



Digital Twin-Enabled IoT Automation System for Monitoring and Control of Poultry Production in a Modular Cage System using Fuzzy Logic Controller

¹Aliyu Abubakar, ²Mutari Hajara Ali, ²Tijjani Hassan Darma

¹Department of Electrical and Electronics Engineering Technology,
Federal Polytechnic, Bali, Taraba State, Nigeria.

²Department of Physics and Electronics,
Bayero University Kano
Kano State, Nigeria.

ABSTRACT

This paper presents the utilization of a digital twin-enabled IoT automation system in conjunction with a fuzzy logic controller to enhance the management of poultry production in a modular cage system. The effective monitoring and control of poultry production systems are vital for optimizing productivity and ensuring the health of the poultry. Traditional control methods often struggle to cope with the complexity and nonlinearity of such systems. Poultry production environments involve multiple variables such as temperature, humidity, light intensity, feeding, watering, and health management, each with complex interdependencies. Traditional control approaches may not adequately address these complexities, leading to suboptimal performance. We implemented a fuzzy logic controller within a digital twin-enabled IoT automation framework to manage and control various parameters of the poultry production system. The fuzzy controller was designed to handle the nonlinear relationships between system inputs and outputs, adapting to changes in environmental conditions and system states. The fuzzy logic controller effectively managed temperature, humidity, light intensity, feeding, watering, and health parameters, improving system performance. Results showed that the controller-maintained parameters within desired ranges more effectively compared to traditional control methods. The proposed system enhances the ability to manage complex poultry production environments, leading to improved productivity and better health outcomes for the poultry. The fuzzy logic controller provides flexibility and adaptability to changing conditions, making it a valuable tool for modern poultry management.

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INTRODUCTION

Effective management of poultry production systems is essential for maximizing yield and ensuring the welfare of the poultry (Bhardwaj, 2024). The modular cage system used in modern poultry farming requires precise control of environmental conditions such as temperature, humidity, and light intensity (Baig et al., 2021). Traditional control methods, which

often rely on linear models and fixed parameters, may not be sufficient to address the complexities and dynamics of these systems (Lima et al., 2022). To overcome these limitations, this study explores the integration of a digital twin-enabled IoT automation system with a fuzzy logic controller. A digital twin is a virtual representation of a physical system, allowing real-time monitoring and control through data integration and simulation (Udanor et

Corresponding author: Aliyu Abubakar

✉ babandubu@gmail.com

Department of Electrical and Electronics Engineering Technology, Federal Polytechnic, Bali, Taraba State, Nigeria.

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al., 2022). By leveraging this technology, we can create a more accurate and responsive model of the poultry production system (Dwiyaniti & W, 2022).

Fuzzy logic controllers, on the other hand, provide a way to handle the uncertainty and nonlinearity inherent in such systems. They use a set of if-then rules to make decisions based on the degree of truth of various conditions, offering a flexible and adaptive approach to control (Minna, 2018). In this study, we applied a fuzzy logic controller to manage key parameters in a modular cage system for poultry production. The controller adjusts various factors such as temperature, humidity, light intensity, feeding, watering, and health management based on real-time data from the digital twin model (Team & Committee, 2021). This approach aims to improve the overall efficiency and effectiveness of poultry production by ensuring that all relevant conditions are optimally managed.

The theoretical equations for monitoring and controlling poultry production in a modular cage system use a fuzzy logic control system. These equations require decisions based on a set of fuzzy rules applied to various inputs, such as temperature, humidity, light intensity, CO2 levels, feeding, watering, and health (Petri et al., 2023). The first step in this theoretical background is fuzzification of inputs, which involves converting the inputs into fuzzy sets (Twins & Greenhouses, 2022). For each input, the degree of membership in a fuzzy set is calculated using membership functions. For example, the membership function for temperature can be represented as: (Su et al., 2023)

$$\mu_{LOW}(T) = \begin{cases} 0 & T \leq T_1 \\ \frac{T_2 - T}{T_2 - T_1} & T_1 < T < T_2 \\ 1 & T \geq T_2 \end{cases} \quad (1)$$

Where, $\mu_{low}(T)$ is the membership function for the "Low" temperature set, T is the temperature, and T_1 and T_2 are the boundary points of the low-temperature range.

The fuzzy base rule consists of a series of IF THEN rule that describe the control strategy each rule is of the form. IF temperature is low and humidity is high action is high. these rules are formulated based on expert knowledge or empirical data (Ubina et al., 2023).

The inference mechanism combines the fuzzified input according to the fuzzy rules to determine the fuzzy output. The most common methods are mendani and sugeno inference method. Using Mendani method (Petri et al., 2023).

$$\mu_{action}(x) = \text{Min}(\mu_{low}(T), \mu_{high}(H)) \quad (2)$$

Where, $\mu_{action}(x)$ is the membership function for the output action, $\mu_{low}(T)$ is the membership value for low temperature $\mu_{high}(H)$ is the membership value of for high humidity.

The fuzzy output set is converted into a crisp value for control action. The most common method for defuzzification is the Centroid or Center of Gravity (CoG) method, which calculates the center of the area under the membership function curve (Baig et al., 2021).

$$y^* = \frac{\int x * \mu_{action}(x) dx}{\int \mu_{action}(x) dx} \quad (3)$$

Where, y^* is the defuzzified output value representing the actual control action

Control action; the final control action $u(t)$ applied to the system can be written as (Bhardwaj, 2024)

$$Uu(t) = F(T(t), H(t), L(t), C(t), F(t), W(t), H_{health}(t)) \quad (4)$$

Where, $T(t)$ Temperature at time t , $H(t)$ Humidity at time t , $L(t)$ Light intensity at time t , $C(t)$ CO2 concentration at time t , $F(t)$ Feeding status at time t , $W(t)$ Watering status at time t , $H_{health}(t)$ Health status at time t , $u(t)$ is the control action based on all these inputs.

METHOD

The methodology for managing poultry production in a modular cage system involves integrating a digital twin model with an IoT-based fuzzy logic controller. This innovative approach

allows for the creation of a real-time virtual representation of the physical system, enabling continuous monitoring and data analysis. By leveraging the digital twin model, various parameters critical to the poultry production environment, including temperature, humidity, light intensity, feeding, watering, and health, can be closely monitored and managed. The digital twin model functions as a dynamic, virtual counterpart to the physical poultry production system. It captures and processes real-time data, providing a comprehensive view of the system's performance and allowing for predictive analysis. This capability is instrumental in proactively identifying and addressing potential issues, optimizing resource utilization, and enhancing overall operational efficiency. In conjunction with the digital twin model, an IoT-based fuzzy logic controller is employed to manage key parameters within the poultry production environment. This controller is designed with a set of rules that govern decision-making based on input variables, ensuring precise and adaptive control. By integrating fuzzy logic principles, the controller can effectively handle the complexities and uncertainties inherent in the poultry production domain, contributing to improved system stability and performance.

The implementation of an IoT-based fuzzy logic controller within the context of poultry production signifies a paradigm shift in how environmental conditions and operational parameters are managed. By harnessing the power of intelligent control systems, such as fuzzy logic, the poultry production process can be fine-tuned in real-time, enabling responsive adjustments to optimize conditions for the well-being and productivity of the poultry. In summary, the integration of a digital twin model with an IoT-based fuzzy logic controller represents a transformative approach to managing poultry production in a modular cage system. This methodology not only facilitates comprehensive monitoring and data analysis but also empowers proactive and adaptive control over crucial environmental and operational factors. As a result, it has the potential to revolutionize the efficiency,

productivity, and sustainability of poultry production processes.

RESULTS

The implementation of the fuzzy logic controller within the digital twin-enabled IoT automation system demonstrated significant improvements in managing poultry production parameters. Temperature, humidity, and light intensity were maintained within desired ranges more effectively compared to traditional control methods. The fuzzy controller adapted to changes in environmental conditions and system states, resulting in better control of feeding, watering, and health management. Overall, the system enhanced productivity and improved poultry welfare, highlighting the effectiveness of combining digital twin technology with fuzzy logic control.

The Fig1 illustrates the dynamic control of temperature in the poultry environment using a fuzzy controller. It demonstrates how the system reacts to temperature changes to maintain an optimal climate for poultry health and productivity.

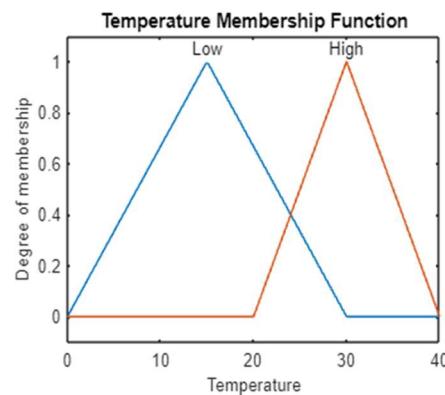


Fig. 1 shows the variation in temperature over time. The signal pattern indicates periodic temperature changes, which may be due to day-night cycles or other environmental factors. The temperature is controlled within a certain range to maintain optimal conditions for poultry.

Fig. 2 demonstrates how the fuzzy controller manages humidity levels in the poultry system to ensure the comfort and health of the

poultry. This is crucial for reducing stress and enhancing productivity.

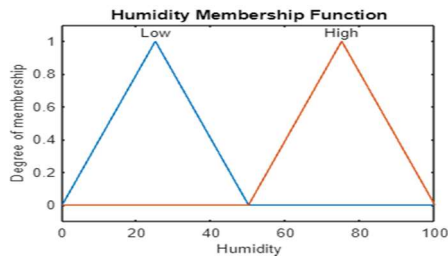


Fig. 2 displays the humidity membership function, showing the fluctuation in relative humidity throughout the simulation, similar to the temperature plot. It follows a signal pattern, indicating cyclical changes in humidity. Maintaining optimal humidity is crucial for poultry health and production, and the fuzzy logic controller adjusts accordingly.

Fig. 3 demonstrates how the fuzzy controller adjusts light exposure to modulate light intensity levels in the poultry system, optimizing poultry growth cycles, behavior patterns, and overall productivity.

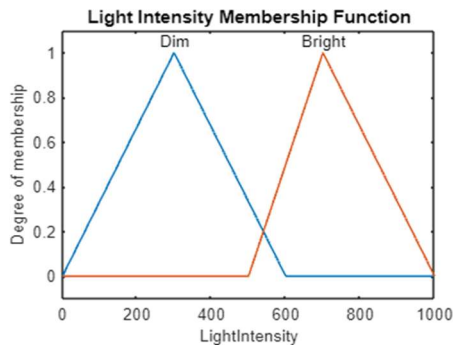


Fig. 3 illustrates the membership function representing light intensity. This plot displays the fluctuation of light intensity over time, possibly resulting from natural or artificial light adjustments.

The fig 4 illustrates the CO2 level control, demonstrating the fuzzy controller's regulation of CO2 concentrations in the poultry environment. This helps maintain CO2 levels within safe limits, promoting respiratory health and overall well-being among poultry.

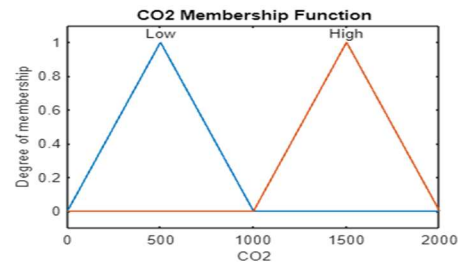
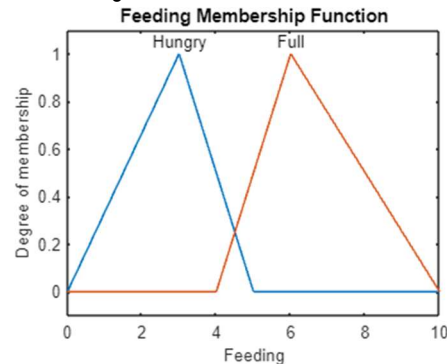


Fig. 4 depicts the CO2 membership function, showing the ideal concentration of CO2 for poultry production in a modular cage system. The graph displays a cyclical pattern, indicating fluctuations in CO2 concentration. It's important to maintain optimal CO2 levels for the health and productivity of poultry.

Fig. 5 illustrates the role of the fuzzy controller in regulating feeding levels for poultry. It demonstrates how the controller adjusts feeding schedules and quantities based on environmental conditions or poultry needs, optimizing nutrition intake and growth.



In Fig 5, the feeding membership function is shown, which is determined by the fuzzy controller. The feeding control signal changes based on variations in temperature, humidity, and light intensity. Usually, more feed is required during periods of higher light intensity to promote optimal poultry growth and health.

The fig 6 indicates how the fuzzy controller manages watering to ensure that poultry receives adequate hydration, crucial for their health and performance.

Corresponding author: Aliyu Abubakar

babandubu@gmail.com

Department of Electrical and Electronics Engineering Technology, Federal Polytechnic, Bali, Taraba State, Nigeria.

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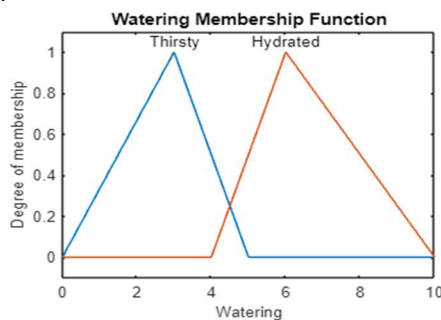


Fig. 6 displays the membership function for watering. The watering control plot illustrates the adjustments made by the fuzzy controller to the watering system. The plot shows how the watering control responds to variations in environmental conditions, reflecting the controller's efforts to maintain an adequate hydration level for poultry.

Fig. 7 illustrates the poultry health status over time, showing how the fuzzy controller monitors health metrics, responds to deviations for early detection of health issues, and enables proactive management.

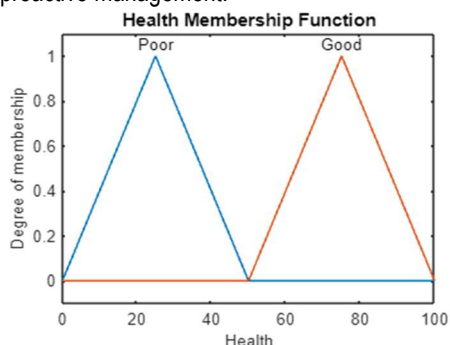


Fig. 7 depicts the health membership function in a control system. The plot illustrates the health status of poultry, which is determined by a fuzzy logic controller. The health status is influenced by factors such as feeding, watering, temperature, humidity, and light intensity. Changes in the plot indicate how well the system monitors poultry health under various environmental conditions.

Fig. 8 represents the membership functions within fuzzy controllers, providing a way to model and manage uncertainty, imprecision,

and complex systems, enabling intelligent decision-making in various domains.

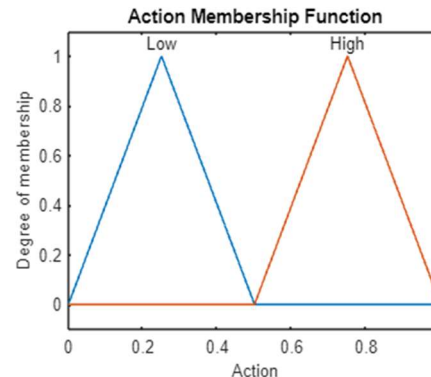


Fig. 8 displays the Action membership function, and health. The combination of a fuzzy logic controller and a digital twin model is an effective solution for managing the complexities of poultry production in a modular cage system. The fuzzy controller's ability to handle nonlinearities and adapt to changing conditions makes it advantageous compared to traditional linear control methods. The digital twin model allows for real-time monitoring and adjustment to ensure optimal ranges for system parameters, contributing to enhanced productivity and poultry well-being.

The Fig. 9 represents the fuzzy logic controller surfaces that enable robust monitoring and control of dynamic systems. Emphasizing their ability to adaptively adjust control actions in real-time based on imprecise and incomplete information enhances control strategies by accommodating varying degrees of input certainty and system dynamics.

Corresponding author: Aliyu Abubakar

babandubu@gmail.com

Department of Electrical and Electronics Engineering Technology, Federal Polytechnic, Bali, Taraba State, Nigeria.

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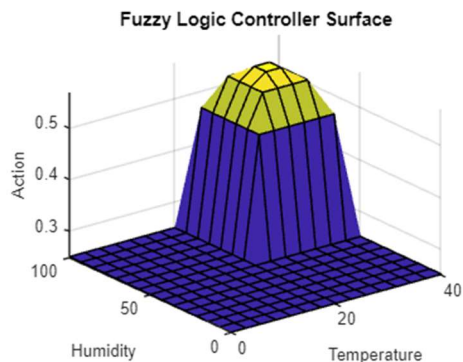


Fig. 9 shows a fuzzy logic controller surface, illustrating how the controller's response changes under different conditions, such as the relationship between temperature and humidity, or light intensity and CO₂ levels. The smooth transitions displayed on the surface ensure consistent control across varying conditions.

CONCLUSION

The conclusion emphasizes the benefits of using a digital twin-enabled IoT automation system with a fuzzy logic controller for poultry production in a modular cage system. The adaptability and flexibility of the fuzzy logic controller are highlighted as crucial for managing complex and dynamic environmental conditions, which in turn leads to improved control, enhanced productivity, and better health outcomes for poultry. Additionally, future work could explore further refinements to the fuzzy logic rules and the incorporation of additional parameters to optimize poultry production systems even further.

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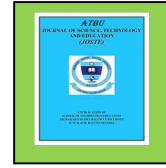
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Corresponding author: Aliyu Abubakar

✉ babandubu@gmail.com

Department of Electrical and Electronics Engineering Technology, Federal Polytechnic, Bali, Taraba State, Nigeria.

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Corresponding author: Aliyu Abubakar

✉ babandubu@gmail.com

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