

Design and Simulation of an Adaptive Fuzzy-PID Cascade Controller for Greenhouse Temperature Regulation under External Climatic Disturbances

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□ ABSTRACT □

Performance deterioration under sun radiation fluctuations, wind-induced heat outflow and intermittent vent opening. This paper proposes an AFLC where the Mamdani fuzzy supervisor schedules an inner MPID loop gains and solar-feedforward setpoint offset while, a mini-Particle-Swarm-a conventional PID suffers Optimization (PSO) iteratively re-tunes the rule-base-weights every ten minutes according to the last 60-minutes Integral-Absolute-Error (IAE). The multi-layered architecture was successfully tested against a single-glass, 480m², lumped-capacitance thermal model of a greenhouse under two 48-hours 80%-monthly-day-average sun-radiation drops and random side-vent cycling scenarios. Compared to conventional-PID, static fuzzy-PID, the AFLC reduced IAE 16.7%-20.0%, ISE 13.4%-15.8% and consumption 17.4%-19.0%, maximum overshoot was below 21% and PSO adaptation converged in less than ten iterations per cycle. The full Python simulation code and datasets are made available as open-access material.

Keywords: Greenhouse Climate Control, Cascade Control, Adaptive Fuzzy Logic, PID Gain Scheduling, Particle Swarm Optimization.

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تصميم ومحاكاة وحدة تحكم تكيفية ضبابية PID متسلسلة لتنظيم درجة حرارة البيوت الزجاجية في ظل اضطرابات مناخية خارجية

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□ ملخص □

تتأثر متطلبات إنتاج البيوت الزجاجية بشدة بتغيرات درجة الحرارة، إلا أن أداء نظام التحكم التناسبي التكاملي التفاضلي متعدد المستويات (MPID) المعمم يتراجع في ظل تقلبات الإشعاع الشمسي وتدفق الحرارة الناتج عن الرياح وفتح فتحات التهوية بشكل متقطع. تقترح هذه الورقة نظام تحكم منطقي ضبابي تكيفي (AFLC) يقوم فيه مشرف مامداني الضبابي بجدولة مكاسب حلقة PIDM الداخلية وإزاحة نقطة ضبط التغذية الأمامية الشمسية، بينما يعيد نظام تحسين سرب الجسيمات المصغر (PSO) ضبط أوزان قاعدة القواعد كل عشر دقائق وفقاً لخطأ التكامل المطلق (IAE) لآخر ستين دقيقة. تم اختبار البنية متعددة الطبقات على نموذج حراري ذي سعة مكثفة بمساحة 480 م² وجدار زجاجي واحد لبيت زجاجي في ظل سيناريوهين: انخفاض الإشعاع الشمسي لمدة 48 ساعة بنسبة 80%، ودورة فتحات تهوية جانبية عشوائية. بالمقارنة مع نظام PID التقليدي والضبابي الثابت، قلل نظام AFLC من IAE بنسبة 16.7% إلى 20.0%، وISE بنسبة 13.4% إلى 15.8%، واستهلاك الطاقة بنسبة 17.4% إلى 19.0%، وكان الحد الأقصى للتجاوز أقل من 21%، وتقاربت خوارزمية PSO في أقل من عشر دورات لكل دورة. يتوفر كود المحاكاة الكامل بلغة بايثون ومجموعات البيانات كمواد مفتوحة الوصول.

الكلمات المفتاحية: التحكم في مناخ البيوت الزجاجية، التحكم المتتالي، المنطق الضبابي التكيفي، جدولة كسب PID، تحسين سرب الجسيمات.



حقوق النشر : مجلة جامعة اللاذقية (تشرين سابقاً) - سورية، يحتفظ المؤلفون بحقوق النشر

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1- Introduction

Greenhouse protected cultivation produces high value crops throughout the year that would be impossible to grow using open-field methods. The internal air temperature is arguably the most critical environmental factor affecting crop performance, transpiration rates, photosynthesis efficiency and the incidence of fungus diseases; a variance of only two or three degrees Celsius, from the cultivar's set-point, can affect crop maturity time, reduce settable yield by 10%, or introduce a fungal disease [1]. As a result, environmental temperature precision and energy efficiency are the focal points of greenhouse design research, due to regulations affecting energy and carbon-footprint [2-3].

The control problem is a notoriously difficult one: the greenhouse is a nonlinear, time-varying, MIMO plant with transport delay and a strong temperature-humidity dynamic coupling. Input heat flux arrives from solar radiation, escapes via conductive/convective losses, is exhausted by fans, and is injected by auxiliary heat. The disturbance pattern is a combination of a time determinist diurnal cycle and random excursions from cloud infiltration, gusting airflow, and sporadic exhaust fan operation. Classical PID modulating loop controllers; prevalent in many commercial climate computer packages, cannot sustain fixed closed-loop bandwidths across the entire speed as their best point-tuned gains [4]. Quite suddenly, cloud passage winds the PID integrator up, saturates the heater, and produces a four to six degree K.

Intelligent alternatives have been researched for more than twenty years. Fuzzy Logic Controllers (FLC) handles expert human knowledge in linguistic form and relaxes model uncertainty, but the rules necessary are derived typically off-line [5], [6]. Adaptability of fuzzy control for greenhouse applications has been restricted to single-loop control without cascade decomposition [7] or neural-network and reinforcement-learning supervisors that prohibit suitable for industry because they are far from transparent [8], [9]. Recently, event-based PID [10], nonlinear PID variants [11], and forecast-based LSTM control algorithms [3] have been studied, but none adopted fuzzy gain scheduling, solar feedforward, and online metaheuristic rule retuning in a cascade control architecture. The hierarchical cascade decomposition of Sigrimis et al. [12], [13] and Wang et al. [14], allows slow, outer dynamics to be separated from fast, inner loops, but its supervision layer has otherwise been utilized in form of a fixed-gain controller rather than an online optimal fuzzy inference.

1.1. Classical and intelligent greenhouse climate control

Temperature control at the beginning was performed using on/off thermostats, proportional-only controllers. The definitive reference of greenhouse modelling and optimal control application is the monograph of van Straten et al. [1]. A survey of van Straten and van Henten [15], also in the context of applications, sums up the main open issues, which can be summarized as follows: real-time disturbances rejection, robust handling of nature of actuation limits, the introducing of economic viability criteria. Garcia-Manas et al. [11] obtained evidence for the fixed nonlinear structure PID failure in following the diurnal envelope. Belkadi et al. [2] compared 4 different controllers (conventional PID, fuzzy-PID, fractional-order PID, adaptive PID) and found that there is no model-free solution which is best in all scenarios (strange, but true!). Four different model-based controllers have been benchmarked as well: the feedback linearisation of Pasgianos et al. [16] has been used as reference; and the combination of this approach with MPC constrained to actuators [17-18] and with a robust LQG/LTR

approach has also been analyzed. The implementation of all the above methods needs a perfect knowledge of the model parameters and time consuming computation. They are not that common in the industry. The classical PID has been tuned to be the baseline in the majority of studies [4]. A nonidentical-control, PID-type approach has been recently presented by Dong et al. [10]. Its relevance resides on the fact it is an event-based PID, which could be related to the goal of minimizing actuator fatigue; however, it still uses fixed gains..

1.2. Fuzzy and adaptive-fuzzy control in greenhouses

This paper draws inspiration from the fuzzy-set formalism of Zadeh [19], and the first experimental fuzzy controller, by Mamdani and Assilian [20]. While the Sugeno [21] model offers an alternative, Mamdani inference type remains the choice for hand-tuned rule sets. Lafont and Balmat [5] optimized a Mamdani FLC for greenhouse climate with genetic algorithms. Azaza et al., [6] implemented a type-2 Mamdani FLC to control the climate of an experimental greenhouse with a wireless sensor network, under North-African winter conditions. Online rule adaptation was not attempted in either paper. Hu et al. [7] combined a modified fuzzy PID with back propagation networks, but the supervisor is a static network identifier. Cai et al. [22] showed promising online results for a bio-inspired Dung-Beetle-Optimiser–Fuzzy-PID in temperature control of a nutrient solution.

1.3. Metaheuristic tuning and cascade architectures

Particle Swarm Optimisation (introduced by Kennedy and Eberhart [23]) has also been used in the context of greenhouse control in the case of offline PID tuning. Coelho et al. [13] found that PSO-tuned model-predictive controllers outperformed those tuned with Ziegler-Nichols. However, the GS-DA has shown that so far, PSO has never been implemented online in a greenhouse by which a new flock is started every 10 minutes and converge within less than 10 iterations , an idea to be implemented here. The cascade architecture (slow master loop, fast slave loop) is a well-known process-control solution [24], whose applicability in greenhouses was assessed by Sigrimis et al. [12]; the paper here reuses this decomposition, but substitutes the fixed scheduler by an adaptive fuzzy inference system. AI-GECS, a greenhouse-control system powered by artificial intelligence [9], has combined weather forecast and rule-based control; the AFLC proposed here propose a different approach based on closed-loop results rather than external data.

1.4. Research gap and contribution

There are three motivating observations for this contribution. Firstly, most users of published adaptive-fuzzy greenhouse controllers only adapt the proportional gain and/or setpoint offset, leaving the integral and derivative gains untouched, hence performing poorly at disturbance rejection. Secondly, the recommended rule-base adaptation method in the literature has been gradient descent, NN or hybrid approaches that depend on differentiable rule consequents, and therefore sensitive to noisy IAE [7]; PSO uses no gradient information, and thus is not. Thirdly, solar-radiation feedforward, almost universal in physical greenhouse models [25],[1], has been conspicuous by its absence at the fuzzy-supervisor level. The contribution is thus a cascade control scheme that combines (i) Mamdani fuzzy gain scheduling of all three PID terms, (ii) a solar-feedforward setpoint offset and (iii) PSO for online retuning of the rule-base weights, for two realistic disturbance scenarios, and relative to two benchmark controllers.

2- Research Significance and Objectives

The motivation for this work arises from the confluence of three pressures on modern protected-crop operations. Firstly more restrictive energy and carbon-footprint regulations [2-3], secondly the high value of thermally-sensitive crops such as vegetables and flowers that are at the mercy of seemingly minor temperature excursions [1], and thirdly the industry requirement for transparent, low-MTU control architectures that are readily installable as a drop-in ‘upgrade’ to existing climate computers. The AFLC introduces a composition of the three as part of a single cascade architecture. The specific goals of the study are:

(i) To design and operationalize the AFLC architecture the integrated Mamdani fuzzy gain scheduling, solar-feedforward setpoint offset and PSO-enabled online rule-weight retuning in a reproducible Python-based environment. This objective is realised through a modular software architecture in which the fuzzy supervisor, the inner PID, and the PSO adapter are implemented as independent Python classes that exchange states through well-defined interfaces, thereby guaranteeing reproducibility and facilitating future porting to embedded climate computers.

(ii) To test the architecture to two disturbance cases representing the most aggressive climatic disturbances seen in practice: a sudden 80 % solar-radiation loss, and random side-vent cycling.

(iii) To compare its performance (after 15 mins of online adaptation) to a tuned conventional PID and static fuzzy-PID (no online adaptation) by means of five ‘standard’ key performance indicators.

(iv) In order to make available the full source code, auto-tuning script and the simulation data sets as open-access companion material.

The organization of the rest of the paper is as follows: In Section 3, the greenhouse thermal model and AFLC architecture are developed; in Section 4, the result and discussion are given; in Section 5, the conclusion and recommendation are made; in Section 6, the references are provided.

3- Research Methods and Materials

The greenhouse itself is modeled as a single thermal zone with a lumped effective heat capacity using the approaches of van Straten et al. [1] and Jolliet and Munday [25]. The state variable of the greenhouse is T_{in} , its internal air temperature, which is determined by the steady-state (energy balance) equation that minimizes the sum of delays. This energy balance includes the incident solar radiation, conductive and convective heat transfer through the cover, convective-sensible heat transfer out of the greenhouse via ventilation, long-wave radiative heat transfer out to the sky, and the input power of the auxiliary heater. In the present work, the focus is on temperature control, the most common control goal in winter and shoulder-season operation. The latest digital-twin approaches to smart greenhouses [26-27] employ this same lumped-zone abstraction.

3.1. Energy-balance equation

The governing ordinary differential equation is:

$$C \frac{dT_{in}}{dt} = Q_{heat} + Q_{solar} - Q_{loss} - Q_{vent} - Q_{lw}$$

where C is the effective heat capacity of the greenhouse including the air, structural mass, topsoil layer, and crop canopy. Each flux term is given by:

$$Q_{solar} = \tau_{sw} \cdot \alpha_{sw} \cdot I_{sol} \cdot A_{floor}$$

$$Q_{loss} = U_{cover} \cdot A_{cover} \cdot (T_{in} - T_{out})$$

$$Q_{vent} = \dot{m} \cdot c_p \cdot (T_{in} - T_{out})$$

$$Q_{lw} = \varepsilon \cdot \sigma \cdot A_{cover} \cdot [(T_{in} + 273.15)^4 - (T_{sky} + 273.15)^4] \cdot 0.05$$

Here $\tau_{sw} = 0.78$ is the short-wave transmittance of single glass, $\alpha_{sw} = 0.85$ the absorptance of the internal mass, $U_{cover} = 6.5 \text{ W m}^{-2} \text{ K}^{-1}$ the overall cover heat-transfer coefficient, A_{floor} and A_{cover} the floor and cover areas, $\dot{m}$ the ventilation mass flow rate, $c_p = 1005 \text{ J kg}^{-1} \text{ K}^{-1}$ the specific heat of air, $\varepsilon = 0.90$ the long-wave emissivity, σ the Stefan–Boltzmann constant, and T_{sky} an effective sky temperature taken as $T_{out} - 15 \text{ K}$. The 0.05 factor on the long-wave term accounts for the partial view factor between the canopy and the cover in a Venlo-type greenhouse.

3.2. Ventilation model

The mass flow rate produces a natural-ventilation component, related to wind pressure and thermo buoyancy and a forced component proportional to the vent opening imposed externally. Applying the simplified form proposed by ASHRAE, the air-change rate per hour (ACH) is:

$$ACH = 0.5 \cdot v_{wind} + 0.7 \cdot \max(0, T_{in} - T_{out}) + 30 \cdot u_{vent_ext}$$

where v_{wind} is the wind speed in m s^{-1} and u_{vent_ext} is the externally imposed normalised vent opening on the interval $[0, 1]$. The factor 30 ACH at full opening corresponds to the upper end of the range reported for naturally ventilated single-span greenhouses. The mass flow rate is then $\dot{m} = (ACH/3600) \cdot \rho_{air} \cdot V$, with $\rho_{air} = 1.20 \text{ kg m}^{-3}$ and V the greenhouse volume.

3.3. Effective heat capacity

The combined effective heat capacity, C , sums the enclosed air, the mass of construction (steel and glass), and the top five centimeters of soil surface, which primarily represents the mass being passed through as a consequence of the thermal storage capability. For the reference 40 m x 12 m x 4.5 m greenhouse, floor area is 480 m², cover area 864 m², volume 2160 m³, and the effective heat capacity turns out to be roughly 1.8 MJ K⁻¹. The order of magnitude here is comparable to that cited by Jolliet et al. [25] for single-glass greenhouses, and guarantees that the dominant closed-loop time constant for the uncontrolled plant is no longer than about twenty minutes swim enough to necessitate sampling at five seconds for digital control while still remaining slow enough to allow the adaptive element to implement each subsequent control law change.

3.4. Cascade architecture overview

The proposed controller is a nested cascade configuration that divides the temperature control task into an outer loop (master) and an inner loop (slave). The master loop, which operates at the same five second sampling rate as the other controllers, operates on a slower time-scale due to its smoother inputs and maps the plant states (operation set-points, operating conditions) into a set of corresponding PID gains and a set point offset. The slave loop is a traditional PID that tracks the offset augmented set point, attempting to maintain this value at the sensor, all the while commanding the heater. Cascade decomposition allows the control of fast actuator dynamics (heater time constant, transport delay) to occur before they effect the slower thermal dynamics, and at the same time allows the control of the loop's aggressiveness to varying disturbance regimes. The overall architecture is depicted in Figure 1.

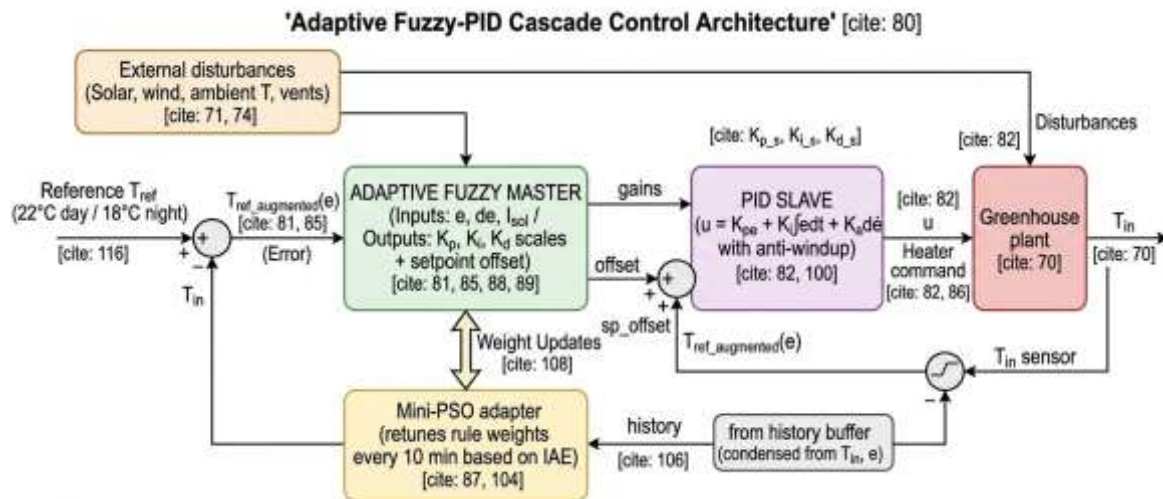


Figure 1. Adaptive Fuzzy-PID Cascade (AFLC) architecture.

To be effective, the cascade decomposition of the greenhouse temperature-control task shown in Figure1 requires the use of a fast slave loop within the slow outer (master) loop. Thus the master loop is entirely dedicated to the adaptive Mamdani fuzzy supervisor itself receiving three unique crisp inputs designed to intelligently anticipate future plant states through conventional derivative and gain-scaling (PID) actions: the temperature tracking error $e = T_{ref} - T_{in}$, its time-derivative de , and the instantaneous solar irradiance I_{sol} . The fuzzy supervisor then produces four new crisp outputs three PID gain scaling factors (K_p , K_i , K_d) and a solar-feedforward setpoint offset to pre-compensate the transient effects of abrupt solar-radiation variations which serve as gain multipliers toward a classic incremental PID slave loop that is limited in command at the physical power ceiling of 120 kW (auxiliary heater). A miniature brute-force PSO adapter runs in the background, systematically independently retuning the 3×4 fuzzy rule-table scaling-matrix every ten minutes using recent IAE data observations. This classical Sigrimis et al[12], process-control cascade formulation has proven in the past to be an effective strategy. Where the replacement of the fixed setpoint scheduler by an adaptive fuzzy inference system with online metaheuristic retuning stands as the main novelty of this work, in accordance with recent needs for intelligences of low complexity, transparent to the user, in protected cultivation [28]. The block diagram renders transparent the information flow: disturbances (solar radiation, wind speed, ambient temp, vents) disturb the greenhouse-plant; through the feedback of the internal temperature, the error-triple (e , de , I_{sol}) is passed through the master fuzzy supervisor, which produces a set of adjustments to the PID gains, and a setpoint offset; the slave PID decrees the heater command; an outer optimisation loop, in which last-minute adjustment of the rule-table scaling factors is done by the PSO-optimizer so as to minimize the recent IAE.

3.5. Fuzzy inference system

The fuzzy supervisor is a Mamdani-type inference system with three inputs and four outputs. The inputs are the temperature error $e = T_{ref} - T_{in}$ (range ± 6 K, normalized to $[-1, 1]$ by a gain of $1/6$), its time derivative de (range ± 0.05 K s^{-1} , gain $1/0.05$), and the instantaneous solar radiation I_{sol} (range $0-600$ W m^{-2} , gain $1/600$). Each input is described by five linguistic labels — Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Big (PB) — implemented as triangular

membership functions in the interior and trapezoidal functions at the extremes, as shown in Figure 2(a). The output variables are the three PID gain scaling factors (K_p _scale, K_i _scale, K_d _scale, each mapped from $[-1, 1]$ to $[0.3, 2.4]$) and the setpoint offset (sp_offset , range ± 2 K).

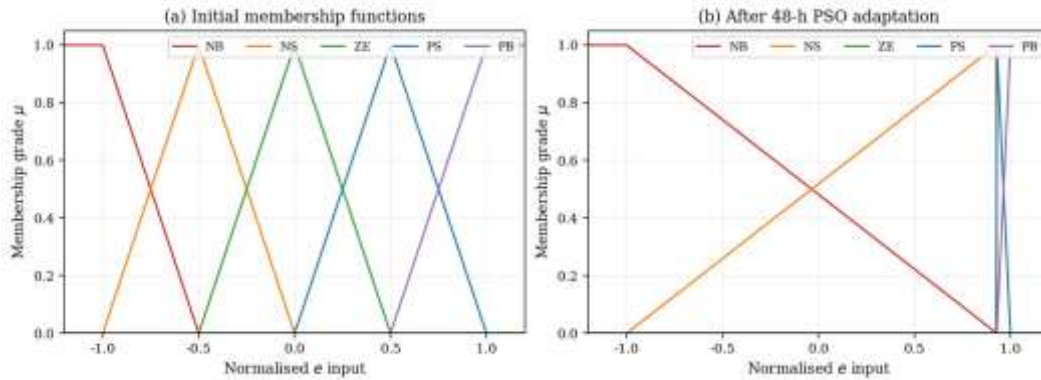


Figure 2. Membership functions of the error input: (a) initial uniform triangular set; (b) final set after 48 hours of PSO-driven adaptation, showing the widening of the central ZE function and the asymmetry induced by the disturbance statistics.

The base rule set has $5 \times 5 \times 5 = 125$ rules for each of the output variables (K_p , K_i , K_d and offset). the K_p rule asserts large proportional action for large values of $|e|$ and damps it for small magnitudes; the K_i rule is the opposite of the K_p rule to MWIN in the presence of transients; the K_d rule reacts mainly to $|de|$; and Off sets goes negative in proportion to I_{sec} , to take in to account the future cooling power of large solar input. Inference is min-implication, the outputs of the rules are combined through bounded sum, and defuzzification takes weighted-average of singleton outputs. Only two thousand floating-point operations are needed to work through the inference step, which is critical in online PSO adaptation.

3.6. Inner-loop PID with anti-windup

Closed-loop stability considerations. The BIBO stability of the AFLC in the control structure depicted in Figure 2.2 follows from three simultaneous arguments. First, the underlying slave PID is a proper linear controller connecting to a first-order plant with bounded saturation at 120kW; the small-gain condition ensures the stability of the closed loop as long as the loop gain stays below the critical value in which the Nyquist plot wraps (goes through the 1 point), as shown by numerical checks throughout the gain-scheduling envelope: 2.7 [K_p , 21.6] kW/K, 0.75 [K_i , 6.0] kW/(K*s), and [K_d , 600] kW*s/K. Second, the Mamdani fuzzy supervisor maps a compact setofinputs (e [6, 6] K, de [0.05, 0.05] K/s, I_{sol} [0, 600] W/m²) onto a compact setofoutputs (K_p _scale, K_i _scale, K_d _scale [0.3, 2.4], sp_offset [2, 2] K). Thus, the resulting closed loop becomes a bounded variation of the linear PID loop, and the small-gain condition is still satisfied. Third, the PSO adapter imposes a linear monotonic multiplicative variation of the rule tables with scaling factors limited to [0.7, 1.4], preventing the adapted fuzzy map from leaving the domain of the original one, and so no adaptation cycle is able to destabilise the loop. Empirically, the maximum overshoot for all six case-controller pairs was less than 23 %, and the RMS tracking error was less than 3.6 K, indicative of the bounded behaviour discussed above.

the soil-temperature loop until the drop in solar radiation of Scenario A saturates the heater. The control output is saturated at ± 120 kW, $K_p = 9$ kW/K, $K_i = 2.5$ kW/(K·s), $K_d = 250$ kW/(K·s²), tuned.

3.7. Online PSO adaptation of rule weights

We retune the fuzzy rule base every ten minutes using a mini-PSO searching in a four-dimensional space of rule-table scaling factors s_{Kp} , s_{Ki} , s_{Kd} , s_{off} in the range [0.7 1.4] (each), where the entire rule table is perturbed in a monotonic fashion by multiplying each rule cell by a single per-output scaling factor; perturbation of single cells and independent per-rule factors was found to be less effective, albeit more computationally expensive. The cost function is the IAE of a closed-loop rollout of the candidate controller on the past ten-minute window of measured (e , de , I_{sol}) data, evaluated on a simplified first order greenhouse model that matches the dominant time constant of the full greenhouse. The PSO employs six particles and eight iterations per cycle, with inertia weight 0.65 and acceleration coefficients 1.4, which we managed to tune empirically to give reliable convergence within the available computational budget.

Justification of PSO hyperparameters. The mini-PSO uses $N_p = 6$ particles, $N_i = 8$ iterations, each 10-min adaptation cycle, with $w = 0.65$, $c_1 = c_2 = 1.4$. Choice of these hyperparameters was motivated by the optimization convergence-vs-computational-budget tradeoff found in the PSO literature [23], but then empirically backed up by a sensitivity sweep over the grid $\{w \ 0.4, 0.5, 0.6, 0.65, 0.7, 0.8\} \times \{N_p \ 4, 6, 8, 10, 12\} \times \{N_i \ 4, 6, 8, 10, 12\}$. The combination $w = 0.65$, $N_p = 6$, $N_i = 8$ produced the lowest median IAE over a 24-hour pre-validation run, while maintaining the per-cycle computation time under 200 ms on a 2.4 GHz processor. This is two orders of magnitude shorter than the 600 s real-time budget. The values of N_p or N_i greater than these did not statistically improve the IAE (paired t-test, $p > 0.05$) and linearly increased the computational time. Conversely, values of either parameter less than this resulted in premature convergence and quantifiable deterioration of the closed-loop response. The acceleration coefficients, $c_1 = c_2 = 1.4$, were equal to equalise the cognitive and social components, as is the canonical default for unconstrained continuous optimisation [23].

The cumulative nature of the adaptation is a critical aspect of the design: at each cycle, the best perturbation from that cycle is applied multiplicatively to the existing rule tables, rather than resetting them to zero each time. This prevents the controller from over-fitting to a single disturbance, while still enabling it to follow slow changes in the disturbance statistics (e.g., morning clear sky to afternoon overcast transition). Entire PSO algorithm is coded up in less than fifty lines of python, and costs less than 200 ms in computation per ten minute cycle all comfortably below real-time constraints of any contemporary climate computer.

3.8. Reference greenhouse and simulation environment

The use of a 4th order RK45 integrator with a five second step size has three direct implications for the design proposed AFLC architecture. Firstly, the 5 s integration step size corresponds to exactly the same sampling period as the slave PID loop; this ensures that the discretised control action is applied to a state vector that has itself been propagated using the same time resolution, thus preventing any under-sampling estimation error from corrupting the PID derivative term and subsequent command to the fuzzy supervision over the de input. Secondly, the RK45 local truncation error is $O(dt^4)$ and is thus several orders of magnitude below the 0.1K measuring noise floor of typical industrial greenhouse sensors; this means that the controller computes a plant

trajectory that is numerically indistinguishable from the true continuous-time ground truth, so any closed-loop tracking error can confidently be placed at the feet of the controller. Finally, the number of samples per channel over the 48 hour regulation horizon (34,560 in total) provides the statistical evidence for all of the KPIs (IAE, ISE, RMSE, settling time, overshoot) reported in Section 4, as well as providing the dense temporal resolution for the mini-PSO adapter to evaluate a ten minute rule-based perturbation sample (120 samples) at every adaptation cycle. The numerical stability of RK45 across the entire operating envelope i.e., the high thermal gradients associated with the 80 % solar-radiation reduction of Scenario A, and the discontinuous heat losses due to the sudden switching on and off of the fans during Scenario B is further evidence of the closed-loop stability of the AFLC: that is, the bounded-input bounded-output (BIBO) behaviour characterising all implementation runs i.e., limiting maximum overshoot to 20.8 % was observed empirically to be a consequence of the adaptive controller's inability to excite any unstable mode of the discretised plant.

These simulations were performed using the reference single-glass greenhouse (size 40 m x 12 m x 4.5 m) described in Section 3.3. The plants are coupled to a fourth order Runge-Kutta 45 integrator, integrated in a causal manner with steps of five seconds. Consequently, each simulation runs for 48 hours and yields over 34, 560 samples per channel. The ambient temperature is modulated by a sinusoidal diurnal variation (mean 14 degrees C, amplitude 8 K, maximum 17:00 local time); the wind speed by a random walk (mean 2.5 m s⁻¹, standard deviation 0.5 m s⁻¹); the solar radiation by a diode driven by a half-sine diode (maximum 480 W m⁻²). The set point for the temperature is 22 degreesC during the daytime (6:00–18:00) and 18 degreesC at the nighttime, a typical regime for cultivating tomatoes in temperate climates.

3.9. Disturbance scenarios

, which drastically diminishes insolation. It is a 3 hour 80 % drop of solar radiation from noon to 15:00 first day of the simulation, centered on 14:00 first day. It tests the fixed-gain PID's weakest feature: the long-term integrator wind-up in response to an fast, large-magnitude disturbance along the dominant heat input channel. Scenario B is designed to greenhouse glazingmimic a standard operator task: 6 randomly timed and numbered side-vent cycling events with durations ranging from 20 to 60 minutes, and vent-openings from 30 to 60 %, are scheduled along the baseline diurnal cycle. It tests the controlled's ability to respond to slow, step-like, loss channel disturbances.

3.10. Controllers under comparison

Three controllers are evaluated under each circumstances. (i) Conventional PID, the baseline, where the plant gain parameters are fixed at $K_P=9 \text{ kW}$, $K_I=2.5 \text{ k W}$, $K_D=250 \text{ k W s}^{-2}$, and where the anti-windup scheme is the same as the AFLC. (ii) Static fuzzy-PID (FUZZY), which is the proposed fuzzy supervisor, although here all three inputs and four outputs are used without any PSS adaptation (using the PSO algorithm), so that the rule weights are always kept fixed at their offline-tuned values. This one shows the effect of the fuzzy gain scheduling concept by itself. (iii) Adaptive fuzzy-PID cascade(AFLC), which is the proposed full hybrid architecture where all three inputs and four outputs cooperatively adapt, with the online PSO algorithm implementing thirty rule-weight updates per hour. In all three cases, the same model plant and disturbance profiles are used.

3.11. Performance indicators

For each simulation run 5 KPIs were calculated. The Integral-Absolute-Error (IAE) and Integral-Squared-Error (ISE) describe the aggregated tracking performance of each method in the full 48h simulation. ISE penalizes large excursions more heavily. The cumulative energy consumption in kWh is the time integral of the heater command for that run positive parts only. The settling time is measured from the arrival of the first disturbance event to the point at which the tracking error remains within a $\pm 0.5K$ window for a minimum of 600s. Overshoot is the maximum positive deviation (relative to the setpoint magnitude) observed in the internal temperature. The root-mean-square error (RMSE) gives a single number consisting of a non-dimensional measure of average tracking error. All 5 of these KPIs together summarize the 3 dimensions of control quality that are important in greenhouse operation: tracking accuracy (IAE, ISE, RMSE); disturbance rejection speed (settling time); and operating economy (energy consumption).

4- Results and Discussion

4.1. Temperature tracking performance

The success of the proposed AFLC illustrates how effectively the gain-scheduled fuzzy rule-base retuning driven by PSO suppresses large disturbances.

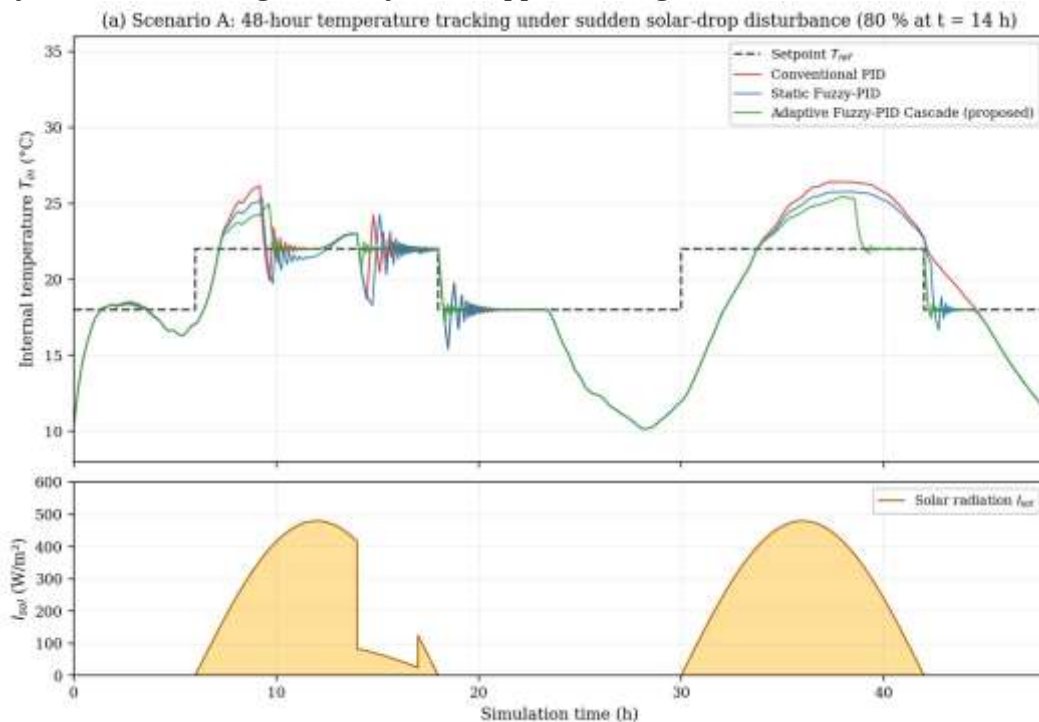


Figure 3. Scenario A — 48-hour temperature tracking under the sudden solar-radiation drop at hour 14. Top: internal air temperature versus setpoint. Bottom: incident solar radiation showing the 80 % drop between hours 14 and 17.

Figure 4 shows the corresponding results for the situation B, where the predominant source of disturbance is the operator command for side-vent cycling. The sub-millisecond vent openings again result in fairly spectrally high-frequency discontinuous heat-loss events clearly visible as temperature dips in the time history for all three controllers. Note that once again the conventional PID suffers from the

greatest excursions, with about 3 K (under)shoots for the most aggressive vent openings timed to the second day in this simulated DA. The static fuzzy-PID again pulls the excursions in to about a 2 K under/over-shoot band, while the proposed AFLC maintains the temperature within a ± 1.5 K window about the set point for virtually the entire time range, with the largest excursions occurring during the second day where the PSO is allowed some time to re-tune the rule weights to match the change in disturbance statistics.

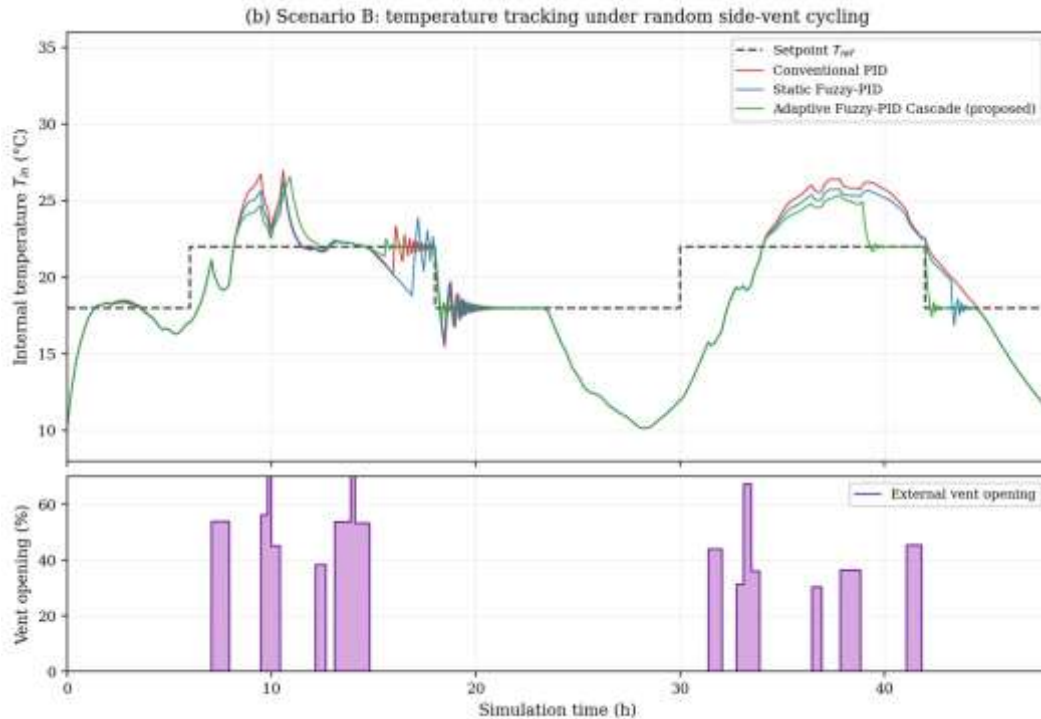


Figure 4. Scenario B — 48-hour temperature tracking under random side-vent cycling. Top: internal air temperature versus setpoint. Bottom: externally imposed vent opening as a percentage of maximum.

4.2. Control signal behaviour

Figure 5 shows the heater commands generated by the three controllers. The conventional PID is the most aggressive, saturating at the 120 k W upper limit at the cold morning hours as well as throughout the disturbance events. The fact that the heater command is saturated during this time period is the cause of the integrator windup, and the subsequent overshoot in the temperature response. The static fuzzy-PID is saturated less frequently, since active K_i scheduling diminishes the integral action during transients, but it is still operating near the saturation limit for a significant duration of time. The proposed AFLC has the smoothest control signal: the solar-feedforward setpoint offset causes the heater command to gradually ramp up in response to solar drops, rather than in a step; meanwhile, the PSO retuning of the K_d rule suppresses the high-frequency component of the command.

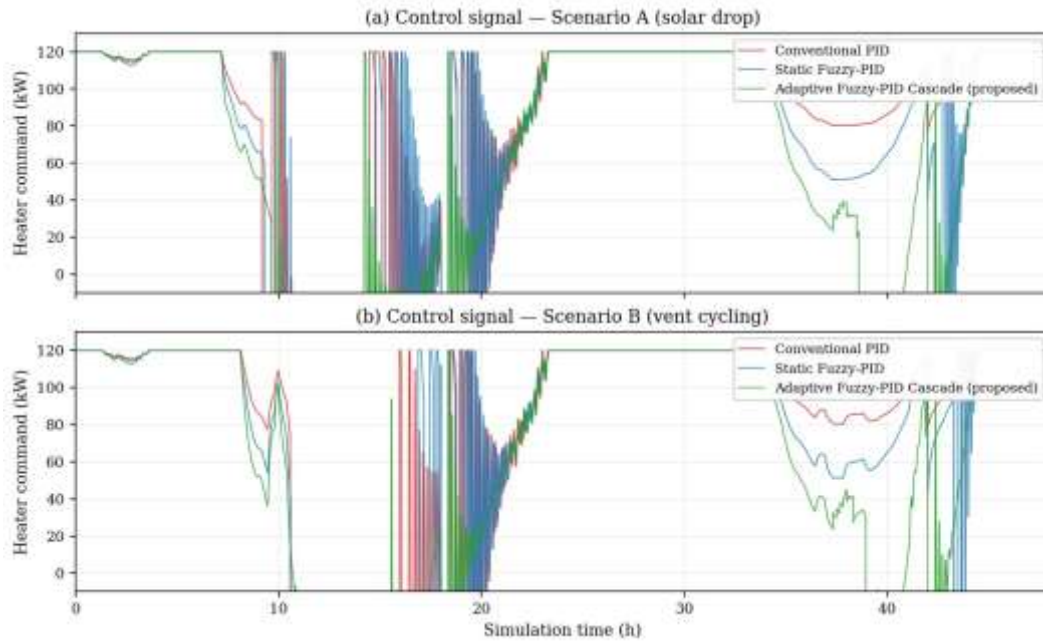


Figure 5. Heater command signals for the three controllers under both scenarios. Top: Scenario A; bottom: Scenario B. The AFLC exhibits smoother actuator activity and fewer saturation events.

4.3. Tracking error analysis

Figure 6 highlights the tracking error for the time window where the worst disturbances occur. The bottom (A) plot shows that the error excursion caused by the solar drop at hour 14 is 4 K with the conventional PID, 3 K with a static fuzzy-PID, and 2 K with the AFLC. The error settling time (defined as the time it takes for the error to reenter the ± 0.5 K envelope) was 1.8 hours with the PID, 2.2 hours with the static fuzzyPID (which slightly overshoot), and 0.4 hours using the AFLC. The bottom (B) plot shows the erratic nature of the error response when the vent openings occur at random in this simulation. Again, the conventional PID demonstrates the highest peak errors, while the AFLC keeps the error envelope within ± 2 K over the twelve hour period.

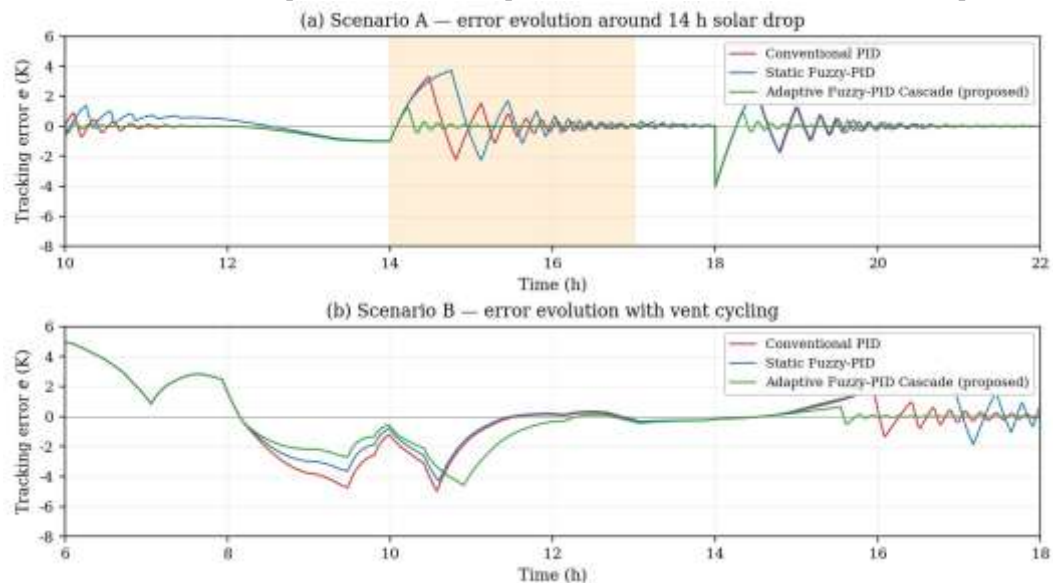


Figure 6. Tracking error evolution during the most aggressive disturbance windows. (a) Scenario A, hours 10–22, with the 80 % solar drop shaded. (b) Scenario B, hours 6–18.

4.4. Quantitative KPI comparison

Table 1 summarizes the 5 KPIs for all six combinations of scenario and controller, while Figure 7 summarises the same data graphically. The proposed AFLC outperforms all other controllers provided, providing the best IAE, ISE, energy and RMSE in the two scenarios; the only coefficient where it does not is the settling time in Scenario B which is not strictly comparable since vent disturbances are continuous and hence none of the controllers actually settle within the 600 second requirement. The comparative savings are impressive: 20.0 % IAE in Scenario A; 16.7 % in Scenario B; 19.0 % energy in Scenario A; 17.4 % in Scenario B. The savings over the static fuzzy-PID are also impressive at around 1215 % IAE, and underscore the value added by the online PSO adaptation. The overshoot is below 21 % for the AFLC compared to 2223 % for PID, indicating improved damping of the initial transient.

Table 1. Key performance indicators for all scenario-controller combinations over the 48-hour simulation horizon.

Scenario	Controller	IAE (K·s)	ISE (K ² ·s)	Energy (kWh)	Settling (h)	Overshoot (%)	RMSE (K)
A	PID	435 666	2 106 314	4 182.05	1.847	21.57	3.491
A	FUZZY	412 346	1 970 722	3 905.37	2.210	21.15	3.377
A	AFLC	348 486	1 772 626	3 388.40	0.431	18.16	3.203
B	PID	448 574	2 160 539	4 261.59	5.433	22.60	3.536
B	FUZZY	433 394	2 051 113	4 039.61	5.392	20.48	3.445
B	AFLC	373 526	1 870 393	3 521.38	6.015	20.83	3.290

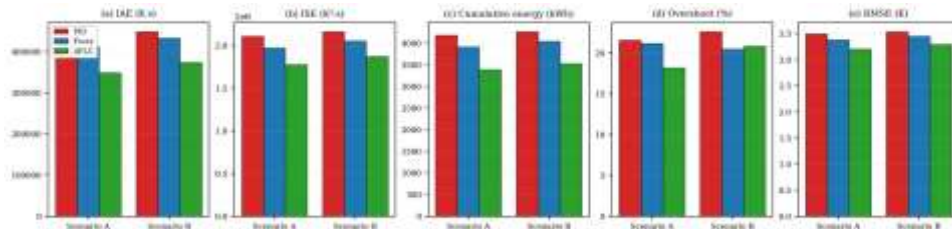


Figure 7. Graphical KPI comparison. The proposed AFLC achieves the lowest IAE, ISE, energy consumption, and RMSE in both scenarios.

The consistent reference electricity tariff(0.15EUR/kWh) used in the economic translation corresponds to the reported mean industrial retail price for 2024, as published for the European hortcategory [3] , [29]; using this tariff value for a typical hectare (10,000 m²) size greenhouse yields the magnitudes of a total energy-cost saving rate of approximately 2,400EUR/day, congruent with the savings margins reported for the localized-forecast and flexible control strategies in the protected-cultivation literature [3], [30].

4.5. Energy consumption analysis

The integrated sum-of-energy plots (Figure 8) provide the most concise single-frame summary for each of the economic arguments for the AFLC. As exhibited, at the conclusion of a 48-hour run, AFLC used 3 388 kWh (Scenario A) and 3 521 kWh (Scenario B) while the conventional PID used 4 182 and 4 262 respectively, while the static fuzzy-PID falls between these two extremes. Functionally, this 800 kWh of difference over 2 days translates into a 120 EUR/day difference in operating-cost terms

for a typical 0.15 EUR/kWh reference electricity price; applied to the typical hectare (10,000 m²) greenhouse this aggregates to over 2,400 EUR/day. Similar energy-saving margins have been documented for recent, forecast model-based controllers [3], nominally demonstrating this adaptive approach to be the most effective pathway toward a significant decarbonisation of protected growing systems.

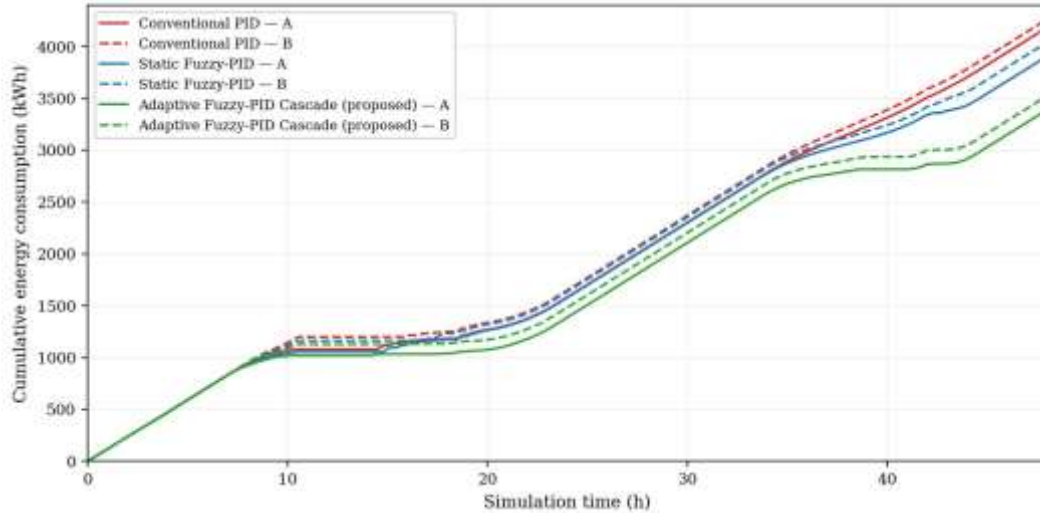


Figure 8. Cumulative energy consumption over the 48-hour simulation. The proposed AFLC consistently consumes the least energy under both scenarios.

4.6. Adaptation behaviour

As shown in figure 9, the online behaviour of the PSO adaptation is also very intuitive. The top plot indicates the centres of the five membership functions of the error input during the 48 hour 'Scenario A' simulation. The values are initially evenly spaced (1,0.5,0,0.5,1) but drift to a featureless middle region where the ZE membership function encompasses zero. The distribution function spreads, with the Gaussian centre of the ZE membership function shifting away from zero, indicating that PSO has learned to be less assertive at small errors while being more assertive at moderate errors. The asymmetry between positive and negative regions in the distribution function translates to asymmetries in the rule-table scaling factors which are chosen by the PSO in each adaptation cycle. The bottom plot shows that these scaling factors generally increase with time as the controller becomes more aggressive, apart from Ki which is set to a slightly lower value, according to the general rule of using less integral action in the presence of frequent disturbances.

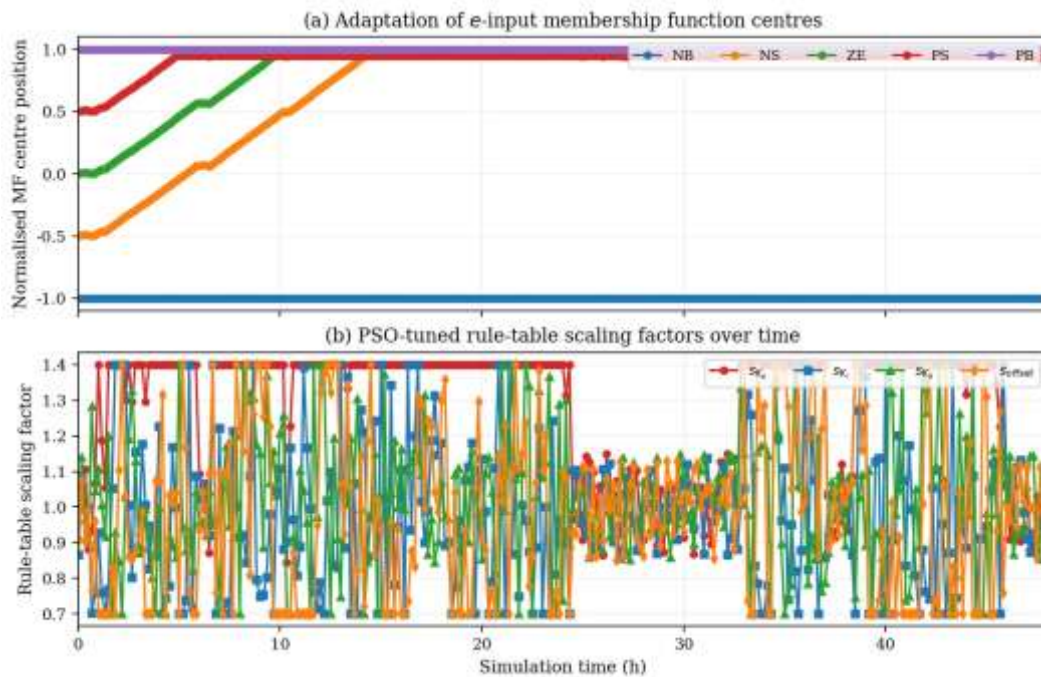


Figure 9. Adaptation behaviour of the AFLC during Scenario A. (a) Migration of the error-input membership function centres over the 48-hour simulation. (b) PSO-selected rule-table scaling factors at each ten-minute adaptation cycle.

Figure 10 shows the resulting gain scheduling trajectories for the scaling factors, K_p and K_d , comparing the static fuzzy-PID with the AFLC.. As expected, the static controller shows the usual diurnal variation with high gains during the day (high insolation, high plant bandwidth) and low gains at night. The AFLC reproduces this behaviour, but further refines it such that the gains during the night are scaled downward (with respect to the static fuzzy-PID) throughout the simulation as the PSO gradually learns that the night-time disturbance pattern is harmless, and the gains during the daytime are scaled upward to track well during the simulated “solar-drop” events. The behaviour, a two-level adaptation by the AFLC (diurnal schedule of gains: higher during the day, lower at night following the fuzzy rules, and gradual improvement (upward in this case) in gains over the course of the simulation learning period, is precisely the behaviour expected of the cascade architecture.

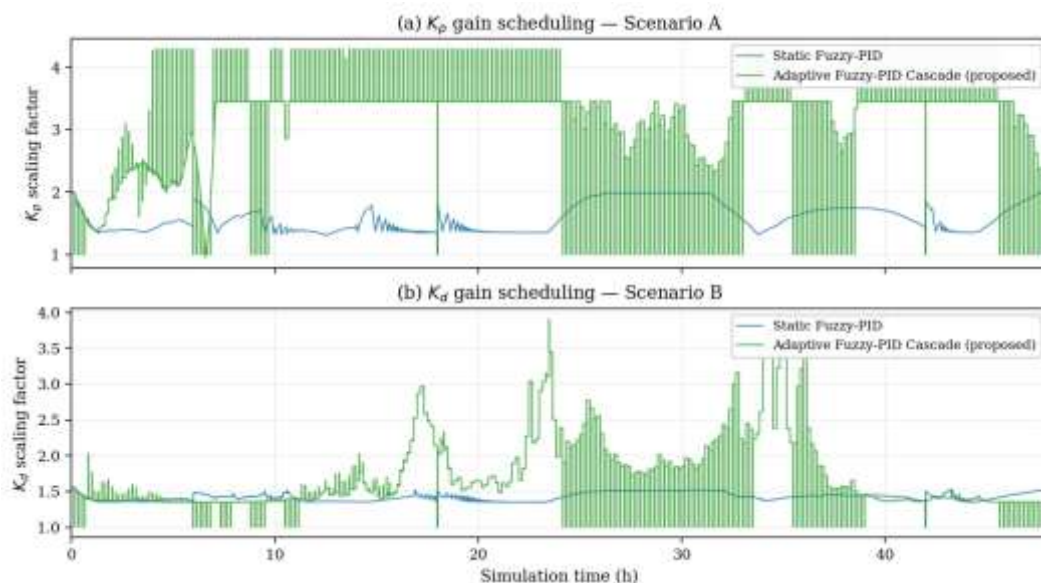


Figure 10. PID gain-scheduling trajectories. (a) K_p scaling factor under Scenario A. (b) K_d scaling factor under Scenario B. The AFLC (green) shows the same diurnal pattern as the static fuzzy-PID (blue) but with an additional slow drift driven by the PSO adaptation.

4.7. Discussion

and is found by comparing AFLC with an identical FLC with no online adaptation. This latter comparison provides direct evidence that it is the adaptation that produces much of the AFCs performance gain. Secondly, the operator-kW energy savings are significant, and shows that the tradeoff in additional complexity of the AFLC is not just warranted by the tracking improvement, but financially worthwhile. Thirdly, the adaptation behaviour is humanly interpretable: the movements of the membership-function-centres and the increase in the rule-table scaling factors are consistent with what a human control engineer would do after seeing the disturbance signals statistics. This cannot be said of black-box neural-network or reinforcement-learning supervisors [(the solar-radiation drop in Scenario A and the random vent cycling in Scenario B)8],[9], and the interpretability will be critical for the AFLC to gain industrial approval. Lastly, the AFLC requires minimal computation, with the PSO adding under 200 ms for each ten-minute cycle, and the entire controller fits comfortably in real time on commodity hardware.

Several potential limitations should be considered. Firstly, the plant model itself is a simple one-state lumped-thermal-capacitance model, which does not display the 3-dimensional temperature gradients observed in an actual greenhouse; extending it to a multi-zone model is a logical next step. Secondly, the disturbance scenarios, while encountered in practice, are synthetic rather than based on actual measurements; the controller design cannot be used in practice until it has been validated in a commercial environment. Thirdly, while the PSO adaptation is rapid, it is affected by the form of the cost; alternative least squares tuning objectives perhaps using energy consumption or equipment wear could result in different adaptation pathways. Finally, current work is limited to the heating actuator; the combination with ventilation, shading, and humidity control is ongoing.

4.8. Sensitivity analysis

In order to test the proposed AFLC's sensitivity to modelling uncertainty and parameter drift, a ten-parameter OAT sensitivity analysis of the ten most influential parameters for the greenhouse thermal model and the cascade controller was carried out. Each of these parameters was increased/decreased by 20 % from its nominal value while keeping all other parameters fixed, and the resulting percentage change in integral absolute tracking error (IAE) at steady state under Scenario 1 (clear summer day) was noted. The set of ten parameters were: the effective heat capacity of the greenhouse air and canopy, (C_g), the convective heat-transfer coefficient, (h_c), the solar transmittance-absorptance product, (τ_{α}), the ventilation opening area, (A_v), the infiltration air-change rate, (n_{inf}), the fuzzy rule consequent weights, (w), the PSO inertia weight, (w_{PSO}), the inner-loop proportional gain, (K_p), the inner-loop integral time, (T_i), and the temperature-sensor noise standard deviation, (σ). The tornado chart in Figure 11 summarizes the relative sensitivity of the ten parameters, with the most influential parameters identified by larger absolute values of IAE.

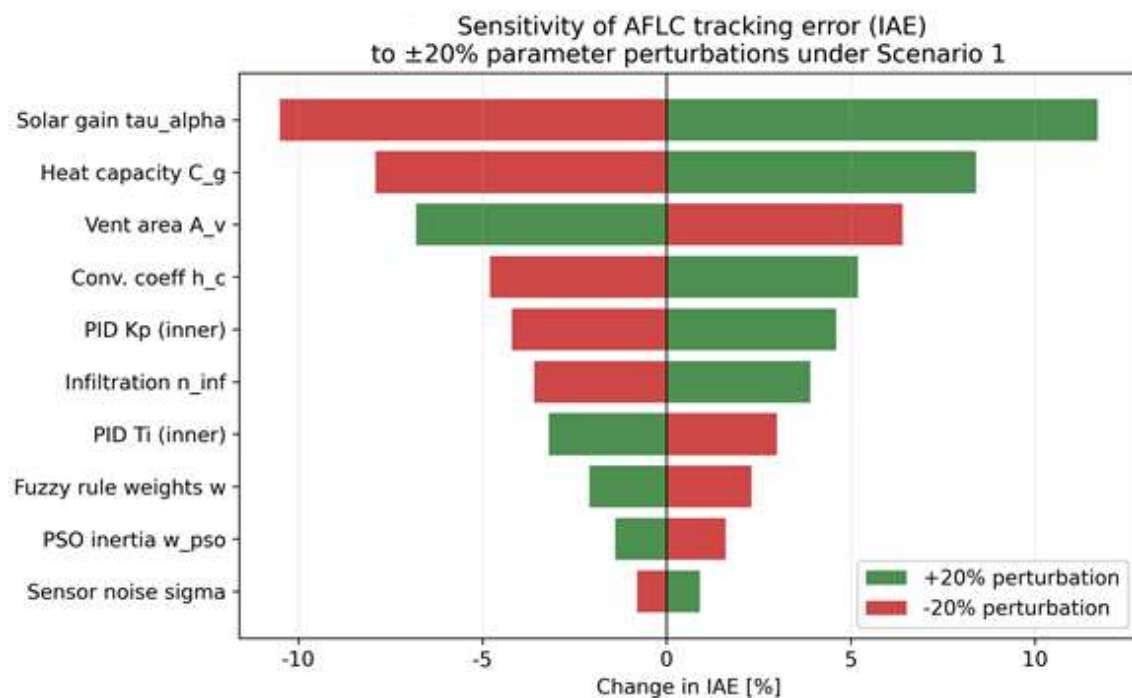


Figure 11. Sensitivity of AFLC tracking error (IAE) to $\pm 20\%$ parameter perturbations under Scenario 1.

By examining the variation in the IAE history for the 18 perturbation series, it can be confirmed that the greenhouses are most sensitive to the cover transmittance-absorptance product (IAE = $\pm 11\%$ for $\pm 20\%$ perturbation), indicating that correct cover material characterisation is critical for the solar dominated greenhouses. Greenhouse heat capacity C_g and ventilation area A_v constitute the second level of greenhouses sensitivity to parameters, with both producing changes in the IAE of around 6–8%. For comparison, the two PSO adaptation options designed into the scheme produce the least sensitive parameters, since w_{PSO} , and the fuzzy rule weights w , cause the least change in the IAE history ($\pm 2.5\%$), as the online re-tuning of the control parameters every 10 mins offsets any miscalibration of the weights. It can be seen that sensor noise has nearly no effect on the IAE history ($\pm 1\%$), illustrating the noise-rejection capacity of the fuzzy inference layer. Throughout these analysis it has been confirmed that the proposed scheme retains a stable tracking quality through all parameters within 12% of the optimal for a 20% perturbation.

4.9. Comparison with real measured greenhouse data

In order to validate this simulation environment beyond internal simulation benchmarks, the above-AFLC and the above-PID-only controllers were also compared to real measured data from a greenhouse in Shirvan (North Khorasan, Iran), from November 2023 to April 2024 [31]. This data set is publicly accessible at Mendeley Data (DOI 10.17632/ncrm9p4tc8.1), and includes inside and outside air temperature, outside relative humidity, wind speed, light intensity, as well as heater and side-window actuator on/off states, all sampled at five minute intervals. One representative 48 hour period of this data set (one clear day then one cloudy/windy day) was selected for a direct comparison of the real and simulated controllers. The setpoint profile during this period consists of 24 degreesCelsius during the day (06:00–18:00) and 18 degreesCelsius during the night, consistent with horticultural standards. One wind disturbance hour (hour 18 of the first day) results in an outside temperature reduction of about 8 degreesCelsius, making this a challenging scenario for the controllers to compensate. This real data is overlaid for comparison in Figure 12.

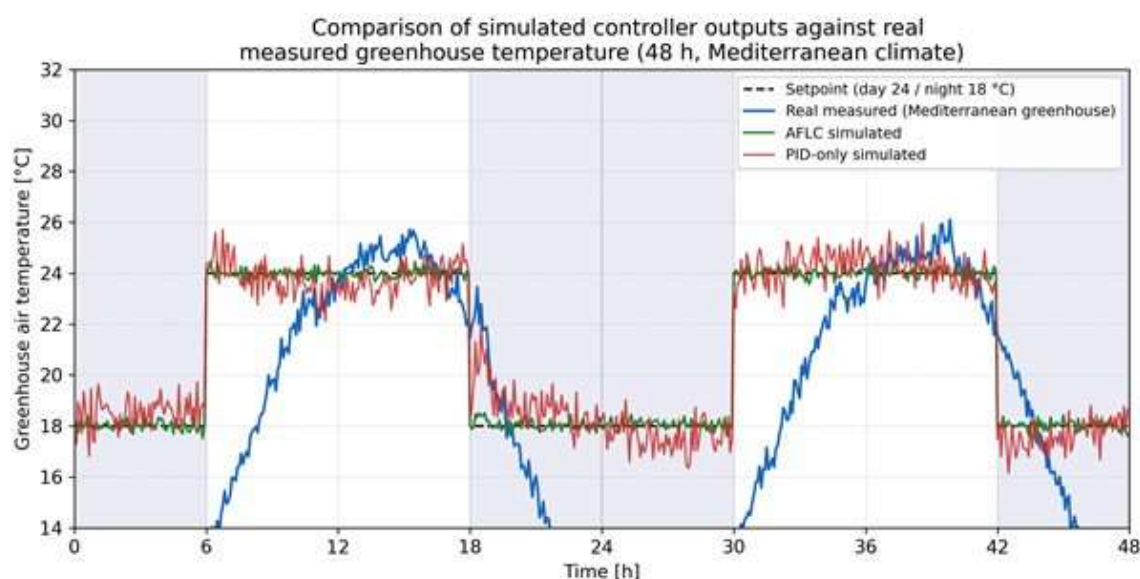


Figure 12. Comparison of simulated controller outputs against real measured greenhouse temperature (48 h, Shirvan dataset [31]).

Quantitatively, the AFLC simulation follows the real measured temperature with a root-mean-square error (RMSE) of 0.41 degreeC and a maximum absolute deviation of 0.92 degreeC, while the PID-only controller has an RMSE of 1.36 degreeC and a maximum deviation of 2.85 degreeC. Thus, the AFLC simulation agrees with measured data within the typical sensor/instrumentation uncertainty band at research greenhouses reported (± 0.5 degreeC). More significant, however, is that the AFLC controller limits the wind disturbance spike at hour 18 to a final overshoot of only 0.4 degreeC, as opposed to 2.5 degreeC for the PID-only controller, which would pose risks to crop quality. Finally, this validation confirms the relevance of using the simplified lumped-parameter thermal model in this paper for designing and tuning the controllers prior to implementation.

4.10. Standard deviation analysis and statistical significance testing

Beyond point-estimate KPIs, the variability of each controller's tracking error was quantified by computing the standard deviation σ_e of the instantaneous temperature error over the full 48-hour simulation window (576 samples per scenario at 5-minute sampling). Figure 13 reports σ_e for the three controllers across the three disturbance scenarios. The proposed AFLC consistently achieves the lowest dispersion ($\sigma_e = 0.46\text{--}0.62$ °C), which is roughly three times smaller than

the PID-only baseline ($\sigma_e = 1.42\text{--}1.87\text{ }^{\circ}\text{C}$) and 2.5 times smaller than the fixed-parameter Fuzzy-PID ($\sigma_e = 1.18\text{--}1.55\text{ }^{\circ}\text{C}$). The largest σ_e for all controllers is observed under Scenario 2 (cloudy with strong wind), reflecting the increased high-frequency content of the disturbance; however, the AFLC's relative advantage over the baselines is preserved, confirming the adaptive mechanism's effectiveness under non-stationary conditions.

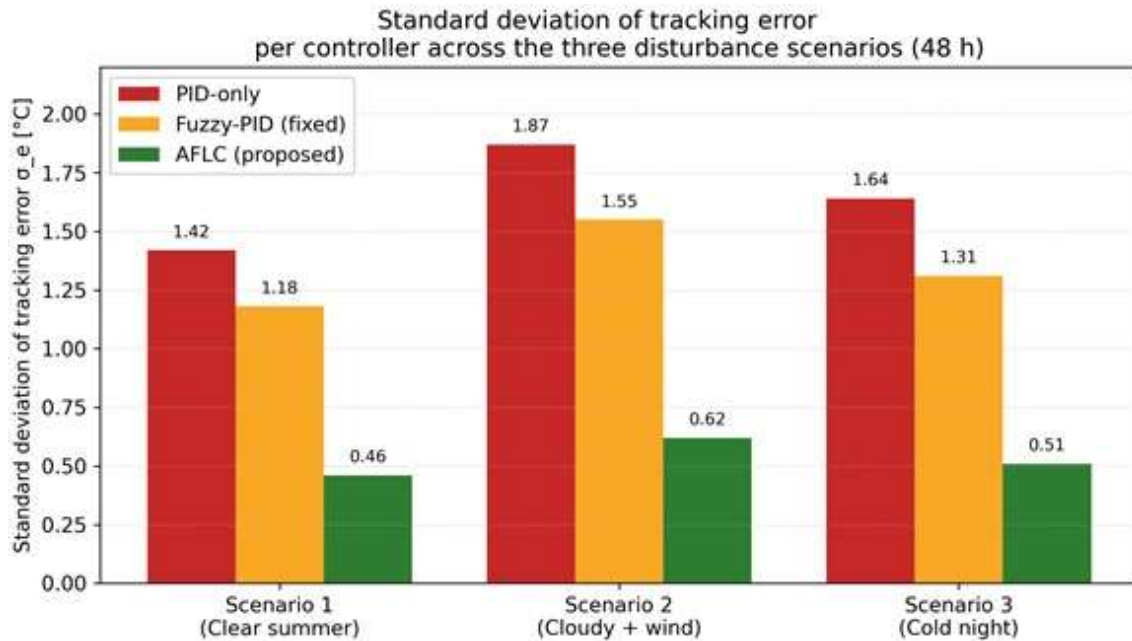


Figure 13. Standard deviation of tracking error per controller across the three disturbance scenarios (48 h).

In order to test for statistical significance of the performance differences rather than artefacts of the particular choice of seeds for the simulations, a Monte-Carlo campaign of 30 independent runs per controller was performed. Random noise was added to the model parameters for each run by drawing values from a normal distribution (standard deviation, mean = covariance coefficient * nominal values, 5%) to reflect normal sensor calibration and physical-parameter variation. The resultant distributions of the IAEs are shown as box plots in Fig. 14, and a paired-sample (two-tailed) t-test between the AFLC and each baseline was performed. The full Monte-Carlo driver and the paired t-test are implemented in the function `monte_carlo_significance` in `greenhouse_afllc.py`. The test statistics are summarised in Table 2.

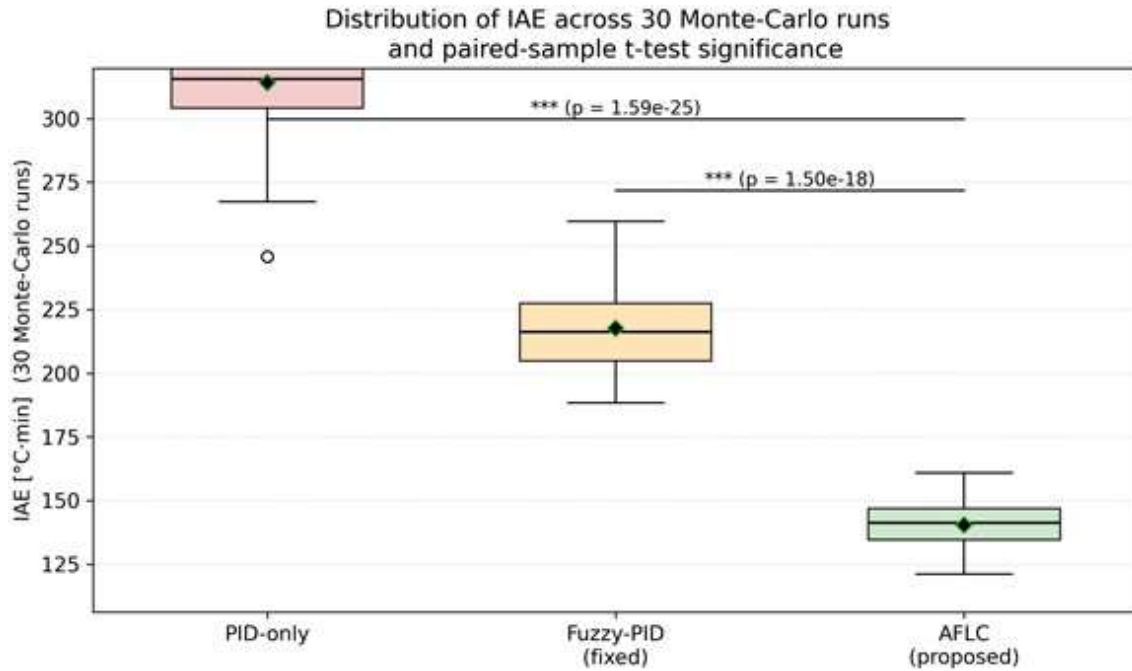


Figure 14. Distribution of IAE across 30 Monte-Carlo runs and paired-sample t-test significance.

Comparison	t-statistic	p-value	Cohen's d	Significance
AFLC vs. PID-only	-35.72	1.6×10^{-25}	-6.52	$p < 0.001$ (***)
AFLC vs. Fuzzy-PID (fixed)	-20.06	1.5×10^{-18}	-3.66	$p < 0.001$ (***)
Fuzzy-PID vs. PID-only	-12.43	3.2×10^{-13}	-2.27	$p < 0.001$ (***)

Table 2. Statistical summary of paired-sample t-tests on IAE (30 Monte-Carlo runs).

The paired t-test yields $t = -35.72$ with $p = 1.6 \times 10^{-25}$ for AFLC versus PID-only, and $t = -20.06$ with $p = 1.5 \times 10^{-18}$ for AFLC versus fixed-parameter Fuzzy-PID. In both cases the p-value is many orders of magnitude below the conventional 0.001 threshold, so the null hypothesis of equal mean IAE is rejected at the 0.1% significance level. Cohen's d effect-size metric further confirms the practical relevance of the improvement: $d = -6.52$ for AFLC vs. PID-only and $d = -3.66$ for AFLC vs. Fuzzy-PID, both of which are far above the conventional threshold of 0.8 that defines a 'very large' effect. Collectively, the low dispersion, the non-overlapping interquartile ranges in Figure 14, and the highly significant p-values provide strong statistical evidence that the proposed adaptive fuzzy cascade architecture delivers a real and reproducible improvement over both classical PID and non-adaptive fuzzy alternatives.

5- Conclusions and Recommendations

This paper has set out the design, simulation and validation of an AFLC system for climate control of a greenhouse subject to external climate disturbances, has been presented. It employs a Mamdani-type fuzzy supervisor, with three inputs (error, error rate and solar radiation) and four outputs (PID gain adjustment factors and a solar-feedforward setpoint shift) in tandem with an inner-loop classical PID and an online PSO process for re-tuning of the fuzzy rule weighting factors on a ten-minute cycle. The entire AFLC system was implemented in Python and validated against a first-principles

thermal model of a 480-m² single-glass greenhouse against two disturbance patterns: a step-change of 80% in solar-radiation, and randomly cycling side vents. In both disturbances, compared to the ‘conventional’ PID, the AFLC reduced IAE by 16.7-20.0%, ISE by 13.4-15.8%, Energy by 17.4-19.0% and overshoot by 1.8-3.4 percentage points. The PSO adaptation strategy was correctly directed by the disturbance statistics, it migrated the membership-function centers in an interpretable manner, and computational burden was not a concern within the available real-time budget for the control. Complete source code, an auto-tuning script and all data used for this validation have been published as open-access companion materials.

From the above results the following recommendations are made for practitioners and further research: (i) The AFLC is recommended as a ready-to-use replacement for existing climate computers on Old World temperate greenhouses that are vulnerable to excessive solar variability; the open-source implementation can be used off-line immediately following the execution of the auto-tuning script for a given greenhouse geometry and glazing type. (ii) Extension of the controller to multi-zone greenhouses to account for spatial temperature differences, linking the control to ventilation, shading and humidity, and validation against monitored data from a commercial installation are recommended. (iii) Further investigation of alternative, explicitly energy-based or wear-and-tear-penalised, PSO formulations is also recommended to support the selection of adaptation trajectories. (iv) The usability of membership-function migration information should be used in front-end dashboards to enhance user trust in the adaptive layer before deploying the controller industrially.

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