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Advanced Fuzzy-Logic-Based Context-Driven Control for HVAC Management Systems in Buildings

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ABSTRACT Control in HVAC (heating, ventilation and air-conditioning) systems of buildings is not trivial, and its design is considered challenging due to the complexity in the analysis of the dynamics of its nonlinear characteristics for the identification of its mathematical model. HVAC systems are complex since they consist of several elements, such as heat pumps, chillers, valves, heating/cooling coils, boilers, air-handling units, fans, liquid/air distribution systems, and thermal storage systems. This article proposes the application of LAMDA (learning algorithm for multivariable data analysis) for advanced control in HVAC systems for buildings. LAMDA addresses the control problem using a fuzzy classification approach without requiring a mathematical model of the plant/system. The method determines the degree of adequacy of a system for every class and subsequently determines its similarity degree, and it is used to identify the functional state or class of the system. Then, based on a novel inference method that has been added to LAMDA, a control action is computed that brings the system to a zero-error state. The LAMDA controller performance is analyzed via evaluation on a regulation problem of an HVAC system of a building, and it is compared with other similar approaches. According to the results, our method performs impressively in these systems, thereby leading to a trustable model for the implementation of improved building management systems. The LAMDA control performs very well for disturbances by proposing control actions that are not abrupt, and it outperforms the compared approaches.

INDEX TERMS HVAC control, control engineering, fuzzy logic, artificial intelligence, LAMDA.

I. NOMENCLATURE

4SID	Subspace-based State-Space System Identification
ACODAT	Autonomous Cycle of Data Analysis Tasks
AI	Artificial Intelligence
ANFIS	Adaptive-Network-based Fuzzy Inference System
ANN	Artificial Neural Networks
ARIMA	Autoregression Integrated Moving Average
ARMAX	Autoregression Moving Average eXogenous
ARX	Auto Regression eXogenous
BMS	Building Management System
CVaR	Conditional Value at Risk
DAT	Data Analysis Tasks
DMC	Dynamic Matrix Control
EEV	Electronic Expansion Valve
EHAC	Extended Horizon Adaptive Control
EPSAC	Extended Predictive Self-Adaptive Control
FAN	Fuzzy Adaptive Network
FBC	Feedback Controllers
FDI	Fault Detection and Isolation
FFBP	Feed-Forward Back-Propagation
FPGA	Field-Programmable Gate Arrays
FL	Fuzzy Logic
GA	Genetic Algorithms

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GAD	Global Adequacy Degree
GPC	Generalized Model Control
HAD	Higher Adequacy Degree
HVAC	Heating, Ventilation and Air-Conditioning
IT	Information Technology
LAMDA	Learning Algorithm for Multivariate Data Analysis
JIT	Just in Time
LAMDA	Learning Algorithm for Multivariable Data Analysis
LQ	Linear Quadratic
LQG	Linear Quadratic Gaussian
ML	Machine Learning
MAC	Model Algorithmic Control
MAD	Marginal Adequacy Degree
MIMO	Multiple-input and Multiple-output
MLP	Multilayer Perceptron
MPC	Model Predictive Control
NNARX	Neural Network Auto Regression eXogenous
PDF	Probability Density Function Approximation
PFC	Predictive Functional Control
PID	Proportional, Integral and Derivative
PLC	Programmable Logic Controller
RBF	Radial Basis Function
RD	Robust Distance
RGA	Relative Gain Array
RNN	Recurrent Neural Networks
SARIMA	Seasonal Autoregressive Integrated Moving Average
SISO	Single Input and Single Output
SP	Set Point
SVM	Support Vector Machines
TCBM	Topological Case Base Modeling
T-S	Takagi-Sugeno
WLAC	Weighted Locally Adaptive Clustering

II. INTRODUCTION

Buildings require most of the total supplied energy, with breakdowns of 40% to 42% in Western countries [1]–[4]. This energy feeds the elevators, plugged-in IT equipment, electronic devices, and lights, along with the HVAC system and the security and fire systems. Above all, the HVAC facility consumes most of the energy that is supplied to the building. As energy production remains contaminating and expensive and has substantial negative impacts on the environment and finances, the optimization of building energy with a focus on HVAC systems is necessary. The energy saving problem can be addressed by retrofitting the building architecture, renovating old installations or adding intelligence to the BMS, thereby leading to a savings of up to 30%. It is far more sustainable and cost-effective to improve the control algorithms to realize higher efficiency than to renovate the HVAC equipment with more efficient modern technologies [1], [2], [4], [5].

System automation enables operation with autonomous optimization principles that maintain comfort and reduce the amount of consumed energy. Automatic control is essential for coping with unforeseen user activities in smart buildings. IT achievements and industrial engineering breakthroughs enable the envisioning of smart buildings with self-adapting facades, shapes and autonomous behaviors, for maximizing the comfort of the occupants in changing contexts with nearly zero carbon emissions. Therefore, the objective that is pursued with the automation of HVAC control is to maximize the thermal comfort while minimizing the energy consumption. The operational efficiency of an HVAC system strongly depends on its control system and optimization parameters.

The construction of an accurate and effective model of an HVAC system is challenging. Modeling its characteristics, nonlinearities, dynamics and highly constrained parameters complicates the design and operation. Advanced control system engineering provides several approaches for improving control systems and reducing the energy consumption while ensuring the indoor thermal comfort with satisfactory robustness and stability. Solving the problem requires the following steps, among others: focusing on the control problem; solving the multiobjective optimization problem; synthesizing the system management at the supervisory level; and proposing new predictive or adaptive models that mimic the system behavior.

There are interesting reviews that address the strengths, weaknesses and performances of HVAC control models and their applicability in practical contexts [4], [5], [7]–[11]. Each proposed control model in HVAC systems requires assumptions regarding the system properties and the environment, to balance its simplicity with its accuracy.

According to current research, online feedback-based data analytics for smart building diagnosis and management require software-intensive solutions. FL can be used in control engineering; it ignores an HVAC system's nonlinearities and does not require parameter tuning, in contrast to other conventional methods. Fuzzy logic controllers show lower performance while adapting to signal variations with respect to MPC techniques [12] and, additionally, prove their robustness in real-time operations since they do not require learning processes, in contrast to ANN models. FL defines a set of control rules and obtains the control output with a fuzzy inference from the current input. The use of fuzzy sets in complex industrial system control is well documented in the literature [11], [13]–[15] and yields superior results to those of classical controllers; however, a key limitation originates from the elucidation with heuristic control rules [14], [15]. To overcome this limitation, various studies propose learning mechanisms for fuzzy controller rules, although their performances are not yet satisfactory.

On the other hand, LAMDA [16] operates on online contextual data and discovers the GAD of a class for each individual with fuzzy clustering. The GAD is a numerical array with values that range from 0 to 1; these values quantify the membership degree of any object/individual to the system classes. Thus, LAMDA assigns an individual to the most suitable class. LAMDA, by detecting the operational system states, becomes a powerful tool for classification and clustering [16]–[18]. LAMDA has been used in FDI to detect the operational states—either normal or abnormal—by identifying faults with the data that are gathered from sensors [19]–[23]. The classification performance of LAMDA has been improved with LAMDA-FAR [24] and LAMDA-HAD [25], [26] and clustering with LAMDA-RD [27] and the LAMDA triple π operator (LAMDA-TP) [28], [29]. More recently, LAMDA has been proven to provide a satisfactory model for control systems by driving the process from its current functional state to the required state with an inference method that assigns a numerical value to the controller output [30].

This article proposes an advanced LAMDA-based control method that provides robustness and intelligence in HVAC systems. LAMDA modeling overcomes the process complexity by designing the controller from currently available data and by avoiding other considerations, such as nonlinearities, operating constraints, time delays and uncertainties. This study proves that LAMDA satisfies the demanding HVAC control requirements due to the following characteristics [26], [27]:

- LAMDA operates in both supervised and unsupervised learning scenarios.
- LAMDA enables the definition of clear control rules (classes) because its structure is known.

Thus, the main contribution of this work is the design of a new type of intelligent controller that is based on LAMDA and applied to regulation of an HVAC system. The main advantages of our method are that it does not require a mathematical model of the system and it requires few variables to be parameterized. HVAC systems are an excellent case study for evaluating our proposed controller since their dynamics are complex due to the many elements that are involved. For the controller design, it is necessary to establish classes (operational states) of the system and their rules. Then, an inference method based on [30] is defined. For the validation of the proposed method, a comparative analysis of the behavior of the LAMDA controller is performed by comparing it against other well-known methods and evaluating its performance and robustness when disturbances are added to the system. Excellent results have been obtained with the LAMDA controller in various scenarios.

This article presents a review of the various control methods that are used in HVAC systems in Section II. Section III introduces the process of HVAC systems and the basic formulation of LAMDA. Section IV describes how the LAMDA control capabilities operate in HVAC systems. Section V evaluates our control approach in a real context and analyzes its performance in comparison with other conventional control models. Finally, Section VI presents the conclusions of the paper.

III. RELATED WORKS

HVAC control modeling can be approached using physics or deduced from the input and output data. HVAC control systems use conventional and advanced methods. Among the conventional methods, the PID controller is still considered in 9% of the literature on HVAC control, which represents a significant interest. Other self-tuning techniques, such as gain scheduling, are also considered in the 9% portion. Decoupling, state-space representation and transfer functions are also considered. Advanced control methods implement techniques to predict the system behavior, optimize several objectives and adapt to it. The LQ and LQG optimization schemas provide higher robustness and stability. With the exponential progress of IT, MPC and its variants attract the attention of researchers in 15% of HVAC-related articles, followed by multiagent architectures, which are studied in 14% of the articles. Fuzzy logic control also provides interesting results and is considered in 13% of studies [1], [9].

A. GENERAL CONTROL MODELS

White box—or forward—models are built with mathematical formulations. They model the mass balance, heat transfer, thermal momentum or flow rates with differential equations. They require knowledge of the physical and/or chemical laws of the system. The key advantage is that they provide an easy analysis with a simple algebraic formulation and robust generalization. These mathematical models are typically used in HVAC system design. They are typically applied in simpler systems, such as SISO and steady-state or quasi-steady-state systems without high-frequency disturbances, e.g., temperature and relative humidity changes in HVAC. In any case, they inherently incur high computational expenses. They outperform black box models when the feedback system information is scarce or incomplete [9].

Black box—or inverse—models approach the problem empirically by collecting system performance data and using these data to establish a relation between the inputs and outputs via ML, statistical or AI methods. Current research considers AI for plant modeling, controller design, system performance improvement, calibration and parameterization. One of the key advantages is that once AI models have been learned, they are very fast and require few computational resources, especially those that are based on neural networks [31]. Other data-driven models of interest in the literature are frequency-domain, data mining, state-space, geometric, case-based reasoning, stochastic and instantaneous methods [9]. ANN have been used in simulations of heat pump operation [32] and models to optimize simultaneously the building energy and comfort [33]. A particular case of neural networks is the modeling of the system dynamics with RNN [34]. RNN can be simulated with evolutionary algorithms [35]. However, studies on ANN models have not been widely conducted in the HVAC industry yet "due to uncertainty, long training periods, and complexity in setting up and maintaining the system" [36]. Other black box approaches utilize statistics and rely on identifying the best sample of a population. Statistical approaches use linear or polynomial time series regression models in control design to fit the system trajectories. Examples include the nonlinear ARX model, the ARMAX model and the ARIMA model [1]. Some of these methods do not consider the system output, whereas others do not consider the inputs [7]. Statistical models cannot simulate nonlinear behaviors standalone and require the support of other methods, such as ANN, as discussed in articles on HVAC control, such as NNARX, FFBP and RBF methods [9].

FL modeling is showing satisfactory performance in control and can interact with ANN models and GA algorithms to provide hybrid models with the best characteristics of black box and white box models [14], [15]. FL uses simple mathematics for nonlinear and complex systems, which are sufficient for HVAC [11]. The FAN and NFIS improve the prediction accuracy, and the T-S fuzzy model can be applied to online models [13]. In [6], an HVAC system for a motor vehicle is proposed and includes a climate control circuit that is coupled to onboard sensors, a human-machine interface, and climate actuators. The control system receives crowd data and at least one weight, which indicates the confidence level that is associated with the crowd data. It generates command parameters using a set of fuzzy rules in response to the crowd data and the weights. It shows high precision and rapid operation; however, for higher accuracy, FL requires more grading, which increases the number of rules exponentially, and more grading is not always available for some components. Other drawbacks of bare FL are its lower speed compared with other models, the lack of a real-time response, and learning from feedback.

Several studies propose optimizing the performance by implementing clustering techniques that are based on a clustering ensemble, such as WLAC [37]; by setting the weights for the fine-tuning of the fuzzy algorithm [38]; or via an iterative fusion of the base clusters [39], which yields visible improvements. Additionally, in [40], a clustering approach is proposed with the objective of minimizing the effect of the differences in the quality and diversity of the base clusters [40]. The contextual information, such as seasonal periods or scheduled activities, and the knowledge of the system's behavior are translated into fuzzy rules that shorten the model training process. FL does not require a mathematical formulation for representing the physics of the system nor mechanisms for overcoming the nonlinearities [11].

Finally, hybrid models combine black box and white box models to balance their drawbacks. Hybrid models use optimization to obtain the system parameters, such as least squares, gradient descent and genetic algorithms (GAs) [1]. For example, a two-stage energy management strategy has been developed for commercial buildings with these models [41]. One of the interesting contributions of that study is the inclusion of uncertainties in electricity prices in the MPC logic for optimizing the energy consumption. They propose balancing the power supply and the building load while minimizing the operational costs. The load demand, wind power and electricity price are forecasted with a SARIMA model and a CVaR is added to consider the price uncertainties. In [12], an HVAC system has been modeled using MATLAB, which uses a fuzzy controlling system and an RBF to define a predictive control system.

B. HVAC CONTROL METHODS

Kozák *et al.* [42] utilize a classical automation of control by looping back the output to the SP input to obtain the difference, or error signal, the amplitude of which regulates the actuators. These FBC stabilize unstable processes and reduce the sensitivity to parameter variations. Performance is guaranteed even when there are uncertainties that do not match exactly the real process. SP, which is typically the thermal expectation in HVAC, may be complemented with other information sources such as timers for regular activity, event scheduling, or weather forecasting for predicting outdoor conditions. In [43], PID controllers for the HVAC industry are described. In the case of HVAC systems, plain PID controllers do not perform well due to the nonlinearities of the system. Installations are designed to work at a full load, but the equipment typically works at a partial load, which is inefficient and requires autotuning techniques such as relay-autotuning or open-loop step tests. Classical methods for tuning the gains of PID controllers include the Ziegler-Nichols method and the Cohen-Coon method [44]. FL realizes higher performance in tuning PID control today. These basic control methods are widely implemented in PLCs and in FPGAs as they have simple control laws that are used in multipurpose applications [36].

In advanced strategies, one of the problems is to work with multiple variables, with techniques that split a MIMO system into SISO subsystems, such as the RGA [42], or that split the decentralizing PID controllers into a number of controllers that equals the number of inputs. These methods encounter challenges when finding Lyapunov functions and proving their stability, are complex and sensitive to parameter variations, have a limited operating range, or require the measurement of all state variables.

The new principles in control [9], [34], [36] , [45] are optimally, robustness and intelligence. In HVAC, the robustness principle aims at addressing the design problem of partial loads attenuating the effects of disturbances and at stabilizing operations to improve the performance. An HVAC control prediction strategy uses models to anticipate the system dynamics, such as MPC, and typically simulates the system dynamic behavior by solving linear or quadratic problems, such as Euler-Lagrange equations. MPC controllers optimize the control for a future time horizon by analyzing possible state trajectories, but the results are applicable only for the current timeslot, and the optimization must be recalculated for the next horizon in the next timeslot. MPC is gaining support in complex systems [1], [7], [8], [33], [46], [47],

TABLE 1. Classification of scientific references according to the addressed problem.

Approach	References
Model-specific	[1, 7, 9, 33]
Classical Control	[11, 36, 42, 43, 49, 50]
Hard Control	[11, 33, 42, 43, 48, 51]
Soft Control	[1, 5, 6, 9, 14, 15, 31, 33, 43, 45, 48, 51]
AI Control	[1, 8, 9, 32, 34, 35, 36, 42, 43, 46, 53, 54]
Supervisory Control	[33, 36, 42, 43, 48, 55, 56]

namely, systems that have high-order dynamics or long delays, while nonpredictive PID controllers are still preferred for simpler systems [43]. Examples of the studied MPC approaches for buildings are DMC, MAC, PFC, EPSAC, EHAC and GPC [47]. MPC can realize robustness against disturbances by predicting possible extreme disturbances, e.g., in min-max MPC; by surpassing the constraints, e.g., in constraint tightening MPC; by using FBC to converge to the nominal model, e.g., in tube MPC; or by collecting several samples online for modeling spaces that are generated by disturbances, e.g., in multistage MPC. When the HVAC control strategy is an optimization strategy, there are multiple aspects to address: the objectives, constraints, disturbances, modeling techniques and receding horizon [33]. Control optimization, which is model-free and is also known as an expert system, is conducted online with incomplete datasets and penalizes the accuracy. A simplified model of central chiller components that uses genetic optimization algorithms realizes 0.73% to 2.55% accuracy [48].

Finally, due to the complexity of HVAC control, it has been approached from various angles. Table 1 presents a classification of the bibliography according to the main field that is addressed in each article. The first approach is for the problem of simulating the system behavior, namely, the modeling problem. The second, third and fourth approaches hardly discuss the problem of control with classical, hard or soft methods. The fifth approach is the introduction of artificial intelligence in the control model. The last approach seeks energy savings from the complete system supervision.

The scientific literature on FL methods in HVAC control looks promising because simple mathematics are used for nonlinear and dynamic systems. However, FL requires more rules for the realization of higher accuracy; this requirement reduces the speed, and such rules are not always available. Real-time response HVAC control with FL has not been studied so far. This limitation is one of the problems the proposed method aims at addressing, by using contextual information or real-time feedback.

IV. AUTONOMOUS ARCHITECTURE

A. HVAC SYSTEMS

HVAC system direct modeling mimics complex structures, such as chillers, heat pumps, heating/cooling coils, boilers, air-handling units, thermal storage systems and liquid/air distribution systems. Sensors and actuators enable the regulation of the controllable plant variables, such as the ambient temperature in the occupied zones, the static pressure in the pipes, the chilled flowing water temperature and the air fan speed. An HVAC system is difficult not only to simulate but also to manage due to the nonlinearities and dynamics of its physical behavior. This difficulty is demonstrated with the following example: A chiller removes heat from a fluid in a vapor compression cycle or an absorption cooling cycle, which consumes almost half the energy. It has a compressor, an evaporator, a condenser, and an EEV, which are typically designed separately under the following assumptions [1], [2]:

- The refrigerant properties are homogeneous in each component.
- The refrigerant flow rate through the compressor is constant throughout the system.
- The expansion process through the EEV/orifice plate is isenthalpic.
- The temperature of the walls does not vary through the cross-section or across the ducts.

If the refrigerant is in quasi-steady state, using the energy balance equations that are proposed in [1], the heat transfer rate in the evaporator (Q_e) and the refrigerant mass flow rate ($\dot{m}_r$) are obtained via Eqs. (1) and (2):

$$\dot{Q}_e = \alpha_{ei} A_{ei} \left(T_{wo} - T_{we}\right) \tag{1}$$

$$\dot{m}_r \left(h_1 - h_6\right) = \alpha_{eo} A_{eo} \left(T_{we} - T_e\right) \tag{2}$$

where h_1 is the enthalpy of the refrigerant at the evaporator outlet-compressor inlet (kJ/kg), h_6 is the enthalpy of the refrigerant expansion valve exit/evaporator inlet (kJ/kg), A_{ei} is the area of the evaporator inlet (m^2), and A_{eo} is the area of the evaporator outlet (m^2). T_{wo} is the return water temperature ($^\circ C$), T_{we} is the temperature of the evaporator wall ($^\circ C$), T_e is the temperature of the refrigerant at the evaporator inlet ($^\circ C$), α_{ei} is the heat transfer coefficient of the refrigerant that is entering the evaporator (W/m^2K) and α_{eo} is the heat transfer coefficient of the refrigerant that is leaving the evaporator (W/m^2K). Via a similar approach, the heat transfer rate of the condenser (Q_c) and the other parameters of the HVAC system, such as the dynamic temperature of the heating/cooling coil, can be obtained by applying the energy balance in the air–water heat exchanger [1].

The mathematical formulation is even more complicated when applied to the case of an existing building HVAC system due to the scarce and unstructured available documentation and because the hidden habits that have been acquired by the engineers and operators hinder the modeling of an identical system.

In contrast, data models are simple to build, but quality data are required for building trustable models. Typically, some of the essential data are not always available or sensors generate interferences. Filtering, sensor networks, detection algorithms, and virtual sensors improve the model, but are insufficient for practitioners. The previous section presented

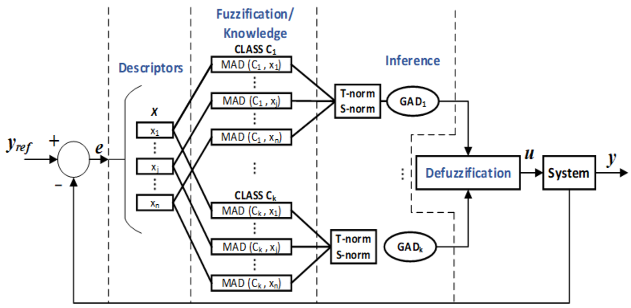

FIGURE 1. **Functional blocks of a LAMDA controller.**

another approach for overcoming modeling issues by perfecting the mathematical simulation with data models, collecting HVAC system data in normal or abnormal conditions, and using statistics, AI [46] or DL [34]. The studied models include TCBM, 4SID, PDF, JIT, MLP, SVM, FAN, T-S fuzzy, ANFIS, linear and polynomial time series regression, ARX, ARMAX, and ARIMA.

B. LAMDA CONTROLLER

LAMDA is a clustering algorithm that uses the degree of adequacy to classify each individual. The analysis of the similarity compares the features of any object $X = [x_1; \ldots; x_j; \ldots; x_n]$, with those of the existing classes $C = \{C_1; C_2; \ldots; C_k; \ldots; C_m\}$ [26]. LAMDA is a noniterative algorithm, and it was intended for use in system supervisory tasks and in the identification of functional states. This study extends its applicability to control systems by identifying the current system operational state and driving it to the target state, which is defined by its variables [30]. The main strategy is to set rules, namely, classes in LAMDA terminology, based upon the knowledge of the system behavior and the context information, as in other conventional fuzzy controllers. Figure 1 illustrates the structure of a LAMDA controller.

The features of the objects are normalized to [0, 1] to improve the performance via the following formula:

$$\bar{x}_j = \frac{x_j - x_{jmin}}{x_{jmax} - x_{jmin}} \tag{3}$$

where x_{jmin} is the minimum value of feature x_j, x_{jmax} is the maximum value of feature x_j and $\bar{x}_j$ is the normalized feature.

With normalized values, LAMDA calculates the marginal adequacy degree (MAD), which describes the similarity of any feature with the corresponding feature of the class. MADs are calculated with probability density functions, such as that of the normal distribution:

$$MAD_{k,j}\left(\bar{x}_j \mid \rho_{k,j}\right) = e^{-\frac{1}{2}\left(\frac{\bar{x}_j - \rho_{k,j}}{\sigma_{k,j}}\right)^2} \tag{4}$$

where $\rho_{k,j}$ is the mean of the jth feature in the kth class and $\sigma_{k,j}$ is the standard deviation of the jth descriptor in the kth class.

After obtaining the MADs, LAMDA calculates the GADs using aggregation functions T-norm (Eq. (5)) and S-norm (Eq. (6)) and the parameter $\alpha \in [0, 1]$, which represents the level of exactitude. As α increases, the classification becomes more selective [27]. When two or more features are considered, the GADs are computed recurrently.

$$T(a,b) = \frac{1}{1 + \sqrt[p]{\left(\frac{1-a}{a}\right)^p + \left(\frac{1-b}{b}\right)^p}} \tag{5}$$

$$S(a,b) = 1 - \frac{1}{1 + \sqrt[p]{\left(\frac{a}{1-a}\right)^p + \left(\frac{b}{1-b}\right)^p}} \tag{6}$$

Parameter p modifies the sensibility and is typically set to $p = 1$. The GADs are computed for every class. The GAD of the kth class is obtained via Eq. (7):

$$\begin{aligned} &GAD_{k,\bar{X}}\left(MAD_{k,1}, \ldots MAD_{k,n}\right) \\ &\quad = \alpha T\left(MAD_{k,1}, \ldots, MAD_{k,n}\right) + (1-\alpha) \\ &\quad \times S\left(MAD_{k,1}, \ldots, MAD_{k,n}\right) \end{aligned} \tag{7}$$

In classification tasks, the normalized object $\bar{X}$ is assigned to the class with the maximum GAD, as expressed in Eq. (8), where the index is the identifier of the selected class.

$$index = \max\left(GAD_{1,\bar{X}}, GAD_{k,\bar{X}}, \ldots, GAD_{m,\bar{X}}\right) \tag{8}$$

The previous steps describe how LAMDA identifies the current operational state of the system. However, in the case of a LAMDA controller, it is not sufficient to identify the functional state in which the system is operating; therefore, the control requires an inference method for driving the system to the desired state. This method is realized by defining the known rules that govern the plant, similar to conventional fuzzy controllers. The following expression defines the generic inference mechanism for LAMDA:

$$\begin{aligned} &R^{(l)}: \\ &\quad IF\ \left\{\bar{x}_1\ is\ F_1^i\ and \ldots,\ and\ \bar{x}_n\ is\ F_n^k\right\}\ THEN\ \left\{y_l\ is\ G^l\right\} \end{aligned} \tag{9}$$

where $\bar{x}_j$ takes values from the universe of discourse U_j. The linguistic output variable y_j is defined in the universe of discourse V_j. F_j^l and G^j are fuzzy sets in U_j and V_j, respectively, $(j = 1, \ldots, n)$, $(l = 1, \ldots, m)$, where n is the number of features and m is the number of rules, which are also known as LAMDA classes.

In this case, LAMDA operates with the GADs using the first-order T-S inference method, where $G^j = q^j$. Eq. (10) expresses how to obtain a crisp output:

$$u = \beta \sum_{k=1}^{n} q^k GAD_{k,\bar{X}} \tag{10}$$

where u is the controller output, q^k is the weight that is applied in the kth class, and β is the parameter for moderating u,

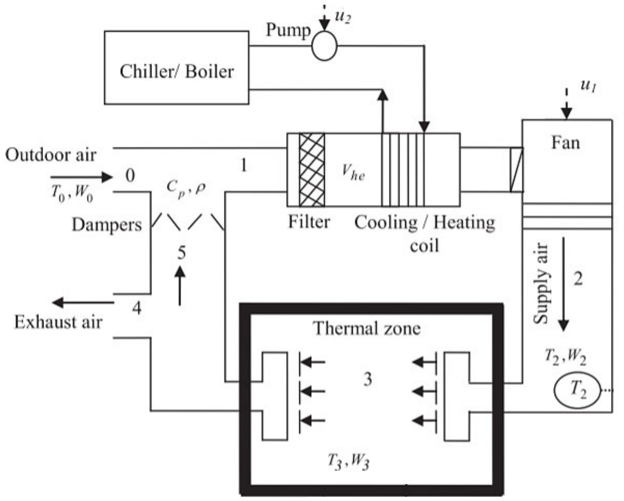

FIGURE 2. Block diagram of a simple HVAC system [53].

thereby limiting the controller's output to the class boundaries. It is calculated in the training phase via Eq. (11):

$$\beta = \frac{\max\left(q^k\right)}{\sum_{k=1}^{n} q^k GAD_{k,\max}(\bar{X})} \tag{11}$$

V. LAMDA CONTROLLER IN HVAC SYSTEMS

As discussed in the previous sections, HVAC systems are nonlinear and dynamic and require complex control methods. Controllable variables in the thermal zone are coupled and interact with each other.

This section tests LAMDA with the HVAC system that was defined by Arguello-Serrano and Velez-Reyes [51], in which the objective is to regulate the temperature ($T_3[°F]$) and relative humidity (W_3 $[lb/lb]$) parameters in a thermal space, namely, Zone 3, as illustrated in Figure 2.

Outdoor air (fresh air) flows into the system, 25% of which mixes with 75% of the returning air, and the remainder is expelled. The mixed air passes through a filter to the heat exchanger, where it is conditioned by following the SP reference. The conditioned air is propelled to the thermal zone with a fan. The system must control variables T_3 and W_3 simultaneously, based on thermal loads by varying the fan speed, u_1, to regulate the air flow rate and the cold-water pumping rate, u_2, from the chiller to the heat exchanger.

The HVAC system differential equations of energy and mass balances from the conventional mathematical model are:

$$\begin{aligned}\dot{T}_3 &= \frac{f}{V_s}(T_2 - T_3) - \frac{h_{fg}}{C_p V_s}(W_s - W_3) \\ &\quad + \frac{1}{0.25 C_p V_s}\left(Q_0 - h_{fg} M_0\right)\end{aligned} \tag{12}$$

$$\dot{W}_3 = \frac{f}{V_s}(W_s - W_3) + \frac{M_0}{\rho V_s} \tag{13}$$

TABLE 2. Numerical values for system parameters.

$\rho = 0.0074\ [lb/ft^3]$	$C_p = 0.24\ [Btu/lb°F]$
$T_{ref} = 55\ [°F]$	$T_{3ref} = 71\ [°F]$
$W_{3ref} = 0.0088\ [lb/lb]$	$V_{he} = 60.75\ [ft^3]$
$f_{ref} = 17{,}000\ [ft^3/min]$	$V_s = 58{,}464\ [ft^3]$
$W_s = 0.007\ [lb/lb]$	

$$\begin{aligned}\dot{T}_2 &= \frac{f}{V_{he}}(T_3 - T_2) - \frac{0.25f}{V_{he}}(T_0 - T_3) \\ &\quad - \frac{f h_w}{C_p V_{he}}(0.25W_0 + 0.75W_3 - W_s) \\ &\quad - 6000\frac{gpm}{\rho C_p V_{he}}\end{aligned} \tag{14}$$

where h_w is the enthalpy of liquid water, W_0 is the humidity ratio of outdoor air, h_{fg} is the enthalpy of water vapor, V_{he} is the volume of the heat exchanger, W_s is the humidity ratio of the supply air, W_3 is the humidity ratio of Zone 3, C_p is the specific heat of air, T_0 is the temperature of outdoor air, M_0 is the moisture load, Q_0 is the sensible heat load, T_2 is the temperature of the supply air, T_3 is the temperature of Zone 3, V_s is the volume of Zone 3, ρ is the air mass density, f is the volumetric flow rate of air (ft^3/min), and gpm is the flow rate of chilled water (gal/min). The assumptions that are made in the derivation of this mathematical model are also detailed in the study of Arguello-Serrano and Velez-Reyes [51].

Representing the system in state-space notation for the design of the control system, let $u_1 = f$, $u_2 = gpm$, $x_1 = T_3$, $x_2 = W_3$, $x_3 = T_2$, $y_1 = T_3$, and $y_2 = W_3$. The following parameters are defined to complete the model: $\alpha_1 = 1/V_s$, $\alpha_2 = h_{fg}/C_p V_s$, $\alpha_3 = 1/\rho C_p V_s$, $\alpha_4 = 1/\rho V_s$, $\beta_1 = 1/V_{he}$, $\beta_2 = 1/\rho C_p V_{he}$, and $\beta_3 = h_w/C_p V_{he}$. The mathematical model of (10), (11) and (12) can be reformulated as:

$$\begin{aligned}\dot{x}_1 &= u_1\alpha_1 60(x_3 - x_1) - u_1\alpha_2 60(W_s - x_2) \\ &\quad + \alpha_3\left(Q_0 - h_{fg}M_0\right)\end{aligned} \tag{15}$$

$$\dot{x}_2 = u_1\alpha_1 60(W_s - x_2) + \alpha_4 M_0 \tag{16}$$

$$\begin{aligned}\dot{x}_3 &= u_1\beta_1 60(x_1 - x_3) + u_1\beta_1 15(T_0 - x_1) \\ &\quad - u_1\beta_3 60(0.25W_0 + 0.75x_2 - W_s) \\ &\quad - 6000u_2\beta_2\end{aligned} \tag{17}$$

$$y_1 = x_1 \tag{18}$$

$$y_2 = x_2 \tag{19}$$

Table 2 and Table 3 list the numerical values that were chosen for the simulation and the system parameters at the operating point, respectively.

f (u_1) and gpm (u_2) are the control actions that modify the target variables T_3 (x_1) and $W_3(x_2)$. Figure 3 illustrates the mutual interactions among these parameters within the differential equations, thereby rendering a MIMO control problem.

In the figure, $G_1(\cdot)$, $G_2(\cdot)$, and $G_3(\cdot)$ are expressions (15), (16) and (17), respectively.

TABLE 3. Numerical values for system parameters at the operating point.

$x_1^0 = 71\ [°F]$	$x_2^0 = 0.0092\ [lb/lb]$
$x_3^0 = 55\ [°F]$	$T_0^0 = 85\ [°F]$
$W_0^0 = 0.0018\ [lb/lb]$	$M_0^0 = 166.06\ [lb/hr]$
$u_1^0 = 17{,}000\ [ft^3/min]$	$u_2^0 = 58\ [gpm]$
$Q_0^0 = 289{,}897.52$	$W_s^0 = 0.007\ [lb/lb]$

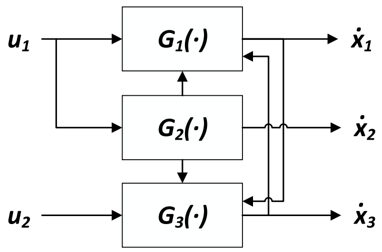

FIGURE 3. Block diagram of the HVAC model (MIMO system).

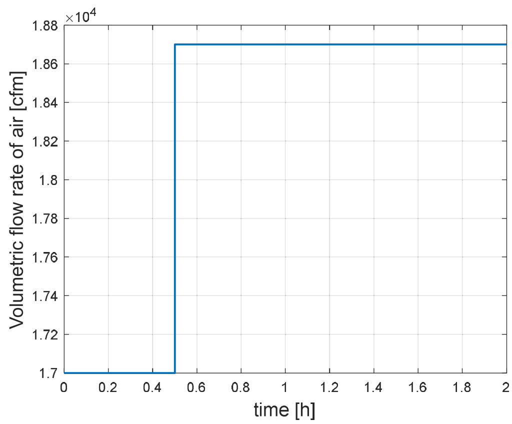

FIGURE 4. Step change of 10% is applied to u_1.

The proposed controller analyzes the data to discover possible relations between inputs and outputs by implementing two LAMDA controllers, one for each of the two output zone variables, namely, x_1 and x_2. To validate this implementation, it is necessary to determine whether the outputs are coupled, in which case a decoupling stage is required.

The method starts applying a step at one of the inputs and monitoring the response at the outputs to obtain the numerical values in the convenient FOPDT (first-order plus dead time) form:

$$\frac{X(s)}{U(s)} = \frac{Ke^{-t_0 s}}{\tau s + 1} \tag{20}$$

In the experiment, a step change of 10% is applied in the HVAC system operating point to u_1, as plotted in Figure 4, to monitor the controllers' responses at outputs x_1 and x_2, while u_2 remains unchanged.

Figure 5 plots the response of x_1 to the step change of u_1.

An approximate model of the transfer function g_{11} is obtained via the reaction curve method. In this case, t_1 is the time for the curve to reach 28% of the total change, and t_2 is the time to reach 63.6%. These parameters are obtained via

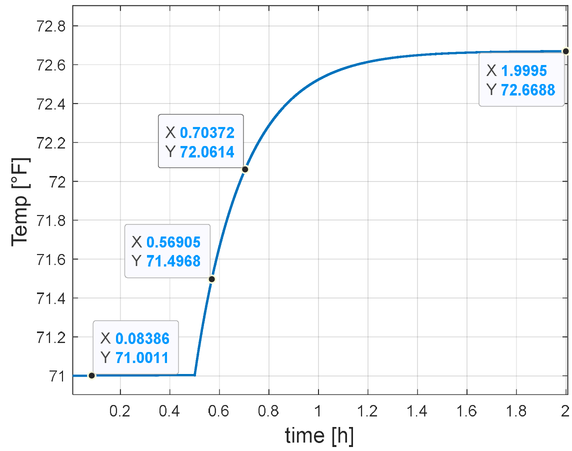

FIGURE 5. Response of x_1 to the 10% step change of u_1.

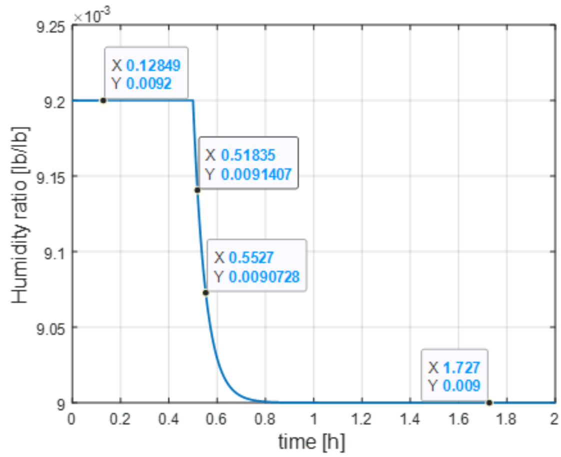

FIGURE 6. Response of x_2 to the 10% step change of u_1.

Eqs. (21) - (24).

$$\begin{aligned} t_1 &= 0.5690 - 0.5 = 0.0690\text{ h};\\ t_2 &= 0.7037 - 0.5 = 0.2037 \end{aligned} \tag{21}$$

$$\tau_D = \frac{3}{2}(t_2 - t_1) = \frac{3}{2}(0.2037 - 0.0690) = 0.2021\text{h} \tag{22}$$

$$K_D = \frac{\Delta x_1}{\Delta u_1} = \frac{72.6688 - 71}{18700 - 17000} = 9.8164 \times 10^{-4} \tag{23}$$

$$\begin{aligned} t_D &= t_2 - \tau_D = 0.2037 - 0.2021 = 0.0016\text{h} \Longrightarrow\\ g_{11} &= \frac{9.8164 \times 10^{-4} e^{-0.0016}}{0.2137s + 1} \end{aligned} \tag{24}$$

Figure 6 plots the response of x_2 to the step change of u_1. An approximate model of the transfer function g_{21} is obtained via the reaction curve method. The parameters are obtained via Eqs. (25) - (28).

$$\begin{aligned} t_1 &= 0.5183 - 0.5 = 0.0183\text{ h};\\ t_2 &= 0.5527 - 0.5 = 0.0527\text{h} \end{aligned} \tag{25}$$

$$\tau_D = \frac{3}{2}(t_2 - t_1) = \frac{3}{2}(0.0527 - 0.0183) = 0.0516\text{h} \tag{26}$$

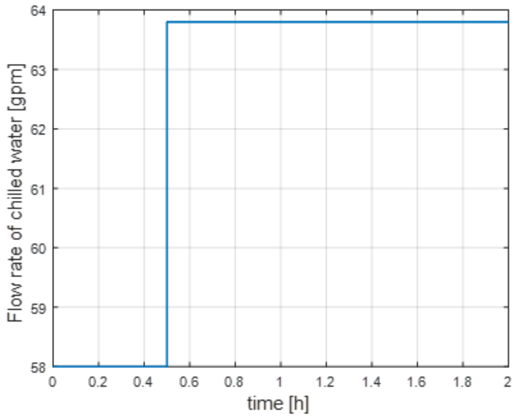

FIGURE 7. Step change of 10% is applied to u_1.

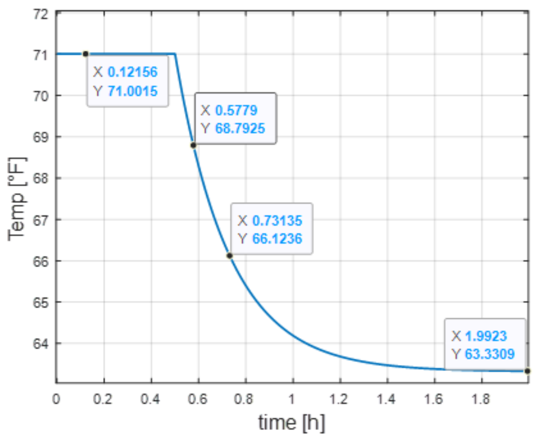

FIGURE 8. Response of x_1 to a 10% step change of u_2.

$$K_D = \frac{\Delta x_2}{\Delta u_1} = \frac{0.009 - 0.0092}{18700 - 17000} = -1.1764 \times 10^{-7} \quad (27)$$

$$t_D = t_2 - \tau_D = 0.0527 - 0.0516 = 0.0011\text{h} \Longrightarrow$$

$$g_{21} = \frac{-1.1764 \times 10^{-7} e^{-0.0011s}}{0.0527s + 1} \quad (28)$$

The next action in the experiment is to apply a step change of 10% in the HVAC system operating point at u_2, as plotted in Figure 7, while u_1 remains unchanged.

Figure 8 plots the response of x_1 to the step change of u_2. An approximate model of the transfer function g_{12} is obtained via the reaction curve method. These parameters are obtained via Eqs. (29) - (32).

$$t_1 = 0.5779 - 0.5 = 0.0779\text{h};$$

$$t_2 = 0.7313 - 0.5 = 0.2313\text{h} \quad (29)$$

$$\tau_D = \frac{3}{2}(t_2 - t_1) = \frac{3}{2}(0.2313 - 0.0779) = 0.2301\text{h} \quad (30)$$

$$K_D = \frac{\Delta x_1}{\Delta u_2} = \frac{63.3306 - 71}{63.8 - 58} = -1.3223 \quad (31)$$

$$t_D = t_2 - \tau_D = 0.2313 - 0.2301 = 0.0012\text{h} \Longrightarrow$$

$$g_{12} = \frac{-1.3223 e^{-0.0012s}}{0.2301s + 1} \quad (32)$$

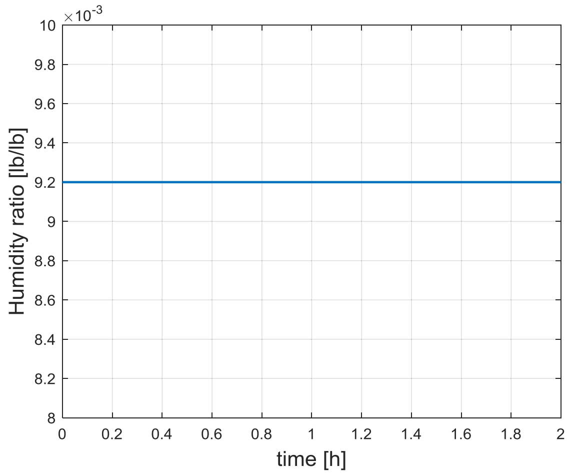

FIGURE 9. Response of x_2 to a 10% step change of u_2.

Figure 9 plots the response of x_2 to the step change of u_2. An approximate model of the transfer function g_{22} is obtained via the reaction curve method. These parameters are obtained via Eq. (33).

According to Figure 9, x_2 remains unchanged with a step change of u_2. Thus:

$$g_{22} = 0 \quad (33)$$

Based on the obtained transfer functions, the linearized model can be represented by matrix $G(s)$:

$$X(s) = G(s)\,U(s) \quad (34)$$

where:

$$G(s) = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \quad (35)$$

Substituting Eqs. (24), (28), (32) and (33) into Eq. (35) yields:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \frac{9.8164 \times 10^{-4} e^{-0.0016}}{0.2137s + 1} & \frac{-1.3223e^{-0.0012s}}{0.2301s + 1} \\ \frac{-1.1764 \times 10^{-7} e^{-0.0011s}}{0.0527s + 1} & 0 \end{bmatrix} \times \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (36)$$

From $G(s)$, the gains of each element are obtained to yield gain matrix K.

$$K = \begin{bmatrix} 9.8164 \times 10^{-4} & -1.3223 \\ -1.1764 \times 10^{-7} & 0 \end{bmatrix} \quad (37)$$

The RGA [57] is a matrix (Bristol's matrix) that is used to measure the interaction between the inputs and outputs in a multivariate process control. It is defined as:

$$RGA(K) = \Lambda(K)\,K \times \left(K^{-1}\right)^T \quad (38)$$

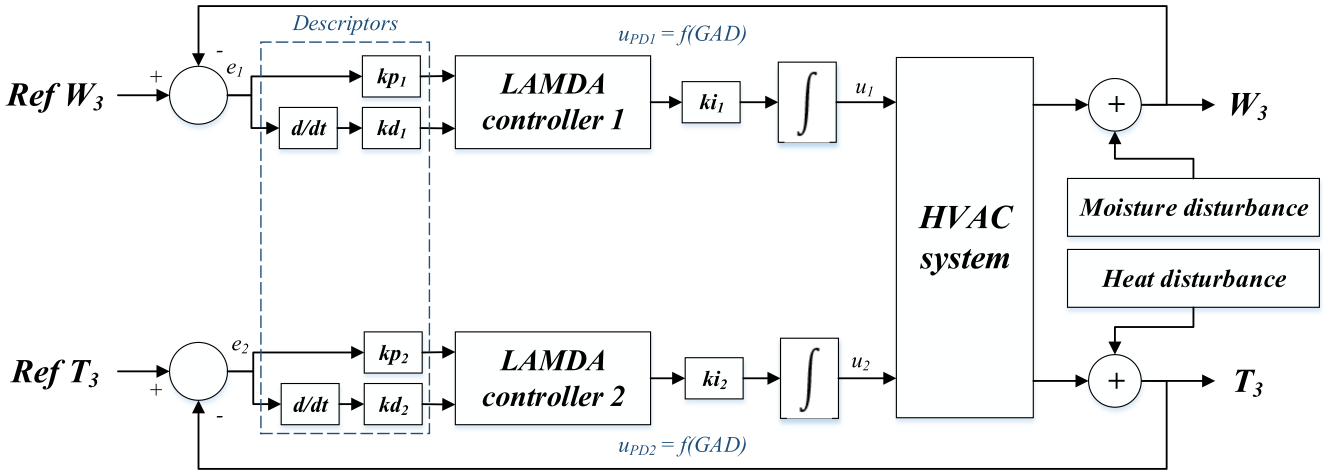

FIGURE 10. HVAC system two-closed-loop LAMDA control scheme (decoupled).

where the operator $\times$ denotes element-by-element multiplication:

$$\Lambda(K) = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

The parameters of $\Lambda(K)$ describe the dependence between the inputs and outputs (Eq. (37)), thereby leading to the conclusion that the decoupling stage is not necessary for this control. Due to the HVAC system characteristics and the resulting parameters of $\Lambda(K)$, the control design with two independent LAMDA controllers, namely, one for the temperature x_1 and another for the relative humidity x_2, is feasible.

$$u_2 \rightarrow x_1 \quad and\ u_1 \rightarrow x_2 \tag{39}$$

Figure 10 illustrates the operational scheme of the proposed control system with two separated control loops, each of which is dedicated to maintaining one of the two variables that are associated with the thermal zone comfort.

This model could be approached as an FOPDT system; however, the transformation uncertainties and the nonlinear effects would degrade its performance. This degradation motivates the design of LAMDA-PI controllers for maintaining the steady-state error as close to zero as possible since the control target is to maintain the temperature at $71[°F]$ and the relative humidity at $0.0092[lb/lb]$. Figure 10 illustrates the LAMDA-PD controllers at the input stage, the signals of which are integrated to obtain the LAMDA-PI controllers [30]. The added blocks have scaling gains of kp_1, kd_1, ki_1, kp_2, kd_2 and ki_2 for tuning the responses of the controllers.

The controllers' inputs are e and $\dot{e}$, where e is the error that is obtained via the subtraction of the SP reference and the current system output and $\dot{e}$ is its derivative. These variables are used to drive the system to the desired zero state, in which the error and its derivative are equal to zero, and to maintain it at zero.

The centers of fuzzy classes C_k and their respective parameters in the consequent q^k are presented in Figure 11; they are the training data for LAMDA operation. Twenty-five classes are defined for each controller, and the centers are set as a combination of the following sets:

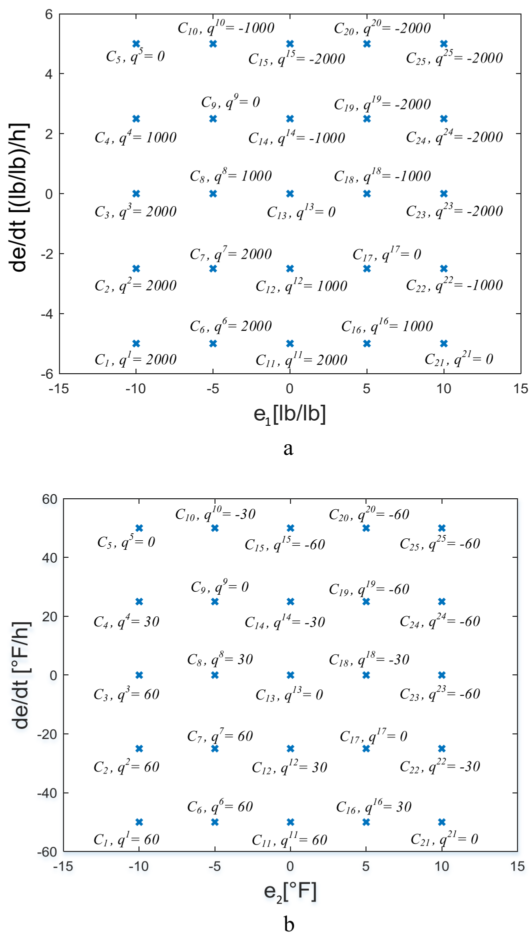

FIGURE 11. Defined classes and outputs for: a) the relative humidity LAMDA controller and b) the temperature LAMDA controller.

$$e_1 = [-1, -0.5, 0, 0.5, 1]\,10^{-4}\left[\frac{lb}{lb}\right] \text{ and}$$
$$\dot{e}_1 = [-0.5, -0.25, 0, 0.25, 0.5]\,10^{-5}\left[\frac{lb/lb}{h}\right] \tag{40}$$

TABLE 4. Numerical values for system parameters at the operating point.

Controller	Gains
PI controller 1	$kp_1 = -103132, ki_1 = -40626460$
PI controller 2	$kp_2 = -1.8, ki_2 = -6.29$
Fuzzy-PI controller 1	$kp_1 = 0.02, kd_1 = 0.0005, ki_1 = 200$
Fuzzy-PI controller 2	$kp_1 = 1, kd_1 = 0.05, ki_1 = 10$
LAMDA-PI controller 1	$kp_1 = 0.02, kd_1 = 0.0005, ki_1 = 200$
LAMDA-PI controller 2	$kp_1 = 1, kd_1 = 0.05, ki_1 = 10$

$$e_2 = [-10, -5, 0, 5, 10]\left[{}^{\circ}F\right] \text{ and}$$
$$\dot{e}_2 = [-5, -2.5, 0, 2.5, 5]\left[\frac{{}^{\circ}F}{h}\right] \quad (41)$$

VI. SIMULATIONS AND RESULTS

In this section, our method is compared against two additional controllers, namely, PI and conventional Fuzzy-PI [59], to evaluate their behaviors in the regulation tasks and to analyze their performances and responses to disturbances. The main criteria for the evaluation of the approaches is the IAE (integral absolute error, see Eq. (42)), which is an index that measures the performances of the controllers. The IAE reflects the cumulative error, namely, how far the response is from the applied reference. Therefore, the controller that realizes the minimum index value performs the best.

$$IAE = \int_0^{\infty} |e(t)|\, dt \quad (42)$$

As discussed above, disturbances that simulate thermal loads in the system are added for evaluating the robustness of the closed-loop system.

The PI controllers are calibrated at the beginning via the Smith and Corripio method [58] to realize the best performance based on the IAE minimization. The Fuzzy-PI controllers have been designed by considering Gaussian membership functions with their maximum values at the center points of the LAMDA classes for the same rules for a fair comparison with the LAMDA-PI controller. The sample time in this experiment is set to 0.01 hours, which is equivalent to 36 seconds, and the gains of the Fuzzy-PI and LAMDA-PI controllers have been empirically calibrated to perform their control actions in the same ranges as the PI controllers. The gains of the studied controllers are presented in Table 4.

The objective of the studied HVAC system is to maintain the temperature T_3 at 71 $[{}^{\circ}F]$ and the relative humidity at 0.0092 $[lb/lb]$; namely, this maintenance is a problem of regulation in the field of automatic control. The experiment begins with the application of a moisture disturbance in Zone 3, as is illustrated in Figure 10. The moisture disturbance signal for robustness consideration that is applied to the system is plotted in Figure 12.

The control actions and system responses of the PI and LAMDA-PI controllers are presented in Figure 13 for comparison.

The resulting IAEs after the application of the moisture disturbance to the HVAC system are presented in Table 5.

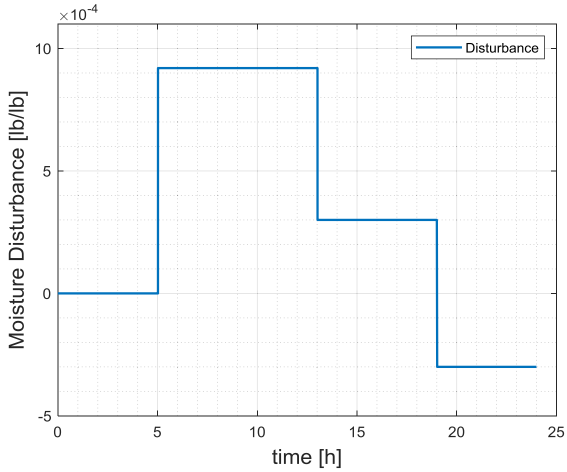

FIGURE 12. Moisture disturbance signal for testing the controller's robustness feature.

Additionally, Table 5 presents the differences and the relative percentages of variation $\Delta\%$ (Eq. (43)) with respect to the best *IAE* value "IAE_B" (the value that is marked in bold text):

$$\Delta\% = \frac{|IAE_X - IAE_B|}{\frac{(IAE_X + IAE_B)}{2}} \quad (43)$$

where IAE_X is the index of the controller that does not perform the best.

The results in Figure 13 and Table 5 demonstrate that the LAMDA controller realizes the best IAE performance when a moisture disturbance is applied in the thermal zone. The applied disturbance affects both the W_3 and T_3 outputs, of which the latter is more affected. However, the LAMDA-PI controller corrects the disturbance faster, thereby leading to lower overshoots in the response. This outcome also implies an energy savings when driving the system to the desired state. This smoother or less abrupt behavior is shown in the magnified frames in Figure 13, thereby proving the improvement both graphically and numerically. In the case of temperature, the improvement over the PI controller is 142%, and that over the Fuzzy-PI is 32%; for humidity, the improvement over the PI controller is 3.5%, and that over the Fuzzy-PI is 13%. The smoother control signal enables faster regulation of the output variables, thereby demonstrating the robustness of the proposed controller.

In the next test, a temperature (heat) disturbance is applied in Zone 3, as plotted in Figure 10. The heat disturbance signal for robustness analysis is presented in Figure 14.

The controllers react to the changes and the responses are plotted in Figure 15, in which the performances of PI and LAMDA-PI are compared.

The resulting IAEs after the application of the temperature disturbance to the system are presented in Table 6. Additionally, Table 6 presents the differences and the relative percentages of variation $\Delta\%$ with respect to the best IAE (the value that is marked in bold text).

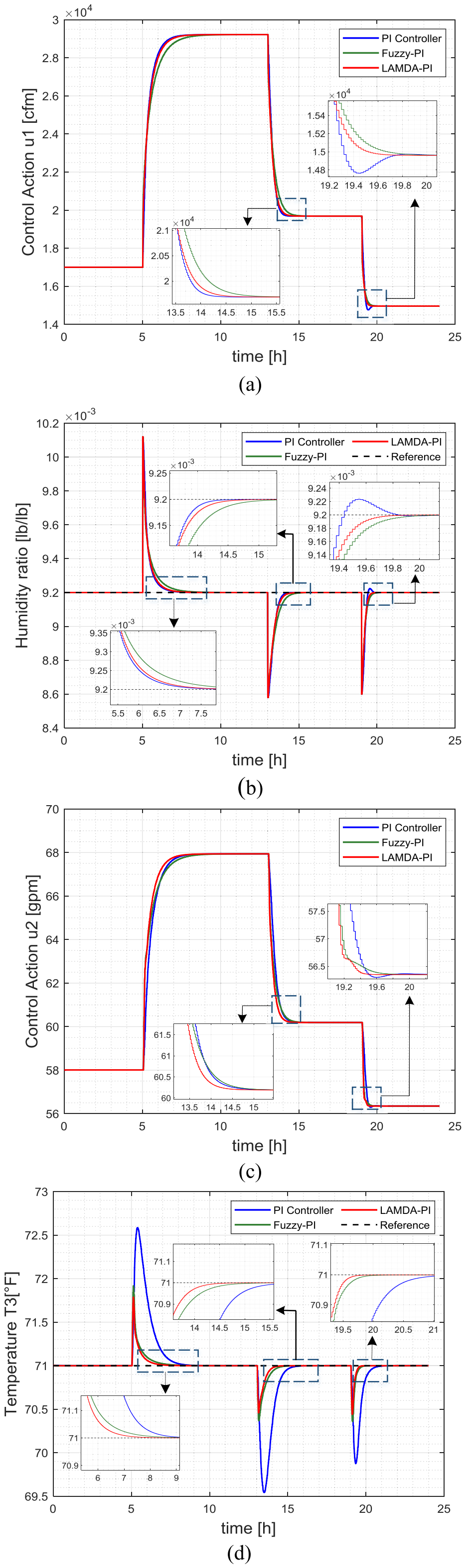

FIGURE 13. Comparative results with a moisture disturbance: (a) control action u_1, (b) humidity ratio W_3, (c) control action u_2, and (d) temperature T_3.

The results in Figure 15 and Table 6 demonstrate again that the LAMDA controller realizes the best IAE performance when a temperature disturbance is applied in the thermal zone. The applied disturbance affects only the T_3 output. Again, the LAMDA-PI controller yields the best results for this test. Our approach shows improvements in the case of temperature over the PI controller of 5% and over Fuzzy-PI of 148%, and for humidity, it shows improvements over the PI controller of 6% and over the Fuzzy-PI of 2.4%. The Fuzzy-PI controller presents a more abrupt control action than that of the LAMDA-PI controller, and the PI controller has a smoother but slower response, which causes the system to take longer to reach the reference values (see the magnified frames in Figure 15), thereby increasing the energy consumption of the actuators (fan and chiller) for maintaining the system at the desired reference values.

TABLE 5. IAE comparison with the application of a moisture disturbance to the HVAC system.

Controller	IAE	Difference	Δ%
PI controller 1	6.62×10^{-4}	0.24×10^{-4}	3.582
Fuzzy-PI controller 1	7.30×10^{-4}	0.92×10^{-4}	13.33
LAMDA-PI controller 1	$\mathbf{6.38 \times 10^{-4}}$	-	-
PI controller 2	3.42	2.85	142.7
Fuzzy-PI controller 2	0.79	0.22	32.13
LAMDA-PI controller 2	**0.57**	-	-

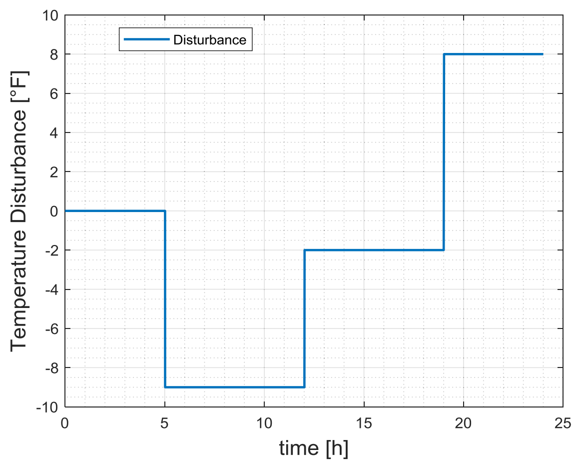

FIGURE 14. Temperature disturbance signal for robustness analysis.

A. DISCUSSION OF THE RESULTS

In the studied HVAC system for buildings, two types of disturbances have been applied separately: temperature (heat) and moisture.

It has been shown that the moisture disturbance that is applied to the thermal zone most affects the behavior of the system and is the most critical for the control system since it causes the two controllers to begin regulating the variables T_3 and W_3.

All the tested controllers realize the control objective of stabilizing the system at the desired reference values, namely, $71°F$ and $0.0092\ lb/lb$. However, it is important to analyze the ways in which the approaches stabilize the system, along with their respective performances. In all the tests that were conducted, LAMDA-PI yields the lowest IAE values,

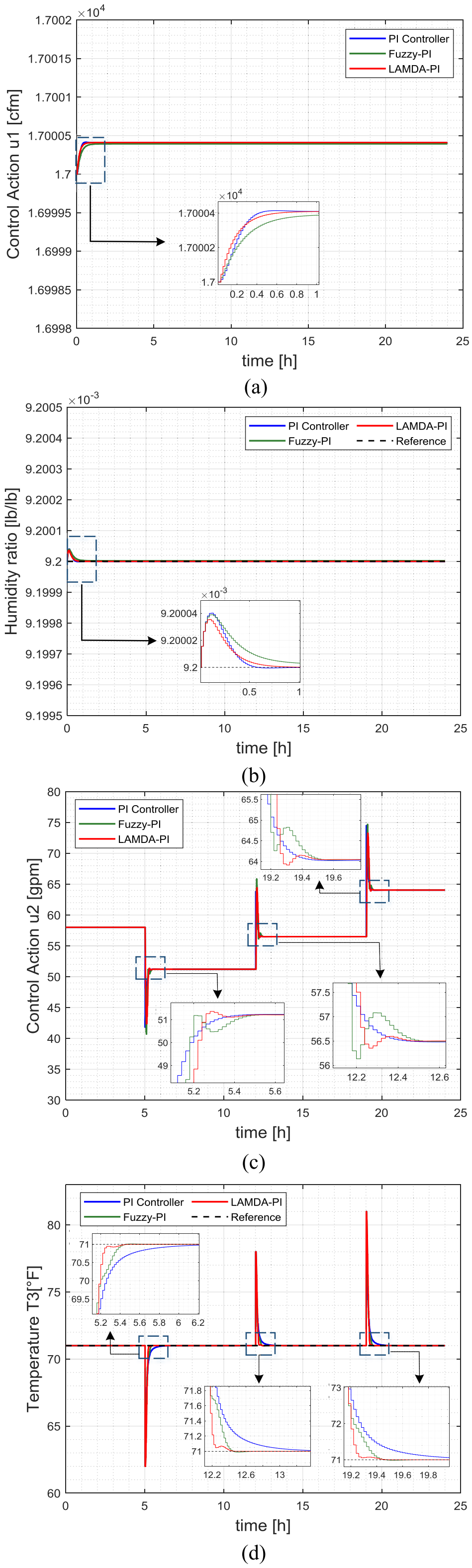

FIGURE 15. Comparative results with a temperature disturbance: (a) control action u_1, (b) humidity ratio W_3, (c) control action u_2, and (d) temperature T_3.

demonstrating that in the presence of significant step-type disturbances (±10% of the reference values), the controller takes the system quickly to the reference without failing or becoming unstable. In the case of humidity (see Figure 13b), it performs without overshoot and faster than the Fuzzy-PI controller, where LAMDA realizes higher performance with values that exceed 30%. In the case of temperature disturbances (see Figure 15c and 15d), the response is the fastest without producing considerable oscillations, such as those observed in Fuzzy-PI, or a very slow response, as in the case of the PI, which results in high energy consumption that must be reduced in systems of this type. The control actions that are produced by the LAMDA-PI controller are not abrupt and can be physically implemented in the studied system.

The implementation of the proposed controller shows advantages in terms of both the performance and the response to disturbances, and its design is simple since no mathematical model of the HVAC system is required and it is only necessary to define the centers of the classes and the rules based on the knowledge of the HVAC system. Our proposed approach also improves the results with respect to Fuzzy-PI, which presents a similar design methodology, but requires the definition of additional parameters for the Gaussian, triangular or trapezoidal membership functions.

With respect to the depreciation of the overall control system, it has been shown that the controller exhibits a satisfactory response to changes in the dynamics of the HVAC system; namely, the system remains stable even though the conditions of the HVAC system to be controlled are modified, demonstrating the excellent features of our method. With respect to controlling system failures, future studies will analyze this problem in the context of a supervision system.

TABLE 6. IAE comparison with the application of a temperature disturbance to the HVAC system.

Controller	IAE	Difference	Δ%
PI controller 1	1.03×10^{-8}	0.51×10^{-9}	5.11
Fuzzy-PI controller 1	6.65×10^{-8}	67.1×10^{-9}	148
LAMDA-PI controller 1	$\mathbf{9.79 \times 10^{-9}}$	-	-
PI controller 2	3.12	0.19	6.07
Fuzzy-PI controller 2	3.01	0.08	2.45
LAMDA-PI controller 2	**2.93**	-	-

VII. CONCLUSION

Advanced building HVAC control is a necessity in our society for ensuring the comfort of the occupants and saving energy. The soft control or AI methods that are based on ANN, FL and evolutionary algorithms are yielding interesting results in terms of accuracy and computational optimization performance. This paper proposes an HVAC control that is based on the LAMDA, which is a fuzzy logic clustering approach for smart buildings. The proposed model outperforms other conventional controllers.

LAMDA control is a powerful technique for knowledge extraction because it supports both the identification of the most relevant system features and control decision-making. This is a singular characteristic from the modeling perspective. Mathematical models are difficult to implement, require assumptions that reduce the accuracy of the simulation, and are unable to support online solutions due to their complexities. Empirical approaches typically suffer from lack of quality data or sufficient information for building reliable models.

Due to the need to save energy, maintain comfort and add objectives to the HVAC control system, a general approach is required that results in a complex and multifaceted problem because multidimensional data are required that are not possible to analyze via simple techniques. The proposed approach enables the definition of the main domain-based features of the studied phenomena, and this definition is used to implement useful strategies for driving the controller from its current state to the desired target state.

The implementation of a LAMDA-based controller drives the HVAC system to the target state by calculating the adequacy with respect to the class (GADs). The versatility of the algorithm has been demonstrated by comparing LAMDA-PI with the conventional PI and Fuzzy-PI controllers. The main advantage of working with LAMDA is that it is only necessary to define the centers of the fuzzy logic classes and the weights for the outputs, and no additional parameters are required, such as in conventional fuzzy controllers.

This article has demonstrated the utilization of contextual information in real time in a LAMDA controller. The proposed approach includes the contextual data in the error input as real-time feedback information with a manageable number of rules. The results of the experiments for evaluating the robustness have proven that higher precision and faster operation of LAMDA-PI are achieved compared with available conventional controllers and that LAMDA-PI provides energy savings, as it manages the actuators using a softer approach. In addition, the proposed controller can be trained with an online learning mechanism for real-time calibration. In future work, the ability to self-adjust the classes for the algorithm without requiring the human expertise of the designer will be extended by using the gradient descent algorithm.

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