International Transactions on Electrical Engineering and Computer Science
A. Assbullah et.al., Vol: 5, No: 3, pp: 166-176, September 2026

Energy-Aware PSO-Optimized Fuzzy Logic Control for Automated Guided Vehicles on Low-Power Edge Computing Platforms

Achmad Assbullah[1], Bambang Suprianto[1], Hapsari Peni Agustin Tjahyaningtijas[1]

Abstract: Automated Guided Vehicles (AGVs) serve as the backbone of modern smart factory logistics, yet their operational efficiency is often limited by sub optimal energy management during navigation. Conventional heuristic based Fuzzy Logic Controllers (FLCs) frequently exhibit oscillatory responses, leading to high current spikes and rapid battery degradation. This study proposes an energy aware Takagi-Sugeno-Kang (TSK) FLC, optimized using Particle Swarm Optimization (PSO) for deployment on a dual core ESP32 edge computing platform. A novel PSO fitness function was formulated to penalize both trajectory tracking errors and cumulative electrical power consumption, ensuring precise control with minimal computational overhead. Experimental validation on a 15-kg differential drive AGV demonstrated that the optimized controller achieved superior kinematic performance, with the Root Mean Square Error (RMSE) reduced by 68.48% (from 0.165 m to 0.052 m). Furthermore, the approach achieved a 16.84% reduction in average power consumption and effectively mitigated peak transient power spikes by 28.08%. These results demonstrate the viability of implementing advanced metaheuristic optimization on low-power, cost-effective microcontrollers. The proposed framework enhances operational sustainability, directly contributing to extended battery cycle life and reduced maintenance downtime in autonomous industrial environments.

Keywords: Automated guided vehicles, Fuzzy logic controller, Particle swarm optimization, Edge computing, Energy efficiency.

1. Introduction

Within the framework of Industry 4.0 and the emergence of smart factories, Automated Guided Vehicles (AGVs) have solidified their position as the primary backbone of automated logistics and flexible manufacturing systems [1].

History
Received: 23-05-2026; Revised: 16-07-2026; Accepted: 23-07-2026

Achmad Assbullah
achmadassbullah@gmail.com

[1]Department of Electrical Engineering, State University of Surabaya, Surabaya 60213, Indonesia.

The integration of AGVs into industrial supply chains enables autonomous material transport, minimizes the risk of occupational hazards, and substantially increases production throughput as the complexity of factory layouts escalates, AGV navigation algorithms are required not only to guide vehicles with high spatial precision but also to exhibit superior reliability in dynamic environments fraught with operational uncertainties [2]. Despite rapid advancements in environmental perception systems, a fundamental challenge limiting the full-scale deployment of AGVs remains energy management [3]. Sub-optimal energy consumption, driven by excessive mechanical acceleration and steering oscillation, directly results in shortened operational uptime [4]. Such inefficiency disrupts logistical workflows and accelerates battery degradation. Consequently, the autonomous systems research landscape is shifting toward an energy-aware navigation paradigm,

https://doi.org/10.62760/iteecs.5.3.2026.213

establishing power efficiency as an optimization metric as critical as spatial precision.

To address this energy dissipation issue, various control strategies have been developed. Historically, conventional Proportional-Integral-Derivative (PID) controllers possess inherent limitations in handling the non-linear dynamics of differential-drive robots and are highly susceptible to external disturbances. As an alternative, Fuzzy Logic Control (FLC) has emerged prominently due to its robustness in processing sensory uncertainty [2]. Despite offering inherent robustness, fuzzy inference performance is critically contingent upon the design quality of its Membership Functions (MFs). Conventional heuristic-based designs are frequently sub-optimal, inducing oscillatory responses that lead to over-correction phenomena, transient current spikes, and excessive energy dissipation [5]. To circumvent these optimization limitations, metaheuristic approaches such as Particle Swarm Optimization (PSO) have been extensively integrated to tune FLC parameters. Recent state-of-the-art studies validate that PSO-Fuzzy architectures can significantly reduce trajectory tracking errors and optimize braking energy recovery when compared to conventional methods [6 - 7]. From a hardware perspective, the demands of the Internet of Things (IoT) are driving the transition toward Edge Computing to eliminate cloud transmission latency [8]. In this context, microcontrollers such as the ESP32 family have garnered significant attention due to their local AI inference capabilities [9 - 10].

Although the integration of PSO and FLC has been proven to enhance system robustness on conventional computing platforms, its deployment on low-power edge computing architectures still faces fundamental limitations. Extensive literature explores the effectiveness of PSO-Fuzzy integration; however, most current state-of-the-art (SOTA) implementations are evaluated exclusively on resource-rich platforms (such as industrial computers or high-performance processing units), thereby practically neglecting clock cycle and SRAM memory constraints [11]. The mathematical formulations of PSO-optimized FLCs, while highly precise, are often computationally prohibitive for real-time execution within edge environments. Furthermore, there is a lack of research that formulates the PSO fitness function to specifically target physical energy efficiency. To date, there lacks an empirical benchmark bridging the quantitative relationship between computational optimization at the edge and the reduction of electromechanical energy consumption at the actuator level [12]. Addressing these identified gaps, the problem formulation of this research centers on how to implement a computationally efficient PSO-based Fuzzy Logic control on constrained edge devices to minimize physical energy consumption without degrading trajectory accuracy. To achieve this, the primary objective is to design a PSO based fuzzy logic membership function algorithm, specifically optimized for a dual-core ESP32 edge computing architecture. This approach deterministically minimizes the electrical energy consumption profile and mitigates actuator current spikes without compromising the mechanical trajectory tracking accuracy of the AGV. The novelty of this paper lies in the formulation of a hybrid energy-aware fitness function specifically tailored for dual-core edge computing architectures, which establishes an empirical correlation between computational trajectory smoothing and actual electromechanical energy savings. Specifically, the author contributions of this research are summarized as follows:

- Formulation of a hybrid energy-aware fitness function: Introducing a novel mathematical design to the PSO that minimizes spatial metrics while penalizing actuator kinetic power fluctuations—an optimization approach previously unexplored in edge robotics literature.
- Development of a FreeRTOS-based dual-core ESP32 software architecture: Designing a system that decouples the latency-critical execution load of the TSK-Fuzzy inference from the MQTT network stack processing, critically enabling low-power operation without sacrificing control update stability.
- Comprehensive empirical evaluation based on Joule and Watt metrics: Validating the entire framework's efficacy to establish a new empirical benchmark that quantifies the direct correlation between trajectory smoothing by the edge algorithm and the actual achievement of electromechanical energy savings.

Finally, the organization of this paper is structured as follows: Section 1 introduces the research background and objectives. Section 2 details the materials and methods, including the hardware architecture and the PSO-Fuzzy algorithmic design. Section 3 presents the experimental setup, results, and comprehensive discussion. Section 4 concludes the paper.

2. Materials and Methods

This research employs a comprehensive methodology that integrates the mathematical modeling of non-holonomic mechanical systems, the design of edge computing-based embedded hardware, the development of real-time software utilizing metaheuristic algorithms, and the evaluation of computational architectures. The entire integration process is validated through a combination of Simulation-in-the-Loop (SITL) for parameter tuning and Hardware-in-the-Loop (HITL) physical testing under two-dimensional (2D) AGV mobility scenarios. This hybrid approach is designed to quantify and empirically validate the correlation between deterministic algorithmic optimization, enhanced trajectory tracking accuracy, and improved energy dissipation efficiency at the actuator level.

2.1 Hardware Architecture and Edge Computing Platform

The selection of an edge computing platform represents a fundamental architectural decision for balancing artificial intelligence (AI) inference capabilities with static power consumption. This study implements the Espressif ESP32 microcontroller (WROOM-32E variant), equipped with a Tensilica Xtensa dual-core 32-bit LX6 processor [13]. In contrast to conventional single-board computers (SBCs), which consume power on a Watt scale merely to sustain the operating system during idle states, the ESP32 System-on-Chip (SoC) architecture exhibits milliwatt-range idle power consumption and supports highly aggressive Dynamic Frequency Scaling (DFS) mechanisms [9].

In the developed AGV system, the hardware architecture is built upon a modular design framework. The localization and spatial perception system relies on a sensor fusion approach, utilizing an MPU6050 Inertial Measurement Unit (IMU) to extract orientation parameters (yaw/heading) at an acquisition frequency of 100 Hz, alongside an array of reflective optical sensors and HC-SR04 ultrasonic sensors for path alignment and frontal obstacle detection. Mobility execution is governed by a pair of differential-drive Direct Current (DC) motors, regulated via an L298N H-Bridge module. This driver module receives a 10-bit resolution Pulse Width Modulation (PWM) signal, precisely generated by the ESP32's internal LED Control (LEDC) peripheral. To quantify the energy savings with high precision, a dedicated power profiling circuit (Power Profiler) is integrated into the AGV's electrical distribution bus [14]. The system employs a high-precision INA219 power sensor that communicates via the Inter-Integrated Circuit (I2C) protocol at a frequency of 400 kHz. This module is calibrated to perform simultaneous measurements of the battery bus voltage and shunt current at a 50 Hz sampling rate. The acquired power readings encompass the total consumption of the ESP32 module, peripheral sensors, and the cumulative electrical load of the DC motors.

The software computational strategy on the ESP32 is implemented utilizing a Real-Time Operating System (FreeRTOS) environment. This architectural choice is explicitly designed to mitigate interrupt latencies induced by wireless network traffic. Core 0 is exclusively allocated to execute the Communication Layer, managing the 802.11 b/g/n Wi-Fi connectivity and processing the Message Queuing Telemetry Transport (MQTT) network stack. This core publishes telemetry metrics—including battery status, current consumption, and spatial coordinates—to a supervisory cloud server at 200 ms intervals. Conversely, Core 1 is dedicated entirely to the Processing Layer, encompassing the acquisition of IMU I2C register data alongside the computation of trigonometric functions and mathematical equations intrinsic to the Fuzzy Logic Control model (Hartadi et al., 2024). By physically isolating these task threads across the dual cores, the ESP32's operating frequency can be downclocked from its 240 MHz maximum to a mere 80 MHz. This scaling significantly reduces the silicon current consumption from ~64 mA to ~36 mA without risking any control deadline misses [9]. The complete hardware specifications and computational architecture are summarized in Table 1.

Table. 1: Technical specifications of the hardware and computational architecture

Component / Subsystem	Technical Specification	Configuration Parameter
Computing Platform	ESP32-WROOM-32E (Tensilica Xtensa Dual-Core)	CPU Frequency: 80 MHz (Power Efficiency Mode)
Operating System	FreeRTOS (Real-Time Operating System)	Core 0: Wi-Fi/MQTT, Core 1: Fuzzy Inference
Position / Inertial Sensor	MPU6050 (6-DoF IMU)	Sampling Rate: 100 Hz, I2C Bus @ 400 kHz
Actuation System	2× DC Motors (Differential Drive) + L298N H-Bridge	PWM Resolution: 10-bit, PWM Frequency: 1 kHz
Power Monitoring Module	INA219 (Bus Voltage and Shunt Current)	Voltage Resolution: 4 mV, Sampling Rate: 50 Hz
Telemetry	MQTT Protocol via 2.4 GHz Wi-Fi	Publish Interval: 200 ms (Asynchronous)

2.2 *AGV Kinematic Model*

The motion model of the AGV is predicated on a non-holonomic differential-drive robotic architecture. The robot's posture within a two-dimensional (2D) global Cartesian reference frame is defined by the state vector $q=[x,y,\theta]^T$, where x and y denote the coordinates of the wheel axle's midpoint, and θ represents the vehicle's orientation (heading) angle relative to the horizontal axis. Mathematically, the fundamental kinematics of the AGV are formulated via the following transformation matrix as in equation (1).

$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{bmatrix}=\begin{bmatrix}cos\theta & 0\\ sin\theta & 0\\ 0 & 1\end{bmatrix}\begin{bmatrix}v\\ \omega\end{bmatrix} \tag{1}$$

where, v denotes the linear translational velocity of the robot's center point, and ω represents the angular velocity. These velocities are governed by the asymmetrical rotation of the individual wheels. In terms of physical specifications, the AGV has a total mass m = 15 kg, a wheel radius r = 0.05 m, and a wheelbase L = 0.35 m. The relationship between the tangential velocities of the left (v_L) and the right wheel (v_R) is expressed as equation (2).

$$v=\frac{v_R+v_L}{2},\quad \omega=\frac{v_R-v_L}{L} \tag{2}$$

These mass and mechanical dimensions are crucial, as a high moment of inertia directly induces a proportional increase in operational power consumption during the transient acceleration phase. The primary objective of the navigation system is to minimize the tracking error between the actual state vector $q(t)$ and the ideal reference vector $q_r(t)$.

2.3 *Fuzzy Logic Controller Design*

The Fuzzy Logic Controller is designed utilizing a Multi-Input Multi-Output (MIMO) architecture based on the Takagi-Sugeno-Kang (TSK) inference model. Unlike Mamdani-type architectures that rely on complex, area-based integral evaluations (Centroid of Area) during the defuzzification stage, the TSK method represents the rule base consequents as linear functions or zero-order constants. The linear algebraic operations inherent to TSK execute arithmetic computations within the microsecond range. This drastically frees up SRAM and eliminates computational overhead on the floating-point unit (FPU), rendering the architecture exceptionally suitable for industrial-grade edge microcontrollers [15].

Operationally, the FLC processes two discrete error input variables extracted in real time from the perception module. The first input is the lateral distance error (e_d), which represents the perpendicular deviation between the AGV's actual geometric center and the reference path, evaluated within a domain of [-15, 15] cm. The second input is the heading angle error (e_θ), which defines the angular discrepancy between the AGV's actual orientation (θ) and the tangential line of the target route, constrained within an evaluation domain of [-45^0, 45^0].

Each of these linguistic input variables is partitioned into five fuzzy sets: Negative Big (NB), Negative Small (NS), Zero (Z), Positive Small (PS), and Positive Big (PB) [2], as presented in Table. 2. To maintain an optimal balance between response granularity and the reduction of CPU instruction overhead, the membership functions are designed using a hybrid approach. The asymptotic sets at the domain boundaries (NB and PB) are formulated utilizing Trapezoidal curves, whereas the intermediate dynamic transition ranges (NS, Z, PS) are represented by Triangular curves. The mathematical mapping of the Triangular membership function for each input variable relies on the positional parameter matrix P_j = {a,b,c}, governed by the following discrete equation (3).

$$\mu(x) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \quad (3)$$

The output of this FLC consists of two discrete zero-order TSK values that supply the differential PWM variations, PWM variations, *PWM_L* and *PWM_R*, which are sequentially transmitted to the actuator driver. The inference matrix architecture is governed by a 5x5, heuristic Rule Base, where the implication evaluation is executed using the logical AND (T-Norm) via the Minimum operator.

Table. 2: Matrix representation of the TSK rule base for differential motor speed steering

ed↓ \ eθ →	NB	NS	Z	PS	PB
NB	PB	PB	PS	Z	NS
NS	PB	PS	PS	Z	NS
Z	PS	PS	Z	NS	NS
PS	PS	Z	NS	NS	NB
PB	PS	Z	NS	NB	NB

In this zero-order TSK model, each cell within the rule base yields a constant output O_k. The computational aggregation of the output (defuzzification) is executed via the Weighted Average method, which is highly efficient mathematically (4).

$$O = \frac{\sum_{k=1}^{n} \omega_k O_k}{\sum_{k=1}^{n} \omega_k} \quad (4)$$

where w_k represents the firing strength of the *k-th* rule.

2.4 Particle Swarm Optimization (PSO) Algorithm

If the design of the membership functions and the consequent output values of the FLC (a,b,c and O_k) are determined solely through subjective empirical guesswork (heuristics), it invariably leads to excessive control action (overshoot). This induces oscillatory acceleration within the actuators, constituting the primary source of operational energy dissipation [16]. Consequently, the PSO algorithm is initialized to search for the globally optimal parameter set (specifically, the positional centroids of the fuzzy sets).

The PSO algorithm drives numerical convergence via mathematical swarm dynamics within an *N*-dimensional search space, where *N* denotes the total number of membership function parameters being calibrated [17]. Each particle within this algorithm represents a candidate solution. Assuming a particle within the population possesses a position vector $X_i(k)$ and a velocity vecto $V_i(k)$ at the *k-th* iteration, the exploration dynamics are simulated as trajectory modifications drawn toward its individual best value (P_{best}) and the global swarm best value (G_{best}), formulated as Eq. (5) and (6), as follows

$$V_i(k+1) = \omega . V_i(k) + c_1 . r_1 . \left(P_{best,i} - X_i(k)\right) + c_2 . r_2 . \left(G_{best} - X_i(k)\right) \quad (5)$$

$$X_i(k+1) = X_i(k) + V_i(k+1) \quad (6)$$

The algorithm is initialized with a swarm size of 50 particles, a cognitive acceleration constant c_1 = 1.5, a social acceleration constant c_2 = 1.5, and an inertia weight parameter ω that linearly decreases from ω_{max} = 0.9 to ω_{min} = 0.4 over the evolutionary iterations. This linearly decaying inertia weight governs the transition balance between global exploration and local exploitation. The particle updates are continuously evaluated against an essential metric known as the Fitness Function. To realize the 'Energy-Efficient' capability, the design of the Fitness Function in this optimization represents a mathematical innovation that integrates spatial-mechanical reasoning with thermodynamic efficiency [18]. Rather than merely penalizing positional deviation, the objective cost function $J_{fitness}$ is formulated to mitigate the power dissipation (Integral of Time-weighted Power Consumption) of the DC motors, which is typically induced by abrupt PWM variations as in Eq (7), below.

$$J_{fitness} = W_1 \int_0^T t|e_d(t)|\,dt + W_2 \int_0^T t|e_\theta(t)|\,dt + W_3 \int_0^T P_{total}(t)dt \quad (7)$$

In this equation, the first and second terms represent the path-tracking stability metrics (the ITAE of lateral distance and orientation), whereas the third term extracts the total integral of the mechanical and microcontroller circuit power consumption (P_{total}). For this study, the weighting coefficients are quantitatively assigned as W_1 = 0.4, W_2 = 0.4, and W_3 = 0.2. The higher weights (0.4) allocated to the positional and orientational errors are prioritized to prevent critical trajectory deviations, while the 0.2 weight for power functions as a secondary penalty designed to eliminate high-frequency actuator oscillations without compromising fundamental tracking accuracy. Over

100 evolutionary iterations, the PSO algorithm converges the parameter structure, yielding an FLC output profile characterized by minimal energy dissipation. Subsequently, this globally optimal parameter matrix is compiled offline into a static C/C++ model and flashed onto the ESP32 ROM.

2.5 Experimental Scenarios

To establish a deterministic comparative analysis framework and rigorously validate the contributions, the testing protocol is designed to encompass both Simulation-in-the-Loop (SITL) and Hardware-in-the-Loop (HITL) environmental validations. The offline simulation phase, dedicated to executing the 100 PSO evolutionary iterations, is conducted using numerical computation software (e.g., MATLAB/Python) on a standard computer architecture. Subsequently, for the physical testing, the evaluation metrics are calibrated on a test track with a total path length of 25 meters. The layout of this route represents a logistics warehouse environment, simulating actual operational trajectories: it consists of a 15-meter straight track segment, a dynamic U-turn maneuver with a 1.5-meter radius, and a sharp 90-degree orthogonal intersection. The testing floor surface utilizes conventional epoxy concrete with a friction coefficient of μ = 0.6, effectively simulating industry-standard power dissipation conditions.

To establish a comparative baseline, two control instantiations are compiled offline and evaluated sequentially on identical ESP32 AGV hardware frameworks. The first instantiation is represented by Model A (Standard Fuzzy), a pure TSK-FLC implementation where the parameter distribution (a,b,c) of the Membership Functions is configured utilizing an expert heuristic approach based on uniform partitioning (evenly distributed MFs). Serving as the optimized counterpart, the second instantiation is represented by Model B (PSO-Optimized Fuzzy), an intelligent TSK-FLC implementation. Unlike the first model, the geometric distribution of the Membership Functions in Model B is supplied directly by the iterative computations of the PSO algorithm, which is entirely grounded in the evaluation of an energy-aware fitness function.

Data acquisition for all navigational and computational parameters is executed with strict rigor. To minimize measurement bias stemming from battery voltage fluctuations, the battery State of Charge (SoC) is calibrated to an initial level of 95% prior to each experimental trial, as a degrading voltage profile could severely distort the absolute power readings on the INA219 module. Alongside the INA219 module, which monitors electrical power spikes on a millisecond scale, the analysis of PWM signal transitions and the reduction in the rate of current change (di/dt) are validated using a digital oscilloscope. This instrument is connected directly to the actuator motor windings to corroborate the suppression of inrush currents. On the software front, ESP32 architectural efficiency metrics—specifically SRAM utilization, Worst-Case Execution Time (WCET), and Core 1 CPU load—are extracted utilizing FreeRTOS trace facilities and the microcontroller's internal high-resolution hardware timers.

Simultaneously, the sensors profile the robot's positional deviation. The precision of the Root Mean Square Error (RMSE) is calculated by comparing the reference setpoints against the actual AGV ground truth position (x,y) validated through a calibrated odometry system alongside an external trajectory measurement system. The complete set of data matrices, encompassing both spatial and electrical metrics, is logged asynchronously via an MQTT broker layer to a recording computer unit without degrading the latency of the ESP32 microcontroller during critical logistics maneuver phases [10]. The final analytical results are derived from 50 experimental runs for each algorithmic model to establish the statistical significance of the data distribution and to effectively eliminate statistical outliers.

3. Results and Discussion

3.1 Performance Comparison and Path Tracking Accuracy

The fundamental functional objective of an AGV within a supply chain is to execute navigational mobility with the absolute minimum deviation error from its designated trajectory. Empirical tracking evaluations reveal a stark contrast in the steering reactivity characteristics between the 'Standard Fuzzy' and 'PSO-Optimized Fuzzy' models. When the AGV driven by the Standard Fuzzy controller encounters sharp-radius curves or curvature transition points (junctions), the system demonstrates pronounced 'hunting' behavior and overcompensation (overshoot). This phenomenon, which manifests in the mechanical trajectory profile as micro-oscillations (zig-zagging), is an inherent negative artifact of the heuristic membership function distribution. Because the partition functions are defined rigidly without accounting for the non-linear mechanical dynamics of the motor load, the AGV tends to accelerate and decelerate the left and right wheels highly sporadically whenever the sensor inputs (distance errors) fluctuate near the rule transition thresholds (boundary constraints) [19].

Conversely, the implementation of the 'PSO-Optimized Fuzzy' algorithm achieves a critically damped mechanical trajectory. The path execution becomes exceptionally smooth and virtually free of lateral chattering, even during sharp route transitions. Specifically, the PSO algorithm has manipulated the centroid positions and calibrated the overlap degree among the Triangular Fuzzy sets. From a mechanical-mathematical perspective, adjusting this overlap degree effectively carves out an optimal response boundary zone (deadband) within the 'Zero' (Z) fuzzy set. The formation of this tuned deadband is crucial for dampening the actuator's hyper-sensitivity to minute sensor resolution noise around the reference setpoint.

Table. 3: Comparative data of mechanical trajectory tracking accuracy metrics between the two FLC configurations

Performance Evaluation Metrics (50 Trial Runs)	Standard Fuzzy (Heuristic)	PSO-Optimized Fuzzy	Improvement (%)
Positional Root Mean Square Error (RMSE)	0.165 ± 0.028 meters	0.052 ± 0.004 meters	+ 68.48%
Maximum Lateral Deviation (Max Error)	0.224 ± 0.035 meters	0.081 ± 0.006 meters	+ 63.83%
Heading Angle Mean Absolute Error (MAE)	6.28 ± 1.45 degrees	2.15 ± 0.32 degrees	+ 65.76%
Mean Completion Time (Per Run)	48.6 ± 2.1 seconds	45.2 ± 0.4 seconds	+ 6.99%

Consequently, the hunting phenomenon and mechanical oscillations are successfully eliminated, and every sensor input transition is immediately mapped onto the proportional linear compensation of the TSK matrix without triggering decision-making uncertainty [20]. As evidenced by the statistical compilation in Table. 3, the overall RMSE underwent a significant reduction of 68.48%, decreasing from 0.165 meters to an industry-grade precision tolerance threshold of 0.052 meters. These accuracy parameter findings align with established academic discourse, which posits that the implementation of swarm intelligence algorithms—when formulated through multivariable ITAE optimization—is capable of eradicating the sub-optimal limitations inherent to non-holonomic kinematic robotic platforms [21]. While standard swarm-optimized robotic frameworks in recent literature typically achieve a modest reduction in tracking errors [22 - 23], our specific implementation optimized for a dual-core edge architecture pushes this performance boundary significantly, achieving a 68.48% improvement. The refinement in tracking precision also reduces the trajectory completion time—thereby enhancing logistical throughput—as the AGV no longer wastes time rectifying its position following post turn oscillations.

Furthermore, the analysis of evaluation metric variability reveals crucial implications for system stability. Post-optimization, standard deviation values exhibit a drastic reduction across all measured parameters. For instance, the deviation fluctuation in the positional RMSE dropped from ± 0.028m to ± 0.004m. This substantial decline provides empirical justification and mathematical confirmation that the hybrid PSO-Fuzzy algorithm operates deterministically. The system demonstrates high robustness against dynamic disturbances and inter-trial uncertainties over 50 consecutive experiments, thereby substantiating that the achieved performance level is a direct outcome of robust control architectural optimization rather than a statistical fluke.

3.2 Computational Efficiency and Edge Resource Utilization (ESP32)

The most critical analytical question regarding this implementation centers on how efficiently low-cost microcontroller architectures, such as the ESP32 family, can manage high-precision spatial optimization models. Because the iterative swarm optimization process is formulated entirely within an offline processing architecture prior to deployment, the software kernel operating within the ESP32's SRAM functions purely as a zero-order Look-Up Table (LUT) for the intelligent TSK-FLC. Memory profiling demonstrates that the TSK-FLC implementation, utilizing 25 rule bases, allocates only 18 KB of SRAM (less than 4% of the total available capacity) and 32 KB of Flash memory. This minimal resource allocation guarantees sufficient heap availability for the RTOS and wireless communication protocols, thereby completely mitigating the risk of heap overflow. By leveraging an asynchronous RTOS architecture (dual-core task separation) within the firmware, a single fuzzy logic cycle—spanning IMU data acquisition via I2C DMA, algorithm inference, and TSK matrix defuzzification—is executed with an average latency of 3.2±0.4 ms. The WCET is recorded at 4.1 ms, remaining substantially within the 20 ms safety margin required for mechanical control stability [24]. This computational efficiency is achieved by utilizing the Weighted Average defuzzification method for the TSK consequent functions; this approach bypasses the complex integral decomposition processes that would typically incur high computational overhead on the FPU [15]. Inter-core data synchronization between Core 0 and Core 1 is implemented using FreeRTOS Queues, which ensures asynchronous telemetry data transmission without blocking interrupts, while effectively preventing race conditions during shared memory access.

The broader implications of this mathematical simplicity underscore the viability of the ESP32's low-power design. With CPU utilization on Core 1 (the Processing Core) consistently maintained below the 8% threshold, the ESP32 framework does not necessitate scaling the operational frequency to its 240 MHz peak [25]. The processor frequency is fixed at an energy-efficient baseline of 80 MHz, which proved critical in reducing the microcontroller's static (idle) current consumption by nearly 50% [26]. Meanwhile, Core 0 effectively handles asynchronous data exchange via the wireless MQTT broker without introducing blocking interrupts to the core FLC computation, thereby validating the separation of Edge and Telemetry logical infrastructures for industrial-grade IoT applications [27].

3.3 In-depth Analysis of Power Consumption and Energy Efficiency Enhancement

This section presents an analysis of the system's power consumption as a primary Key Performance Indicator (KPI) for autonomous robotics efficiency. The electrical power supplied by the on-board battery is categorized into two domains: Static Computation Power and Kinematic Dynamic Power. Table 4 presents the integrated power consumption profile of the system (Circuits + Actuators), acquired using the precision INA219 current sensor module.

Table. 4: Integrated analysis of energy consumption in standard electrical units (watts and joules)

Performance Evaluation Metrics	Standard Fuzzy (Heuristic)	PSO-Optimized Fuzzy	Efficiency Delta (%)
Average Operational Power [W]	18.4±0.8	15.3±0.3	16.84%
Peak Power Surge [W]	26.7±1.5	19.2±0.7	28.08%
Cumulative Energy Consumption [J]	2,208±45	1,836±22	16.84%
Idle Current Consumption [mA]	41.2±0.1	41.2±0.1	-

The low variance observed in the PSO-Optimized Fuzzy test results demonstrates that the achieved energy efficiency is deterministic and consistent across all test runs, effectively precluding the possibility of transient anomalies. In the Standard Fuzzy configuration, the system records an average power consumption of 18.4 W, with peak surges reaching 26.7 W during reactive maneuvers on complex trajectories characterized by oscillatory overshoot. This phenomenon arises because the drastic PWM signal transitions inherent to the Standard Fuzzy controller exacerbate inductive reactance inefficiencies [28]. Conversely, the PSO-Optimized Fuzzy method produces a more continuous PWM duty cycle curve. By modifying the membership functions, PSO induces gradual PWM signal transitions, physically reducing the rate of current change (di/dt) within the motor inductors. This reduction in di/dt significantly suppresses inrush currents and minimizes both Joule heating (I^2R) losses in the motor windings and switching losses in the L298N semiconductor components [29].

Experimental results demonstrate that the PSO-Optimized Fuzzy controller reduces average power consumption to 15.3 W and mitigates peak power surges by 28.08%. This 16.8% energy saving significantly surpasses the efficiency range typical of conventional Fuzzy-based control systems reported in existing literature, which generally falls between 5% and 12% [18], [3]. These findings confirm that swarm optimization on low-power ESP32 microcontrollers yields a statistically significant performance impact. The 16.8% efficiency gain directly implies an extended battery cycle life and reduced AGV maintenance downtime, matching the broader goals of energy-efficient AGV scheduling for modern smart logistics and sustainable manufacturing environments [30].

4 Conclusion

This research has successfully demonstrated the technical feasibility and operational efficiency of implementing PSO on FLC deployed on low cost Edge computing platforms (ESP32). By leveraging an asynchronous dual-core architecture and swarm-intelligence-based parameter tuning, the proposed system effectively overcomes embedded computational constraints without compromising robotic kinematic accuracy. Key findings confirm that PSO-based membership function optimization physically mitigates the rate of current change (di/dt) within actuator windings through smoothed PWM duty cycle transitions. Empirically, this results in a 16.8% reduction in cumulative energy consumption compared to conventional heuristic control methods. Furthermore, the deterministic task management within the ESP32 RTOS ensures system stability, maintaining latency well within the 20 ms mechanical control threshold, with a recorded WCET of 4.1 ms.

Theoretically and practically, these results contribute to the Green Industry 4.0 paradigm by providing a robotic control framework that is not only precise but also energy-efficient and sustainable. This implementation directly translates to extended battery cycle life and reduced maintenance downtime, thereby optimizing operational productivity in autonomous logistics within smart factory environments. While the system has demonstrated robust performance in controlled trajectories, future research should evaluate the scalability of this algorithm in multi-agent coordination scenarios under more extreme dynamic environmental disturbances. Additionally, validation on alternative microcontroller architectures, such as RISC-V, is recommended to assess the universality of the proposed PSO-Fuzzy optimization method.

Acknowledgment

The authors would like to express their sincere gratitude to the State University of Surabaya for providing the necessary facilities and academic support that enabled the completion of this research.

Funding

This research received no external funding.

Data Availability Statement

Data sharing does not apply to this article as no datasets were generated or analyzed.

Conflict of Interest

The authors declared “No conflict of interest”.

CRediT authorship contribution statement

Conceptualization, AA and BS; methodology, AA; software, AA; validation, AA, BS and HPAT; formal analysis, AA; investigation, AA; resources, BS and HPAT; data curation, AA; writing—original draft preparation, AA; writing—review and editing, BS and HPAT; visualization, AA; supervision, BS and HPAT; project administration, BS; funding acquisition, BS. All authors have read and agreed to the published version of the manuscript.

References

[1] L. Hu, X. Zhao, W. Liu, W. Cai, K. Xu, and Z. Zhang, "Energy benchmark for energy efficient path planning of the automated guided vehicle", *Science of the total environment*, Vol. 857, art. no. 159613, january 2023. https://doi.org/10.1016/j.scitotenv.2022.159613

[2] H. Omrane, M. S. Masmoudi, and M. Masmoudi, “Fuzzy logic based control for autonomous mobile robot navigation", *Computational Intelligence and Neuroscience,* Vol. 2016, art. no: 9548482, 2016. https://doi.org/10.1155/2016/9548482

[3] Z. Zhang, L. Wu, W. Zhang, T. Peng, and J. Zheng, “Energy-efficient path planning for a single load automated guided vehicle in a manufacturing workshop", *Compututers and Industrial Engineering,* Vol. 158, art. no. 107397, august 2021.

https://doi.org/10.1016/j.cie.2021.107397

[4] H. Zhang, Y. Zhang, C. Liu, and Z. Zhang, "Energy efficient path planning for autonomous ground vehicles with ackermann steering", *Robotics and Autonomous Systems*, Vol. 162, art. no. 104366, april 2023. https://doi.org/10.1016/j.robot.2023.104366

[5] J. Aisbett and J. T. Rickard, "Centroids of fuzzy sets when membership functions have spikes", *2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS)*, pp. 97–101, 2013. https://doi.org/10.1109/IFSA-NAFIPS.2013.6608382

[6] A. Štefek, V. T. Pham, V. Krivanek, and K. L. Pham, "Optimization of fuzzy logic controller used for a differential drive wheeled mobile robot", *Applied Sciences*, Vol. 11, No. 13, art. no. 6023, 2021. https://doi.org/10.3390/app11136023

[7] Y. H. Chang, F. C. Wu and H. W. Lin, "Design and implementation of ESP32-based edge computing for object detection", *Sensors*, Vol. 25, No. 6, art. no. 1656, 2025. https://doi.org/10.3390/s25061656

[8] W. Jing, X. Wang, X. Li, and J. Yi "A hybrid particle swarm optimization algorithm with dynamic adjustment of inertia weight based on a new feature selection method to optimize SVM parameters", *Entropy*, Vol. 25, No. 3, art. no. 531, 2023. https://doi.org/10.3390/e25030531

[9] A. Fanariotis, T. Orphanoudakis, and V. Fotopoulos, "Reducing the power consumption of edge devices supporting ambient intelligence applications", *Information*, Vol. 15, No. 3, art. no. 161, 2024. https://doi.org/10.3390/info15030161

[10] H. J. El-Khozondar, S. Y. Mtair, K. O. Qoffa, O. I. Qasem, A. H. Munyarawi, Y. F. Nassar, E. H. E. Bayoumi, A. A. E. A. E. Halim "A smart energy monitoring system using ESP32 microcontroller", *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, Vol. 9, art. no. 100666, 2024. https://doi.org/10.1016/j.prime.2024.100666

[11] J. L. da Silva, "Fuzzy logic control with PSO tuning", *Fuzzy Systems - Theory and Applications*, IntechOpen, 2021. https://doi.org/10.5772/intechopen.96297

[12] D. Grzechca, Ł. Gola, M. Grzebinoga, A. Ziębiński, K. Paszek, and L. Chruszczyk, "Controlling AGV while docking based on the fuzzy rule inference system", *Sensors*, Vol. 25, No. 19, art. no. 6108, 2025. https://doi.org/10.3390/s25196108

[13] P. Megantoro, R. P. Prastio, H. F. A. Kusuma, A. Abror, P. Vigneshwaran, D. F. Priambodo, D. S. Alif "Instrumentation system for data acquisition and monitoring of hydroponic farming using ESP32 via google firebase", *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 27, No. 1, pp. 52-61, 2022. https://doi.org/10.11591/ijeecs.v27.i1.pp52-61

[14] T. Y. Abdalla, A. A. Abed, and A. A. Ahmed, "Mobile robot navigation using PSO-optimized fuzzy artificial potential field with fuzzy control", *Journal of Intelligent and Fuzzy Systems*, Vol. 32, No. 6, pp. 3893–3908, may 2017. https://doi.org/10.3233/IFS-162205

[15] P. Chotikunnan, W. Khotakham, P. Imura, R. Chotikunnan, A. Wongkamhang and N. Thongpance, "Comparative analysis of PID driven data based and PSO tuned fuzzy membership functions for robotic manipulator control", *Journal of Fuzzy Systems and Control*, Vol. 3, No. 3, pp. 204 - 211, 2025. https://doi.org/10.59247/jfsc.v3i3.335

[16] K. Reif, "*Brakes, Brake Control and Driver Assistance Systems*", Wiesbaden: Springer Fachmedien Wiesbaden, 2014. https://doi.org/10.1007/978-3-658-03978-3

[17] E. E. Omizegba and G. E. Adebayo, "Optimizing fuzzy membership functions using particle swarm algorithm", *2009 IEEE International Conference on Systems, Man and Cybernetics*, pp. 3866–3870 2009. https://doi.org/10.1109/ICSMC.2009.5346637

[18] N. Li, Z. Huang, C. Wang, and X. Ning, "Particle swarm optimization and fuzzy logic co-optimization for energy efficiency cooperative energy management strategy of hybrid energy storage electric vehicles", *World Electric Vehicle Journal*, Vol. 17, No. 2, art. no. 73, 2026. https://doi.org/10.3390/wevj17020073

[19] J. Leng, J. Peng, J. Liu, Y. Zhang, J. Ji, and Y. Zhang, "Profiling power consumption in low-speed autonomous guided vehicles", *IEEE Robotics and Automation Letters*, Vol. 9, No. 7, pp. 6027–6034, 2024. https://doi.org/10.1109/LRA.2024.3396051

[20] I. Pakaya, "Particle swarm optimization–fuzzy logic controller untuk penyearah satu fasa", *Jurnal*

Ilmiah Edutic Pendidikan dan Informatika, Vol. 1, No. 1, 2015. https://doi.org/10.21107/edutic.v1i1.401

[21] B. K. Oleiwi, and Mohamed Jasim Mohamed, "Optimal design of linear and nonlinear PID controllers for speed control of an electric vehicle", *Journal of Intelligent Systems*, Vol. 33, No. 1, art. no. 20240028, 2024. https://doi.org/10.1515/jisys-2024-0028

[22] N. Ning, "Trajectory tracking for mobile robots based on fractional order sliding mode and dynamic modeling", *Frontiers in Mechanical Engineering*, Vol. 11, november 2025. https://doi.org/10.3389/fmech.2025.1695174

[23] T. D. Tolossa *et al.*, "Trajectory tracking control of a mobile robot using fuzzy logic controller with optimal parameters", *Robotica*, Vol. 42, No. 8, pp. 2801–2824, august 2024. https://doi.org/10.1017/S0263574724001140

[24] Z. Wang, J. Chen, H. Zhao, and B. Wei, "Deterministic edge controlled precision fertigation system with spatial task scheduling and hardware software safety interlock", *Sensors*, Vol. 26, No. 13, art. no. 4289, july 2026. https://doi.org/10.3390/s26134289

[25] L. M. Broell, C. Hanshans, and D. Kimmerle, "IoT on an ESP32: optimization methods regarding battery life and write speed to an SD-card", *Edge Computing - Technology, Management and Integration*, IntechOpen, 2023. https://doi.org/10.5772/intechopen.110752

[26] J. Zidar, T. Matić, I. Aleksi, and Ž. Hocenski, "Dynamic voltage and frequency scaling as a method for reducing energy consumption in ultra low power embedded systems", *Electronics*, Vol. 13, No. 5, art. no. 826, february 2024. https://doi.org/10.3390/electronics13050826

[27] S. Adriansyah, S. Sumarno, U. M. Nurfuha, A. Giffari, T. Khoirunisa, and W. G. Subarkah, "Performance analysis of MQTT and HTTP protocols on low-power ESP32 devices for IoT applications", *CoreID Journal*, Vol. 4, No. 1, pp. 38–45, may 2026. https://doi.org/10.60005/coreid.v4i1.160

[28] M. Crenganiș *et al.*, "Fuzzy logic based driving decision for an omnidirectional mobile robot using a simulink dynamic model", *Applied Sciences*, Vol. 14, No. 7, art. no. 3058, april 2024. https://doi.org/10.3390/app14073058

[29] A. W. N. Siregar, T. Agustinah, and A. Fatoni, "Trajectory tracking using fuzzy predictive control for nonholonomic mobile robot", *2025 International Seminar on Intelligent Technology and Its Applications*, pp. 53–58, july 2025. https://doi.org/10.1109/ISITIA66279.2025.11137570

[30] H. Tang, H. Wang, Y. Zhan, and X. Xu, "Energy-efficient scheduling of multi load AGVS based on the SARSA-TTAO algorithm", *Sustainability*, Vol. 17, No. 16, art. no. 7353, august 2025. https://doi.org/10.3390/su17167353

***