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An Internet of Things-Based Monitoring and Temperature Control System for Baby Incubators Using Mamdani Fuzzy Optimized with Ant Colony Optimization and GY-906 Infrared Sensor

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Abstract*—Preterm infants have an immature thermoregulatory system, making them prone to hypothermia and unstable body temperature. Conventional incubators generally still rely on manual temperature settings or simple ON-OFF control that does not automatically adjust the setpoint to the infant's body weight and ambient temperature. This study designs a prototype Internet of Things (IoT)-based monitoring and temperature control system for baby incubators using the Mamdani Fuzzy method to automatically determine the temperature setpoint based on the infant's body weight and incubator air temperature. The fuzzy rule base, compiled from a synthesis of World Health Organization (WHO) recommendations, was further optimized using the Ant Colony Optimization (ACO) algorithm to obtain a rule combination with a smaller prediction error. The Positive Temperature Coefficient (PTC) heater and Peltier cooler actuators are controlled non-fuzzily based on a threshold, while chamber humidity is controlled through a hysteresis mechanism. All sensor data and actuator status are sent to the Firebase Realtime Database and displayed on a web dashboard for real-time monitoring by medical staff. The ACO optimization results show a Mean Squared Error (MSE) reduction of 45.97% under weighted-average evaluation and 42.26% under full Mamdani (apple-to-apple) evaluation compared to the initial rule base, with three of nine rules adjusted under extreme ambient temperature conditions. Testing of the GY-906, DHT22, and Load Cell sensors showed average errors of 3.29%, 2.39%, and below 0.05%, respectively. These results demonstrate that ACO-based optimization improves the accuracy of the fuzzy system in determining the incubator temperature setpoint compared to a rule base compiled solely from literature references.

Index Terms*—Baby incubator, Internet of Things, Fuzzy Mamdani, Ant Colony Optimization, temperature control.

I. INTRODUCTION

Preterm infants, defined as those born before 37 weeks of gestation, are a highly vulnerable group prone to health complications because their organs have not fully developed. Data show approximately 13.4 million preterm births worldwide in 2020, with Indonesia ranking fifth globally and contributing to around 35% of neonatal deaths [11], [12]. One of the main problems faced by preterm infants is their inability to maintain body temperature independently due to an immature thermoregulatory system, requiring care in a controlled environment through a baby incubator.

Baby incubators are designed to provide a thermal environment resembling intrauterine conditions so that infants can maintain body temperature within the range of 36.5–37.5°C, with recommended chamber temperature adjusted to the infant's body weight, referring to the WHO Neutral Thermal Environment principle. However, conventional incubators in many healthcare facilities still rely on ON-OFF control or static manual settings that do not automatically adjust the setpoint when the infant's body weight changes, and lack automatic feedback systems [2]. This condition risks causing temperature fluctuations that trigger thermal stress and delayed detection of temperature deviations.

Internet of Things (IoT) technology offers a solution to these limitations because it enables real-time remote monitoring and control through the integration of sensors, microcontrollers, and network connectivity [2]. The ESP32 microcontroller is widely chosen for IoT applications due to its integrated Wi-Fi connectivity, adequate computing performance, and low power consumption. Non-contact body temperature measurement using an infrared sensor has proven safer than contact sensors [13], while automatic weight measurement using a load cell and HX711 module has been proven accurate for baby scale applications [5].

For temperature control, fuzzy logic methods have proven more adaptive than conventional control in handling nonlinear environmental uncertainty [8], [10]. However, previous studies generally evaluate IoT monitoring and fuzzy control separately, and the fuzzy rule base parameters in those studies are generally still determined heuristically without further optimization. Metaheuristic algorithms such as Ant Colony Optimization (ACO) have proven effective in refining fuzzy system rule bases across various control domains [4], yet their specific application to optimizing incubator temperature setpoint determination based on body weight is still rarely found in the literature. On the actuator side, the Peltier thermoelectric element has proven effective as an active cooler in various IoT-based systems [9], so its combination with a PTC heating element has the potential to provide more adaptive bidirectional temperature control compared to systems relying on a single heater.

Based on this research gap, this study proposes the integration of three aspects into a single unified system, namely: (1) automatic setpoint determination based on the infant's body

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weight and incubator chamber temperature using Fuzzy Mamdani optimized with ACO; (2) a closed-loop feedback system based on the DHT22 sensor combined with staged threshold control for the PTC Heater and proportional PWM control for the Peltier module; and (3) real-time IoT monitoring based on non-contact sensors and a web dashboard. The purpose of this study is to design and evaluate the performance of this prototype system, as well as to analyze the improvement in fuzzy rule base accuracy after ACO optimization compared to the initial rule base.

II. METHOD

A. Research Type and Location

This study employs a Research and Development (R&D) approach to design, implement, and test a prototype monitoring and temperature control system for baby incubators. The research was conducted at the Electronics Engineering Laboratory, Automation Engineering Technology Study Program, Faculty of Engineering, Universitas Negeri Jakarta, during the period of January–July 2026. The research stages included literature study, hardware and software design, Fuzzy Mamdani control system design, rule base optimization using ACO, closed-loop control implementation, IoT monitoring integration, and system performance testing.

B. Tools and Materials

The prototype uses an ESP32 microcontroller as the central controller that reads sensor data, runs fuzzy inference, and controls the actuators. The main components used are presented in Table I.

TABLE I. MAIN COMPONENTS OF THE SYSTEM PROTOTYPE

No.	Component	Function
1	ESP32 WROOM-32	Main microcontroller
2	Load Cell + HX711	Measures the infant's body weight
3	DHT22	Measures chamber temperature & humidity (control feedback)
4	MLX90614 (GY-906)	Non-contact infant body temperature monitoring
5	PTC heating element	Heater actuator (4 units, staged)
6	Peltier module (TEC1-12706)	Cooler actuator (2 units, proportional PWM)
7	BTS7960 driver	Controls Peltier PWM
8	8-channel relay module	PTC, fan, and humidifier switch
9	Humidifier	Maintains chamber humidity
10	20×4 I2C LCD	Status display interface

Source: research data 2026

C. System Design

The system consists of three main parts: power supply, control, and remote monitoring. The ESP32 receives data from the DHT22 sensor (chamber temperature and humidity), a load cell with an HX711 module (infant weight), and an MLX90614 sensor (infant body temperature, used only as a safety alarm basis and not as a control input). Based on the infant's weight and chamber temperature, the ESP32 runs a Fuzzy Mamdani computation to determine the setpoint, then compares it with the actual temperature to calculate the error value that forms the basis for controlling the relay module (staged PTC heating elements, fan, humidifier) and the BTS7960 driver (Peltier module). All data is sent to the Firebase Realtime Database every ten seconds and displayed on a web dashboard.

D. Fuzzy Mamdani Design and ACO Optimization

The control system uses two input variables, namely infant weight (Light, Medium, Normal) and incubator temperature (Low, Medium, High), and one output variable in the form of the temperature setpoint (Low 33°C, Medium 34.5°C, High 36°C). Gaussian membership functions were compiled based on a synthesis of WHO recommendations regarding the Neutral Thermal Environment. The initial rule base before ACO optimization is presented in Table II.

TABLE II. INITIAL RULE BASE BEFORE ACO OPTIMIZATION

Rule	Infant Weight	Incubator Temperature	Setpoint
1	Light	Low	High (36°C)
2	Light	Medium	High (36°C)
3	Light	High	Medium (34.5°C)
4	Medium	Low	Medium (34.5°C)
5	Medium	Medium	Medium (34.5°C)
6	Medium	High	Low (33°C)
7	Normal	Low	Medium (34.5°C)
8	Normal	Medium	Low (33°C)
9	Normal	High	Low (33°C)

The initial rule base was then optimized using the Ant Colony Optimization (ACO) algorithm against a research dataset of 100 data points (15 anchor points resulting from supervisor discussions and 85 simulated interpolation data points based on WHO NTE principles), covering an infant weight range of 517–3461 grams and an incubator temperature range of 30.1°C–37.9°C. ACO discretely optimizes the consequent category of each rule to minimize the Mean Squared Error (MSE) against the reference data, using the fitness function = 1/(1+MSE). The ACO parameters used are presented in Table III.

TABLE III. ANT COLONY OPTIMIZATION (ACO) PARAMETERS

Parameter	Value	Description
Number of ants	30	Number of solution-search agents per iteration
Maximum iterations	150	Number of optimization cycles
Alpha (α)	1	Pheromone influence weight
Beta (β)	2	Heuristic influence weight
Rho (ρ)	0.5	Pheromone evaporation rate
Q	1	Pheromone reinforcement constant
Number of rules	9	3 (weight) × 3 (temperature)

E. Actuator Control and Data Analysis

The setpoint resulting from Fuzzy Mamdani serves as the reference for a closed-loop control system based on the DHT22 sensor. The PTC heating element is controlled in stages (staged threshold, four levels) based on the magnitude of the temperature error, while the Peltier module is controlled proportionally (PWM) through the BTS7960 driver. Chamber humidity is controlled separately through hysteresis on the humidifier. Sensor performance is evaluated using the percentage error against a reference measuring instrument (Eq. 1) and the average error (Eq. 2), while the performance of the fuzzy rule base before and after ACO optimization is evaluated using Mean Squared Error (Eq. 3), Root Mean Squared Error (Eq. 4), Mean Absolute Error (Eq. 5), and Mean Absolute Percentage Error (Eq. 6).

$$Er\,(\%) = |\Delta - \alpha| / \Delta \times 100\% \qquad (1)$$

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$$\bar{E}r = \Sigma\, Er(\%) / n \tag{2}$$

$$MSE = (1/n)\, \Sigma\, (yi - \hat{y}i)^2 \tag{3}$$

$$RMSE = \sqrt{MSE} \tag{4}$$

$$MAE = (1/n)\, \Sigma\, |yi - \hat{y}i| \tag{5}$$

$$MAPE = (1/n)\, \Sigma\, |yi - \hat{y}i| / yi \times 100\% \tag{6}$$

where Δ is the sensor-read temperature/weight, α is the value from the reference measuring instrument, yi is the target value (reference setpoint), ŷi is the Fuzzy Mamdani prediction result, and n is the number of data points.

III. Results and Discussion

A. Sensor Accuracy

Accuracy testing was carried out by comparing sensor readings against a reference measuring instrument. The GY-906 sensor was tested on the forehead, palm, and arm of human subjects as well as on an infant manikin and a bottle across 11 test trials, yielding an average error of 3.29% against a digital thermometer, with the smallest error at 1.50% and the largest at 6.86% for objects with different emissivity (the bottle). The DHT22 sensor was tested 13 times against an HTC-2 digital hygrometer and produced an average error of 2.39%. The Load Cell sensor, which had been calibrated using a 1000-gram reference load (calibration factor −100.1911), was tested against a digital scale over a range of 500–2000 grams and showed an error below 0.05% across all tests. A summary of sensor accuracy is presented in Table IV.

TABLE IV. Summary of Sensor Accuracy

Sensor	Reference instrument	Number of tests	Average error
GY-906 (MLX90614)	Digital thermometer	11	3.29%
DHT22	HTC-2 hygrometer	13	2.39%
Load Cell + HX711	Digital scale	11	< 0.05%

These results show that all three sensors have adequate accuracy for use in an IoT-based baby incubator monitoring and temperature control system, with the Load Cell showing the highest accuracy due to the more stable nature of its measurement compared to non-contact temperature measurement, which is influenced by distance, angle, and the emissivity of the object's surface.

B. Fuzzy Rule Base Optimization Using ACO

The ACO optimization process on the nine initial rules produced adjustments to three rules, namely Rule 1 (Light + Low), Rule 3 (Light + High), and Rule 7 (Normal + Low), all of which involve extreme chamber temperature categories (Low or High). This indicates that ACO adjustments tend to occur under the most critical conditions that most require setpoint precision, while the six unchanged rules indicate that the initial knowledge base derived from WHO/EENC recommendations was already appropriate for those condition combinations. The rule viewer before optimization, the surface viewer after optimization, and the fitness convergence curve during the optimization process were also examined.

Rule base performance was evaluated using two approaches: the weighted-average method used during the optimization process, and the full Mamdani inference method (evalfis), which is identical to the method implemented on the ESP32 firmware, to ensure the results were not biased toward the evaluation method used during the solution search. The results of both evaluations are presented in Table V.

TABLE V. Comparison of Rule Base Evaluation Metrics Before and After ACO Optimization

Evaluation method	Condition	MSE (°C²)	RMSE (°C)	MAE (°C)
Weighted-average	Initial rule	0.4851	0.6965	0.5328
Weighted-average	ACO rule	0.2621	0.5120	0.3696
Weighted-average	Improvement	45.97%	26.50%	30.63%
Full Mamdani	Initial rule	0.7202	0.8486	0.7217
Full Mamdani	ACO rule	0.4158	0.6449	0.5325
Full Mamdani	Improvement	42.26%	24.00%	26.23%

Table V shows that all error parameters consistently decreased across both evaluation methods. The 42.26% MSE reduction under the full Mamdani (apple-to-apple) evaluation proves that the improvement produced by ACO stems purely from a better rule combination, not from leniency in the evaluation method used during optimization. Accordingly, the ACO-optimized rule base is suitable for use as the basis for setpoint determination in the implementation of the baby incubator temperature control system.

C. Temperature Control and IoT Monitoring Testing

Temperature control testing was carried out at three fixed setpoint values (33°C, 34.5°C, and 36°C) in manual mode, as well as in automatic mode with the setpoint determined by the Fuzzy Mamdani-ACO system based on the infant's weight and the initial chamber temperature. Testing in automatic mode with a setpoint of 34.5°C showed that the incubator temperature and humidity moved closer to the reference value over time, with gradual heating by the PTC Heater (levels 1–4) decreasing proportionally as the temperature approached the setpoint.

During testing, all data on incubator temperature, infant body temperature, humidity, infant weight, actuator status, and operating mode were successfully transmitted to the Firebase Realtime Database every ten seconds and displayed on the web dashboard in real time, thereby supporting remote monitoring functions for medical staff without needing to be physically near the device. Overall, these results show that the closed-loop control system based on a combination of PTC threshold and Peltier PWM is able to maintain the incubator temperature close to the setpoint resulting from Fuzzy Mamdani-ACO optimization, while also providing a responsive IoT monitoring function.

IV. Conclusion and Recommendations

A. Conclusion

A prototype Internet of Things-based monitoring and temperature control system for baby incubators has been successfully designed using an ESP32 microcontroller integrated with GY-906, DHT22, and HX711 Load Cell sensors, as well as PTC Heater and Peltier module actuators, with Firebase serving as the real-time monitoring medium. The Fuzzy Mamdani method optimized using Ant Colony Optimization successfully determined the incubator temperature setpoint based on infant weight and chamber temperature, achieving an MSE reduction of 45.97% (weighted-average evaluation) and 42.26% (full Mamdani evaluation) compared to the initial rule base, with three of the nine rules adjusted under extreme chamber temperature conditions. The closed-loop control system based on the DHT22 sensor, combining staged threshold control on the PTC Heater and proportional PWM on the Peltier, was able to maintain the incubator temperature close to the determined setpoint, while testing of the GY-906, DHT22, and Load Cell sensors showed average errors of 3.29%, 2.39%, and below 0.05%, respectively. The Firebase and web dashboard integration was successfully used as a remote monitoring medium displaying temperature, humidity, infant weight, and actuator status data in real time.

B. Recommendations

Future research is recommended to use sensors with higher accuracy levels and calibration using standard medical measuring instruments, to develop more adaptive control methods such as Fuzzy-PID, to add other physiological parameters such as oxygen levels and heart rate, to provide real-time notification features through an Android application or website, and to conduct testing over a longer period and under more varied environmental conditions in order to obtain more comprehensive system performance data.

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REFERENCES

[1] A. Alhumami, "Meningkatkan akses dan kualitas pendidikan untuk mewujudkan SDM unggul yang produktif," Bappenas Working Papers, vol. 8, no. 3, pp. 537–550, 2025.

[2] P. A. Aya-Parra, A. J. Rodriguez-Orjuela, V. Rodriguez Torres, N. P. Cordoba Hernandez, N. Martinez Castellanos, and J. Sarmiento-Rojas, "Monitoring system for operating variables in incubators in the neonatology service of a highly complex hospital through the Internet of Things (IoT)," Sensors, vol. 23, no. 12, p. 5719, 2023.

[3] A. Aziz, D. I. Saputra, A. K. Mainil, and R. I. Mainil, "Perancangan kotak pendingin dan pemanas menggunakan modul thermoelectric cooling sebagai sumber kalor," Universitas Riau, 2022.

[4] O. Kozlov, "Information technology for designing rule bases of fuzzy systems using Ant Colony Optimization," International Journal of Computing, vol. 20, no. 4, pp. 471–486, 2021.

[5] Y. Mukhammad, A. Santika, and S. Haryuni, "Analisis akurasi modul amplifier HX711 untuk timbangan bayi," Medika Teknika: Jurnal Teknik Elektromedik Indonesia, vol. 4, no. 1, pp. 24–28, 2022.

[6] M. Munisankar and T. Ramashri, "IoT-based secure health monitoring system for neonatal incubators," in Artificial Intelligence and Internet of Things for Smart Healthcare, vol. 1356, Springer, 2025, pp. 13–23.

[7] N. P. Puspita and M. Yusfi, "Desain dan implementasi sistem pendingin berbasis Peltier TEC 12706 dengan pemantauan jarak jauh melalui aplikasi Blynk pada smartphone," Jurnal Fisika Unand, vol. 14, no. 1, pp. 8–14, 2025.

[8] N. P. Reddy, G. Mathur, and S. I. Hariharan, "Toward a fuzzy logic control of the infant incubator," Annals of Biomedical Engineering, vol. 37, no. 10, pp. 2146–2152, 2009.

[9] P. Songsree and C. Thongchaisuratkrul, "Peltier water cooling system with solar energy and IoT technology demonstration set," Energy Engineering, vol. 122, no. 11, pp. 4541–4559, 2025.

[10] W. Widhiada, T. G. T. Nindhia, I. N. Gantara, I. N. Budarsa, and I. N. Suarndwipa, "Temperature stability and humidity on infant incubator based on fuzzy logic control," in ACM International Conference Proceeding Series, 2019, pp. 155–159.

[11] World Health Organization, Thermal Protection of the Newborn: A Practical Guide. Geneva: WHO, 1997.

[12] World Health Organization, "Preterm birth," WHO, 2020.

[13] Y. Zhao and J. H. M. Bergmann, "Non-contact infrared thermometers and thermal scanners for human body temperature monitoring: A systematic review," Sensors, vol. 23, no. 17, p. 7439, 2023.