functioning of AGVs[4]. Since position systems like GPS are not robust enough to be used in obscured environments, technologies like UWB, IMU, and WiFi are used to compensate for this limitation. However, these systems are afflicted by integration and environmental effects that cause accuracy and reliability problems[5].

Position detection systems are technologies that determine the location of objects or persons and provide position determination through the utilization of diverse technologies in both indoor and outdoor environments [6], [7]. ANFIS [8] is an artificial intelligence model that is a combination of artificial neural networks (ANN) [9] and fuzzy logic (FL) [10] systems. The combination of ANN's learning capability with FL's heuristic inference power allows for effective modelling and control of complex systems [11]. The ANFIS method yields more precise results by processing a variety of sensor data in position detection and by combining UWB, IMU, and WiFi signals, which minimizes errors and improves position accuracy, particularly in dynamic indoor environments [12].

AGV systems are designed to navigate a predetermined route, utilizing a range of technologies, including magnetic tapes, underground cables, lasers, optical sensors and RFID (Radio Frequency Identification) tags [13]. The principal benefit of these systems is their capacity for high precision in the operation of a specific route. However, this advantage is accompanied by two significant drawbacks: a lack of flexibility and the difficulty of rapidly adapting to changes in the route [12]. The use of UWB based AGV navigation systems is becoming increasingly prevalent in industrial contexts, largely due to their capacity for highly precise positioning. By offering precise positioning with a wide bandwidth and low power consumption, these systems facilitate the safe movement of AGVs, particularly in complex and dynamic indoor environments [14]. UWB technology offers consistent performance even in harsh environmental conditions, as the signal is resistant to multipath effects. However, UWB-based systems have a high installation cost, and the correct placement of base stations can be challenging in large-scale applications [15]. Furthermore, the presence of certain materials, including metallic surfaces, has the potential to impede the transmission of UWB signals, resulting in a decline in signal performance [16].

The present research aims at enhancing the precision, reliability and efficacy of AGVs in dynamic indoor settings. UWB technology and ANFIS are proposed as options, particularly in precision-demanding and complex industrial settings. The primary objective of the research is to enhance the flexibility, scalability, and versatility of AGV systems in Industry 4.0, beyond the current technologies' limitations. In addition to the disadvantages of UWB systems like high initial installation costs and vulnerability to environmental factors, the integration of UWB technology with the Internet of Things (IoT), artificial intelligence, and data analysis is likely to boost the industrial value of such systems. Besides the enhancement of indoor navigation, the study hopes to offer a crucial solution to key criteria such as safety, speed and cost-effectiveness in the industry. The approach is regarded as a pioneering work to both academic and industrial community.

Theoretical Background

AGVs are now an integral component of modern-day industrial automation, particularly in the form of Industry 4.0. In the wake of growing pressures for efficiency, accuracy and regulation in industrial procedures, technologies to support AGV systems have been a priority area of research in recent times. This chapter presents a theoretical model to integrate UWB technology and ANFIS for the navigation of AGVs. The chapter goes on to look at the independent principles and capability of UWB and ANFIS, bearing in mind their potential use combined in dynamic indoor environments, and demonstrating their potential to solve problems in existing AGV systems. The technical and theoretical foundations of these technologies are presented in an attempt to facilitate facile comprehension of their synergies and their potential in improving AGV performance in the Industry 4.0 revolution.

AGV Positioning System with ANFIS Integration

AGVs utilize various navigation technologies, i.e., GPS, RFID, and LIDAR, which are accurate along pre-mapped routes but struggle indoors due to signal interference and walls. Hence, alternative tools like Ultra-Wideband (UWB), IMU, and WiFi are increasing their popularity for indoor location. Latest technologies utilize smart systems like ANFIS, ANN, and FL to improve AGV navigation. These systems combine the neural network adaptability with the fuzzy logic understandability, enabling dynamic adjustments to changing surroundings. ANFIS enhances navigation by integrating neural learning and fuzzy inference, improving trajectory planning and obstacle avoidance in complicated indoor environments [17]. UWB systems, based on ANFIS or hybrid ANFIS-ANN configurations, reduce errors and improve positioning accuracy in dynamic environments. Simulations show ANFIS controllers navigate AGVs effectively through congested spaces, performing real-time adjustments to optimize routes [18]. The integration of ANFIS with sensor data fusion such as UWB, LIDAR, and IMU significantly improves obstacle avoidance and positioning in GPS-denied indoor environments by allowing real-time data interpretation and adaptive path adjustment[19]. These advancements emphasize the importance of intelligent navigation in AGV technology, with ANFIS, ANN, and Fuzzy Logic enabling robust and precise navigation in dynamic, obstructed environments.

Ultra-Wide Band (UWB) Technology

UWB technology, being a system that is more than 500 MHz wireless communications, has high speeds of transmission and very precise positioning ability. It has very useful applications where communication needs to have short distance range, ideal examples being intricate interior navigation which can be managed with it very conveniently. [20], [21]. UWB technology employs a wide frequency range, from 3.1 GHz to 10.6 GHz, and operates at low energy levels, thereby creating minimal interference with other wireless technologies [22]. These characteristics render UWB an optimal choice for applications that necessitate precise indoor positioning. UWB offers the advantages of a wide bandwidth, low power consumption, high-resolution positioning, and low latency [23]. UWB signals can penetrate walls and obstacles, providing accurate location data even in complex indoor environments, especially where multiple paths and signal reflections are present [20]. The minimal interference with other wireless systems makes this technology a reliable solution [20]. Nevertheless, the utilization of UWB is constrained by several factors, including its limited range, high cost, and regulatory restrictions in certain regions [24]. Ultra-wideband (UWB) signals utilize time difference-based (TOA) or time difference of arrival (TDOA) techniques for location. The broad frequency band reduces the effect of multipath and signal reflections, offering high accuracy in indoor environments. UWB is therefore most appropriate for applications requiring centimeter-level positioning and tracking accuracy[25]. The theoretical basis of UWB is based on the Shannon-Hartley Theorem [26]. According to this theorem, as the bandwidth of a communication channel increases, the data transmission rate also increases. UWB technology in AGV systems provides precise positioning and navigation, enhancing operational efficiency and reducing the probability of collision within complicated indoor environments. UWB technology provides centimeter precision, which is crucial for safe and efficient AGV navigation. Literature also explores how UWB is combined with AI-based systems like ANFIS to create more flexible and versatile AGV guidance in dynamic environments.[22].

ANFIS (Adaptive Neuro-Fuzzy Inference System)

The ANFIS offers a robust and adaptable modelling approach by integrating FL and ANN. By combining the adaptability of fuzzy logic with the learning capacity of neural networks, this system is a noteworthy solution, particularly in modelling non-linear and intricate systems [27]. ANFIS is a model-based data modeling technique widely used in prediction, classification, and control systems. It combines two key elements: FL and ANN. FL processes imprecise or uncertain data, and variables can take any value within a range, which is useful for modeling non-linear systems. ANN, derived from the biological nervous system, learn as they process input data and are especially good at dealing with large sets of data and learning from them.[28], [29], [30], [31].

ANFIS architecture contains five layers (Figure 1). The input layer receives the system variables and assigns each one to a fuzzy set in which each node is a fuzzy membership function. In the second layer, the inputs are transformed into fuzzy sets and each node calculates the antecedent degree of membership of a rule. The third level is the rule level, applying the fuzzy rules and computing the product of antecedents. The fourth is the inference level, computing every rule's consequences. The output level then gathers all rule outputs with a weighted average approach in order to come up with the output[27].

The learning process of ANFIS is typically conducted in two stages. In the initial stage, the forward pass, the input data are fed through the network, and the resulting output values are calculated. During this stage, the neural network optimizes the outcomes of the fuzzy rules [32][33]. In the second stage, the back propagation process, the discrepancy between the calculated output value and the actual value is reduced. This process entails the updating of the neural network weights through the application of the back propagation algorithm [34]. The two-step process enhances the modelling capacity of ANFIS, facilitating the attainment of precise results in nonlinear systems.

UWB Based Signal Detection

In the system, the use of a UWB signal as the radio frequency technology in the positioning system of the AGV vehicle is preferable. The Asymmetric Duplex Two-Way Ranging (ADS-TWR) method, which is the focus of the study, necessitates two signal transmissions and measurements, thereby enabling the calculation of two distinct round-trip times[35], [36]. Figure 2 depicts the time of arrival (ToA)-based asymmetric duplex two-way ranging (ADS-TWR) method between two devices. Round time is employed to represent the total time utilized for a signal to go between the devices and back, considering the time from transmission of the signal to receiving the signal and then the receiving-transmission interval of the response. The response time is the time required by a device to generate and send a response upon receiving the signal, from receiving the signal to sending the response.

Using the ADS-TWR method, the time of flight (ToF) of the signal between two devices is calculated using Equation 2.a and the distance is calculated using Equation 2.b.

$$T_{ToF} = \frac{\left(T_{round1} \times T_{round2} \times T_{reply1} \times T_{reply2}\right)}{\left(T_{round1} + T_{round2} + T_{reply1} + T_{reply2}\right)} \qquad (2.a)$$

$$d = c \times T_{ToF} \qquad (2.b)$$

The DWM1000 Ultra-Wideband (UWB) module, integrated with the DW1000 System-On-Chip, is a key component of the developed positioning application. This module adheres to the IEEE 802.15.4-2011 UWB standard and operates across four RF bands (3.5–6.5 GHz), supporting both Two-Way Ranging (TWR) and Time Difference of Arrival (TDoA) signal measurement techniques. Controlled via an SPI interface, the DWM1000 facilitates precise positioning in indoor environments. Its application circuit, shown in Figure 3, highlights the seamless integration of the UWB module with the microcontroller, ensuring efficient data acquisition and processing.

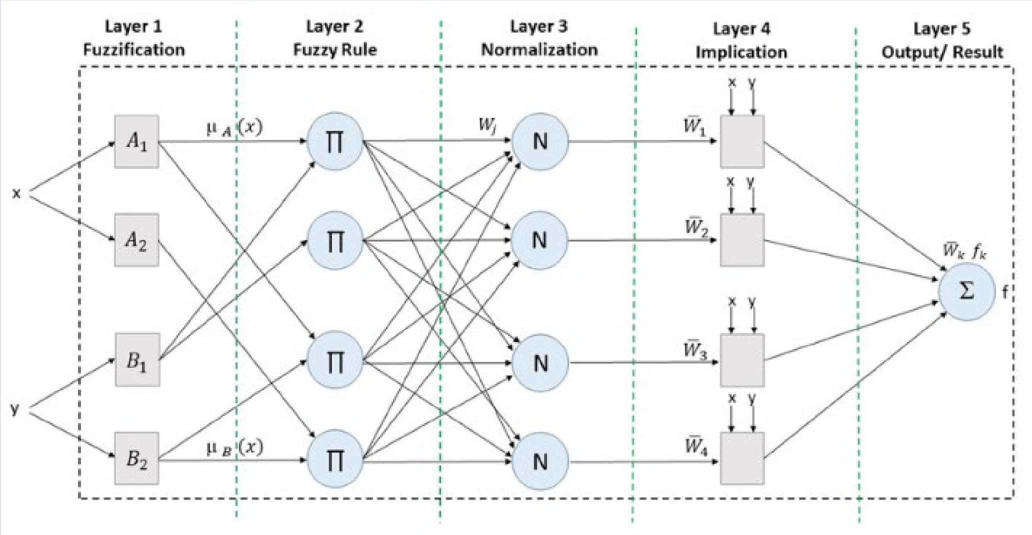


Figure 1. Five layer-based working of the ANFIS architecture [30].

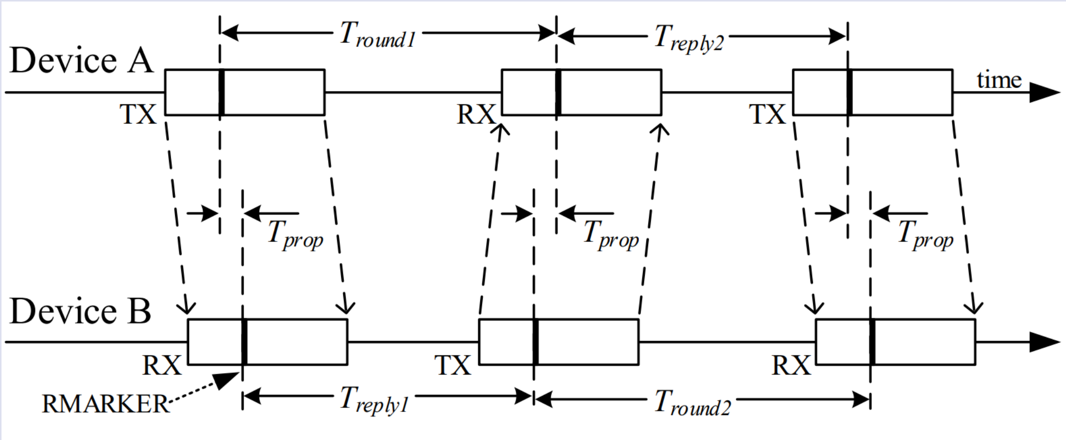


Figure 2. Asymmetric Double Sided Two-Way Ranging Method

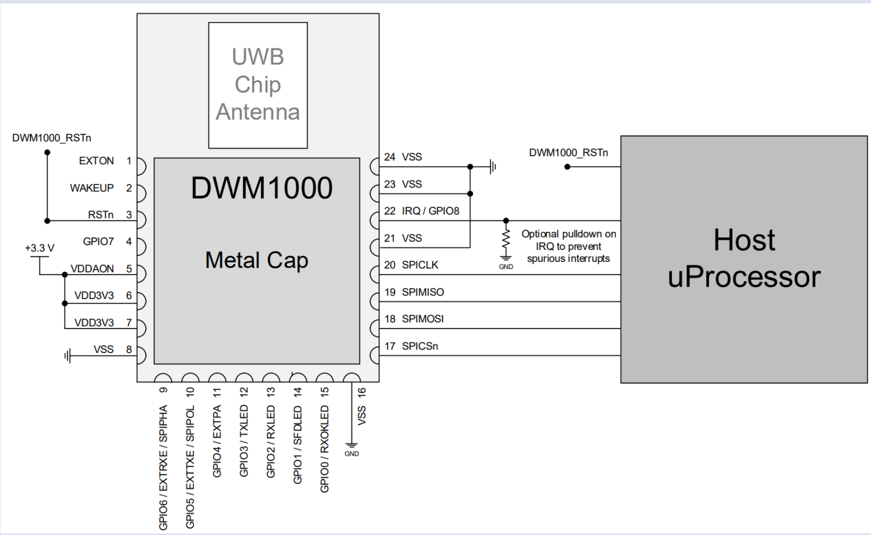


Figure 3. DWM1000 UWB Module Application Circuit Diagram.

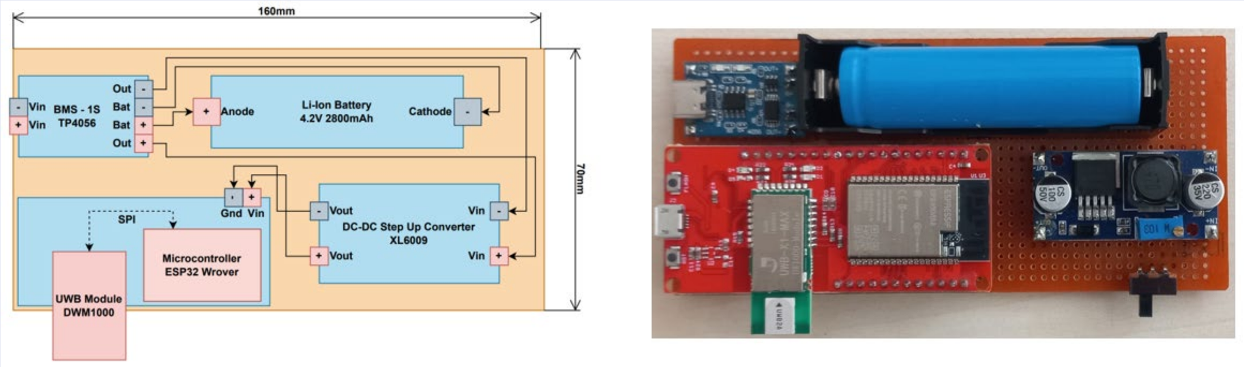


Figure 4. Prototype Indoor Positioning Board Circuit Diagram and Visualization.

ESP32 UWB Pro development board uses Ultra Wideband technology and ESP32 microcontroller, supporting precise positioning and wireless communication with increased speed for real-time positioning systems (RTPS). ESP32 Wrover module features a dual-core Tensilica Xtensa LX6 CPU with 32-bit Harvard architecture. Widely used in IoT applications, it supports WiFi, Bluetooth v4.2, and BLE protocols on the 2.4GHz band with 80-240 MHz clock speed and minimum power requirements like deep sleep modes. The board has the DW1000 chip as the UWB module. The prototype of the indoor positioning board, as indicated by Figure 4, integrates the ESP32 UWB Pro development board with the ADS-TWR technique for distance measurement using UWB signals. The ESP32 microcontroller supports dual-core processing and communication protocols like WiFi and Bluetooth, enabling high data transmission rates for real-time positioning systems, as shown in the circuit diagram.

Architecture of AGV Guidance System on ANFIS Theory

The primary objective of this study is to investigate the potential of ANFIS theory as a robust tool for the planning of routes for AGV systems, particularly in indoor environments characterized by complexity and dynamism. The proposed system comprises the following processes, as illustrated in Figure 5.

Initially, a system for detecting locations indoors was developed based on the fingerprint method. [37], [38]. To ensure the feasibility and precision of the system, a 25x25 meter indoor space was defined with four UWB transmitters mounted at the corners, as shown in Figure 6. The transmitters recorded the x and y coordinates at regular intervals, populating a full database. Figure 6 also shows the communication network between the receivers and the system during the online training and offline testing stages of the fingerprint positioning method used in the research.

The UWB Tag module periodically transmits Time-of-Flight (ToF) data to the Edge Computing (EC) unit, implemented on a Raspberry Pi 4. This communication occurs via the HTTP protocol over a wireless local area network (WLAN) established within the experimental area. A LAMP (Linux, Apache, MySQL, PHP) server was configured to acquire, process, store, and visualize the transmitted data [40]. The signal vectors retrieved via the HTTP protocol are dealt with in the EC unit using a PHP script and are stored in the fingerprint database. This database forms the basis of the accurate determination of location and thus improves the system's efficiency and reliability regarding indoor positioning. In order to understand the data as measured more easily, the statistical decision measures are shown in Table 1 and the system parameter correlation in Table 2.

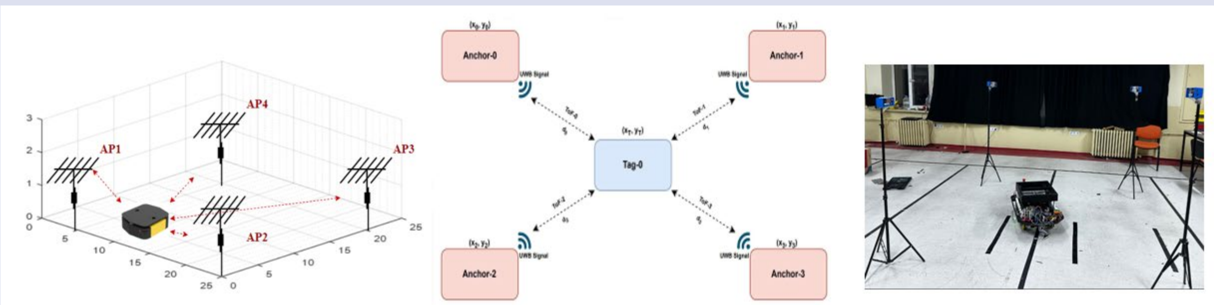


Figure 5. Illustration of the Physical Environment where Measurements were Taken

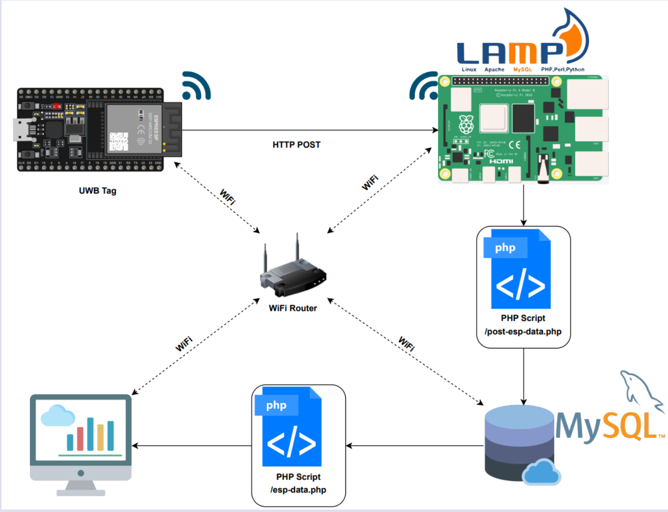


Figure 6: Communication Architecture

Statistical Analysis of Measurement Data

Statistical characteristics of the data show the data to be apt for ANFIS models. X and y coordinates are symmetrically distributed with minimal skewness, indicating minimal effect of outliers. Access point (Ap) values are consistent, with minimal standard deviation and variance, and grouped around lower times. Negative kurtosis indicates that the data is clear from the effect of extreme values. Consistency within the dataset enables good learning in ANFIS, which enables greater accuracy. Finally, the balance and stability of the dataset provide a good basis for ANFIS models, ensuring stable performance in both theoretical applications and practical applications, especially in signal detection and range measurement.

The correlation matrix from Table 2 is of critical significance in the understanding of dataset variable relationships. The low correlation between X and Y coordinates (-0.027) illustrates independent variable distribution, enhancing spatial variability. Positive relationships between Ap1 and X and Y coordinates (0.65 and 0.70) confirm the high relationship of Ap1 with the measurement points. Low correlation between Ap1 and Ap2 (0.04) illustrates independent signal times, controlled by diverse factors. The strong negative correlation of Ap3 and Ap4 (-0.91) suggests that these points vary inversely and should be modeled together. Similarly, the strong negative correlations of Ap3 with Ap1 and Ap2 (-0.89 and -0.05) suggest the predominant effect of Ap3 on the data and its complex distribution. Overall, the matrix suggests the consistency of the dataset and its systematic nature. Some variables are independent, and others are highly correlated, as needed by multivariate analysis for adaptive models like ANFIS. The low correlations also indicate that access points are influenced by environmental factors, and the model must account for this variability, offering both data validity and modeling flexibility.

Table 1. Statistical Decision Measures of Measurement Values Used for ANFIS Models

	x Coord.	y Coord.	Ap1	Ap2	Ap3	Ap4
Average	12.34971	12.93344	0.06221	0.06256	0.06095	0.06048
Standard Error	0.05973	0.06309	0.00020	0.00020	0.00020	0.00021
Median	12.37293	13.03086	0.06525	0.06551	0.06348	0.06310
Standard Deviation	6.91291	7.30149	0.02305	0.02363	0.02312	0.02374
Sample Variance	47.78833	53.31176	0.00053	0.00056	0.00053	0.00056
Kurtosis	-1.21159	-1.25372	-0.56770	-0.55728	-0.61243	-0.59531
Skewness	0.00052	-0.04843	-0.36143	-0.33249	-0.29579	-0.28643
Smallest	0.34806	1.04839	-0.00008	0.00132	0.00300	0.00168
Biggest	24.03432	24.04719	0.11110	0.11281	0.11260	0.11144

Table 2. Correlation Between System Parameters

	y Coord.	**y Coord.**	**Ap1**	**Ap2**	**Ap3**	**Ap4**
x Coord.	1					
y Coord.	-0.027455642	1				
Ap1	0.650586632	0.704712058	1			
Ap2	-0.682587395	0.716642044	0.043161631	1		
Ap3	-0.668862677	-0.687243534	-0.896854088	-0.054212614	1	
Ap4	0.682142024	-0.716363812	-0.078978256	-0.911198064	0.018144616	1

Proposed Methodology: Adaptive Navigation via Virtual Coordinate Systems

Accurate path tracking is critical in autonomous vehicle control systems and navigation. Traditional AGVs use physical guidance, but virtual coordinates are proposed in this work for more dynamic and flexible path tracking. The vehicle continuously compares its own calculated x and y coordinates with the target and calculates the steering angle. Through differential drive mechanism, the vehicle trajectory is an arc depending on right-left wheel differential rotational rates computed dynamically to minimize the angular difference. After calculation of steering angle, ANFIS-trained fuzzy rules are applied to vary the wheel speeds in order to allow quick and effective drive system response. The system is a closed-loop feedback that constantly updates the vehicle's position to stay on track. The approach eschews physical tracks and enables accurate navigation in dense space. Fuzzy rules with ANFIS provide smooth control and facilitate scalability, flexibility, and enable quick and dependable movement, particularly indoors in real-time.

In the proposed study, the real-time position of the AGV was determined using indoor positioning theory based on the ANFIS and fingerprint approach. The measured data (Table 1) were utilized to develop two distinct models using the ANFIS methodology. The first model was designed to predict the y position by employing data obtained from four different access points. The second model was developed to estimate the x position using the same data set [39], [40], [41]. The two models in question process the input data with the aid of fuzzy rules and neural networks, thereby achieving high accuracy in the estimation of locations. This approach demonstrates the effectiveness of the ANFIS method in improving the accuracy and reliability of the positioning system. One of the main objectives of this study is to determine the instantaneous x and y positions accurately with the data received from the access points while the AGV is moving in a closed environment. To this end, the Fuzzy Inference System (FIS) functions generated by the trained ANFIS models are employed [42], [43]. The system is integrated into the AGV for deploying the rule sets necessary to deliver real-time position information. Integrated into the AGV, this allows the AGV to get a quick and accurate estimation of its position through the x and y coordinates using the data collected while moving. As such, the AGV can have very accurate position information in real-time while moving indoors, thus significantly enhancing the efficiency and performance of the system.

Development and Evaluation of the Model

In an indoor setting, access points (APs) were positioned at the designated x and y coordinates. In this environment, time-difference (ToF) values of ultra-wideband (UWB) signals emitted from four different access points (APs) were collected using a mobile system and stored in a database as a training set. Two distinct ANFIS models (ANFIS_I and ANFIS_II) were developed using the aforementioned data [39], [40], [41]. The ANFIS_I model was developed with the objective of predicting the y coordinate, while the ANFIS_II model was developed with the objective of predicting the x coordinate. Following the training phase, a series of statistical analyses were conducted on the test datasets in order to evaluate the performance of both models (Figure 7). The results of the tests are presented in Tables 3 and Table 4, which demonstrate the efficacy of the ANFIS models in indoor location estimation.

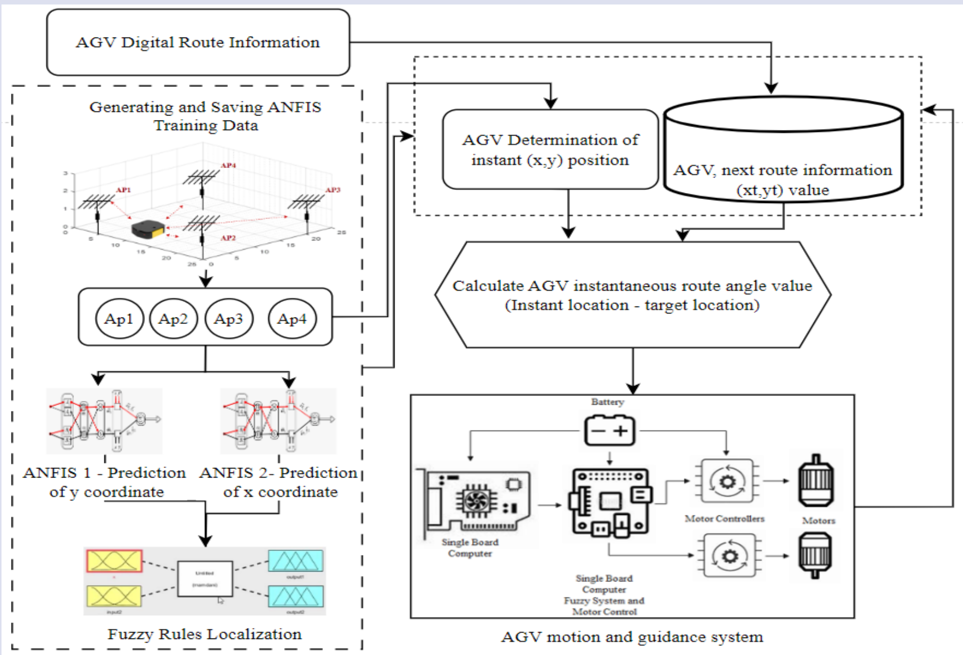
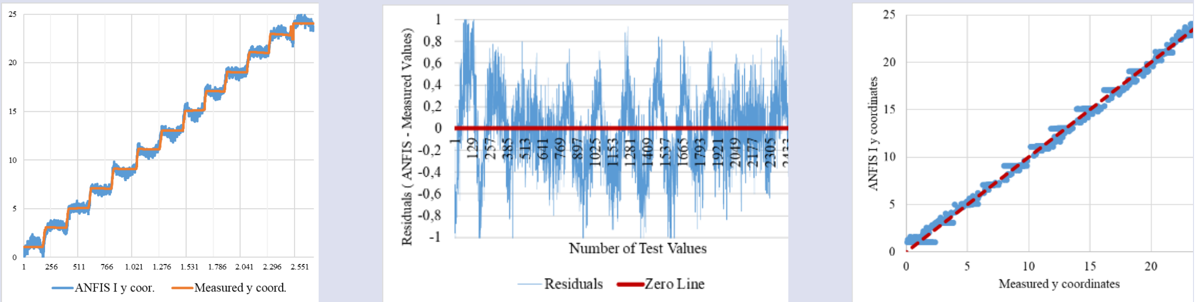


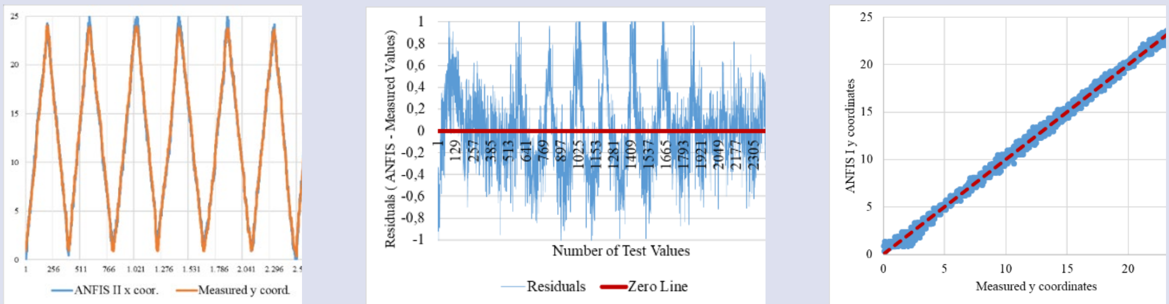
Figure 7. Process Flow of the Proposed System

Table 3. Correlation Between System Parameters

	ANFIS Model I [x, Ap1, Ap2, Ap3, Ap4] [y]			ANFIS Model II [y, Ap1, Ap2, Ap3, Ap4] [x]		
	Training	Testing while Model Train	Generated Model Testing	Training	Testing while Model Train	Generated Model Testing
R^2	0.9976	0.9975	0.9974	0.9973	0.9972	0.9971
RMSE	0.3558	0.3561	0.3650	0.3668	0.3686	0.3679
MAPE	0.0940	0.0926	0.0865	0.0661	0.0688	0.0687
MAE	0.2841	0.2836	0.291	0.2917	0.293	0.2893



a- Comparations b- Residuals c- Regression



a- Comparations b- Residuals c- Regression

Figure 8.1 ANFIS Model I, x coordinate Input y coordinate Output
Figure 8.2 ANFIS Model II, y coordinate Input x coordinate Output

Coefficient of Determination (R^2): This metric indicates the extent to which the variance in the dependent variable is explained by the model. The R^2 value ranges from 0 to 1, with values close to 1 indicating that the model has a high explanatory power [44]. Root Mean Square Error (RMSE): RMSE is the square root of the mean square of the squares of the differences between predicted values and actual values. It is sensitive to large errors and gives more weight to the magnitude of the errors [45]. The Mean Absolute Error (MAE) is a metric that provides an indication of the average absolute value of the discrepancies between the predicted and actual values. It is less sensitive than the Root Mean Square Error (RMSE) and offers insight into the overall magnitude of the errors inherent to the model ***[46]***. The Mean Absolute Percentage Error (MAPE) is a statistical measure that allows for the expression of errors as a percentage. It is a valuable tool for comparing models at varying levels of complexity and scale [44].

Training ANFIS Models for Location and FIS structure

In the measurement area depicted in Figure 6, the signal values emitted by the access points (APs) at various (x, y) coordinates within the indoor environment were measured using the architectural configuration illustrated in Figure 7. The ANFIS I and ANFIS II models were trained with the flows presented in Figure 7, using the measured values as inputs. During the training process, the potential membership functions for each input were modified sequentially, and the parameters that provided the best results were identified. The FIS structures developed with these parameters were then used for position determination. The resulting values are presented in Table 4.

Table 3 shows the values obtained by statistical decision-makers during the training of the ANFIS models, which are used throughout the process. The graphical representations in Figure 8, illustrating the relationships between the measured values and the position values generated by the ANFIS model, demonstrate the predictive capabilities of the models. The steps summarized in Table 4 detail how an Automated Guided Vehicle (AGV) or a similar system determines its position using UWB signals and ANFIS models and regulates its motor movements. The pseudo code is a human-readable draft that clearly demonstrates the operational principles of the system.

Table.4. System Model Pseudo Code

```
// Start: Collect sensor data and feed it into the ANFIS model
   WHILE TaskNotCompleted:
  // Step 1: Collect real-time data from UWB sensors
    uwb_signal_data = Collect_UWB_SensorData(AP1, AP2, AP3, AP4)
  // Step 2: Feed the signal data into the ANFIS I model to estimate the current Y position
    y_position = ANFIS_I_Model(uwb_signal_data)
  // Step 3: Feed the same signal data into the ANFIS II model to estimate the current X position
    x_position = ANFIS_II_Model(uwb_signal_data)
  // Step 4: Retrieve the next target position (x1, y1) from the route table
    (x1, y1) = GetNextPositionFromRouteTable()
  // Step 5: Calculate the angle between the estimated X, Y positions and the target X1, Y1
    angle = CalculateAngle(x_position, y_position, x1, y1)
  // Step 6: Send the calculated angle to the FIS system that controls the motors
    FIS_ControlMotors(angle)
  // Step 7: Ensure the motors move according to the calculated angle
    MoveMotors(angle)
  // Step 8: Check if the current position matches the target position (x1, y1)
    IF (x_position == x1 AND y_position == y1):
   // Step 9: Once the target position is reached, retrieve the next target (xn, yn) from the route table
      (xn, yn) = GetNextPositionFromRouteTable()
    ENDIF
  // Step 10: If the route table is completed, finish the task
    IF (IsTaskCompleted()):
      BREAK // Exit the loop, task is completed
    ENDIF
  // Step 11: Repeat this process iteratively for each point in the route table
  END WHILE
```

This pseudo code models a system where UWB sensor data is used to determine the current position, calculate the path towards a target, and control motor movements iteratively until the task is completed. This process is repeated each time the vehicle reaches a new destination point, continuing until all points in the route table have been completed. The following pseudo code models the overall operation of the system. In the actual implementation, the sensor data collection, signal presentation to the ANFIS model and motor control steps will be detailed with more specific algorithms and hardware-level code.

Implementation of the ANFIS-Based Positioning System in an Indoor Environment

To validate and assess the applicability of the model, measurement points were established at specific intervals across the x (horizontal) and y (vertical) coordinates within an indoor environment. At each measurement point, Time of Flight (TOF) values obtained from the access points (Ap1, Ap2, Ap3, and Ap4) were recorded to create a dataset. Based on this dataset, two distinct ANFIS models were developed: ANFIS I, which is sensitive to the x coordinate, and ANFIS II, which is sensitive to the y coordinate. During the training process of both models, the hyperparameters of the positioning system were optimized, enhancing the accuracy of the location estimation processes. The performance of the developed models was evaluated using a test dataset, with the results presented in Table 3. Following the training and validation of the ANFIS models, the control board responsible for the AGV's navigation mechanism was programmed with code to implement the Fuzzy Inference System (FIS) rules defined by ANFIS. This coding enabled the AGV to estimate its real-time x and y coordinates based on signals collected from the Ap1, Ap2, Ap3, and Ap4 access points while in motion. The parameters and structures of the membership functions used in the FIS rules are detailed in Figure 9. Therefore, the system has undergone an extensive validation process in both the data collection and model implementation phases, ultimately providing a reliable positioning mechanism that can operate effectively in dynamic indoor environments (Table 4 and Figure 7). The algorithmic code used for all these processes is given in Table 5. With this code, the (x,y) value is continuously calculated based on the values received from the sensor data.

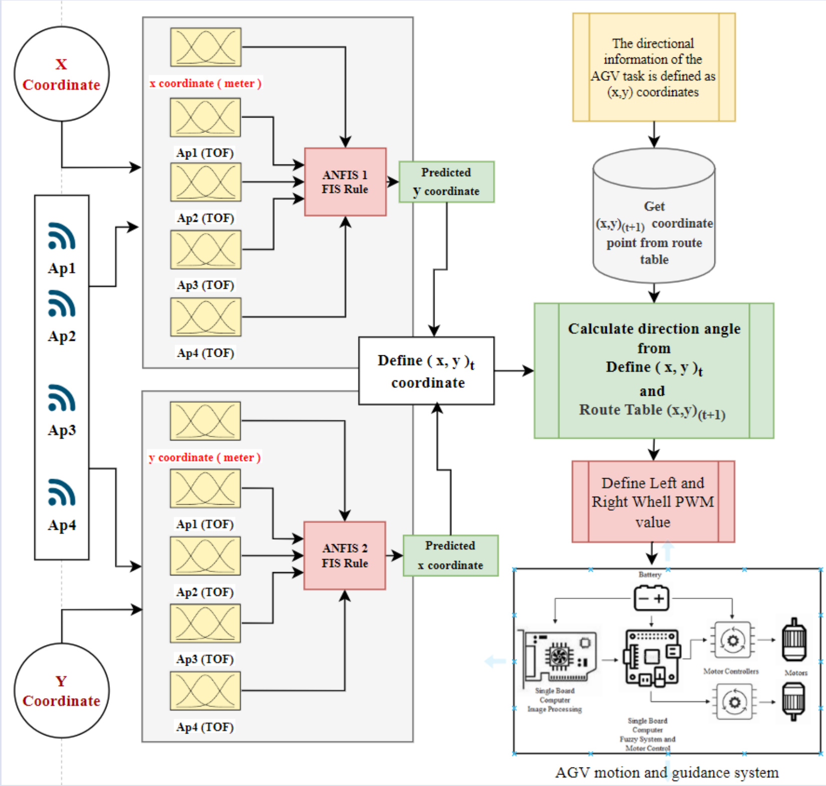


Figure 9. AGV Routing Process

Table.5. Pseudo Code for Arduino Fuzzy Logic System Localization Systems

```
Initialization:
    1. Initialize the fuzzy system.
    2. Define two fuzzy inputs:
      - Input1 with membership functions: "low", "medium", "high".
      - Input2 with membership functions: "low", "medium".
    3. Define one fuzzy output:
      - Output1 with membership functions: "low", "high".
    4. Define fuzzy rules:
      - Rule 1: IF Input1 is "low" AND Input2 is "low" THEN Output1 is "low".
      - Rule 2: IF Input1 is "high" OR Input2 is "high" THEN Output1 is "high".
Setup:
    1. Initialize the serial communication.
Main Loop:
    1. Read sensor data:
      - Collect real-time data for Input1 and Input2.
    2. Set inputs:
      - Assign the collected data to Input1 and Input2 in the fuzzy system.
    3. Fuzzification:
      - Compute the membership degrees of the inputs.
    4. Rule Evaluation:
      - Evaluate all fuzzy rules based on the input memberships.
    5. Defuzzification:
      - Calculate the crisp output value by combining the outcomes of the rules.
    6. Output Control:
      - Send the defuzzified output to control the system (e.g., motors).
    7. Debugging:
      - Print the output value for monitoring.
    8. Repeat:
      - Introduce a delay and repeat the loop for real-time operation.
```

In order to optimize the positioning processes of autonomous guided vehicles (AGVs) in indoor environments, ultra-wideband (UWB) signals and adaptive neuro-fuzzy inference system (ANFIS) models were integrated. In the initial phase of the study, time-of-flight (ToF) signals obtained from ultra-wideband (UWB) access points (Ap1, Ap2, Ap3, Ap4) were recorded at various measurement points along predetermined x and y coordinates, forming a comprehensive database. The data were employed to train the ANFIS models, resulting in the development of ANFIS I (sensitive to the x-coordinate) and ANFIS II (sensitive to the y-coordinate). During the training process, the hyperparameters were optimized with the objective of enhancing the models' accuracy in real-time predictions of the x and y coordinates.

The developed models were subsequently deployed in real-time test scenarios to predict positions based on UWB signal measurements. The signals collected from access points Ap1-Ap4 were fed into the ANFIS models in order to calculate the current position of the vehicle, which was represented as (xt, yt). The aforementioned predictions were integrated with a route table in order to guarantee that the AGV reached its designated target points. The route table was employed to ascertain the subsequent target position (xt+1, yt+1). The angle between the current position (xt, yt) and the target position (xt+1, yt+1) was calculated and transmitted to the motor control system, enabling the AGV to move towards the next target.

The discrepancies between the predicted (xt, yt) values from the ANFIS models and the target points (xt+1, yt+1) in the route table were minimized, thereby ensuring precise route tracking by the vehicle. During this process, the motor control system dynamically adjusted wheel speeds based on information obtained from the ANFIS models, thereby optimizing the vehicle's movement. The aforementioned measurement, prediction, and real-time control processes were executed using the application code presented in Table 5.

Table 6. Pseudo Code for Arduino Fuzzy Logic System Left and Right Motor PWM value

```
// Pseudo Code for Fuzzy Logic Control System
1. Initialize Fuzzy System:
    - Create a fuzzy logic system instance.
    - Define input variable `angle_diff` with membership functions:
      - "low", "medium", "high"
    - Define output variables `leftMotor` and `rightMotor` with membership functions:
      - "low", "medium", "high"
2. Define Fuzzy Rules:
    - Rule 1:
      IF `angle_diff.` IS "low" THEN:
        - `leftMotor` IS "low"
        - `rightMotor` IS "high"
    - Rule 2:
      IF `angle_diff.` IS "medium" THEN:
        - `leftMotor` IS "medium"
        - `rightMotor` IS "medium"
    - Rule 3:
      IF `angle_diff.` IS "high" THEN:
        - `leftMotor` IS "high"
        - `rightMotor` IS "low"
3. Setup System:
    - Initialize serial communication for debugging and monitoring.
4. Main Loop:
    - Input Collection:
      - Read input value for `angle_diff.` (e.g., from a sensor).
    - Set Inputs:
      - Assign the input value to `angle_diff.` in the fuzzy system.
    - Fuzzification:
      - Compute membership degrees for `angle_diff.`.
    - Rule Evaluation:
      - Evaluate fuzzy rules based on membership degrees.
    - Defuzzification:
      - Compute crisp output values for `leftMotor` and `rightMotor`.
    - Output Control:
      - Use the computed values to control the motor speeds.
    - Monitoring:
      - Print output values (`leftMotor`, `rightMotor`) for debugging.
    - Repeat:
              - Wait for a short delay and repeat the loop.
```

Fuzzy Logic-Based Motor Control

In this study, the determination of motor speeds is conducted through the utilization of a control system that is based on fuzzy logic rules and calculated angle difference values. The system utilizes the measured angle difference as an input variable, generating the requisite PWM values to control the motor speeds accordingly. Pulse-width modulation (PWM) signals enable the motors to move at specific angles, thereby enabling the vehicle to accurately follow the desired route. The fuzzy logic system classifies the angle difference into three membership functions: low, medium, and high. Based on this classification, the system calculates the appropriate PWM values for motor speeds. When the angle difference is low, the speed of the left motor is reduced, and the speed of the right motor is increased. At medium levels, the speeds of both motors are balanced. In the event of a high angle difference, the left motor is accelerated while the speed of the right motor is decreased. These processes comprise three principal stages: fuzzification, wherein the membership grades of the input values are ascertained; rule evaluation, wherein the prescribed rules are applied in accordance with the membership grades; and defuzzification, wherein the rules' outcomes are integrated to calculate the final PWM values that regulate the motors [47], [48], [49]. The computed PWM values are applied to the motors, enabling the vehicle to adapt to dynamic environmental conditions and to follow the designated route with precision. This method enhances the system's accuracy and flexibility, providing a reliable solution in situations where the environment is closed or complex. PWM (Pulse Width Modulation) is a technique used to control power or signal transmission by modulating the pulse width of a signal. PWM typically adjusts the average output voltage or power level by changing the ratio of "on" and "off" times of a signal. This technology is widely used in applications such as motor speed control, light brightness adjustment, and precise power delivery in electronic circuits. The main advantage of PWM is its ability to provide high efficiency by reducing energy loss. A PWM signal is defined by a metric called the "duty cycle." The duty cycle is the ratio of the time the signal is "on" to the total cycle time, expressed as a percentage (%). For instance, if the duty cycle is 50% to control the speed of a motor, the signal will be on for half of the cycle and off for the other half, allowing the motor to operate at medium speed [50] (Table 6).

Table.7. PWM Motor Control Table for Angle-Based Adjustments

Differences of Angle	Right Motor PWM	Left Motor PWM
0	2	2
1	1	-1
2	1	-1
22	1	-1
44	1	-1
68	2	-2
89	2	-2
90	2	-2
-1	-1	1
-2	-1	1
-17	-1	1
-41	-1	1
-67	-2	2
-81	-2	2
-89	-2	2
-90	-2	2

PWM values for motor control were systematically derived using a predefined training table, which correlates angular discrepancies with corresponding adjustments for the left and right motors. This structured approach enables precise and real-time motor adjustments, ensuring the AGV maintains its trajectory with high accuracy, even in dynamic indoor conditions.This approach enables the system to dynamically adapt motor speeds based on the angular disparity, enhancing stability and performance. For illustration, Table 7 presents example PWM values for selected angle differences. These values demonstrate the relationship between the angular discrepancy and the PWM output, showcasing how the system adjusts the left and right motor speeds to maintain balance and control. This structured methodology ensures that the system operates effectively across various scenarios, with PWM values carefully calibrated to respond to specific angular conditions. The use of a comprehensive training table ensures consistency and accuracy in motor speed adjustments, ultimately contributing to the system's overall reliability and efficiency. The example coefficient structure is summarized in **Table 7**. This table primarily aims to provide the reader with an understanding of the relationship between PWM coefficients and angular adjustments.

Testing the Model and Discussion of Results

To validate and test the control and operational accuracy of the developed AGV system, a structured testing scenario was implemented. The steps involved in the scenario are systematically described below. A specific route was planned for the AGV system to evaluate the performance of the developed **ANFIS-based indoor positioning model**. This route was uploaded into the system as precise xx and yy coordinates, representing the key target points along the AGV's navigation path. The uploaded route served as a benchmark for real-time position comparison during the test.

A structured test scenario was devised for the purpose of testing and verifying the control and operational accuracy of the developed AGV system. The following section provides a detailed account of the methodology employed in this scenario. In order to evaluate the performance of the developed ANFIS-based indoor positioning model, a specific route was planned for the AGV system. The route was loaded into the system with precise x and y coordinates to represent the main target points on the AGV's navigation path. These coordinates were used as a reference for real-time position comparisons during testing. The coordinates represented by the '■' symbol and colored in red in Figure 10 are the coordinates that the AGV is required to follow in a closed environment and were entered into the system.

An indoor positioning system that integrates an adaptive neuro-fuzzy inference system (ANFIS) with a fingerprinting approach is employed to ascertain the real-time position of the automated guided vehicle (AGV) as it traverses the planned route. The process is comprised of the following steps:

- Data Collection: Real-time signals were gathered from Ultra Wideband (UWB) access points situated within the experimental setting.
- The ANFIS model was employed for the following purposes: The collected signal data were processed in two separate ANFIS models, designated ANFIS I and ANFIS II. ANFIS I was responsible for estimating the y-coordinate, while ANFIS II was tasked with estimating the x-coordinate.
- Real-time Location Output: The ANFIS models provided continuous and accurate updates regarding the current position of the AGV, expressed as (x,y) coordinates. The ANFIS models continuously and accurately updated the current position of the AGV as (x,y) coordinates. In Figure 10, the points represented by x in blue and '♦' symbol are the coordinates that the AGV is desired to follow in the closed environment and entered into the system.

The ability of ANFIS models to represent real-time position data with high precision is critical for the system's performance. To assess the accuracy of the models, the **actual x and y coordinates along the "Actual Route" path** were compared with the instantaneous values generated by the ANFIS models.

The accuracy analysis is presented through two key graphs:

- **Figure 11-a:** Displays the regression relationship between the actual x coordinates and the estimated x coordinates produced by the ANFIS models. This graph illustrates the accuracy of the ANFIS models in predicting x-axis values.
- Figure 11-b: Depicts a difference graph representing the discrepancies between the actual values and those generated by the ANFIS models. In this graph, the proximity of the differences to the zero line indicates how closely the ANFIS models align with the actual values.

  This analysis was conducted to validate the ability of the ANFIS models to accurately and consistently predict real-time position data along the actual route, providing critical insights into the reliability of the system

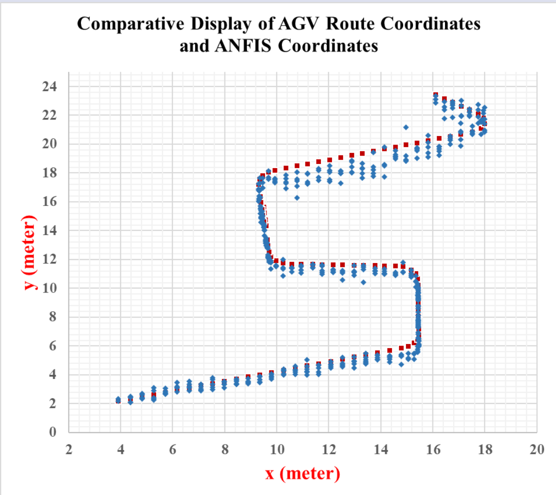


Figure 10. AGV Routing Process

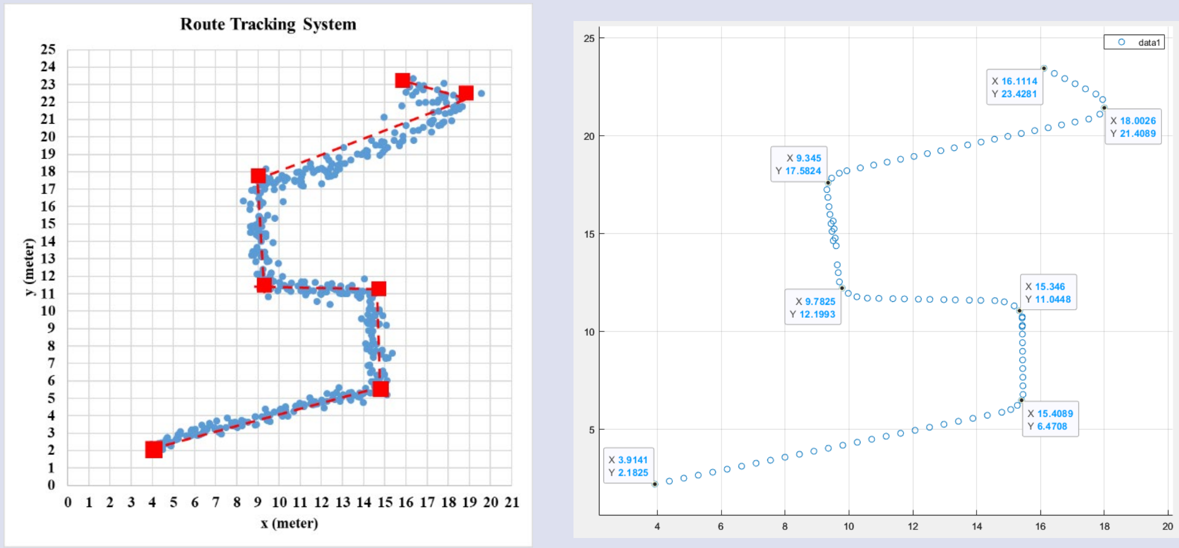


Figure 12. Identification of Sharp Turning Points for Optimized Route Navigation

During the real-time route comparison and angular adjustment process, the AGV's current position was continuously compared with the next target position on the planned route. In this process, the angular difference between the AGV's current position and the target position was calculated, and directional adjustments were made accordingly. However, calculating the angle for every point along the route significantly reduced system performance. Frequent angular adjustments resulted in excessive directional changes for the AGV, increasing computation time and decreasing overall efficiency. To address this issue, **sharp turning points** along the route were identified, as shown in Figure 12. The AGV estimated its current position in real time using the ANFIS model and calculated the angle only for the next sharp turning point on its path. This method effectively reduced computation time, eliminated unnecessary directional changes, and optimized the AGV's navigation performance. Based on the calculated angular difference, the system dynamically adjusted the AGV's direction to align it with the planned route, ensuring smoother and more efficient navigation. The red points shown in Figure 12 represent the sharp turns along the route, indicating the locations where the AGV system will execute a turn within the algorithm. The blue points, on the other hand, represent the possible (x,y)(x, y) positions determined by the ANFIS models at specific intervals as the AGV progresses toward the target sharp points.

The movement and directional control of the AGV were achieved through a wheel mechanism integrated with **ANFIS-based fuzzy logic rules**. In this system, the **calculated angular difference** served as the input variable for the fuzzy logic controller. Based on this input, the fuzzy logic rules generated **Pulse Width Modulation (PWM)** coefficients for the left and right wheels. These coefficients dynamically adjusted the forward or backward motion and the individual speeds of each wheel, ensuring that the AGV moved accurately in the desired direction. The generated PWM values were transmitted to the motor control board, and the speed and direction of the wheels were adjusted accordingly.

Application of the Developed Method for Calculating PWM Coefficients

The control mechanism was enhanced with a **continuous feedback loop**, enabling precise and reliable route tracking. The AGV's current position was updated at regular intervals in real time and continuously compared with the next **sharp turning point** on the planned route. When deviations from the planned path were detected, the system recalculated the angular difference and applied necessary corrections instantly, ensuring alignment with the route. This dynamic correction process was executed within the pre-programmed logic of the control system, maintaining accurate position tracking for the AGV.

Integrating the fuzzy logic-based control mechanism with the real-time feedback loop minimized unnecessary directional changes and optimized processing time. With **ANFIS-based position estimation** and dynamic adjustments, the AGV achieved smooth and precise navigation even in complex environments. This approach not only reduced the system's computational load but also significantly improved route tracking performance, providing a reliable navigation solution.

The process described above can be summarized using a block diagram representation similar to **Table 8**. This representation provides a clear and systematic overview of the steps involved in calculating PWM coefficients and controlling the AGV's movement. The block diagram highlights the integration of **ANFIS-based position estimation**, **angular difference calculation**, and **fuzzy logic-based motor control** to achieve smooth and precise navigation. The process can be outlined as follows:

Table.8. flow diagram representation

1. *Start Process*
   - *Initialize inputs: $\Delta\vartheta$ and S_{base}*
2. *Acquire Real-Time Position*
   - *Read current ($x_{current}$,$y_{current}$) and target (x_{target},y_{target}) positions.*
3. *Calculate Angular Difference*
   - *Compute $\Delta\vartheta = atan2(y_{target} - y_{current}, x_{target} - x_{current})$*
4. *Apply PWM Calculation Logic*
   - *Use proportional or fuzzy logic rules to calculate PWM_{left} and PWM_{right}*
5. *Constrain PWM Values*
   - *Ensure PWM values are within acceptable operational ranges.*
6. *Transmit PWM Coefficients*
   - *Send the calculated values to the motor control system.*
7. *Feedback Loop*
   - *Compare the AGV's real-time position with the planned route.*
   - *Recalculate $\Delta\vartheta$ and update PWM values if necessary.*
8. *End Process*
   - *Terminate the process upon reaching the final target.*

Conclusion

In this study, the aim is to enhance indoor navigation of Automated Guided Vehicles (AGVs) by utilizing Ultra-Wideband (UWB) technology with the Adaptive Neuro-Fuzzy Inference System (ANFIS). With Industry 4.0 advancing and the environment indoors becoming more complicated, the AGV must navigate effectively, accurately, and safely. UWB boasts centimeter-level positioning accuracy, power efficiency, and insensitivity to multipath effects, rendering it an appropriate choice for indoor navigation. While problems such as installation costs and environmental sensitivity typify ANFIS integration, higher accuracy and effectiveness are gained with the application of the capabilities of fuzzy logic and neural network learning.

Experimental outcomes indicate that the system's high accuracy measures an R^2 of 0.997 and low values for RMSE and MAE, proving its dependability. Flexibility and responsiveness over traditional systems with physical guides like magnetic strips are made possible through the virtual coordinate-based approach. Dynamic control of motors by the system through PWM techniques provides optimal time and energy. Real-time data integration allows AGVs to be highly responsive to varying environments, sustaining smooth movement. This approach offers great benefits in industrial and logistics applications, improving material handling in factories, warehouses, and smart manufacturing facilities, boosting security and cost savings. It also has potential for broader application, including in smart cities and medicine, showing its versatility and scalability.

Conclusionarily, the integration of UWB with ANFIS is a groundbreaking solution for AGV navigation in indoor environments, addressing significant issues like accuracy, cost savings, and flexibility. The study finds usefulness in academic and industrial use with prospects for smart navigation systems extensions. The next line of research would be examining UWB in swarm robotics to improve coordination and accuracy in settings that are complex, with integrating into swarm intelligence algorithms like PSO or ACO. Hybrid systems that combine UWB with other sensors like LIDAR or visual odometry would also improve reliability in interference- or obstacle-rich environments, unlocking new applications for Industry 4.0 and beyond.

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Declaration Conflict of Interest Statement

The authors declare that there are no conflicts of interest associated with this study titled **"ANFIS-Driven Optimization of Indoor Navigation Systems for Automated Guided Vehicles Utilizing UWB Signals."** The work presented in this paper is the result of original research conducted solely by the authors, Ahmet Gürkan Yüksek and Ahmet Utku Elik, without any financial or non-financial support that could influence the study's findings, results, or interpretation.The authors confirm that the study has not been previously published, is not under consideration elsewhere, and has been approved for submission to the target journal. There are no competing interests, relationships, or activities—whether financial, personal, or professional—that could be perceived as influencing the integrity or objectivity of this research.Additionally, no third-party funding or sponsorship was received for the conduct of this research or the preparation of the manuscript. All the hardware, software, and tools used in the study were acquired through the institutional resources of Sivas Cumhuriyet University. The study does not include any involvement or affiliation with commercial entities or organizations that could create a potential conflict of interest.The authors assert their full responsibility for the accuracy and integrity of the data, results, and conclusions presented in this work. All contributors to the study have been acknowledged, and no undisclosed parties were involved in the research, data analysis, or manuscript preparation. Finally, the authors confirm that all ethical standards, data confidentiality guidelines, and institutional protocols have been adhered to during the execution of this study.

Special Note :

In the preparation phase of my project: Artificial Intelligence Language Models were definitely not used in the creation of data, design of the system, generation and analysis of results. The whole process of the study was prepared by the authors. However, while translating the Manuscript file from the original language to English DeepL , and Chat GPI 4.0 was used for some textual editing.