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Research Article

Modeling, Analysis, and Design of a Fuzzy Logic Controller for an AHU in the S.J. Carew Building at Memorial University

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Proper functioning of heating, ventilation, and air conditioning (HVAC) systems is important for efficient thermal management, as well as operational costs. Most of these systems use nonlinear time variances to handle disturbances, along with controllers that try to balance rise times and stability. The latest generation of fuzzy logic controllers (FLC) is algorithm-based and is used to control indoor temperatures, CO_2 concentrations in air handling units (AHUs), and fan speeds. These types of controllers work through the manipulation of dampers, fans, and valves to adjust flow rates of water and air. In this paper, modulating equal percentage globe valves, fans speed, and dampers position have been modeled according to exact flow rates of hot water and air into the building, and a new approach to adapting FLC through the modification of fuzzy rules surface is presented. The novel system is a redesign of an FLC using MATLAB/Simulink, with the results showing an enhancement in thermal comfort levels.

1. Introduction

Heating, ventilation, and air conditioning (HVAC) systems are installed in millions of commercial and noncommercial buildings as a means to provide the desired thermal comfort standards at an affordable cost and with minimal maintenance requirements. The HVAC approach to heating and cooling has become much more complicated, with the latest HVAC components using control algorithms, sensing technology, and artificial intelligence [1].

Energy saving is a key feature of HVAC systems and is increasing in importance [2, 3]. As the housing and business needs of the developed world generally include buildings that require HVAC systems, the percentage contribution of the total energy consumption of these buildings has increased from 20% to 40% in Western countries [4, 5]. Typically, an HVAC system requires more energy per building than any other system, given optimal comfort in home and work environments. However, there is a rising demand for costs to remain reasonable but efficiency to be high without sacrificing comfort levels. Recent research indicates that intelligent control might be a viable method of achieving optimal comfort levels at high energy efficiency. Intelligently controlled HVAC systems have been shown to reduce energy consumption by up to 30% [6] or higher [7]. Due to the potential these systems have for future energy needs, this paper proposes identifying advanced novel HVAC system models that employ intelligent control algorithms to produce energy savings without sacrificing comfort levels. Modeling HVAC systems and components mathematically has been demonstrated in the literature to be a viable approach for designing controls and detecting faults.

Earlier research in the field reveals modeling strategies that fall into two distinct categories: grey box and black box. The grey box approach depends on the existence of physical knowledge, while the black box method requires no previous knowledge. In the literature, black box is more common due in large part to issues related to thermodynamic modeling. Some black box options used in modeling HVAC systems include linear parametric models and polynomial forms such as OE, BJ, ARMAX, and ARX. However, this approach does consider a system's physical characteristics, which can be a drawback in practical application of designs.

Chi-Man Yiu et al. [8] investigated black box identity in an air conditioning system. They compared a single-input single-output (SISO) system ARMAX model with a multi-input and multioutput (MIMO) system ARMAX model, and they they devised the latter using parameters obtained from the Recursive Extended Least Squares (RELS) technique. Mustafaraj et al. [9] investigated humidity and temperature models (OE, BJ, ARMAX, and ARX) to be applied in an office environment, identifying them with a black box strategy. This research was extended by Mustafaraj et al. [10], where they explored nonlinear autoregressive models with eXogenous (NARX) inputs. Using this approach, they estimated humidity and temperature and compared the performance of these models with linear ARX models. Mustafaraj et al. [10] also investigated carbon dioxide concentrations' impact on the models, as there is a direct relationship between CO_2 and occupancy levels.

In other studies, Qi and Deng [11] reviewed a MIMO control strategy in air conditioning systems for modulating humidity and temperature indoors, using an air conditioning model that was based on principles of mass and energy conservation. Maasoumy [12] researched temperature models applicable to a three-room suite, designing a suitable HVAC control algorithm for the system using an analogue of electric circuits along with the thermal circuit technique. More recently, Wu and Sun devised a room temperature model for an office building using a linear parametric model that was physics-based; the researchers used thermodynamics equations to develop structure and order in the linear regression model. The outcome indicated that the physics-based ARMAX (pbARMAX) model showed improved functioning over black-box models [13]. Finally, in [14] and based on physical dynamic systems, the researchers developed MISO ARMAX models to investigate humidity, temperature, and CO_2 levels in a standard bedroom. This model also makes allowances for the impact of room occupants, as occupants were deemed a "disturbance" in the room temperature pbARMAX model was designed in.

The present study develops a simulation for a whole building, using IDA Indoor Climate and Energy 4.7 as a simulation program. The IDA Indoor Climate and Energy program was founded in 1998 to study thermal climate zones [15]. The simulation will test the energy consumption (heating and cooling) at Memorial University's S.J. Carew building in Newfoundland, Canada. It will investigate a heat model that is dependent on a range of parameters, a three-dimensional (3D) model, and IDA ICE model library components. The present work will also examine results from [16, 17], which used real data as a basis for developing whole structures.

There are three primary aims in this study. Our first aim is to test system identification viability as a means for shortening the calculation times needed to simulate more complicated structures in air handling unit one (AHU_1). Our second aim is to test the usefulness of system identification in the dynamics identification for structural climate control design when applying discrete time data for one-hour samples. Our third aim is to develop fuzzy logic controller structures that feature 6 inputs and 3 outputs and use this to develop a controller in an AHU_1 state space model.

2. Description of System

2.1. Building Structure. Our analysis will use the S.J. Carew building at Memorial University in St. John's, Newfoundland. S.J. Carew building measures approximately 25,142 m^2 and houses the university's Faculty of Engineering and Applied Science, as well as teaching rooms, research labs, and a cafeteria. From a structural perspective, the building houses four AHUs across 300 zones. The energy report of building is presented in Table 1 and Figure 1 shows 3D model of building using IDA ICE (IDA Indoor Climate and Energy) program. A more detailed description of the structure and amenities of the S.J. Carew building can be found in earlier studies [16, 17]. As the building's HVAC system is based on the IDA ICE program, good approximation results can be obtained from the model regarding power and hot water data, which can then be compared to real data.

2.2. AHU_1 Structure. Figure 2 illustrates an AHU_1 with a variable air volume (VAV) system. There are valves, hot water pumps, heating and cooling coils, supply and return fans, and fresh air dampers. To maintain a constant point of internal air quality (IAQ), the building employs fresh air control dampers. An economizer mixes outdoor air with recycled building air, while a supply fan funnels the air mixture into cold-deck and hot-deck ducts. The return fan located in the room's return duct is around 10% slower than the supply fan. The fan keeps the ducts set at fixed pressure points.

Figure 3 depicts Room 347 at the S.J. Carew building; also alternating the fan speed is a means to balance any duct system resistance changes caused by opening/closing dampers located at VAV terminal units. Controllers are employed in the heat exchanger for keeping zonal temperatures set at fixed points through the use of modulating control valves. During the cold season (October to May), the heating system is turned on and the cold system is turned off. The present study used data from October to December 2016, so the cold system was off, as illustrated in Figure 2.

2.3. Simulation Model. The IDA Indoor Climate and Energy 4.7 simulation tool is used for assessing the indoor climate and energy performance. This simulation tool is suitable for modeling HVAC systems located in multiple-zoned structures, such as the S.J. Carew building. The tool can assess IAQ, dynamic simulation, required energy, and overall thermal comfort. For the real system, a hot water valve (Figure 2) provides data on hot water usage for the heating coil, as the system has a single valve for the building's entire hot water generation. However, with the IDA-ICE software, the hot water valve is divided into four valves, such that every AHU can have its own valve. Hence, every AHU includes 3 inputs and 3 outputs. This information will be used as a reference model and identification data when modeling the AHU_1.

Table 1: Energy report for the building.

EQUA SIMULATION TECHNOLOGY GROUP		Energy report for "S.J. Carew Building"	
Project		**Building**	
		Model floor area	25141.7 m^2
Customer		Model volume	128952.9 m^3
Created by	Almahdi Abdo-Allah	Model ground area	10544.5 m^2
Location	Newfoundland (St. John's Airport)_718010 (ASHRAE 2013)	Model envelope area	29440.0 m^2
Climate file	CAN_NF_St.Johns.718010_CWEC	Window/envelope	2.40%
Case	building2017_fuzzy logic	Average U-value	0.3031 W/(m^2 K)
Simulated	5/23/2017 10:04:07 AM	Envelope area per volume	0.2283 m^2/m^3

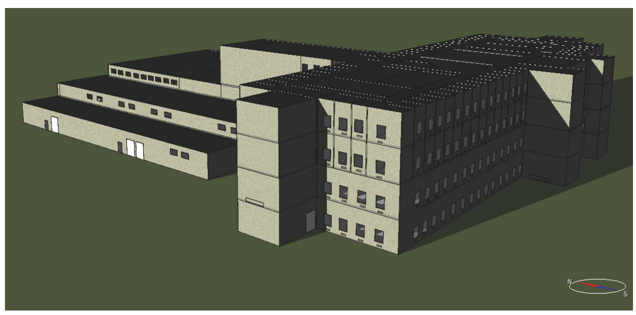

Figure 1: 3D model of S.J. Carew building.

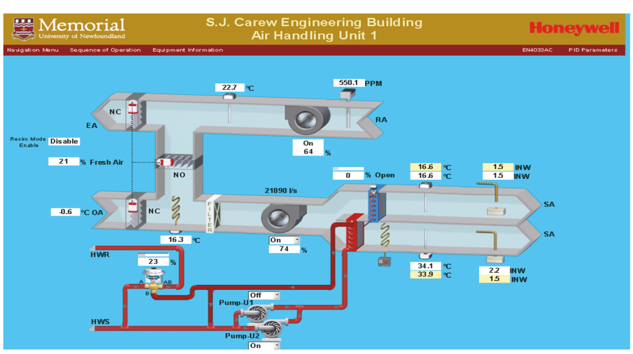

Figure 2: AHU_1 for S.J. Carew building.

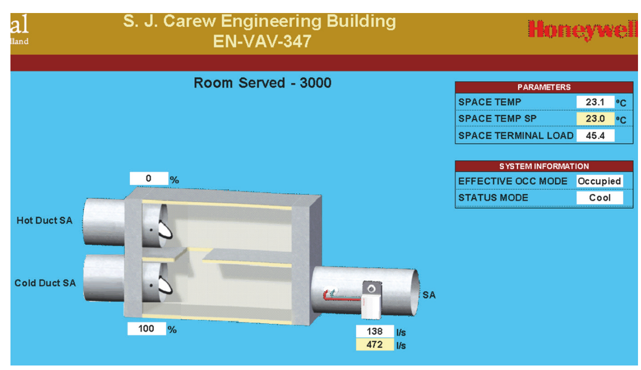

Figure 3: VAV terminal units of room 347 at the Carew building.

2.4. System Identification. *System identification features three separate steps:*

(a) Data gathering

(b) Choosing the model structure

(c) Building a model that provides the highest system functionality

AHUs are useful in system identification. There are three inputs to the AHU: (1) hot water valve for the heating coil/zones, (2) supply fan speed, and (3) fresh air from outdoors. The outputs show data for three different system elements: (1) return air temperature (degree Celsius (°C)) for controlling the valve aperture of hot water, (2) static air pressure, P_S (inches of water (INW)) in ducts for controlling supply fan speed, and (3) CO_2 levels (parts per million (PPM)) for controlling fresh air dampers.

2.5. Inputs and Outputs Signals. Figure 4 shows the inputs of the AHU_1 as percentage of the hot water valve aperture, supply fan speed, and fresh air dampers position. As illustrated in Figure 5, an output is zone temperature. The second output is static air pressure (Figure 6) and the third output is CO_2 quantity (Figure 7).

A model structure is selected from a range of structures that are roughly categorized as being either linear or nonlinear. The identification toolbox of MATLAB is used

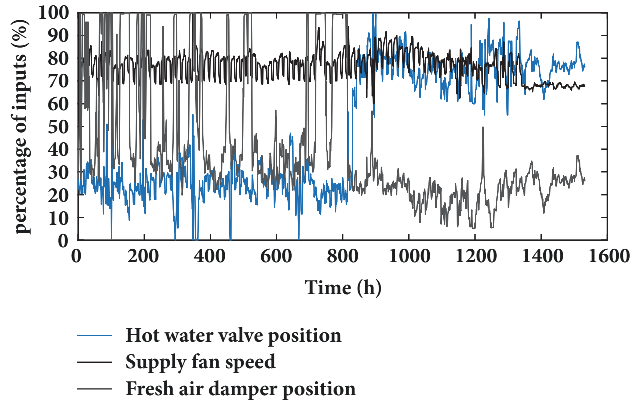

Figure 4: Inputs of AHU_1 as percentage (%).

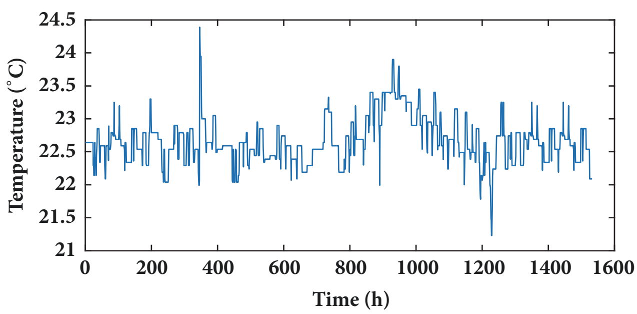

Figure 5: Zone temperature (in °C).

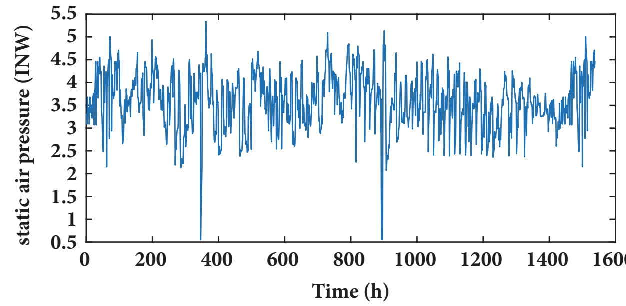

Figure 6: Static air pressure P_S (INW).

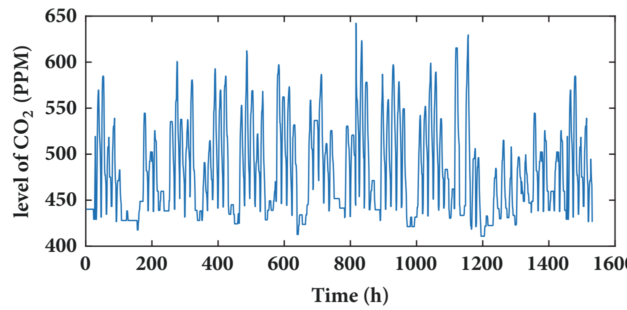

Figure 7: Level of CO_2 (in PPM).

in preprocessing the data. The decision process can be categorized into a few steps of optimal model structure (e.g., ARX, ARMAX, and process models), model order, optimal estimation approach, and launching the identification process.

3. Control Strategies

3.1. Fuzzy Logic Controller. Comfort levels and energy savings are the two main driving forces that have led researchers to create intelligent systems (i.e., Building Intelligent Energy Management Systems (BIEMS)) as a means to manage energy use in buildings. BIEMS are usually employed only in large structures, such as commercial buildings, office towers, and hotels. These systems can control and monitor a building's environmental parameters, creating a comfortable microclimate while reducing energy consumption and operational costs.

Fuzzy techniques have been used in BIEMS, giving significantly better outcomes than traditional control systems. Practical applications employing fuzzy and neural control in HVAC systems are also being used, with the overall aim of lowering energy consumption and costs [18–22].

In traditional control methods, mathematical models of the building's operations are needed, but when using intelligent systems (i.e., model-free automatic controllers), mathematical modeling is unnecessary. Hence, through the introduction of higher-level comfort variables in intelligent controllers, such as PMV [23], comfort can be managed without the need to regulate lower-level variables such as humidity, air speed, and temperature. Users participating in intelligent systems are able to choose their preferred comfort levels with optimized fuzzy controllers that employ genetic algorithms and adaptive control strategies. Fuzzy logic control is already being applied in the latest furnace controllers, using adaptive heating control as a means to optimize comfort and energy efficiency in domestic heating systems [24]. Fuzzy controllers are also used to control natural ventilation, visual comfort, and thermal comfort; there are notable results in these subsystems [25, 26].

3.2. Design of Fuzzy Logic Controller. There are several approaches for applying fuzzy logic for closed-loop control. The most common technique is the fuzzy PI controller [27, 28] that uses process-derived measurement signals as fuzzy logic controller inputs and outputs to operate the actuators. A fuzzy PI controller represents an incremental controller. A traditional fuzzy PI controller can be expressed as in (1), with fuzzy rules determining the output [29].

$$u(k+1) = u(k) + \Delta u(k) \tag{1}$$

where k is the sampling instance and $\Delta u(k)$ is the incremental change in controller.

The present study uses a traditional fuzzy PI controller for the AHU_1 model. The proportional (P) and integral (I) actions are combined to benefit from the inherent stability, which is a feature in proportional controllers, as well as to benefit from the integral controllers' offset elimination feature. Incremental controllers are most suitable for use

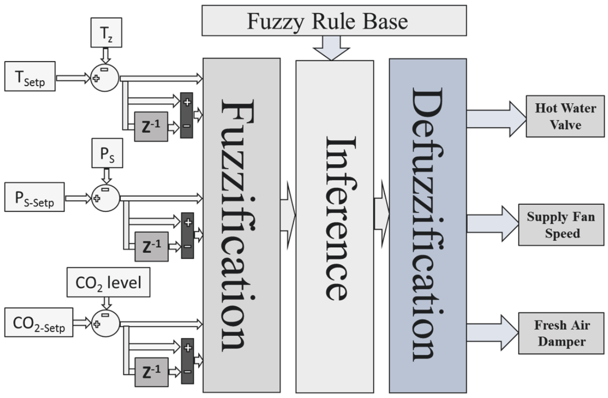

Figure 8: Structure of fuzzy logic controller.

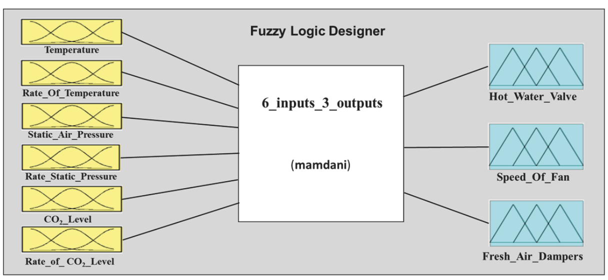

Figure 9: Fuzzy logic designer app.

in situations where a valve or motor serves as actuator. Additionally, it can be beneficial when controller output is derived from an integrator due to its ease in handling noise and wind-up. As shown in Figure 8, a fuzzy PI controller applies error signals and change of error as inputs.

Another benefit in using a fuzzy PI controller is its lack of operational or setpoint. A rule-driven control strategy weighs differences between a setpoint and measured values, measuring any modifications to these differences as a means to determine if increments or decrements should be applied to a building's control variables. While a fuzzy logic controller is able to perform nonlinear control strategies, applying a fuzzy logic technique in real applications must be done in the following three-step process [30]:

(i) *Step 1. Fuzzification* changes crisp/classical data into membership functions (MFs) or fuzzy data.

(ii) *Step 2.* In the *fuzzy inference process*, MFs are added to control rules to obtain the required fuzzy output.

(iii) *Step 3. Defuzzification* employs a variety of strategies as a means to formulate every associated output, to place them within a table framework, and to choose the output in a look-up table in accordance with the current input obtained for the specific application being performed.

As it is illustrated in Figure 8, fuzzy controller is assigned to control zone temperature, static air pressure, and CO_2 level. Error signals and their changes are fed to a fuzzy controller. The output of fuzzy controllers is assigned as inputs of the

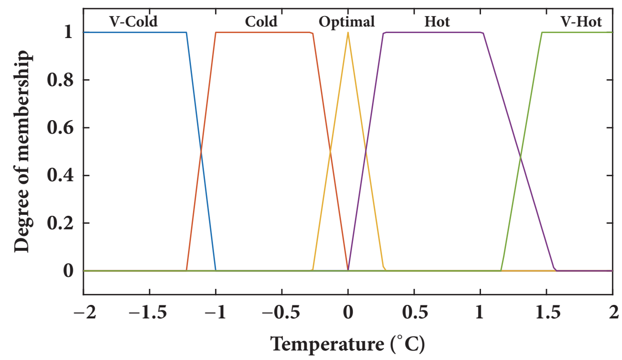

Figure 10: MFs of zone temperature difference.

system. The system outputs are sent to the fuzzy controller to make a closed-loop controller.

Fuzzy Logic Designer App of the system is shown in Figure 9; with this App, the FLC can be designed to add or remove input or output, fuzzy membership function, and IF-Then rules and select fuzzy inference functions.

3.3. Fuzzy Membership Function. The MFs editor is used in unpacking the fuzzy tool box, which is applied in shape-defining any MFs that are related to variables in the membership. The AHU_1 control system indicates 3 outputs and 6 inputs. Brief definitions of the MFs for the input and output variables are presented in Sections 3.3.1 and 3.3.2.

3.3.1. Input Variables

(1) Temperature Differences (ΔT). Current zone temperature of return air as recorded by an electronic sensor (Figure 2) illustrates that (2) expresses differences between setpoint (T_{setp}) and current zone temperature (T_z) for time (k), while Figure 10 and Table 2 show the 5 MFs of V-hot, hot, okay, cold, and V-cold.

$$\Delta T(k) = T_{setp}(k) - T_z(k) \quad (^\circ C) \tag{2}$$

(2) Change in ΔT ($d\Delta T$). Error input variables related to changes in temperature are formulated through finding the ratio for the difference of past and present temperature error values in relation to sampling time (Δt), as expressed in (3). The building's real system, Honeywell Software, gives a system sampling time of 3 seconds (Department of Facilities Management and Honeywell Offices at Memorial University). As shown in Figure 11 and Table 3, three membership functions can be used to define error variable changes: Positive (P), Negative (N), and Zero (Z).

$$(d\Delta T) = \frac{(\Delta T(k) - \Delta T(k-1))}{\Delta t} \quad (^\circ C/s) \tag{3}$$

(3) Static Air Pressure P_S *Differences*. Figure 2 illustrates changes in present duct P_S; these differences were noted by sensors located in both cold- and hot-deck ducts. As can be

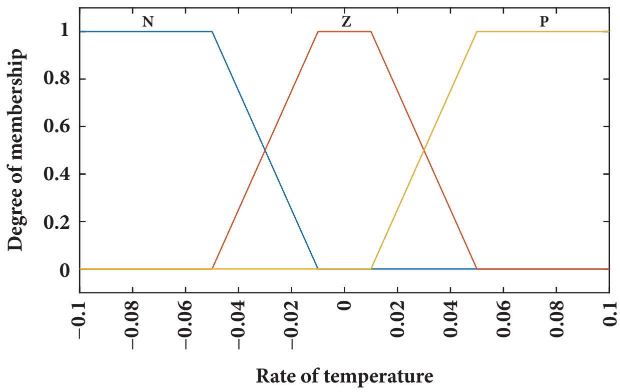

Figure 11: MFs of change in ΔT.

Table 2: MFs of zone temperature difference.

Input field	Range	Fuzzy set
	[-10.52 -8.48 -1.222 -1]	V-cold
Temperature	[-1.222 -1 -0.268 0]	Cold
difference	[-0.268 0 0.2714]	Optimal
(ΔT)	[0 0.268 1.02 1.563]	Hot
	[1.159 1.465 3.549 13.26]	V-hot

Table 3: MFs of change in ΔT.

Input field	Range	Fuzzy set
Change of	[-0.118 -0.1031 -0.05 -0.01]	N
temperature error	[-0.05 -0.01 0.01 0.05]	Z
	[0.01 0.05 0.1534 0.1794]	P

Table 4: MFs of static pressure difference (ΔP_S).

Input field	Range	Fuzzy set
	[-0.8213 -0.1584 -0.08317 -0.06853]	V-low
Static air	[-0.0826 -0.0668 -0.00836 0]	Low
pressure	[-0.00771 0 0.00956]	Optimal
difference ΔP_S	[0 0.00836 0.071 0.0816]	High
	[0.07052 0.08278 0.1399 1.239]	V-high

Table 5: MFs of change in ΔP_s.

Input field	Range	Fuzzy set
Change of	[-0.005433 -0.005032 -0.002833 -0.001478]	N
P_s error	[-0.002833 -0.001478 0.001478 0.002833]	Z
(d ΔP_S)	[0.001478 0.002833 0.005835 0.005935]	P

seen, the static pressure $P_{S\text{-setp}}$ setpoints occur for time (k), given in (4). Figure 12 and Table 4 present five membership functions of V-high, high, optimal, low, and V-low.

$$\Delta P_S(k) = P_{S\text{-setp}} - P_S(k) \quad (\text{INW}) \tag{4}$$

(4) Change in ΔP_S ($d\Delta P_S$). As expressed in (5), any alterations in the P_S error input variable are formulated using ratios for differences between present and past P_S error values in relation to sampling time (Δt). Figure 13 and Table 5 illustrate three of the membership functions that indicate changes in error variables, expressed as Positive (P), Negative (N), and Zero (Z).

$$d\Delta P_s(k) = \frac{(\Delta P_s(k) - \Delta P_s(k-1))}{\Delta t} \quad (\text{INW/s}) \tag{5}$$

Table 6: MFs of CO_2 level difference (ΔCO_2).

Input field	Range	Fuzzy set
	[-25.9 -20.19 -16.43 -14.2]	V-low
Level of CO_2	[-16.47 -14.03 -2.92 0]	Low
difference	[-1.92 0 1.92]	Optimal
(ΔCO_2)	[0 2.92 8.84 12.33]	High
	[8.39 12.1 120 178]	V-high

Table 7: MFs of change in ΔCO_2.

Input field	Range	Fuzzy set
Change of CO_2	[-2.1 -1 -0.5 -0.3]	N
error	[-0.5 -0.3 0.3 0.5]	Z
(d ΔCO_2)	[0.298 0.498 0.998 1.1]	P

(5) Differences in CO_2 Levels (ΔCO_2). As shown in Figure 1, this is the difference between the present CO_2 level in the return air from the sensor in the AHU_1 return duct and the CO_2 level $CO_{2\text{-S-setp}}$ setpoint, as recorded at time (k) and expressed by (6). The 5 MFs of V-high, high, optimal, low, and V-low are shown in Figure 14 and Table 6.

$$\Delta CO_2(k) = CO_{2\text{-setp}} - CO_2(k) \quad (\text{PPM}) \tag{6}$$

(6) Change in ΔCO_2 ($d\Delta CO_2$). As expressed in (7), CO_2 error input variable changes can be formulated through finding the ratio for the difference between present and past CO_2 error values in relation to sampling time (Δt). Figure 15 and Table 7 show the three MFs error variable changes as sets labelled Positive (P), Negative (N), and Zero (Z).

$$d\Delta CO_2(k) = \frac{(\Delta CO_2(k) - \Delta CO_2(k-1))}{\Delta t} \quad (\text{PPM/s}) \tag{7}$$

3.3.2. Output Variables. The three inputs of AHU_1 (fresh air, air flow, and hot water) serve as FLC outputs. The values are introduced as gains to the system in order to move system responses towards a stability state. As a means to increase output gains, PI controller tuning can be used, as detailed in the following subsections.

(1) Aperture on Hot Water Valve. The process involving the hot water valve's opening and closing is indicated through the 5 MFs for the fuzzy controller output in order to find the zone temperature setpoint (T_{setp}). Figure 16 depicts MFs using MATLAB/Fig, while Table 8 shows MFs and the related valve operation percentages.

(2) Supply Fan Speed. The FLC's second output serves as the speed control for the supply fan in order to reach the ducts'

Table 8: MFs of first output.

Output field	Range	Corresponding	Fuzzy set
	[-1320 -10000 -7894 -5060]	0%-20%	Close-fast
Hot	[-7264 -5570 -1580 0]	20%-40%	Close
water	[-689 0 768]	40%-60%	No-change
valve	[0 1580 5100 6594]	60%-80%	Open
aperture	[5067 6607 10220 10260]	80%-100%	Open-fast

Table 9: MFs of second output.

Output field	Range	Corresponding	Fuzzy set
	[-1060 -913.1 -601 -371]	0%-20%	V-slow
Supply	[-527.9 -449 -105 50]	20%-40%	Slow
fan	[-105.3 50 205.4]	40%-60%	No-change
speed	[46.3 201 661 800]	60%-80%	Fast
	[658 811 1002 1010]	80%-100%	V-fast

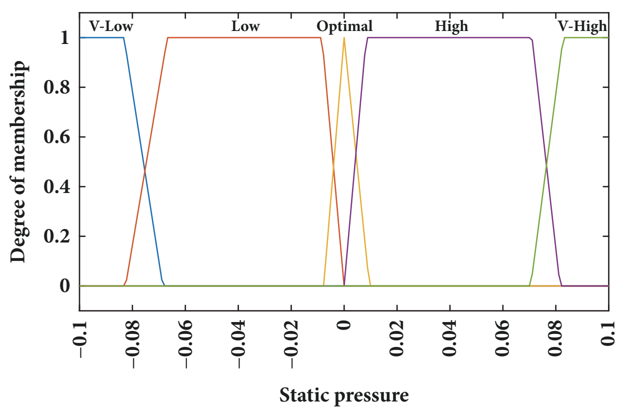

Figure 12: MFs of static pressure difference.

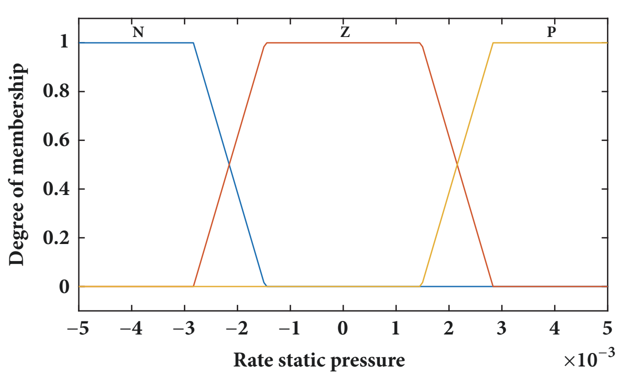

Figure 13: MFs of change in ΔP_s.

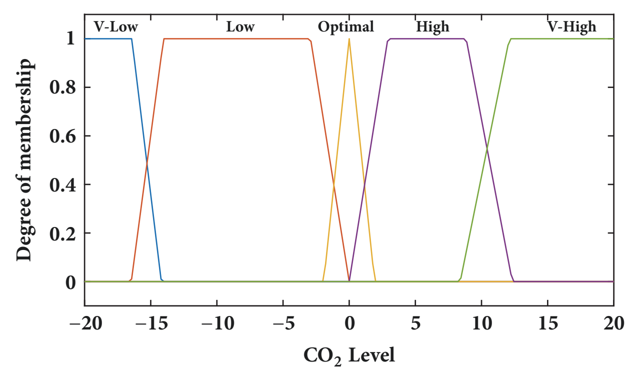

Figure 14: MFs of CO_2 level difference (ΔCO_2).

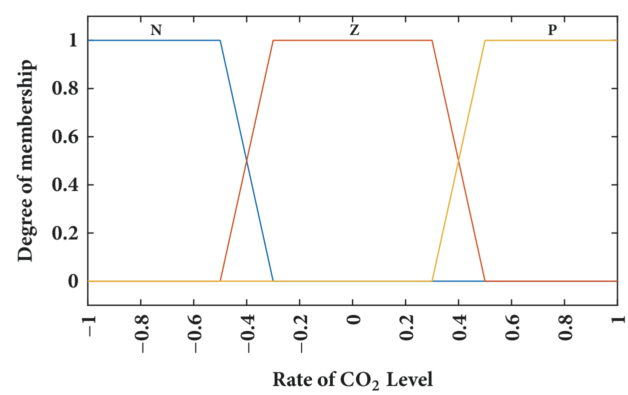

Figure 15: MFs of change in ΔCO_2.

static air pressure setpoint. Figure 17 and Table 9 show the five MFs for this process.

(3) Fresh Air Dampers Position. Five MFs of the fuzzy controller output were for opening and closing operation of the fresh air dampers position in order to find the zone CO_2 level setpoint; the range of this operation is presented in Table 10 and Figure 18.

3.3.3. Fuzzy Rule Base. The rule base controls output variables as the most crucial part within the fuzzy inference system. In simplified terms, a fuzzy rule is represented as a basic IF-THEN rule that includes a condition and conclusion. The fuzzy membership functions can first be applied for

Table 10: MFs of third output.

Output field	Range	Corresponding	Fuzzy set
	[-5200 -5028 -3910 -2980]	0%-20%	Close-fast
Fresh	[-4056 -2860 -1140 -250]	20%-40%	Close
air	[-1139 -250 641.6]	40%-60%	No-change
dampers	[-250 642 1610 2677]	60%-80%	Open
position	[1860 2660 4509 4810]	80%-100%	Open-fast

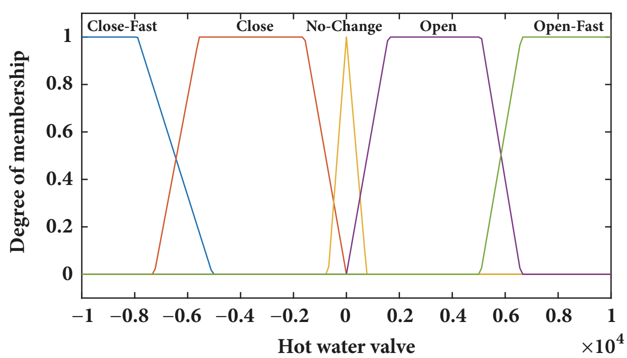

Figure 16: MFs of first output.

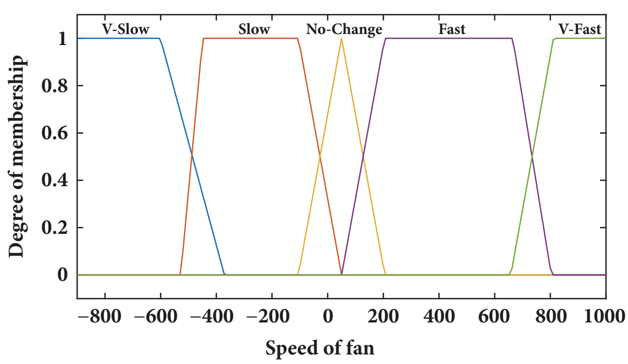

Figure 17: MFs of second output.

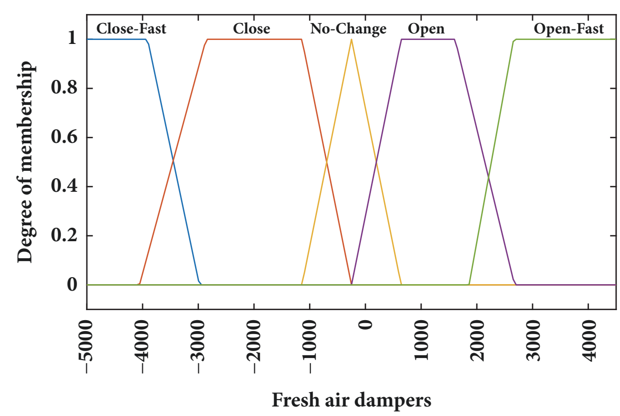

Figure 18: MFs of third output.

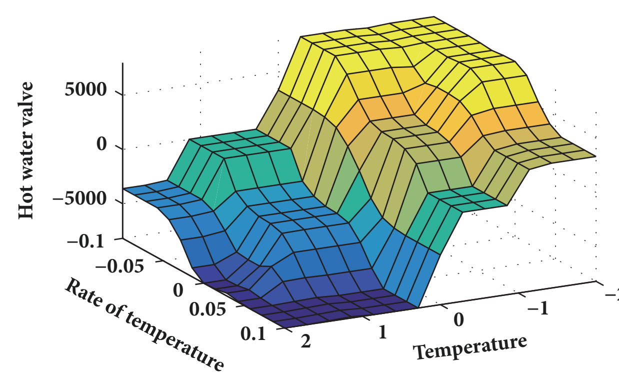

Figure 19: Control surface of the first output.

converting both the input errors ($\Delta T, \Delta P_S, \Delta CO_2$) and the error changes ($d\Delta T, d\Delta P_S, d\Delta CO_2$) to their fuzzy values. Furthermore, in every output (damper position, fan speed, and hot water valve), the control action is represented by fuzzy rules in different error/change of error values. In every control signal output, the default fuzzy rule is 5 × 3, thus indicating 45 rules for system control [31].

3.3.4. Defuzzification. In the process of defuzzification, convert the fuzzy output variable back to the crisp variable for the control objective. This process is required for hardware applications that exchange crisp data. Generally, defuzzified output has to be the most appropriate solution. The two mechanisms are the maxima method, which looks for the highest pack, and the centroid method, which relies on determining a property's balance point. The present study uses the centroid approach.

In Figure 19, the control surface for MFs implemented using zone temperature error values, as well as fuzzy rule-implemented change of error values, is presented. The values for the control output are associated with every potential input combination for controlling hot water valve processes.

Figure 20 shows the control surface for implementing MFs for static air pressure error values as well as fuzzy rule-implemented change of error values. The values for the control output are associated with every potential input combination for controlling the supply fan speed in order to obtain static air pressure setpoints for the ducts.

Figure 21 illustrates the control surface for error/change of error values for MFs related to CO_2 levels. Fuzzy rules are applied for controlling output values for every potential input combination to achieve the CO_2 setpoint.

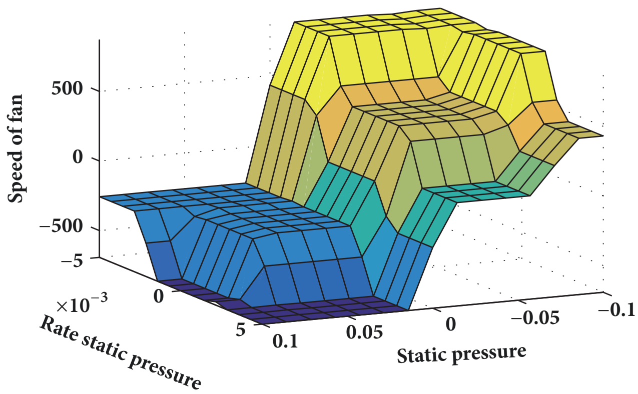

Figure 20: Control surface of the second output.

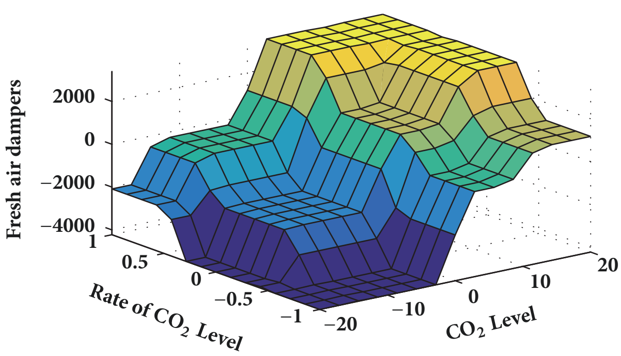

Figure 21: Control surface of the third output.

4. Simulation Model and Results

The Simulink model and simulation results are presented in this section. Figure 22 shows a block diagram for the AHU_1 state space model for a fuzzy controller with MATLAB/Simulink. The initial conditions selected for temperature, air pressure, and CO_2 levels are 20.7°C, 3.62 INW, and 374.2 MMP, respectively. The sampling time is three seconds for the control action, which is the same as that for the real system. Furthermore, the real system's indoor air quality setpoints are a zone temperature of 23°C, air pressure of 4 INW, and a CO_2 level of 500 MMP. A fuzzy-PI type adaptive controller controls the AHU_1 system, with T_{setp}, $P_{S\text{-}setp}$, and $CO_{2\text{-}Setp}$ as input references for temperature, air pressure, and CO_2 level, respectively. Control signals are obtained from FLC to reduce error as well as error change. The control signals can alter the system inputs which include fresh air, air flow rate, and hot water to achieve the reference setpoints.

Figure 23 shows the first of the system's output responses that demonstrate the system's stability. Zone temperature T_z achieves the setpoint of 23°C at a rise time of only 10.83 minutes and no overshoot.

Figure 24 depicts the second response of static pressure, with a rise time of 6.71 minutes and no overshoot.

Figure 25 shows the CO_2 level response, achieving the setpoint, again with no overshoot, at a rise time of 14.13 minutes.

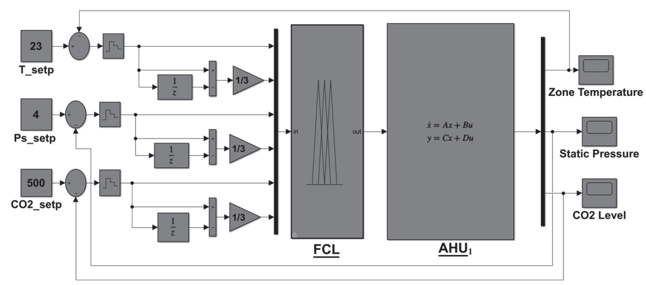

Figure 22: Block diagram for the AHU_1 state space model with controller.

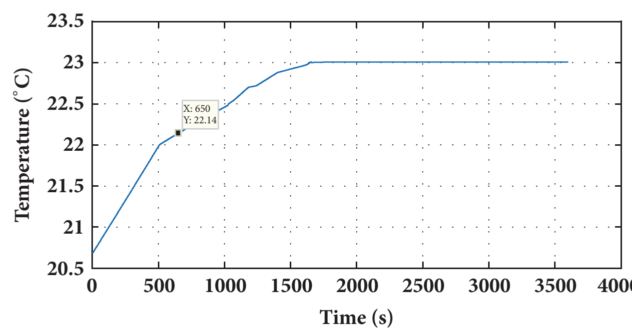

Figure 23: Zone temperature T_z response.

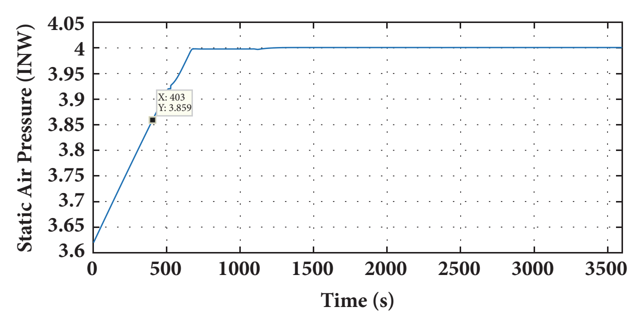

Figure 24: Static pressure P_s response.

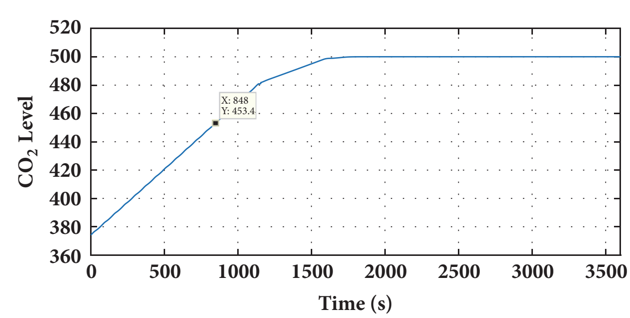

Figure 25: CO_2 level response.

5. Conclusion

This research paper presented a simulation of the S.J. Carew building's AHU_1 system using MATLAB's system identification toolbox along with real data and results from the IDA ICE program to formulate system parameters for both inputs and outputs. A fuzzy logic controller modulated the three AHU_1 inputs (fresh air, air flow, and hot water), while FLC was implemented in the multi-input/multioutput system state space model for the AHU_1. The results indicate that the fuzzy expert controller performance exceeded that of traditional algorithms, such that sufficient control was obtained from the fuzzy controller HVAC system. Furthermore, across all lab conditions, the FLC algorithm gave a stable response and could deal better with several different parameters, including steadying errors, response time, and overshoot.

Data Availability

All data are available with us.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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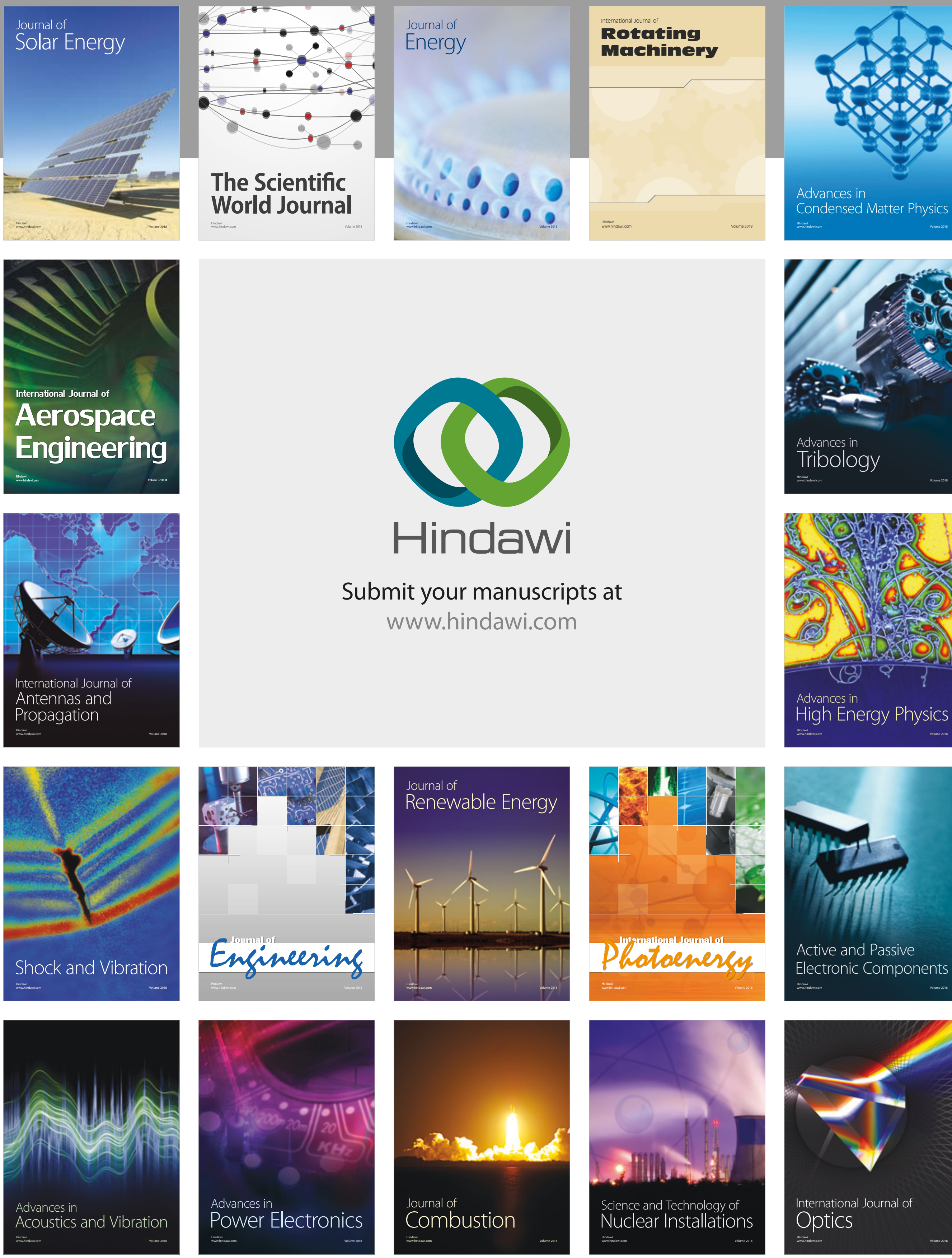
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