

Soilless Indoor Smart Farming: A Review of Developments and Emerging Technologies in Fuzzy based Self-Optimising Nutrient Management

T.S.Y. Moh^{1,*}, M.C. Tiong^{1,*}, A.C.H. Ting¹, L.A. Wong¹, M.A.A. Ahmad¹, C.C. Koh², S.L. Hii²

School of Engineering & Technology, University of Technology Sarawak, Sibu, Sarawak, Malaysia:

¹Electrical Engineering Programme, ²Food Technology Programme.

*Corresponding Author

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ABSTRACT

Soilless indoor smart farming has emerged as a promising approach to controlled-environment agriculture, offering improved resource efficiency and year-round crop production. This review examines the development of intelligent nutrient management through the integration of Internet of Things (IoT) technologies, artificial intelligence, data analytics, and automated control systems in hydroponic cultivation. Particular emphasis is placed on self-optimising nutrient management, which enables nutrient delivery to adapt to changing crop requirements throughout different growth stages. The review highlights the transition from conventional fixed and manually adjusted nutrient strategies to closed-loop control systems that integrate continuous real time nutrient, environmental, and plant growth information back to the system for further regulation. Although intelligent technologies offer opportunities to reduce nutrient wastage and improve resource utilisation, the nonlinear and time varying nature of nutrient uptake and plant growth presents significant control challenges. The review further highlights the importance of growth aware control strategies that integrate plant indicators with nutrient and environmental sensing to support adaptive and autonomous soilless farming systems.

Keywords— Autonomous Farming System, Smart Farming, Fuzzy Logic Control, Nutrient Control, Self Optimizing Control

INTRODUCTION

Soilless indoor smart farming represents a transformative shift in agricultural practice, utilizing controlled-environment cultivation to mitigate the escalating pressures on global food security caused by land degradation and climate instability [1-3]. By integrating IoT sensor networks and advanced automation, these systems facilitate highly efficient resource management and year-round crop productivity regardless of external environmental volatility [4-5]. Within this paradigm, the development of self-optimising nutrient management has emerged as a primary technological challenge, necessitating the precise, automated adjustment of ion concentrations to align with the dynamic physiological requirements of crops throughout their growth cycles [6]. Advanced intelligent systems now leverage machine learning and deep neural networks to process high-frequency data streams, enabling the real-time recalibration of hydroponic solutions to minimize waste and optimize uptake [7]. These innovations bridge the gap between static fertigation models and autonomous, closed-loop architectures, allowing for the circular reuse of nutrient solutions that significantly reduces both operational costs and environmental footprints [8-9].

By shifting from reactive monitoring to proactive algorithmic control, these systems address the inherent complexity of maintaining chemical equilibrium in aquaponic and hydroponic environments [10-11]. Integrating these intelligent control frameworks with robust sensing technology ensures that nutrient delivery is no longer a static calibration but a dynamic response to real-time plant demand [12-13]. Furthermore, this evolution toward intelligent environmental control facilitates a cohesive integration of sensors, artificial intelligence, and automated actuators that continuously collect key parameters data for later processing in indoor soilless farming

architectures [14]. This integration of predictive modeling and real-time sensing effectively mitigates the risk of wastage thus ensuring that recirculated solutions maintain optimal chemical profiles throughout the crop cycle [15-16]. This paradigm shift towards intelligent, sensor-informed systems addresses the inherent limitations of static input control, which historically failed to reconcile the dynamic interplay between nutrient uptake rates and fluctuating microclimatic variables [17-18]. Recent advancements in IoT (Internet of Things) systems have enabled the tight coupling of these computational intelligence modules with physical actuation layers, ensuring that real-time responsiveness remains at the core of resource optimization [19]. By leveraging IoT-interfaced miniaturized ion sensors and cloud-based data management, these next-generation architectures transform traditional hydroponics into precision-engineered production ecosystems [20].

Central to this technological progression is the challenge of self-optimizing nutrient management, which requires moving beyond traditional farming of nutrient replenishment strategies to address the complex, non-linear kinetics of nutrient uptake [21-22]. These intelligent agricultural frameworks integrate controlled environment systems with IoT-enabled automation to minimize resource wastage and enhance crop productivity [23-24]. Through this integration, these systems establish a closed-loop "feedback optimization" cycle that continuously reconciles crop growth indicators with environmental control measures [25]. This synergy of data analytics and automated actuation allows for the continuous refinement of growth parameters, effectively transforming hydroponic setups into responsive, self-correcting ecosystems [26-27].

This evolution represents a significant shift in industrial agriculture, as IoT-integrated sensors and machine learning algorithms move beyond simple monitoring to provide fully automated, predictive adjustments that maximize sustainability [28-29]. Such advancements address the persistent limitations of manual oversight in vertical hydroponic systems, where traditional labor-intensive practices often impede large-scale resource efficiency [30-31]. By integrating real-time data analytics with automated nutrient delivery, these intelligent platforms ensure that growth conditions remain optimal regardless of operational scale or crop variety [32-33]. This integration of autonomous systems not only diminishes reliance on manual labor but also enhances the overall scalability and ecological viability of vertical farming within urbanized environments [34-35].

Type of Soilless Indoor Farming Systems

The classification of these systems often centers on the medium used for root support and the methods employed for nutrient solution delivery, such as deep water culture, nutrient film technique, or aeroponics [36-37]. These frameworks are generally categorized by the method of nutrient delivery to the root zone, ranging from passive wick systems to active techniques like Nutrient Film Technique, aeroponics, and deep water culture [38]. Each methodology presents unique requirements for solute distribution and hydraulic management, dictating the specific architecture required for sensor deployment and automated feedback loops [39]. For instance, the Nutrient Film Technique relies on a continuous, thin flow of nutrient-rich water, demanding high-frequency monitoring of flow rates and electrical conductivity to maintain stable growth conditions [40-41]. Conversely, aeroponic systems utilize high-pressure misting to deliver nutrients directly to suspended roots, necessitating advanced actuator control to prevent root dehydration during system disturbances [42-43]. The selection of an optimal system architecture requires balancing these delivery methods against the specific predictive capabilities of machine learning models to maximize resource utilization and crop yield [44-45]. Figure 1 summarize all types of soilless indoor farming system in the literatures.

Key Parameters for Plant Growth

Soilless indoor farming requires coordinated management of the growing environment, root-zone conditions, and plant response. Environmental conditions regulate the physiological processes that determine crop productivity. Temperature and relative humidity influence photosynthesis, respiration, transpiration, nutrient uptake, and disease development, while light intensity, spectral quality, photoperiod, and daily light integral (DLI) affect photosynthetic activity, biomass accumulation, and plant morphology. Carbon dioxide (CO₂) availability supports carbon fixation, while adequate air movement promotes gas exchange and helps maintain a uniform canopy microclimate [46-47]. Collectively, these factors determine the conditions under which plants can efficiently utilise water and mineral resources.

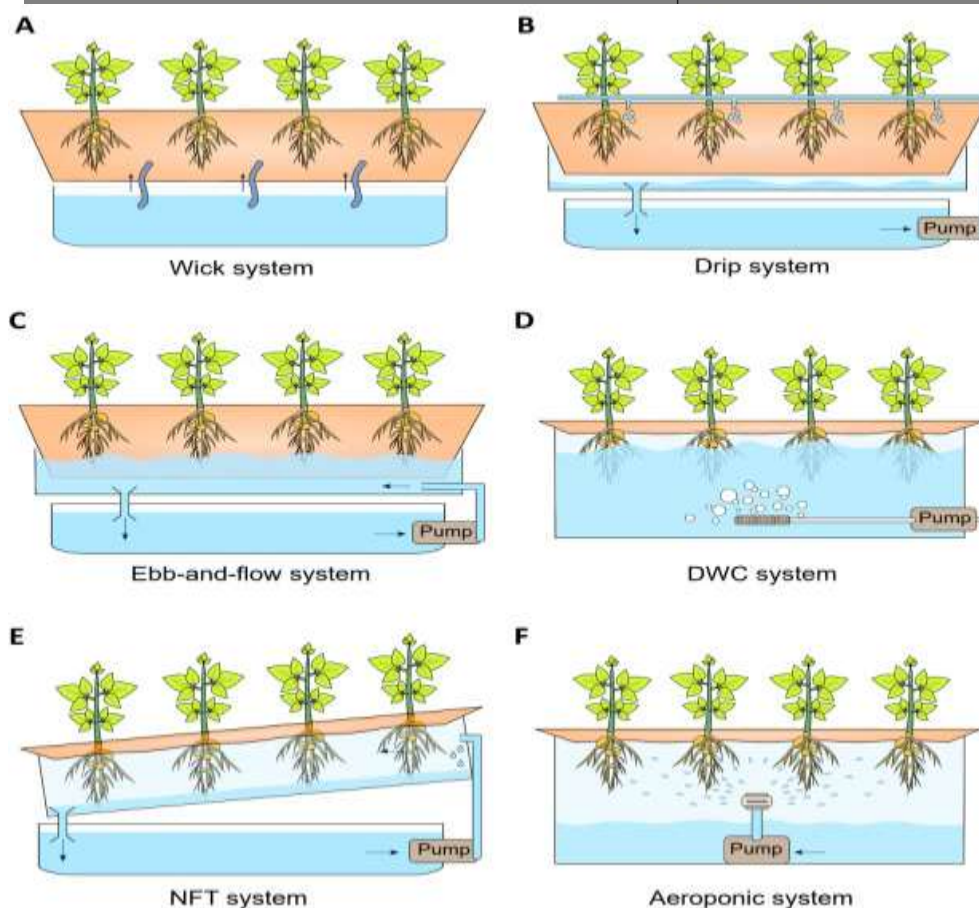


Figure 1: Type of soilless indoor farming system [1]

The root zone environment directly affects nutrient availability and uptake. Solution pH influences mineral solubility, while EC or TDS provides an overall indication of ionic concentration and helps identify conditions associated with deficiency, osmotic stress, or ion toxicity. Plant growth also depends on an appropriate balance of essential macro- and micronutrients, together with sufficient dissolved oxygen and suitable solution temperature. Water level, flow rate, irrigation frequency, moisture content, and salinity must also be controlled according to the cultivation system to ensure adequate root-zone supply and avoid drying, stagnation, waterlogging, or salt accumulation [22], [48-49]. In recirculating systems, measurements of individual ions and nutrient ratios can further reveal selective uptake and changes in ionic balance.

Plant-based indicators provide an important feedback layer for intelligent control. Leaf area, canopy development, biomass, chlorophyll status, transpiration, growth rate, root-zone condition, and visible deficiency symptoms reflect the integrated response of the crop to its surrounding conditions. When combined with environmental and root-zone measurements, these indicators can be used to assess crop status, estimate changing requirements, and evaluate the effects of control actions. Such feedback enables the system to progressively adjust environmental conditions and nutrient inputs according to observed crop responses, providing a pathway from conventional monitoring and fixed-setpoint control toward adaptive and self-optimising cultivation.

Table I compares the reported operating conditions across studies and reveals a clear distinction between crop types. Leafy greens, including lettuce and basil, are generally maintained within relatively narrow ranges of pH (5.5–7.5), EC (1.5–3 mS/cm), and temperature (18–25 °C), as their production typically focuses on the seedling and vegetative stages without flowering or fruiting [18-20], [50]. In contrast, fruiting crops such as tomato require stage-specific management, with EC and nutrient concentrations generally increased during flowering and fruit development [21]. Thus, leafy greens can be effectively managed using relatively stable control strategies, whereas fruiting crops require more dynamic and adaptive control to accommodate changing developmental and nutritional demands.

TABLE I: KEY HYDROPONIC PARAMETERS AFFECTING PLANT GROWTH AND THEIR DOCUMENTED OPTIMAL RANGES

First Author	Year	Crop Type	Optimal Range of Parameter									Effective for Plant Growth Stage					Reference
			NPK Ratio	pH	EC (m S/cm)	TD S (ppm)	Temp (°C)	D O (mg/L)	Light	RH (%)	CO2 (ppm)	Seedling	Veg etative	Flower	Fruit	Harvest	
Lakhia et al.	2018	Potato	-	5-6	2-2.5	-	15-25	-	-	-	-	✓	✓	✗	✗	✓	[51]
Palande et al.	2018	Leafy Greens Crop	-	5.5-6	-	-	24-25	-	14h On / 10h Off	-	-	✓	✓	✗	✗	✗	[52]
Hadis et al.	2021	Basil	15-2-20	6	1.2	-	16-21	-	215 ± 5.5	50-60	450	✓	✓	✗	✗	✓	[53]
Thakulla et al.	2021	Lettuce	3-1-4.5	5.5-6.5	1.5-2.5	-	18-21	-	10-15	44	-	✓	✓	✗	✗	✓	[54]
Deng et al.	2022	Aeschynanthus longicalis	3-1-2	-	3.5	-	-	-	-	-	-	✓	✓	✗	✗	✗	[55]
Shareef et al.	2024	Lettuce	-	5-7.5	0.8-3.5	500-1800	18-30	3-10	80-600	40-80	450-1200	✓	✓	✗	✗	✓	[46]
Tupili et al.	2024	Tomato	Veg: 7-9-5 Flower: 5-15-14 Fruit: 5-15-14	5.5-6.5	2-5	Veg : 1715 Flower: 2380 Fruit: 2730	-	-	-	-	-	✓	✓	✓	✓	✗	[56]
Sharkey et al.	2024	Bibb Lettuce	4-1-5	5.5-6.5	-	-	21.5	-	14.69	50-70	-	✓	✓	✗	✗	✓	[57]

Nutrient control system in hydroponics

Maintaining appropriate nutrient conditions is essential in hydroponic systems because EC, pH, and nutrient concentrations continuously change due to plant uptake, evaporation, dilution, and microbial activity [58]. These variations have motivated the use of feedback control loops, in which sensor measurements are compared with predefined setpoints and corrective actions are applied through pumps or valves [59]. This feedback principle forms the basis of both conventional and automated nutrient-control strategies. Figure 2 illustrates the general feedback-control structure commonly applied to hydroponic nutrient management.

Nutrient-control approaches have evolved from manual monitoring to closed-loop automated systems [14], [60]. Manual control relies primarily on operator judgement, with EC or TDS measured using handheld instruments before nutrients or water are added [60]. On-off control automates this process by activating nutrient pumps

when EC falls below a predefined threshold. Although simple and capable of satisfactory EC regulation, it can cause oscillations and prolonged stabilisation periods [61]. PID controllers provide more continuous control through proportional, integral, and derivative actions, enabling smoother responses and reduced steady-state error. However, their performance remains sensitive to controller tuning, particularly the trade-off among stability, overshoot, and response time [62]. Comparative studies further demonstrate differences in controller performance. Solahudin et al. reported that on–off control achieved a Mean Absolute Percentage Error (MAPE) of 0.82 for EC regulation at low EC concentrations, indicating its suitability for relatively simple applications [61]. Nurmahaludin et al. found that PID control provided better accuracy than PI and PD control, with a reported error of 0.83 and delta error of 1804, compared with a delta error of 16194 for PI and an error of 8.49% for PD [62]. Despite these advantages, conventional controllers generally respond to deviations from predefined setpoints rather than to changes in crop requirements. Their limited use of plant physiological feedback restricts their ability to adapt to dynamic growing conditions and changing nutrient demands, highlighting the need for more intelligent and crop-responsive control strategies.

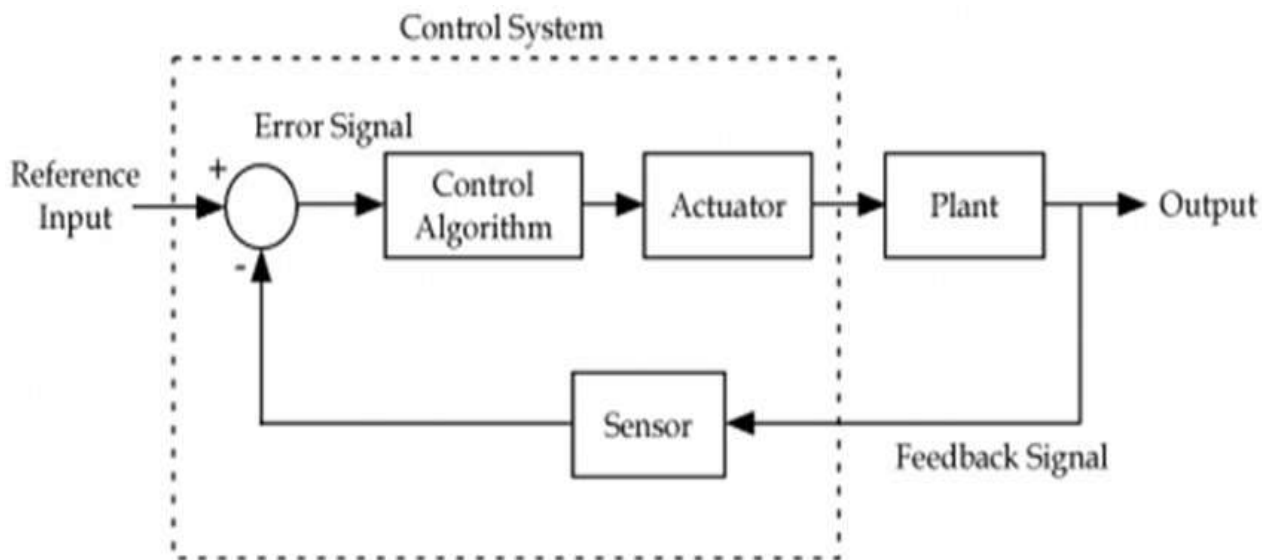


Figure 2: Feedback Control System Block Diagram [30]

The Internet of Things (IoT) has turned standalone hydroponic rigs into connected, intelligent systems [63]. A steady data stream between physical sensors and cloud services supports real-time monitoring, remote control, and data-driven decisions that keep nutrient conditions near optimal [64-65]. Recent work shows the value of IoT-based management. Anjaneyulu et al. built a cloud platform on Arduino Nano and ESP32 boards with NPK sensors that send live data to Google Firebase for analysis [64]. Lamsal et al. presented the low-cost Medhayantra NodeMCU-Azure system, which costs 5 to 18 times less than commercial equipment [66]. Nguyen et al. ran a three-layer IoT design with pH, EC/TDS, temperature, humidity, and light sensors, moved the data over ZigBee to a NodeMCU gateway, and showed it on a Node-RED cloud dashboard [67].

The overall design of an IoT-based hydroponic system usually falls into five layers. which are Layer 1: Perception Layer. This layer meets the hydroponic environment. It carries pH, EC, TDS, temperature, humidity, and water-level sensors; microcontrollers such as Arduino or NodeMCU that acquire and preprocess the data; and actuators such as pumps and valves that apply the control action [45], [68]. Layer 2: Communication/Transport Layer. This layer moves data between the field devices and the cloud. It holds the IoT gateways, wireless networks, and cloud servers that route data, process protocols, and manage the connection [45], [68]. Layer 3: Processing Layer. This layer stores, analyses, and processes the data, which lets vendors offer different services [69]. Layer 4: Application Layer. Top-level cloud platforms store, visualise, and analyse the data and give users dashboards or mobile apps to monitor remotely, raise notifications, and regulate nutrient dosing and ambient conditions [68]. Layer 5: Business Layer. The IoT system handles the business and profit-model applications in a user-friendly, privacy-preserving way [69]. IoT integration strengthens nutrient control through steady sensing, cloud analytics, and automated actuation, and it forms the base for the AI-driven self-optimising systems discussed next.

The emergence of Artificial Intelligence (AI) has further propel higher ground in hydroponic nutrient management for the adaptive, predictive control that traditional strategies cannot reach [70]. AI models the complex, nonlinear coupling among EC, pH, temperature, and nutrient concentration and optimises plant nutrition as conditions move [34], [71]. Figure 3. traces how agricultural technology has grown toward AI-powered decisions.

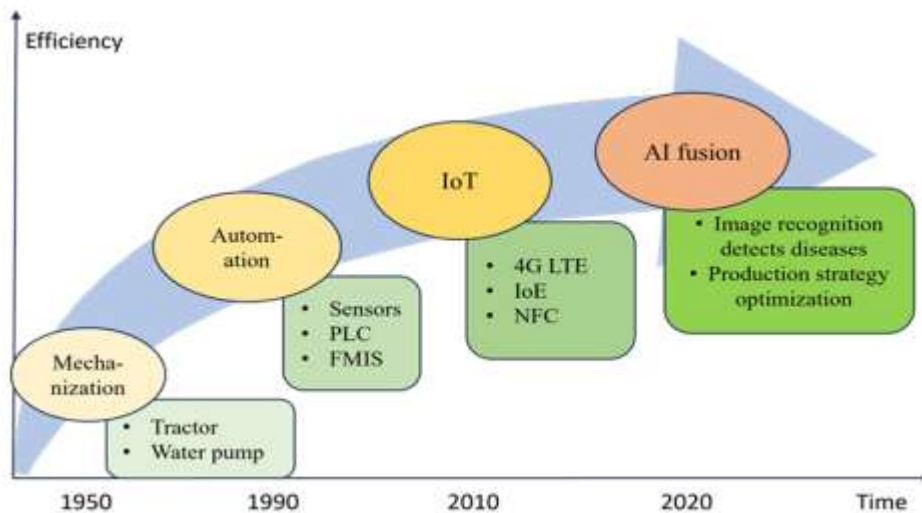


Figure 3: The trends of methods used in agriculture [72]

Comparative studies separate conventional control, untrained AI, and trained AI. On-Off and PID controllers [29], [73] give acceptable accuracy but bend little to multi-parameter change. Untrained AI raises plant growth and energy efficiency: the expert system in [74] and the fuzzy controller of Aisyah et al. offer interpretable, rule-based, resilient multi-parameter control [71]. Khafajeh et al. sharpened the adaptability further, tuning a fuzzy controller with a genetic algorithm to cut settling time from 72 to 64 minutes and to hold temperature and humidity tighter [75]. Untrained AI models thus strike a practical balance between interpretability and control, which carries them into real-time hydroponic use. Trained AI reaches the highest accuracy and adaptivity. Herman et al. classified nutrient state at 93.3 percent with k-NN [76], and Vincentdo et al. found ANFIS 67 percent more accurate than a Sugeno fuzzy system [77]. Usman et al. held environmental variables inside 2 percent error with a neural controller, ahead of a threshold scheme [78]. On harder pattern-recognition tasks, the deep convolutional network of Pandian et al. reached 99.97 percent accuracy in plant-disease detection [79]. Trained AI methods thus read as more accurate, flexible, and predictive across complex hydroponic control. Table II compares traditional control against AI methods and sets out the gains that intelligent control brings to hydroponic nutrient management.

Intelligent Control Techniques

Fuzzy Logic Control (FLC)

Fuzzy Logic Control (FLC) copies human reasoning and handles the uncertainty and imprecision of a system head-on [80]. Binary logic reads a condition as true or false; fuzzy logic reads it as partly true, with a value between 0 and 1 [81]. That property suits hydroponic systems, where operators state the control variables in words such as slightly low pH or optimal nutrient level [32], [70]. FLC encodes expert knowledge as plain IF-THEN rules and reaches flexible, adaptive decisions without a precise model of the system [51], [82].

Architecture and Working Principle of Fuzzy Logic Controllers

Fuzzy Logic Control (FLC) is a smart control method which is an imitation of human rationalities in that it explicitly manages uncertainty and system variables imprecision [83]. Opposite to the binary logic, which considers conditions to be true or false, fuzzy logic considers them to be partially true with a value between 0 and 1 [84]. This property makes FLC especially applicable to hydroponic systems, where the control variables

may be generally specified linguistically, e.g., slightly low PH or optimal nutrient level in the solution [15], [22]. FLC can allow flexible and adaptive decision-making by encoding expert knowledge as simple IF THEN rules without the need to have a precise mathematical model of the system [66-67].

A Fuzzy Logic Controller works under a systematic arrangement to transform exact sensor readings into knowledgeable management activities [85]. The FLC architecture as shown in Figure 2.5 has four primary phases namely fuzzification, fuzzy rule base, inference engine and defuzzification [86]. Combined, these phases recreate the process of human decision-making, which converts numerical inputs into language-based reasoning and translates it into control instructions.

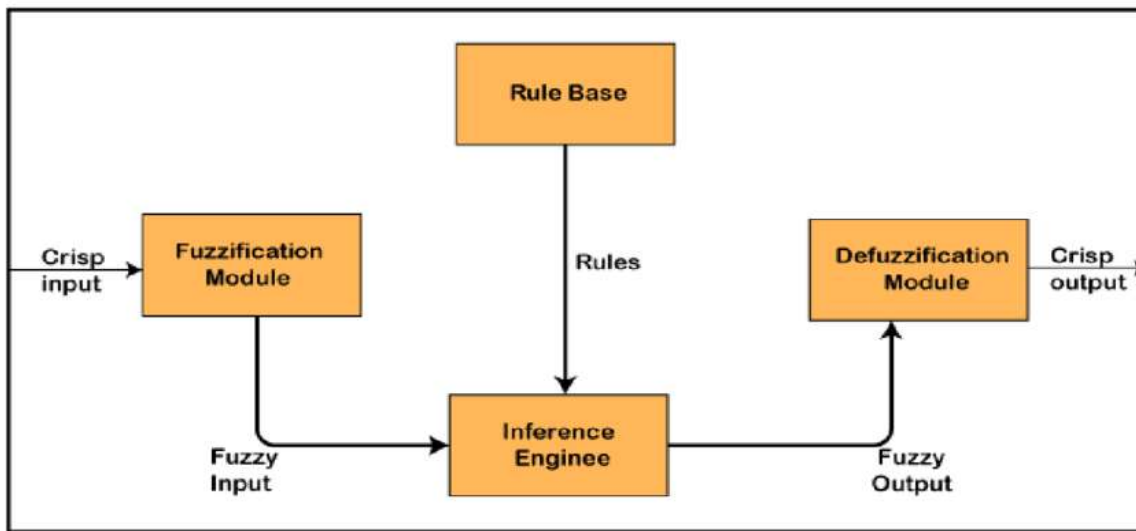


Figure 4: Fig. 1.Architecture design of Fuzzy Logic System [87]

Table II. Comparison Of Conventional And AI-Based Nutrient Management Systems

First Author	Year	Method Category	Control Method	Microcontroller	Sensors	Actuator	IoT	Key Performance			Reference
								Error	Range	Settling Time	
Nurmahaldin et al.	2022	Conventional Method	PID	Arduino	TDS & Temp	Nutrient & Water Valve	✗	0.83% Delta Error: 1804	600ppm	-	[73]
Solahudin et al.	2023	Conventional Method	On-Off	Raspberry Pi 4	EC	Peristaltic Pump A, B (Nutrient mixing)	✓	MAPE: 0.82% RMSE: 4.62	300ppm – 1000ppm	7210 sec	[88]
Saputra et al.	2017	Untrained AI Based	Expert System	Arduino Mega 2560	pH, EC, Temp, Ultrasonic	7 Water Pumps, Cooling Fan	✓	-	-	23 minutes	[74]
Khafajeh et al.	2023	Untrained AI Based	GA - Fuzzy	Custom Board (C++/Proteus)	Temp, Humidity, CO ₂ , Light	Heater, Fan, Pad, Mister, CO ₂ Injector	✗	Day Temp: +6.2°C, RH: 14.8%	Temp: 19-26°C, RH: 70-80%, CO ₂ : 350-1000 ppm	64 minutes	[75]

Aisyah et al.	2025	Untrained AI Based	Fuzzy Family	Arduino Mega	pH, TDS, BH1750 Light	Solenoid Valves (x3), PWM LED Array	✗	-	pH: 6-8, TDS: 600-900 ppm	10-15 minutes	[71]
Usman et al.	2010	Trained AI Based	NN Family	-	Air Temp, Soil Moist, Radiation, Humidity	Valve	✗	< 2% (Simulation)	-	-	[78]
Herman et al.	2019	Trained AI Based	ML Family	Arduino Leonardo (Sensor) & NodeMCU (Actuator)	pH, TDS, Water Temp, Air Temp & DHT11	5 Water Pumps	✓	6.70%	-	-	[76]
Pandian et al.	2022	Trained AI Based	DL Family	NVIDIA DGX-1 & Mobile	Camera	-	✗	0.03%	-	-	[79]
Vincent-donet al.	2023	Trained AI Based	ANFIS	Raspberry Pi 4 & Arduino Uno (x2)	pH, TDS, Ultrasonic	Peristaltic Pumps (x4), Water Pumps, Aerator	✓	-	pH 5.5-6.5, TDS 600-900 ppm	-	[77]

Fuzzification leads the FLC. It converts crisp numerical sensor inputs into linguistic variables through preset membership functions [51], [82], [89]. Most systems adopt triangular membership functions for their simplicity and low computational cost. Kurniasari et al. and Daud et al. modelled pH, TDS, temperature, and moisture with triangular functions [51], [82] and Catota-Ocapana et al. named them the most common membership-function type in smart farming [70].

Three parameters (a, b, c) fix the shape of a triangular membership function, and the designer sets them against crop-specific needs during design [90]. Most studies write the triangular function in the form reported by Kurniasari et al. [90]:

$$\mu(x) = \begin{cases} 0, & \text{if } x \leq a \\ x - a / b - a, & \text{if } a < x \leq b \\ c - x / c - b, & \text{if } b < x \leq c \\ 0, & \text{if } a > c \end{cases} \quad (1)$$

where x is the crisp input value, a, b, and c set the triangular parameters, and the function returns the membership degree between 0 and 1.

This equation computes the membership degree for each linguistic set (Low, Medium, High) and forms the base for the inference that follows [90]. The fuzzy rule base holds the expert knowledge that defines the control strategy, written as a set of linguistic IF-THEN rules [51], [82]. Each rule ties the fuzzified inputs to the output action the actuator should take [90]. Rule-based reasoning raises reliability in hydroponic nutrient control and guards against improper dosing. Daud et al. built rules where high substrate moisture or poor temperature started a pump, with the output duration set from the readings [82]. Hairu et al. blocked fertiliser dosing once EC ran high or the water level sufficed, and set pump duration from sensor calibration, reaching a maximum EC of 3.5

mS/cm in 75 s [58]. Sensor conditions inside the rules raise reliability and stop over- or under-dosing. The inference engine is the processing core of the FLC. It reads the rule base against the current fuzzified inputs and produces a fuzzy output [89], fixing how far each output action should run from the fired rules and their strengths [90]. The literature treats the Mamdani method as the leading approach in hydroponics for its interpretability and its fit with linguistic rules [56], [59]. A Mamdani FLC fuzzifies the inputs and then runs implication and aggregation to set the output. The output membership function usually takes the form [90]:

$$\mu_{output}(y) = \min(\mu_{input}(x), \mu_{rule}(x, y)) \quad (2)$$

Most implementations use the minimum operator for implication and the maximum operator to aggregate the rules into the final output [58], [90-91]. The experimental record backs the Mamdani FLC as accurate and responsive in real-time hydroponic control, reaching dosing accuracy up to 94.24 percent [92] and pH settling inside 7.27 seconds [93]. Defuzzification turns the fuzzy output into a clear number for the actuators [51], [82]. Agricultural FLC leans on the centroid, or centre-of-gravity, method because it yields a smooth, stable output [51], [82]. The centroid computes the crisp output as [94]:

$$Z = \frac{\sum_{j=1}^n Z_j \mu(Z_j)}{\sum_{j=1}^n \mu(Z_j)} \quad (3)$$

where Z is the crisp output value, Z_j the j -th output value, and the weight is the membership value of Z_j . Centroid defuzzification computes cheaply and stays stable, which suits real-time embedded work.

An Artificial Neural Network (ANN) learns the input-output behaviour of a system directly from data through layers of weighted connections, which lets it follow nonlinear dynamics without an explicit model or a written rule base [91]. The approach needs a large, representative training set, and the learned weights carry no readable meaning, so the resulting controller is hard to inspect or verify [91]. An Adaptive Neuro-Fuzzy Inference System (ANFIS) joins the two ideas: it keeps the IF-THEN structure of a fuzzy controller and tunes the membership-function parameters through neural learning, which adds adaptability while retaining part of the interpretability of FLC [84]. Reported applications in hydroponic nutrient control and in power electronics place ANFIS ahead of a plain fuzzy system on accuracy [77], [83].

Comparative Analysis of FLC, ANN and ANFIS in Control System

A choice of control method rests on how each AI controller behaves under dynamic, nonlinear conditions. Many engineering applications show ANN and ANFIS adapting and settling better than a rule-based FLC, above all where the system changes without pause. Table III collects the quantitative record of four control studies [66], [83] and evaluated each controller against error, rise time, overshoot, and settling time in real settings.

TABLE III. PERFORMANCE COMPARISON OF AI CONTROLLERS ACROSS CONTROL SYSTEMS

First Author	Year	System	Control Method	Key Performance				Reference
				Rise Time	Error	Overshoot (%)	Settling Time	
Moon et al.	2011	Building Thermal Control	FLC	-	SD = 0.22	high	slow	[91]
			ANN	-	SD = 0.13	low	fast	[91]
			ANFIS	-	SD = 0.13	low	fast	[91]
Kılıç et al.	2015	Motor Control	PI	0.038s	0.15%	1.2	0.05s	[84]
			FLC	0.035s	0.1%	0.5	0.04s	[84]
			ANFIS	0.035s	0.0%	0.6	0.04s	[84]
Farah et al.	2020	Photo-voltaic MPPT	FLC	-	0.016%	-	0.005s	[83]
			ANFIS	-	0.020%	-	0.011s	[83]
	2024		PID	1.1816%	-	0.5213	1.0052%	[85]

Tuhin et al.	Power System AVR	FLC	1.0091%	-	0.658	0.9993%	[85]
		ANFIS	0.9632%	-	0.9794	0.9816%	[85]

Table III shows the quantitative spread, and a qualitative read adds the characteristics that steer the choice. Table IV sets out the strengths, limits, and resource needs of FLC, ANN, and ANFIS for adaptive hydroponic nutrient control. Meanwhile, Tables III and IV support Fuzzy Logic Control for this project. ANN and ANFIS reach high flexibility and lower error in some applications, yet FLC reads clearer, needs less training data, and drops onto real-time embedded hardware with ease. Its rule base also matches professional hydroponic knowledge, which keeps the system behaviour transparent and simple to verify.

TABLE IV. SUMMARY OF AI TECHNIQUES FOR SYSTEM CONTROL

Feature	Fuzzy Logic Control (FLC)	Artificial Neural Network (ANN)	Adaptive Neuro-Fuzzy Inference System (ANFIS)
Control Approach	Rule-based (IF-THEN)	Data-driven learning	Hybrid rule-based + learning
Interpretability	High – Transparent rule	Low – Decisions are not explainable	Medium – Semi-transparent
Adaptability	Fixed	Self-adaptive	Self-adaptive
Performance Stability	Moderate fluctuation	High stability	High stability

Applications of FLC in Agricultural and Environmental Systems

The structural strengths of FLC show up in wide, successful use across modern agriculture. Over the past decade FLC has handled the complex, nonlinear settings of hydroponic, aquaponic, and greenhouse systems. Table V collects the main results and lines up the control goals, methods, and performance on common ground. These studies [58], [82], [86] show FLC holding pH, EC, water volume, and nutrient level with high accuracy and quick response. They guide the nutrient-control FLC in this work on input variables, rule-base size, and actuator strategy for precise, real-time control. They also share one limit: an engineer tunes the parameters by hand. The next section answers that limit through Genetic Algorithm optimisation, which tunes the membership functions and rule weights automatically.

Genetic Algorithm (GA)

A Genetic Algorithm (GA) optimises a population of candidate solutions by copying natural selection and biological evolution [95]. Holland first defined the method: a GA builds a series of candidate solutions across generations through selection, crossover, and mutation [70], [95]. It keeps and recombines the fitter solutions, and it produces more of them, which lifts solution quality over time [96]. The algorithm starts from a generated population. It selects the fitness gains, recombines parent solutions to explore new regions of the search space, and adds mutations to hold diversity and avoid stagnation [72], [97]. A Standard Genetic Algorithm (SGA) searches the space well, yet it can converge early and run slow [97]. Later variants, the Multi-Objective GA (MOGA) and the Non-Dominated Sorting GA (NSGA) family, answer those limits for problems with several conflicting objectives [98].

TABLE V. APPLICATIONS OF FUZZY LOGIC CONTROL IN AGRICULTURAL SYSTEMS

System	Input	Rules	Actuator	IoT Availability	Error	Accuracy (%)	Response / Settling Time (s)	Operating Range / Tolerance	Reference
Ebb & Flow Hydroponics	Temp, Soil Moisture	16 (Mamdani)	Water Pump (PWM)	No	-	-	28-day stable	PWM control 0–98%	[82]

							growth cycle		
Hydroponic Nutrient Control	Error, Δ Error	9 (Sugeno)	Servo Valves	No	-	-	157, 143	5% allowable deviation	[86]
Aquaponics	pH, Turbidity	15 (Mamdani)	Acid Pump, Base Pump, Circulati on Pump	No	Acid: 1.23% , Base: 0.33% , PWM: 4.29%	-	11.10 (alkaline) , 21.41 (acid)	Turbidity reduced from 8.11% to 0.46%	[93]
Greenhouse Chili Control	EC, Water Level	9 (Mamdani)	Fertiliser Pumps A & B	Yes	-	-	Stable EC	EC within $\pm 0.1-0.2$	[58]
NFT Hydroponic s	TDS, Water Volume	16 (Mamdani)	Nutrient Pumps A/B, Solenoid, Drain Pump	No	-	94.24%	829	TDS within ± 15 ppm	[92]
Hydroponic IoT System	pH, TDS, Soil Moisture, Temp, RH	8 (Mamdani)	Fan, Misting, Water & Nutrient Pump	Yes	-	-	< 2 (actuator response)	Latency < 2 s	[90]

A GA runs an iterative evolutionary loop, where each candidate sits as a chromosome of genes that stand for the decision variables [99]. The conventional GA moves through population creation, fitness evaluation, selection, crossover, mutation, and termination, as Fig. 5 shows. The GA opens by creating an initial population at random, often in the hundreds or thousands, to cover a wide space and hold enough diversity [99]. Research [76], [100] shows that seeding part of the population with heuristic solutions speeds convergence, above all on real-valued controller-tuning problems such as PID optimisation. Fitness evaluation scores each solution through a preset fitness function, where a higher value marks better performance [101]. In GA-based controller optimisation, the fittest individuals win the higher chance to reproduce, which pulls the population toward better solutions across the generations [101].

Earlier work [99], [102-103] stresses the fitness function as the route to stable, correct control. The Integral of Time multiplied by Absolute Error (ITAE) is a widely used index because it weighs sustained error heavily and sharpens the transient response [103]. ITAE is defined as:

$$ITAE = \int_0^{\tau} t|e(t) dt| \quad (4)$$

where t is time and $e(t)$ is the system error, the difference between the desired setpoint and the actual output.

A GA that minimises ITAE favours short settling and small long-term deviation. This single-objective form tunes the controller parameters well without a complex weighting scheme. The selection operator picks parents by fitness on the survival-of-the-fittest principle and balances exploration against exploitation [104]. Tournament selection is the most common form for its simplicity and strength [105]. A comparative study [104] found tournament selection converging faster and steadier than a proportional method such as roulette-wheel selection, above all were fitness spreads wide. Fig. 6 traces one tournament round. Cross over builds new offspring by mixing the genetic material of the parent chromosomes, and it drives the search in a GA [106]. Single-point crossover suits binary-coded problems but thins diversity in real-valued optimisation [107]. Fig. 7 shows the single-point operation on one pair of parents.

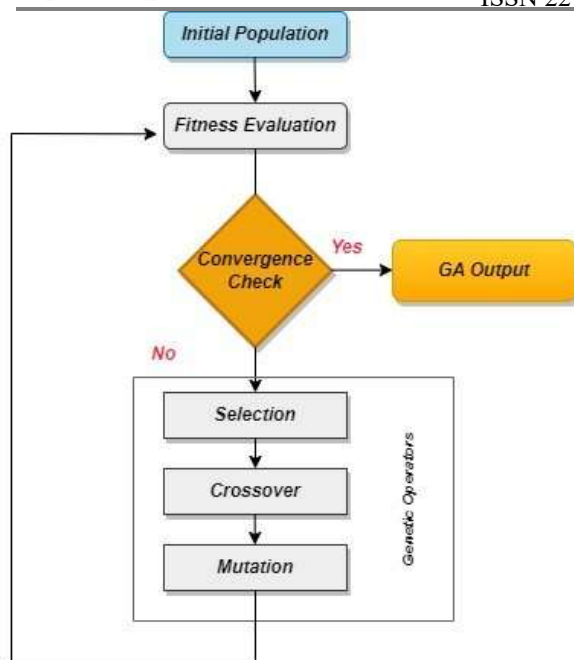


Fig. 1. Workflow of GA [99]

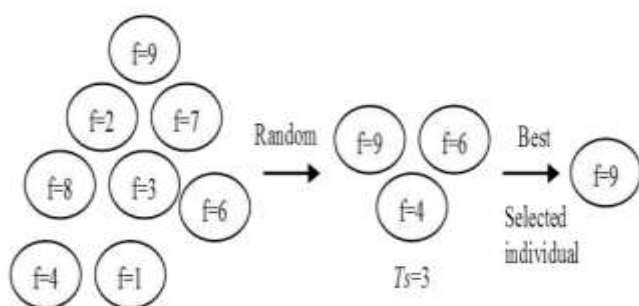


Fig. 2. Tournament Selection [104]

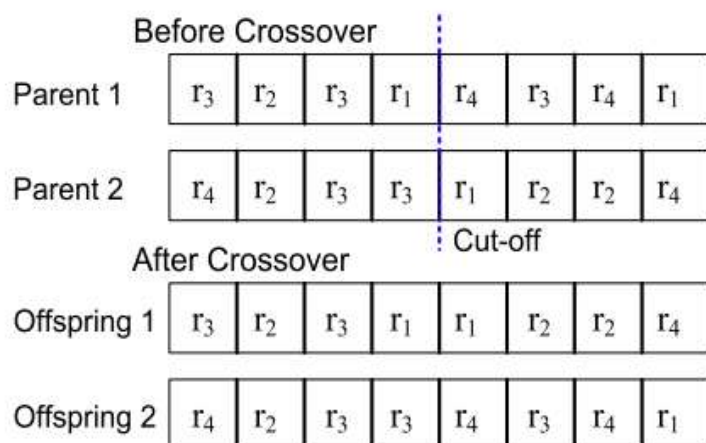


Fig. 3. Single-Point Crossover Technique [106]

For real-valued optimisation, the Simulated Binary Crossover (SBX) of Deb and Agrawal sees wide use [108]. SBX places offspring near the parents, which sharpens convergence on multimodal and multi-objective problems. The following equations govern the SBX offspring [108]:

$$x_i^{(1,t+1)} = 0.5 [(1 + \beta_{qi})x_i^{(1,t)} + (1 - \beta_{qi})x_i^{(2,t)}] \quad (5)$$

$$x_i^{(2,t+1)} = 0.5 [(1 - \beta_{qi})x_i^{(1,t)} + (1 + \beta_{qi})x_i^{(2,t)}] \quad (6)$$

where the parent parameter values and the offspring parameter values relate through the spread factor that controls exploration: a small factor yields similar offspring, and a large factor yields more diverse solutions. The operator holds a firm balance between keeping high-quality parent traits and adding enough diversity for the search across continuous domains [108]. Empirical studies place the optimal crossover probability between 0.6 and 0.95, which balances the spread of good solutions against genetic diversity [109]. Mutation adds random perturbation to the offspring chromosomes, which levels off early convergence and opens the search space [110]. In real-valued optimisation, Gaussian mutation sees wide use, adding normally distributed noise to the chosen genes [99]. Fig. 8 shows the operator acting on a single chromosome. Table VI records how the GA measures up against other tuning algorithms on published error indices.

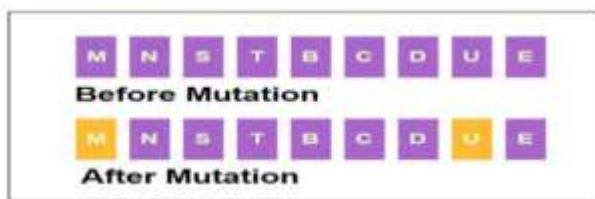


Fig. 4. Mutation Operator [100]

TABLE VI. COMPARISON OF OPTIMISATION ALGORITHMS FOR CONTROLLER TUNING

System	Tuning Method	ISE	ITSE	IAE	ITAE	MSE	Over-shoot (%)	Settling Time (s)	Rise Time (s)	References
Level Control (PID)	GA	5.31 x 10 ⁴	1.4 x 10 ⁶	2.3 x 10 ³	15 x 10 ⁴	-	-	-	-	[111]
Level Control (PID)	PSO	9.3 x 10 ⁴	11 x 10 ⁶	5.8 x 10 ³	89 x 10 ⁴	-	-	-	-	[111]
Level Control (PID)	ACO	5.34 x 10 ⁴	1.5 x 10 ⁶	2.7 x 10 ³	30 x 10 ⁴	-	-	-	-	[111]
AVR System (PID)	GA	-	-	-	0.5445	-	4.54	2.526	0.3438	[112]
AVR System (PID)	PSO	-	-	-	0.6543	-	3.09	2.525	0.3385	[112]
Heating Tank (PID)	GA	0.0008	-	73.18	170.54	0.00023	12.8	17	4.6	[113]
Heating Tank (PID)	CHR (Conventional)	0.0032	-	701.58	884.08	0.00037	36.5	64	4.5	[113]

For real-valued parameters, Gaussian mutation adds normally distributed noise to the selected genes [90], [114]:

$$x'_i = x_i + N(0, \sigma) \quad (7)$$

where the parameter value before mutation, the value after mutation, and the random noise from a normal distribution with mean zero and standard deviation sigma set the mutation size. Table VII sets the same algorithms side by side on their published strengths and limits.

TABLE VII. SUMMARY OF OPTIMISATION TECHNIQUES FOR CONTROLLER TUNING

Feature	Genetic Algorithm (GA)	Particle Swarm Optimisation (PSO)	Ant Colony Optimisation (ACO)	Reference
Optimisation Approach	Evolutionary selection	Swarm intelligence	Pheromone-based exploration	[88], [98], [111], [115]
Convergence Behaviour	Global search, avoids premature convergence	Fast initial, prone to premature convergence	Slow initial, steady improvement	[88], [98], [111], [115]
Performance	High	Low	Medium	[88], [98], [111], [115]
Implementation Complexity	Medium	Low	High	[88], [98], [111], [115]
Limitation	Slow Convergence	Sensitive to parameters	Susceptible to local optima	[88], [98], [111], [115]

Studies [109] place mutation rates of 0.001 to 0.5 at a good trade-off between exploration and convergence, while excess mutation disturbs the evolution. Gaussian mutation works well across many benchmark problems, though it does not beat every other mutation strategy [116]. Termination criteria decide when the GA stops and balance solution quality against computational cost [102]. The common routes cap the number of generations, watch fitness convergence, or set a target performance level [76], [100]. Hybrid criteria that combine several rules usually read best, since they trim wasted computation and hold off early termination in real-valued problems.

Comparative Analysis of GA, PSO and ACO for Controller Tuning

A choice of optimiser for a hydroponic FLC rests on algorithm performance against the control measures that matter. Table VI shows earlier work in which the GA carries lower error indices (ISE, IAE, and ITAE) than PSO, ACO, and conventional methods. PSO tends to run a little worse on overshoot, while the GA holds a better balance of the overall dynamics, with shorter settling and larger ITAE cuts, above all where long-term deviation hurts stability. These traits mark the GA as a strong global searcher and support its use as the key optimiser in this work. Table VII adds the theoretical strengths and limits of GA, PSO, and ACO for hydroponic FLC tuning. Tables VI and VII support the Genetic Algorithm as the FLC optimiser in this hydroponic system. Across a wide range of control applications, the GA beats PSO and ACO on global search, error-reduction consistency, and balanced dynamics. Its guard against early convergence and its handling of nonlinear tuning matter for hydroponic nutrient control, where stable, accurate parameter optimisation is the goal.

Applications of Genetic Algorithm

The GA has spread through engineering and computation on the strength of its global search, its escape from local minima, and its multi-objective reach. Table VIII collects representative studies where the GA tunes control parameters, sharpens decisions, and lifts system performance across fields. Together these studies [94], [101], [117] show the GA delivering measurable gains across control applications: lower error, better accuracy, shorter convergence, and higher success rates. The GA tunes controller parameters, rule structure, and system responsiveness even in a highly dynamic environment. Those numbers mark the GA as a fit optimiser for hydroponic nutrient control, where precise, adaptive change of the parameters holds the nutrients stable.

TABLE VIII. REPRESENTATIVE APPLICATIONS OF GENETIC ALGORITHMS

System	Target	Enc.	Sel.	Cross.	Mut.	Pop. size	Gen.	Crossover probability	Mutation probability	Opt. result	Err.	Success rate	Conv.	Refs.
Neural Network	Weight	Binary	Roulette	Uniform	Bit-flip	50	-	-	-	-	10^{-10} – 10^{-30}	93%	-	[118]
Mobile Robot	Path Planning	Binary	Roulette + Elite	One-point	Point	10	10	0.8	0.05	-	Min. dev	100%	0.48s	[119]
Stereo Vision	3D point matching	Real-Value	Rank-based	BLX- α	-	40	500-700	-	-	-	± 1 pixel	97.45 %	4 min	[117]
Real-time System	Task Scheduling	Priority based	-	-	-	-	50	-	-	-	2045 μ s latency	100%	-	[120]
Hydroponic (Tomato)	EC levels	Binary	Tournament	-	-	10	22	0.6	0.05	EC = 1.4, 10.2, 9.7	-	TSS $R^2=0.92$ Weight $R^2=0.64$	-	[101]

GA-TUNED FLC FOR SELF-OPTIMISING CONTROL

Architectural Framework of the Hybrid GA-FLC System

The hybrid Genetic Algorithm-Fuzzy Logic Controller (GA-FLC) is a meta-heuristic control architecture built for self-optimising behaviour in complex systems. Bonissone et al. define meta-heuristics as high-level strategies that steer or solve lower-level problem-solvers to raise performance and efficiency [121]. In this framework the Fuzzy Logic Controller (FLC) is the object-level controller and the Genetic Algorithm (GA) is the offline meta-heuristic that optimises the FLC structure and parameters [114].

Splitting the roles lets the system handle nonlinearities and uncertainties that defeat conventional controllers. Several studies [75], [98], [122] read GA-FLC systems as more accurate, lower in overshoot, and more robust than hand-tuned FLCs, above all in nonlinear settings with variable parameters. In the first stage the GA automates the FLC design offline, as Fig. 9 shows. It optimises a set of FLC parameters by scoring candidate controllers against performance standards, and the result then runs in real time [121]. The GA develops the controller settings across this evolution, through fitness selection, crossover, and mutation. Mohammed et al. showed a GA-optimised FLC raising photovoltaic efficiency to 96.72 against 96.28 for a conventional FLC by refining its membership functions and rule base [123]. GA-based tuning thus sharpens adaptability and performance through steady refinement of the controller across the generations.

After optimisation the FLC runs on its own in real time on the optimised knowledge base, as Fig. 9 shows. The GA rests at this stage, its offline design done [121]. Review articles read GA-tuned FLCs above traditional FLCs on setpoint stability, undershoot, and transient response. Khafajeh et al. found a GA-optimised fuzzy controller more precise on greenhouse climate, narrowing temperature from 34.25 °C to 31.17 °C and lifting humidity from 39.4 to 60.22 [75]. Shorter settling times backed the gain and marked the GA-FLC as effective in service.

The GA tunes the FLC knowledge base offline through three components that recur across the literature which are outlines below [101], [121], [124]:

1) Scaling Factor. Scaling factors set the intensity of the FLC inputs and outputs and act on stability and response speed. They sit as real-valued genes and tune against an index such as ITAE. Research [125] reports GA-tuned scaling factors cutting overshoot and settling time well below hand-set gains.

2) Membership Function. The GA chromosome carries the membership-function parameters directly. Wang and Bridges showed shape parameters defining triangular membership functions (a, b, c) [126]. The GA searches for the values that raise coverage, overlap, and sensitivity across the operating range.

3) Rule Base. Integer genes carry the fuzzy rule consequents, which the GA develops into high-performance control strategies. Studies [124] show GA-tuned rule bases cutting rule complexity by 30 to 50 percent while holding or raising control accuracy. The process often turns up non-intuitive rules that improve performance under dynamic conditions.

Case Study of GA-FLC in Engineering and Agriculture

Hydroponic Greenhouse Climate Control [75]. Khafajeh et al. used a GA-optimised FLC to control temperature, humidity, and CO₂ in a hydroponic greenhouse through a cascaded fuzzy structure with separate day-night rule sets [75]. The GA tuned the input/output scaling factors and the triangular membership functions offline. The environment settled: daytime temperature fell to 31.17 °C from 34.25 °C, and humidity rose from 39.4 percent to 60.22 percent. The optimised controller also sharpened the transient, cutting settling time from 72 to 64 minutes, rise time from 47 to 38 minutes, and delay time from 34 to 26 minutes. The optimisation ran offline, which left the controller unable to meet seasonality, crop growth phases, and long-term system drift. Table IX sets this case study beside other reported GA-tuned fuzzy applications in engineering and agriculture.

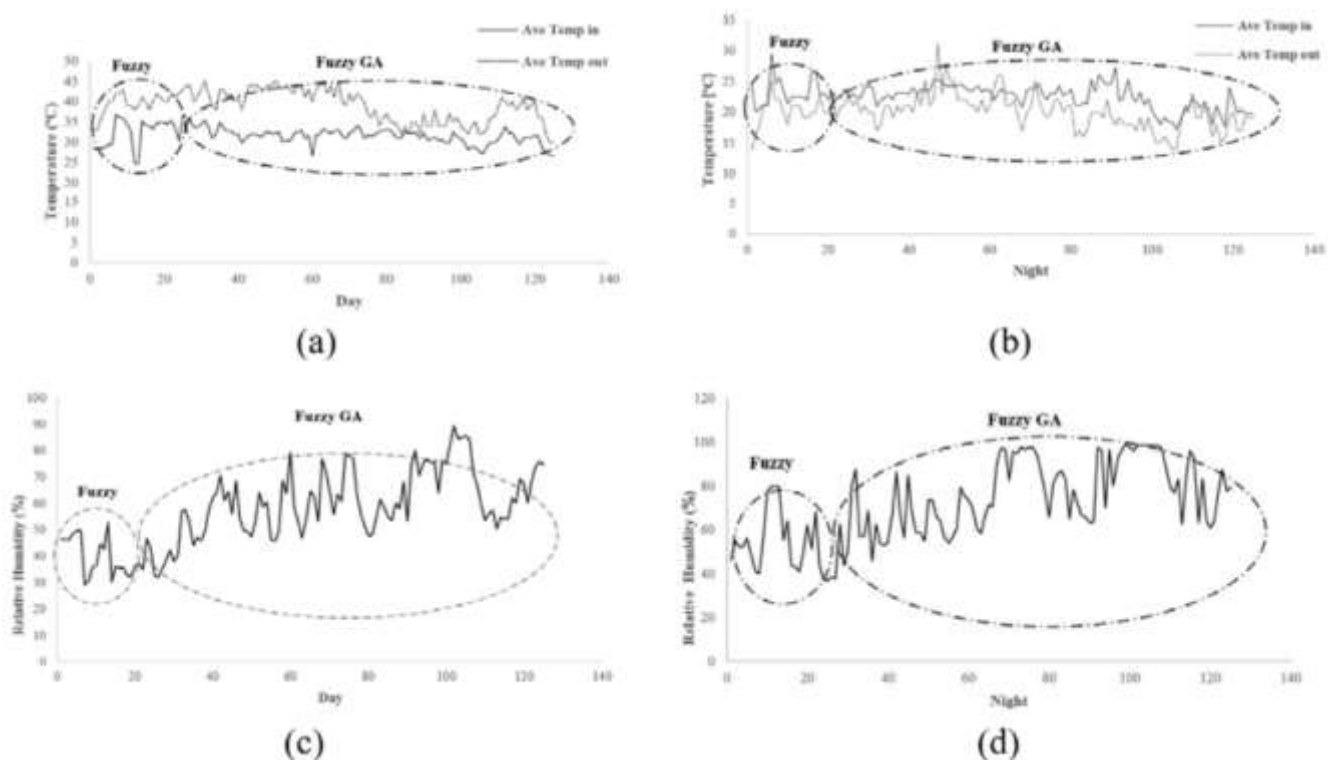


Fig. 5. The greenhouse performance during the cultivation period before and after optimisation [75]

TABLE IX. CASE STUDIES OF GA-TUNED FUZZY LOGIC CONTROL IN ENGINEERING AND AGRICULTURE



Application	Optimised Parameter	Key Performances					References
		Accuracy / Error	Overshoot	Settling Time (s)	Rise Time (s)	Delay Time (s)	
Network IDS	MF Shapes (Z, II, S)	Accuracy increased from 0.74 to 0.81–0.85 Intrusion reduced by 0.31 to 0.00–0.07	-	-	-	-	[126]
Solar PV MPPT	MFs & Rule Base	Efficiency: 96.72%	-	Fast	-	-	[123]
Greenhouse Climate	Scaling Factors, MFs	Error reduced by Temp: 34.25 to 31.17 °C; RH: 39.4 to 60.22%	-	4320 to 3840	2820 to 2280	2040 to 1560	[75]
UAV Trajectory	Input Scaling Factors (Gain)	Error reduced by up to 30%	< 0.5%	< 0.85	-	-	[127]
Microgrid Management	Gains & Fractional-Order (τ)	TDH: reduced by up to 86% V _{dc} Overshoot Error: reduced by 65.7%	-	Fast	-	-	[122]

SUMMARY

In conclusion, this chapter reviewed developments in soilless indoor farming, focusing on hydroponic cultivation, nutrient regulation, intelligent control, and optimisation. While conventional methods such as manual, on–off, and PID control provide increasing levels of automation, they remain limited by fixed setpoints and limited adaptation to changing crop requirements. IoT-based systems improve real-time monitoring but often lack direct plant-growth feedback. These limitations highlight the potential of intelligent approaches, particularly Fuzzy Logic Control (FLC) for handling uncertainty and Genetic Algorithms (GA) for controller optimization. Collectively, these developments demonstrate a clear transition from fixed-setpoint automation toward self-optimizing nutrient management, where environmental, root-zone, and plant-growth feedback can be integrated to enable more adaptive and responsive soilless indoor farming.

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