Decision Making: Applications in Management and Engineering
Vol. 6, Issue 2, 2023, pp. 948-974.
ISSN: 2560-6018
eISSN: 2620-0104
DOI: https://doi.org/10.31181/dmame622023825

ENERGY EFFICIENT SMART HOME HEATING SYSTEM USING RENEWABLE ENERGY SOURCE WITH FUZZY CONTROL DESIGN

János Simon[1*] and Róbert Sánta[2,3]

[1] Department of Mechatronics and Automation, Faculty of Engineering, University of Szeged Szeged, Hungary
[2]Aziz Sanjar Food Safety Laboratory
Azerbaijan State University of Economics (UNEC), 6, Istiglaliyyat str., Baku, AZ1001, Azerbaijan
[3]Department of Mechanical Engineering and Material Sciences, University of Dunaujvaros, Tancsics Mihaly 1/A, 2400 Dunaujvaros, Hungary

Received: 17 June 2023;
Accepted: 5 September 2023;
Available online: 15 September 2023.

Original scientific paper

Abstract: *This research article presents an energy- efficient smart home heating system that uses a renew-able energy source and incorporates fuzzy control design. The objective of the study is to design a heating system that optimizes energy consumption while providing a comfortable indoor temperature. The main methods used in the study include the integration of a renewable energy source, such as solar energy or geothermal energy, with a fuzzy control system that adjusts the heating power based on indoor and outdoor temperature, humidity, and occupancy. The main results of the study show that the proposed heating system can reduce energy consumption by up to 40% compared to conventional heating systems, while maintaining a comfortable indoor temperature. The fuzzy control system provides precise control of the heating power and ensures efficient use of the renewable energy source. The main conclusion of the article is that the proposed smart home heating system is a viable solution for reducing energy consumption and promoting a sustainable lifestyle, especially in areas with abundant renewable energy sources.*

Key words: *Smart home heating system, Fuzzy control design, Fuzzy system, Energy efficiency, Sustainable living, Renewable energy source.*

* Corresponding author.
E-mail addresses: simon@mk.u-szeged.hu (J. Simon), santar@uniduna.hu (R. Sánta)

1. **Introduction**

A type of artificial intelligence called fuzzy logic can be used to control complex systems, such as underfloor heating systems with heat pumps. Instead of the usual True or False values in classical logic, it is based on the concept of fuzzy sets, which can have a degree of membership between 0 and 1.

The fuzzy control strategy and the heat pump air-conditioning system model were analyzed by Lin et al. (2022). The indoor temperature adjustment of the electric vehicle was analyzed when the ambient temperature is 0 ℃ and the humidity is 40% in winter, and the heat pump air-conditioning heating mode was used under three vehicle speed conditions. The fuzzy control strategy set in the paper, the heating performance of the air conditioning system of the electric vehicle, was established. The fuzzy control table to adjust the supplied water temperature of the air-to-water heat pump was established by Duhui et al. (2020). Comparisons were made between the conventional 45 ℃ supplied water temperature, and the simulation results showed that the system energy consumption saved by 11.3% and unsatisfied time saved by 9.0% in the whole heating season. The potential use of heat pump air conditioning instead of the original PTC heating system is proposed by Miao (2023). First, the advantages and disadvantages of different heat pump models for new energy vehicles are analyzed and compared. Second, a fuzzy inference system is constructed based on the machine learning model to observe the temperature of the passenger compartment using the temperature sensor inside the tram and to determine the need for the air conditioning system to be turned on in the heating/cooling mode by comparing it with the set temperature. The key features of the three above types of fuzzy systems were reviewed by Nguyen et al. (2019). Through these features, the historical rationale for each type of fuzzy systems and its current research mainstreams were pointed out. However, the focus is put on fuzzy model-based approaches developed via Lyapunov stability theorem and linear matrix inequality (LMI) formulations. A study to obtain different types of hyperbolic type solutions of the (2+1)-Ablowitz-Kaup-Newell-Segur (AKNS) equation was presented by Durur et al. (2021). In order to construct exact solutions of the AKNS equation, the $(1/G')$-expansion method was successfully applied. The paper by Marín et al. (2019) proposes a new prediction interval modeling methodology based on fuzzy numbers to solve the aforementioned drawbacks. Fuzzy and neural network prediction interval models are developed based on this proposed methodology by minimizing a novel criterion that includes the coverage probability and normalized average width. The fuzzy number concept is considered because prediction intervals that can handle uncertainty without requiring assumptions about the data distribution are generated by the affine combination of fuzzy numbers, as defined. A promising technology on electric vehicles, the heat pump air-conditioning system operating with trans-critical CO2, and the vital role played by the scroll compressor in the micro heat pump air-conditioning system were investigated by Zheng et al. (2020). To achieve improved performance of the scroll compressor for CO2, an investigation into the internal flow characteristics was conducted. In this paper, an unsteady Reynolds Average Navier-Stokes of the working process in a scroll compressor operating with trans-critical CO2 was firstly carried out, and the effect of CO2 properties tables resolution on numerical simulation was investigated in detail. A novel intelligent control strategy based on the maximum heating capacity of the ASHP system, with appropriate start and end points for defrosting designed to operate accurately under different outdoor temperature ranges, was proposed by Xi et al. (2021), based on a theoretical analysis of the characteristics of a hot gas bypass defrosting system. This defrosting method was verified in a well-structured environmental laboratory, and the performance was compared to the conventional system through experiments. The results showed that the heating capacity of the hot gas bypass defrosting was 10.17% higher, and the overall energy efficiency was 4.06% higher. Xie et al. (2020) established a coupled thermal model of the air conditioning system and cabin for electric vehicles. The effects of solar radiation, vehicle speed, and the external environment on the heat exchanged with the cabin were considered in this model. An intelligent air conditioning system control strategy was proposed, which could learn passengers' thermal comfort preferences. The preferred predicted mean vote of passengers was predicted by this strategy based on their thermal comfort preferences and converted into a target temperature for the air conditioning system. The thermal comfort of passengers was improved, and less energy was consumed by the proposed strategy. In a simulated driving cycle, its energy consumption was 31.8% less than that of the on-off controller and 10% less than that of the fuzzy PID controller, and its COP was respectively 20.4% and 18.7% more than those of the on-off controller and the fuzzy PID controller. Xie et al. (2022) proposed a two-layered control strategy for the air conditioning (AC) systems of electric vehicles. Unlike traditional rule-based controllers, this strategy included a decision layer and a control strategy. The core algorithm in the decision layer was the dynamic programming (DP), which integrated information from the thermal habit predictor of the passenger, vehicle velocity planner, and weather information receiver. The DP optimized the development of the cabin temperature to minimize the energy consumption of the AC system and sent the planned temperature to the control layer. The control layer used a fuzzy PID algorithm to adjust the compressor speed based on the planned temperature profile, such that the real-world cabin temperature approached the planned temperature. This two-layered control strategy was applied to a car whose AC-cabin system was verified by test data, and the results were compared with those obtained by the on-off controller and PID. Wang et al. (2021) experimentally investigated the reverse cycle defrosting in a transcritical carbon dioxide heat pump with a microchannel evaporator. The effect of water flow rate, initial water tank temperature, compressor frequency, and electronic expansion valve opening was respectively studied, and an optimized control strategy was proposed considering the defrosting time and stability. Results showed that thermal energy was considerably affected by water side parameters, and stability was more sensitive to the water temperature and electronic expansion valve opening. With the optimized reverse cycle defrosting, defrosting time and total energy consumption were reduced by 95 s and 21.8% compared with the pre-set basic control strategy, and the total energy consumption was also saved by 38.6% compared with the other defrosting method. A new control system with an intelligent optimizer, which can be applied to energy and comfort management in smart and energy-efficient buildings, was developed by Wang et al. (2010). An attempt to review the applications of fuzzy logic-based models in renewable energy systems, namely solar, wind, bio-energy, micro-grid, and hybrid applications, was made by Suganthi et al. (2015). A fuzzy logic-based energy management system (EMS) for use in grid-connected residential DC microgrids with hybrid energy storage systems (HESS) was proposed by Vivas et al. (2022). A low-cost intelligent controller system for Smart Homes was implemented by Gozuoglu et al. (2019) using fuzzy logic calculations as an application of home automation and medium-voltage (MV) network demand management. A novel energy management system with two operating horizons for a residential microgrid application was proposed by Jafari et al. (2018). The conception and development of an efficient multi input-output fuzzy logic smart controller, to manage the energy flux of a sustainable hybrid power system based on renewable power sources, integrating solar panels and a wind turbine associated with storage, applied to a typical residential habitat, were presented by Derrouazin et al. (2017). The conception, design, and implementation of an intelligent multi-input multi-output fuzzy logic controller for the energy management of a hybrid renewable energy system, including solar power and storage battery in laboratory dimensions, were worked on by Zangeneh et al. (2022). A fuzzy framework for smart home monitoring systems (FF-SHMS) effective in energy using the Internet of Things (IoT), demand monitoring, green energy conservation, energy conservation, and microgrids was presented by Alowaidi (2022). Wang et al. (2022) proposed a detailed dynamic control logic of the operation process from heating and frosting to defrosting. The development of the electric vehicle industry was promoted by the research, as it improved defrosting efficiency and met the requirements of socially sustainable development through energy-saving measures. Severe performance deterioration, energy waste, and reduced comfort could be caused by improper defrosting operations. The dynamic control strategy of electric vehicle heat pumps was stated to be more complicated than that of other heat pumps. To find an efficient defrosting control logic, a transcritical $CO2$ heat pump test bench for electric vehicles was built, and a method for accurately determining the end of defrosting was proposed based on the analysis of thermodynamic dynamic characteristics in the defrosting process. New experimental data on the influence of phase shift, air velocity, heat sink base surface temperature on heat transfer coefficient, and pressure drop of airflow through sinusoidal wavy plate fin heat sinks (SW-PFHS) and crosscut sinusoidal wavy plate fin heat sinks (CCSW-PFHS) were presented in the article by Nilpueng et al. (2019). The methodology that overcomes one of the critical issues in using detailed building energy models in MPC optimizations—computational time—was presented in the paper by German et al. (2019). The methodology explained how to resolve this issue through a case study. Three main novel approaches were developed: a reduction in the search space for the genetic algorithm (NSGA-II) thanks to the use of the curve of free oscillation; a reduction in convergence time based on a process of two linked stages; and, finally, a methodology to measure, in a combined way, the temporal convergence of the algorithm and the precision of the obtained solution. Jiang et al. (2019) developed a transient simulation model of a floor radiant heating system with air-to-water heat pumps for a 100 m2 building in the Beijing rural area using TRNSYS software, and combining the Hooke-Jeeves algorithm on the GenOpt platform, they studied the influence of building exterior wall insulation on the building heat storage strategy of the floor radiant heating system with air-to-water heat pumps on the current peak and valley period electricity price. The law of the best heat-lag temperature and heat-lag time was obtained under different building exterior wall insulation methods and thickness by optimizing the whole heating season operation cost. Killian and Kozek (2018) presented the design and implementation of a nonlinear model predictive controller (MPC) scheme for an energy-efficient office building. To model the nonlinear building behavior, they used local linear model networks. They implemented a dedicated Fuzzy model predictive controller (FMPC) for each of the building's zones, and in addition, designed a global MPC to control the coupling zone (concrete core activation). To coordinate the overactuated system, they designed a cooperative iteration-loop, which led to cooperative Fuzzy model predictive control (CFMPC). The CFMPC was successfully implemented in a real office building, and the first results after commissioning were presented and discussed.

The gap analysis of the above literature survey clearly explores that though previous researchers have applied some existing control approaches, still there exists absolute necessity of introducing new control model for solving and making appropriate decision regarding Fuzzy Logic Smart Energy Control (FLSEC) under new criteria and specific environment. In this study, a Fuzzy Logic Smart Energy Control method has been proposed for renewable energy resources in form of an air to water heat exchanger. This allows for the best cost-performing solution with an optimum use of renewable energy. The main contribution of this paper is to propose a Fuzzy Logic Smart Energy Control (FLSEC) method for renewable energy sources in the form of an air-water heat exchanger. Experimental results show high performance and cost efficiency.

The paper is presented by dividing it into some sections for better illustration. Section 1 presents the short introduction and literature survey. Section 2 presents the proposed systematical approach which is the heart of the paper. Section 3 covers the discussions with the real world scenario. Section 4 furnishes some essential concluding remarks and scope for further research.

2. Proposed system approach

The correct temperature setting for the heat pump is determined by the fuzzy logic controller based on sensor data such as temperature and humidity. For example, if the temperature sensor determines that the room is too cold, the fuzzy logic controller increases the output of the heat pump to raise the temperature. On the other hand, the fuzzy logic controller will reduce the heat pump's output if the temperature sensor determines that the room is too warm (Alowaidi, 2022). To enhance the overall effectiveness of the heating system, fuzzy logic can also be utilized in conjunction with other control methods, such as Proportional-Integral-Derivative (PID) control. Fuzzy logic can have a number of benefits over conventional control techniques when used in underfloor heating systems. By changing the heat pump's output based on real-time sensor data, it can increase energy efficiency and also create a more comfortable indoor climate by keeping a constant temperature. Overall, fuzzy logic is an effective tool for controlling sophisticated systems, such as floor heating systems with heat pumps, by using sensor data to make decisions and adjusting the system's performance accordingly. It provides a more effective and efficient way to control the energy consumption and temperature of the heating system. The typical structure of a fuzzy system (Figure 1) consists of four functional blocks: the fuzzification, the fuzzy inference engine, the knowledge rule base, and the defuzzification (Vivas et al., 2022). Fuzzy logic can be used with floor heating systems to control the temperature of the heating system more effectively and efficiently.

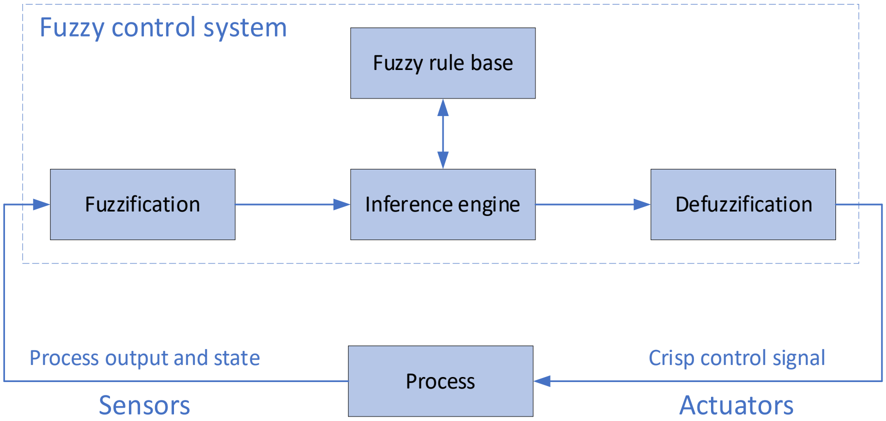

Figure 1. Fuzzy control system design (Abraham et al., 2023)

On the basis of the high share of radiation energy in floor heating and cooling systems, the feeling of comfort in the case of heating appears already at significantly lower air temperatures in the room (Vivas et al., 2022). These temperatures can therefore be 1 or 2 °C lower. This enables annual energy savings of 3 to 6%. Practical experience has shown that energy savings can be up to 40% (El Zerk & Ouassaid, 2023).

2.1 The heat pump system

Heating and cooling modern buildings is now unthinkable without systems that use renewable energy sources, as modern societies and economies require more and more energy, but the use of fossil fuels is causing more and more real problems. Therefore, special attention must be paid to environmental impacts and national energy policies (Santa, 2021). The greatest energy savings can be achieved through the rationalization of energy production and use, and through the optimal selection and operation of heating systems. It is expected that in the near future, with the modernization of heating technologies, heat pumps will become indispensable devices that can be excellently used for heating and cooling purposes. The coefficient of performance COP of today's modern air-source heat pumps is generally lower than that of water-source or ground-source heat pumps (Nyers & Nyers, 2023). However, they are still the most widely used type of heat pumps because they are easy and inexpensive to install and the heat source is unlimited. The efficiency of the heat pump system is evaluated based on the following criteria:

$$COP = \frac{\dot{Q}_c}{W} \tag{1}$$

The heat flux from the refrigerant through the condenser wall on the hot water side:

$$\dot{Q}_c = \dot{m}_{ref} \cdot \left(\Delta h_{cond} + cp_{vap} \cdot \left(T_{vap,i} - T_{vap,cond}\right)\right) = \dot{m}_w \cdot cp_w \cdot (T_{we} - T_{wv}) \tag{2}$$

The heat capacity of the condenser is the same as the heat demand of the consumer:

$$\dot{Q}_c = \dot{m}_w \cdot cp_w \cdot (T_{we} - T_{wv}) \tag{3}$$

The heat demand evaluated by:

$$\dot{Q}_{cons} = k_{fl} \cdot A_{fl} \cdot \left(\frac{T_{we}+T_{wv}}{2} - T_{in}\right) \tag{4}$$

The total heat loss is determined is the sum of the transmission and ventilation heat loss and neglected the radiation and infiltration heat loss.

$$\dot{Q}_{heat\ loss} = \dot{Q}_{tr} + \dot{Q}_{filt} = \sum k_{tr} \cdot A_{tr} \cdot (T_{in} - T_{out}) + \sum \rho_{air} \cdot \dot{V}_{air} \cdot cp_{air} \cdot (T_{in} - T_{out}) \quad (5)$$

Equations (3-5) show that the heat capacity of the condenser must be equal to the demand of the consumer, i.e., it must be able to cover the heat loss of the building at a given constant outdoor temperature.

The flow water temperature T_{we} and returning water T_{wv} temperatures determined by the Equation (3) and Equation (4):

$$T_{wv} = T_{we} - \frac{\dot{Q}_{cons}}{\dot{m}_w \cdot cp_w} = T_b + \frac{\dot{Q}_{cons}}{k_{fl} \cdot A_{fl}} - \frac{\dot{Q}_{cons}}{2 \cdot \dot{m}_w \cdot cp_w} \quad (5)$$

$$T_{we} = T_{wv} + \frac{\dot{Q}_{cons}}{\dot{m}_w \cdot cp_w} = T_b + \frac{\dot{Q}_{cons}}{k_{fl} \cdot A_{fl}} + \frac{\dot{Q}_{cons}}{2 \cdot \dot{m}_w \cdot cp_w} \quad (6)$$

The energy efficiency of the hot water circuit is assessed by the coefficient of performance, COP. The final goal of energy optimization is to achieve the maximum energy efficiency i.e. to achieve the maximum COP (Santa, 2021).

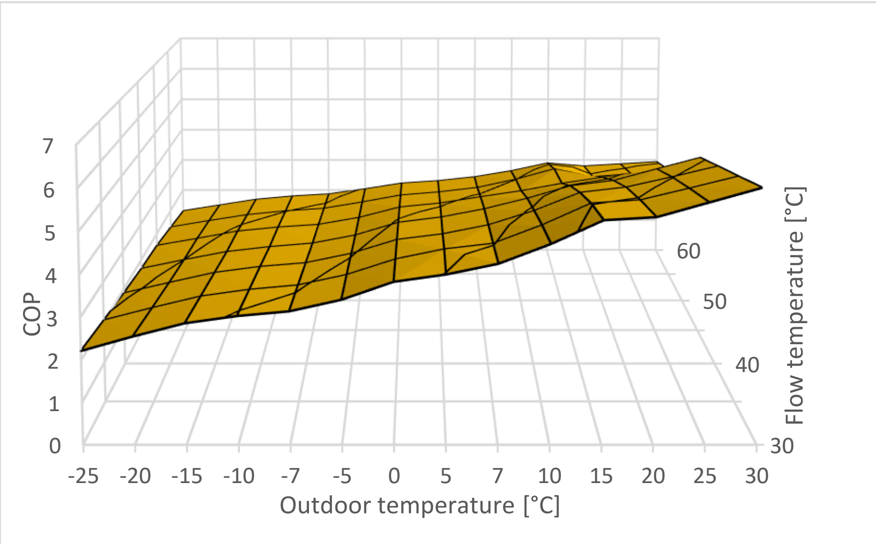

Figure 2. COP versus outdoor and flow temperatures (Fujitsu, 2020)

Figure 2 present the values of heating capacity and Figure 3 present the COP are based on measurement of EN14511 standard (Nyers et al., 2018). The $T_{we} < 45°C$: The flow rate obtained during the test at the standard rating conditions of out temperature 7°C and water temperature flow/return 35°C / 30°C, 2,773 l/h, when the $T_{we} \geq 45°C$ was, the flow rate obtained during the test at the standard rating conditions of outdoor temperature was 7°C and water temperature flow/return 45°C / 30°C, 2,653 l/h (Nyers et al., 2018).

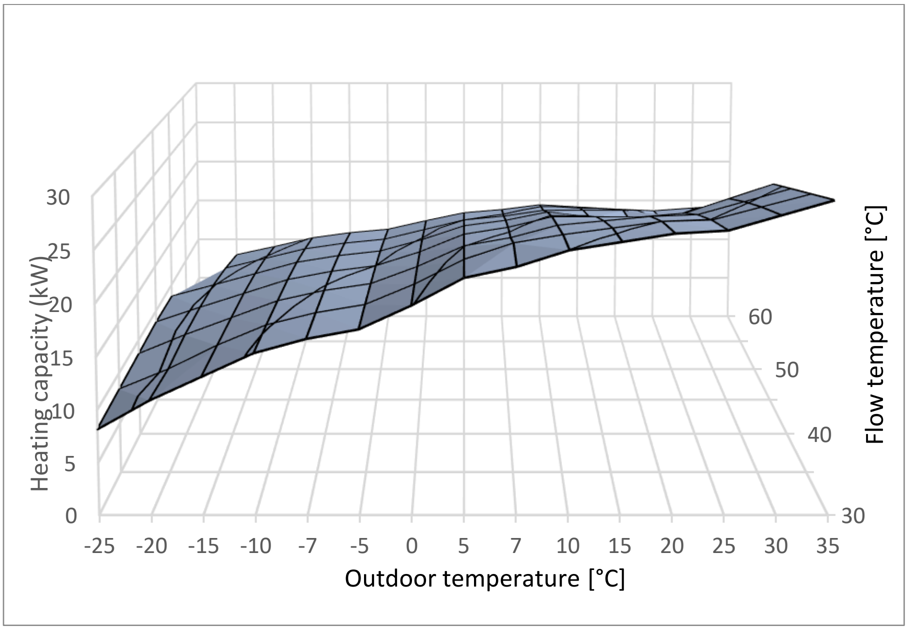

Figure 3. The heating capacity versus outdoor and flow temperatures (Fujitsu, 2020)

When the $T_{we} \geq 55°C$ was, the flow rate obtained during the test at the standard rating conditions of outdoor temperature 7°C and water temperature flow/return 55°C / 30°C, 1,583 l/h. The declared capacity was for heating for part load at indoor temperature 20 °C (Nyers et al., 2018).

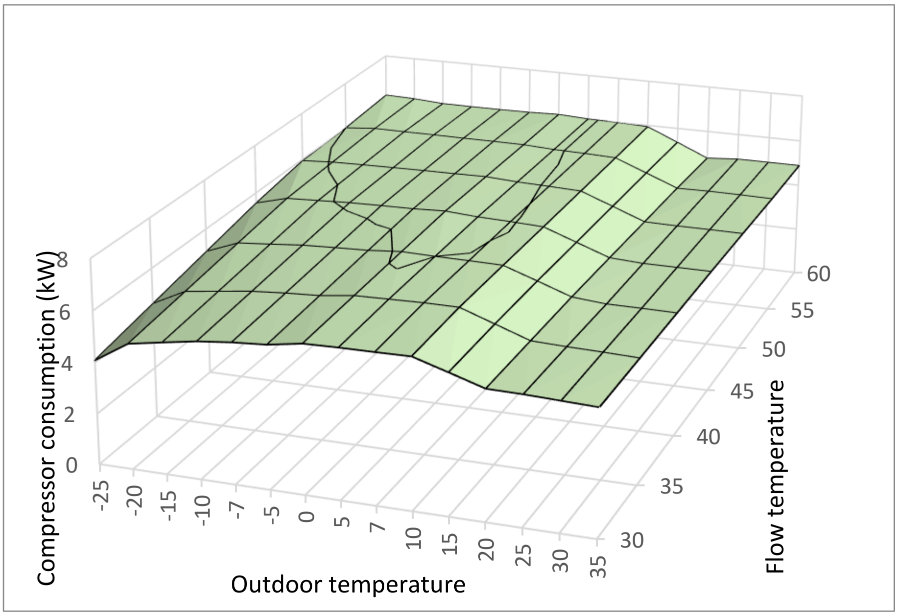

Figure 4. Compressor consumption (Fujitsu, 2020)

The compressor consumption of an air to water heat pump is directly related to the outside temperature as depicted on Figure 4. Generally speaking, as the outside temperature drops, the compressor needs to work harder to extract heat from the air and maintain the desired indoor temperature. This means that the compressor consumption will increase as the outside temperature decreases. However, the exact relationship between outside temperature and compressor consumption will depend on a variety of factors, including the specific make and model of the heat pump, the size of the system, the efficiency of the compressor, and the design and insulation of the building being heated. In general, air to water heat pumps are designed to work efficiently across a range of outside temperatures, and they typically have a coefficient of performance (COP) that describes the amount of heat output per unit of energy input. The COP of a heat pump will typically decrease as the outside temperature drops, which means that the compressor will need to consume more energy to maintain the same level of heating. In colder climates, it may be necessary to supplement the heat pump with an additional heating source, such as electric resistance heating or a backup boiler, to ensure that the building remains comfortable and energy-efficient during extreme cold snaps. This can help to reduce the overall energy consumption of the heat pump system and ensure that it operates efficiently over the long term.

2.2 Overall architecture of smart home heating system

To ensure effective temperature control, a smart home heating system usually consists of several important parts. The general architecture of a smart heating system consists of the following components:

- Sensors: These are tools that measure the humidity and temperature in various parts of the house. They can be installed in ceilings, on walls, or in rooms. The central control unit receives data from the sensors.
- Central Control Unit: This device acts as the heating system's brain. It uses the data it receives from the sensors to decide the ideal temperature settings for each room. Additionally, it collects user input such as preferred temperature settings and schedules.
- Actuators: these are devices that control how much hot water or air is pumped into the different rooms of the house. To change the temperature in each room, they can be managed by the central control unit.
- User Interface: The user interacts with this interface to manage the smart home heating system. It might take the shape of a web portal, a mobile app, or a special control panel.
- Networking: This is the framework that links together each element of the intelligent heating system for homes. Both wired and wireless connections are possible.
- Cloud-based platform: This platform enables remote access to and management of the smart home heating system by the user. It enables the system to deliver notifications to the user and allows the user to access the system from any location.
- Power supply: This is the power source that powers all of the heating system's smart home components.

The central control unit uses the data sent by the sensors to evaluate and regulate the temperature in each room, which is how the smart heating system works in general. To function effectively, the system also includes a user interface, a network, a cloud-based platform, and a power supply. Figure 5 shows the holistic approach of the proposed control system. The system supports six special microclimate zones that can be individually adjusted as needed in order to reduce energy consumption. This concluded that to maintain a room temperature of 20 ºC with a variation of only ± 1 ºC during a period of 24 hours, the system only needed an average of 40% of its nominal power.

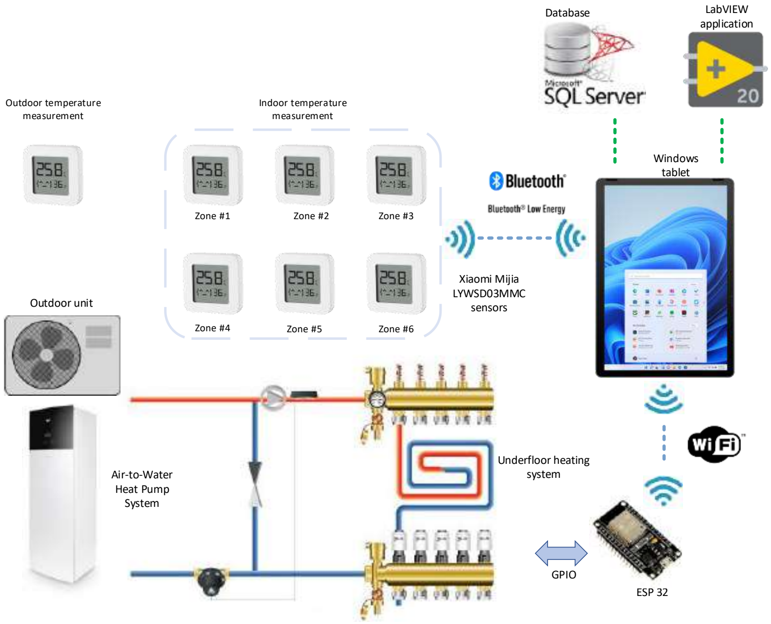

Figure 5. Overall architecture of the proposed smart home heating system.

The Xiaomi Mijia LYWSD03MMC sensor is a popular IoT sensor that uses Bluetooth Low Energy (BLE) and the MQTT (Message Queue Telemetry Transport) protocol to transfer environmental data, such as temperature, humidity, and air pressure, to a relational database. This makes it possible to measure and monitor indoor environmental parameters in real time, which can help to improve the efficiency of home heating, cooling, and other appliances. To give consumers notifications and warnings when specific circumstances are reached, this sensor can also be coupled with other smart devices, such as smartphones and tablets. It is a good option for a wide range of IoT applications since it uses BLE and MQTT to enable low-power and effective data transfer between the sensor and the database. Table 1 shows the specification of the measurement equipment.

Table 1. XIAOMI LYWSD03MMC smart sensor specification

Brand:	XIAOMI Mijia
Model:	LYWSD03MMC
CMIT ID:	2019DP8115
Material:	ABS+PMMA
Size:	43 x 43 x 12.5mm
Voltage:	DC2.5V-3V
Battery:	CR2032
Wireless Connection:	Bluetooth 4.2 BLE
Measure range:	0° C - 60° C

Temperature display resolution:	0.1° C
Humidity range:	0 % - 99 % RH
Humidity display resolution:	1 % RH

Xiaomi LYWSD03MMC is a bluetooth sensor that measures the temperature and relative humidity of the room through the Mi Home application, but it can be easily implemented in one of the open source home hubs (Home Assistant, Openhab...) or it is possible to develop your own application.

2.3 LabVIEW control of smart home heating system

LabVIEW is a graphical programming language that can be used to control smart home heating systems. In combination with Fuzzy Logic Smart Energy Control (FLSEC), it can provide an efficient and intelligent way to manage heating systems in a smart home. Here are the general steps to implement this:

- Define the input and output parameters of the FLSEC. For an underfloor heating sys-tem, the inputs could include the current indoor temperature, the desired temperature, the outside temperature, and the time of day. The output could be the amount of delivered heat.
- Develop a Fuzzy Logic System (FLS) model that maps the inputs to the output. This involves defining the membership functions for the input and output variables and creating the fuzzy rules that govern how the inputs are combined to generate the output.
- Implement the FLS in LabVIEW using the Fuzzy Logic Toolkit. This involves defining the membership functions and rules in the toolkit and connecting them to the input and output variables.
- Interface the FLSEC with the underfloor heating system. This could involve control-ling the heat pump, adjusting the thermostat, and/or controlling the flow of hot water.
- Fuzzy controller adjustment. This could involve adjusting the membership functions, rules, and inputs/outputs to optimize the performance of the system.

Using FLSEC in conjunction with LabVIEW provides a smart and energy-efficient way to control an underfloor heating system in a smart home. The FLSEC can intelligently adjust the underfloor heating system based on the inputs to optimize energy usage and maintain a comfortable indoor temperature. LabVIEW is well-suited for rapid prototyping of SCADA (Supervisory Control and Data Acquisition) systems. Its graphical programming language allows users to easily create and manipulate data flow diagrams that rep-resent their SCADA system. This can help to visualize the system architecture and quickly iterate on design changes. LabVIEW's modular programming approach allows users to break down complex SCADA systems into smaller, more manageable modules. This can simplify the development process and make it easier to test and debug individual components. LabVIEW comes with a wide range of pre-built libraries for data acquisition, signal processing, and control. This can save developers time and effort by providing a set of commonly used functions that can be easily integrated into their SCADA system. It can easily interface with other systems such as databases, industrial controllers, and other software programs. This allows developers to create a more comprehensive SCADA sys-tem that can interface with a variety of devices and applications.

3. Results

In this case, the developed Fuzzy Logic Smart Energy Control (FLSEC) method has two objectives. The first objective is energy optimization and the second is temperature stabilization. FLSEC predicts the amount of energy needed to reach the desired temperature. The energy demand is then reduced proportionally, smoothing the initial curve by lowering the peak temperature. Once the desired temperature is reached, FLSEC reduces energy consumption to maintain a stable temperature within a thermal variation of only ± 1 ºC. Defined fuzzy membership functions are presented on Figure 6.

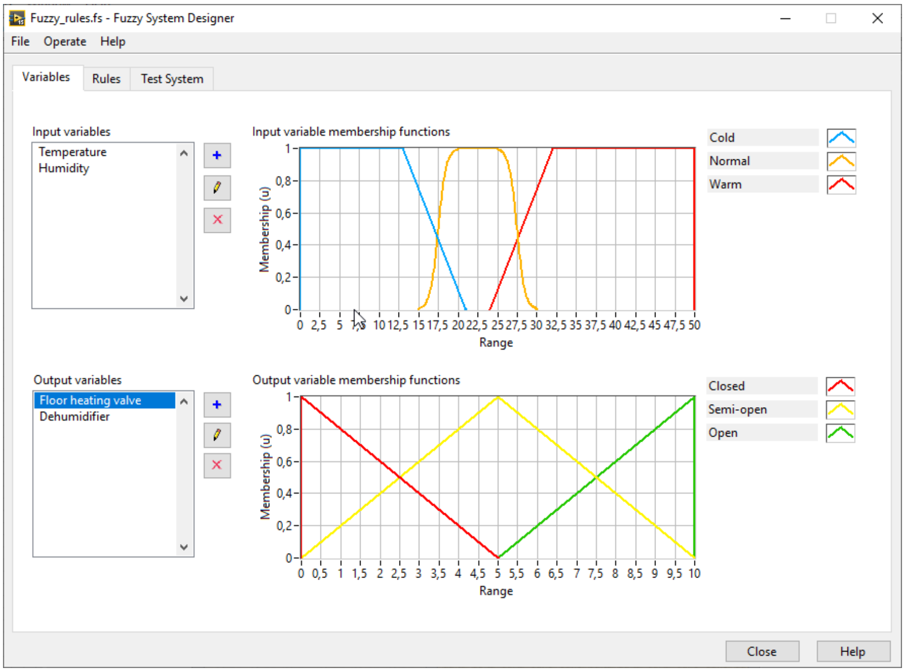

Figure 6. Defined fuzzy membership functions

A collection of rules used to operate a system utilizing fuzzy logic is known as a fuzzy rule base. The fuzzy rule basis for an underfloor heating system would be made up of a set of criteria that specify how the system ought to react to various humidity and temperature levels. A fuzzy rule basis for an underfloor heating system, for instance, might have the following criteria:

- If the room temperature is low and the humidity is high, then increase the heat out-put of the underfloor heating system.
- If the room temperature is high and the humidity is low, then decrease the heat out-put of the underfloor heating system.
- If the room temperature is moderate and the humidity is moderate, then maintain the current heat output of the underfloor heating system.
- If the room temperature is low and the humidity is low, then increase the heat output of the underfloor heating system.
- If the room temperature is high and the humidity is high, then decrease the heat out-put of the underfloor heating system.

These rules are based on the idea that high humidity levels can make a room feel colder, while low humidity levels can make a room feel warmer. The fuzzy rule base would use the data from the temperature and humidity sensors to determine which rule to apply at any given time as presented on Figure 7.

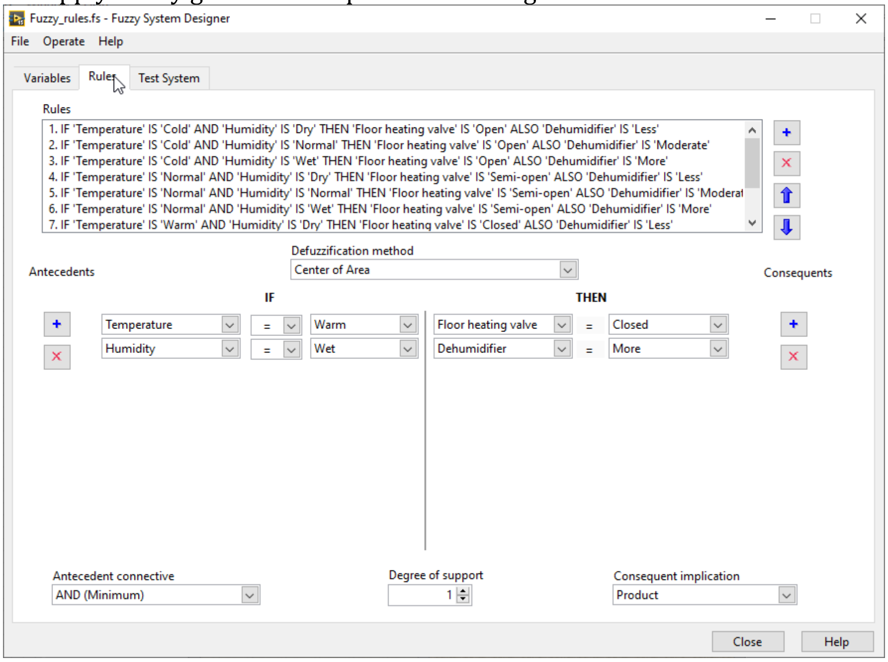

Figure 7. Fuzzy rules of the controller

In fuzzy logic, the input-output relationship describes how the input variables (also known as antecedents or linguistic variables) are used to determine the output variable (also known as consequent or control variable). In a fuzzy logic-controlled heating system, the input variables might be the temperature and humidity levels in a room. The output variable would be the heat output of the underfloor heating system. The input-output relationship is defined by a set of fuzzy rules that describe how the underfloor heating system should respond to different temperature and humidity levels as depicted in Figure 8.

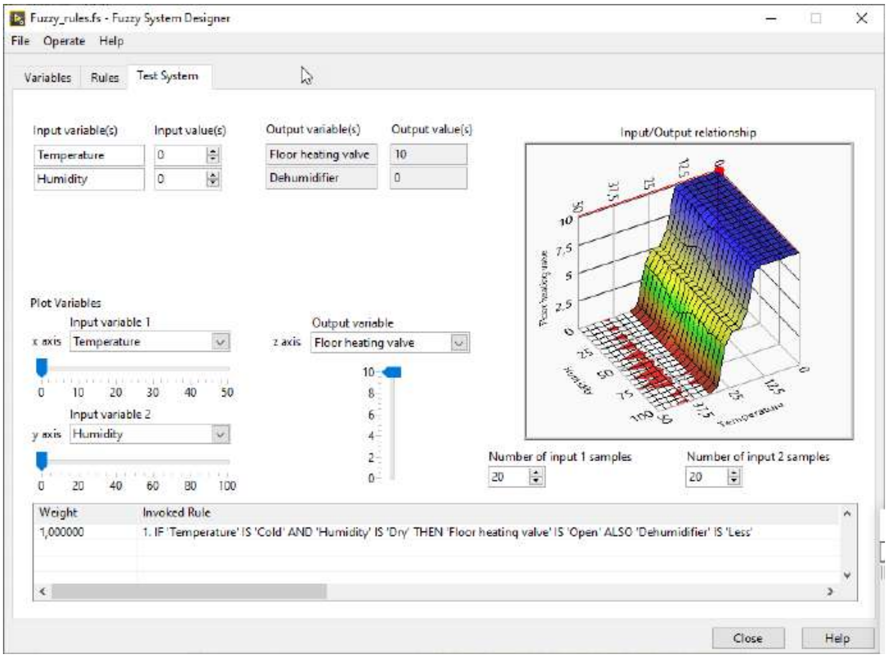

Figure 8. Fuzzy input/output relationship

Fuzzy COA (Center of Area) defuzzification method is a technique used to convert the fuzzy output of a fuzzy logic controller into a crisp, numerical value. The basic idea be-hind the COA method is to calculate the center of area of the fuzzy output membership function, and use that value as the crisp output. The COA method is based on the following steps:

- Compute the area under the membership function curve.
- Divide the area under the curve into a series of trapezoids, each with a different height and width.
- Calculate the center of each trapezoid by taking the average of the width of the trapezoid, multiplied by the height.
- Sum up the centers of all the trapezoids to get the overall center of area.
- The COA method is considered one of the most accurate defuzzification methods among the others such as Centroid, Mean of Maximum and Bisector. It is important to note that the performance of the fuzzy logic controller strongly depends on the choice of the defuzzification method used. Therefore, it is important to evaluate the different methods and choose the one that is best suited for the application at hand.

3.1 Real world scenario

The energy demands for a 94 square meter household floor heating system will de-pend on several factors, including the insulation of the home, the number of occupants, the desired temperature, and the local climate. To determine the energy demands for a floor heating system, a heat loss calculation must be done. This calculation takes into ac-count the insulation of the walls, floors, windows and roof, as well as the number of occupants and the desired temperature. The calculation will provide an estimate of the heat loss in watts (W) or British thermal units per hour (BTU/h). Once the heat loss is known, the size of the heating system can be determined. Typically, a floor heating system will require around 50-70 watts per square meter (W/m2). For a 94 square meter home, this would equate to around 4,700 - 6,580 watts or 16,095 - 22,534 BTU/h (Santa et al., 2022). The local climate also plays a role in determining the energy demands of the floor heating system. In colder climates, a larger heating system may be required to maintain a comfortable temperature inside the home. It is important to note that the energy demands for a floor heating system will also depend on the type of heating system used There are many advantages to using an underfloor heating system like invisible hardware installations in livable areas, energy-efficient and cost-effective and smart thermostat compatibility. In summary, the energy demands for a 94 square meter household floor heating system will depend on several factors, including the insulation of the home, the number of occupants, the desired temperature, and the local climate. A heat loss calculation should be done to determine the size of the heating system, typically it would be around 50-70 watts per square meter. Figure 9 shows the basic settings of the system, the current measured temperature values by zone, as well as the graph of the change in temperature and relative air humidity.

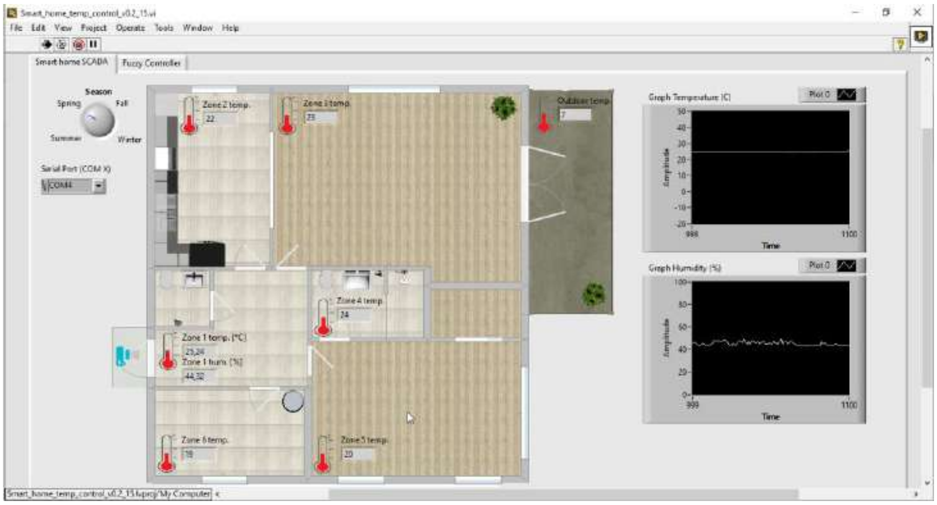

Figure 9. Fuzzy Logic Smart Energy Control - SCADA

A LabVIEW based fuzzy controller for a heat pump based underfloor heating system with valve control uses a LabVIEW's built-in fuzzy logic functions to control the valves regulating the flow of heated fluid through the underfloor heating system. The controller takes input from sensors measuring the temperature of the heated fluid, or the temperature of the room, and possibly the outdoor temperature, as well as the desired room temperature set by the user. The controller then uses fuzzy logic algorithms to determine the appropriate valve positions to maintain the desired room temperature while minimizing energy consumption (Abraham et al., 2023). The controller also has a user interface implemented in LabVIEW that allows the user to adjust the controller settings and view the status of the system. Additionally, the controller is also connected to a data logging system to record system performance and energy consumption over time, which can be used for performance analysis and system optimization.

Figure 10. Fuzzy Logic Smart Energy Control - Setup

Figure 10 shows the current values of the fuzzy controller based on real-time measured values separately by zone. A triangular fuzzy numeric decision value is created from the basic linguistic decision values. Where $f_{ki} = (l_{ki}, m_{ki}, u_{ki})$, are the corresponding triangular fuzzy number for the level of performance of i evaluation criteria for k expert group rating with 1≤k≤K. Finally, the center of area (COA) defuzzification method, using Eq. (8) is used to get crisp data x_{ki}.

$$x_{ki} = \frac{[(u_{ki}-l_{ki})+(m_{ki}-l_{ki})]}{3} + l_{ki} \quad (8)$$

The crisp decision matrix is then converted into a normalized decision matrix P_{ki} using Eq. (9):

$$P_{ki} = \frac{x_{ki}}{\sum_{k=1}^{K} x_{ki}} \quad (9)$$

The information entropy E_j can be determined for each criteria by using Eq. (10):

$$E_i = -[ln(K)]^{-1} \sum_{k=1}^{K} P_{ki} ln\, P_{ki} \quad (10)$$

Where w_i is the weight for each criterion and it can be computed by using Eq. (11):

$$w_i = \frac{(1-E_i)}{(m-\sum_{i=1}^{m} E_i)} \quad (11)$$

Let $0 \le w_i \le 1$ and $\sum_{i=1}^{m} w_i = 1$. A fuzzy value is then defuzzified to get the appropriate crisp value. The center of area (COA) method can be used at this point.

4. Discussion

Fuzzy temperature control and classical on-off control are two different approaches to controlling temperature in heating and cooling systems. Fuzzy temperature control utilizes fuzzy logic to determine the desired temperature based on input variables such as room temperature, set point temperature, and temperature error.

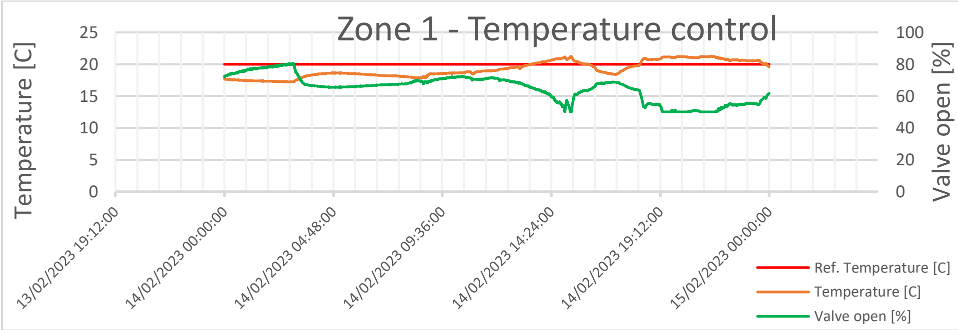

Figure 11. Zone 1 temperature control

Figures 11 and 12 show the reference values of the temperature of the given zone as well as the measured temperature value. Parallel to those values, the percentage value of the opening or closing of the control valve is also given.

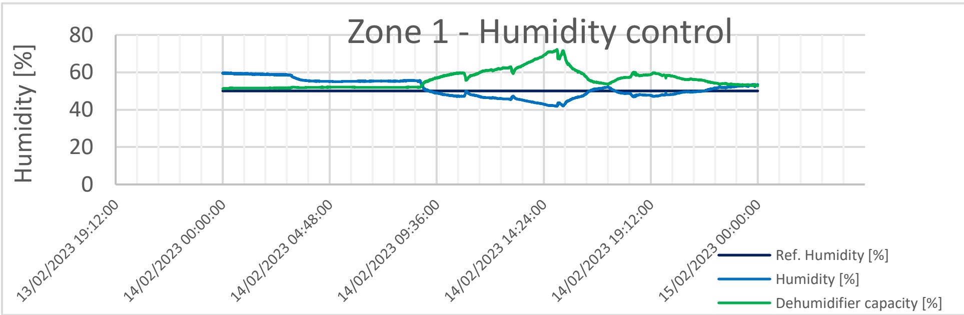

Figure 12. Zone 1 humidity control

As we can see, the response of the system is extremely fast and there are no major deviations from the reference values.

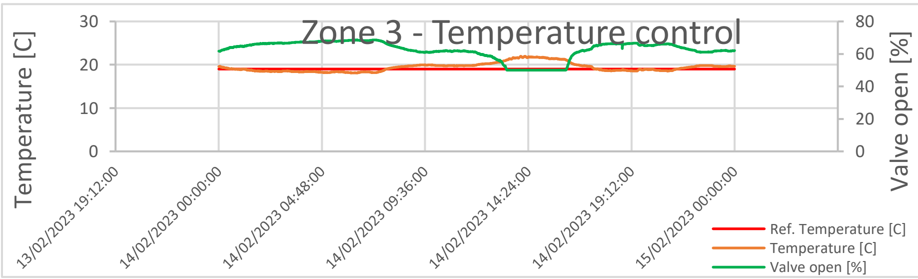

Figure 13. Zone 3 temperature control

Measurements of the zone parameters were made every two seconds. The data is stored in the relational database for further analysis. Figures 13 and 14 show the reference values of the temperature of the given zone as well as the measured temperature value. Parallel to those values, the percentage value of the opening or closing of the control valve is also given.

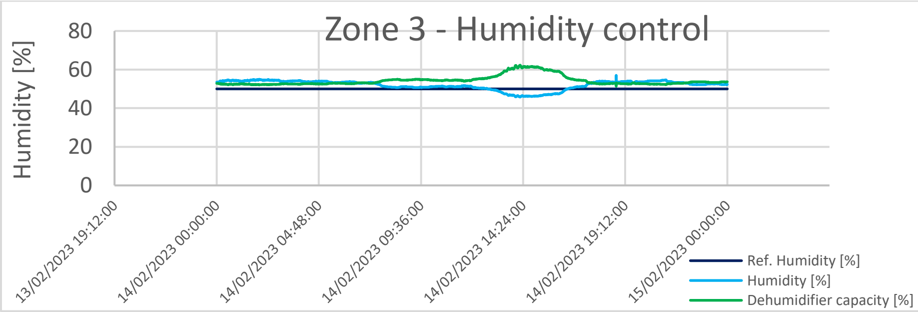

Figure 14. Zone 3 humidity control

The advantage of fuzzy temperature control is its ability to handle uncertainty and non-linearity in the system, which can lead to more precise temperature control. Classical on-off control, on the other hand, uses a simple control algorithm that turns the heating or cooling system on or off based on the difference between the room temperature and the set point temperature. It does not take into account any other variables and can lead to over-shooting or undershooting of the set point temperature. As depicted on Figure 15 the temperature control with FLSEC is very stable compared to classical on-off control. This figure depicts temperature control without any disturbances as door or window openings. On the other hand Figure 10 shows a real life like environment of the temperature control with FLSEC.

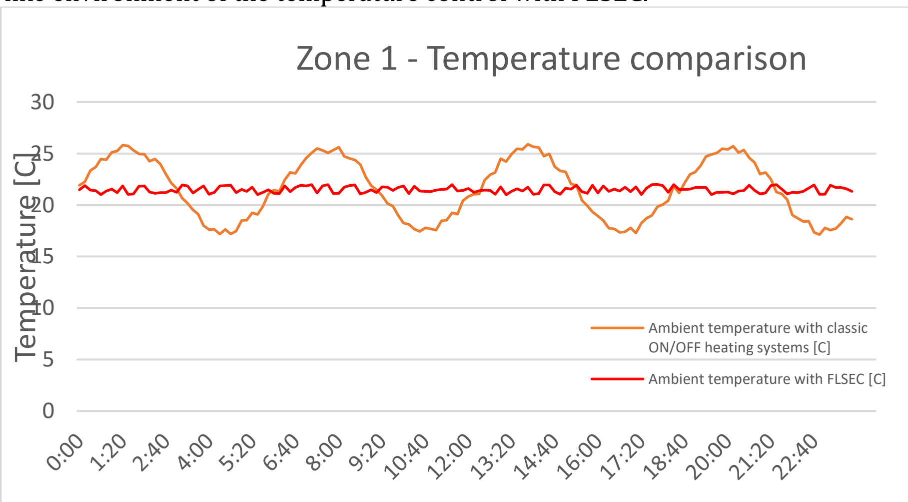

Figure 15. Ambient temperature comparison

The external temperature and relative humidity are shown in Figure 16. Measurements were made every hour by the outdoor measurement smart module.

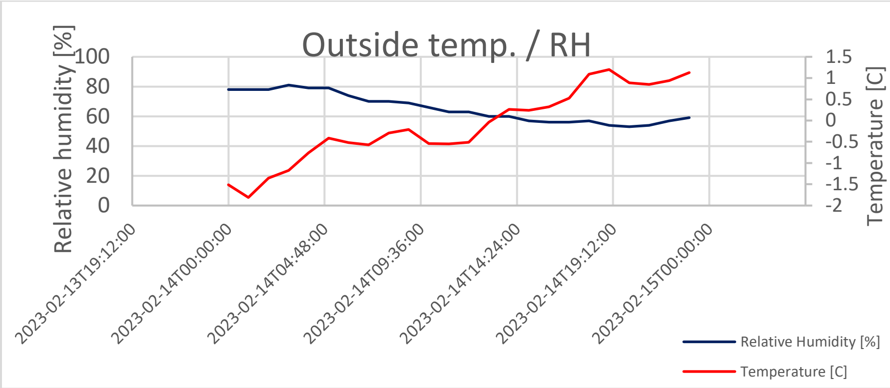

Figure 16. Outside temperature and relative humidity parameters

In general, fuzzy temperature control is considered to be more effective and efficient than classical on-off control, due to its ability to handle uncertainty and non-linearity in the system. However, its implementation can be more complex and require more re-sources than classical on-off control. Table 2 shows the summary of the reduction in energy by using fuzzy control by other authors.

Table 2. Reduction in energy consumption by using fuzzy control

Authors	Control application	Simlation	Experimental study	Energy saving
Duhui et al. (2020)	Air to water heat pump	X		11,3%
Sahin et al. (2011)	air source heat pump	X		10,23%
Yuan et al. (2019)	Open loop heat pump	X	X	39,56%
TeGrotenhuis et al. (2017)	Hybrid heat pump	X		50%
Duhui and Cui, (2020)	Air to water heat pump	X		15,9 %
Barelli et al. (2003)	Chiller	X		1%
Aprea et al. (2004)	Industrial plant		X	13%
Ekren and Kücüka (2009)	Chiller		X	17%
Schmitz et al. (2014)	Chiller	X		-3.15% 5.27%

Chu et al. (2005)	Air conditioning		X	35.59% daily
Parameshwaran et al. (2010)	Air conditioning		X	36% annual
Nasution (2008)	Air conditioning		X	39.14% to 64.35%
Khayyam et al. (2011)	Air conditioning		X	12%
Mraz (2001)	Domestic refrigerator	X		3%
Arfaoui et al. (2015)	Domestic refrigerator	X		0.3957 W
Belman-Flores et al. (2019)	Domestic refrigerator		X	3%

The Table 2 summarizes various control applications examined by different authors. It is evident that the authors either analyzed only the cycle itself or used either simulation or experimental methods. In this study, not only the cycle but also the associated primary and secondary circuits, i.e., the heat source and the heating circuit, were analyzed. Furthermore, our investigations encompassed both simulation and experimental approaches.

The advantages of the Fuzzy Logic Smart Energy Control (FLSEC) Model:

- Flexibility and Adaptability: Fuzzy Logic allows for the modeling of complex and uncertain relationships, making the FLSEC model highly flexible and adaptable to various energy systems. It can handle a wide range of input data and adapt its control strategies based on changing conditions, such as weather patterns, occupant behavior, and energy demand fluctuations. This adaptability enables the FLSEC model to respond effectively to dynamic energy management requirements.
- Real-time Decision Making: One of the significant advantages of the FLSEC model is its ability to make real-time decisions based on real-world data and feedback. This enables the model to respond quickly to changing conditions and optimize energy consumption accordingly, leading to more efficient energy management. Real-time decision-making also ensures that the model can adjust its control strategies as needed to maximize energy savings and maintain occupant comfort.
- Reduced Energy Consumption: By using fuzzy logic-based control strategies, the FLSEC model can optimize energy consumption and minimize waste. It can intelligently adjust heating, cooling, lighting, and other energy-intensive processes to match actual demand. This leads to reduced energy costs and a more sustainable energy use pattern, benefiting both the environment and building owners.
- Improved Energy Efficiency: The FLSEC model's ability to optimize the use of energy resources and reduce unnecessary energy consumption during non-peak periods contributes to improved energy efficiency. By

dynamically adjusting energy use based on real-time data, the FLSEC model ensures that energy resources are utilized more efficiently, resulting in overall energy savings.

- Handling Uncertainty: Fuzzy Logic excels in dealing with uncertainty, making it well-suited for modeling energy systems where variables may not have precise values. The FLSEC model can account for uncertain factors, such as variations in weather conditions or occupancy patterns, and make informed decisions based on probabilistic information.

Limitations of the Fuzzy Logic Smart Energy Control (FLSEC) Model:

- Complexity of Rule Development: The development of fuzzy rules can be complex and time-consuming, especially for large-scale energy systems. Constructing accurate and comprehensive rule sets requires expertise and extensive data analysis. The need for expert input can increase implementation costs and make the model less accessible to non-experts.
- Interpretability: Fuzzy logic models are known for their interpretability, as the linguistic rules are understandable to humans. However, in complex systems, the number of rules and their interactions can make it challenging to interpret the reasoning behind specific control decisions. As a result, users may have difficulty understanding the model's outputs and may need further explanation.
- Calibration and Tuning: Fine-tuning the parameters of the fuzzy logic model to achieve optimal performance can be a challenging task. This process requires expert knowledge and can be time-consuming. Incorrect calibration may lead to suboptimal control decisions and reduced energy savings.
- Data Requirements: The FLSEC model relies heavily on accurate and real-time data, including weather conditions, occupant behavior, and system performance. The availability and quality of data can significantly impact the model's effectiveness. Insufficient or unreliable data may lead to inaccurate control decisions and reduced energy savings.
- Scalability: While fuzzy logic is effective in modeling complex systems, the scalability of the FLSEC model is a crucial consideration when implementing it in larger and more complex energy systems. Ensuring that the model can handle increased data inputs and decision-making processes is essential for its practical application in large-scale buildings or smart grids.

The application of the FLSEC model in a case study provides valuable insights into its real-world performance. Some key considerations for the case study are as follows:

- Case-specific Application: The effectiveness of the FLSEC model may vary depending on the specific building or energy system it is applied to. Factors like building size, location, energy sources, and user behavior will influence its performance. The case study should be representative of the targeted application domain to draw meaningful conclusions.
- Data Collection and Validation: The case study should involve extensive data collection and validation to ensure accurate modeling and performance evaluation of the FLSEC model. Real-world data on energy consumption, weather conditions, and occupant behavior should be collected and compared with the model's predictions.

- Model Calibration: Proper calibration of the FLSEC model is essential to achieve optimal performance. The case study should involve a thorough calibration process to fine-tune the model parameters and ensure accurate energy-saving predictions.
- Comparison with Baseline: To assess the effectiveness of the FLSEC model, it should be compared with conventional control strategies or baseline energy management methods. A side-by-side comparison will provide valuable insights into the energy-saving potential of the FLSEC model.
- User Feedback: Feedback from building occupants or system operators is crucial to evaluate the user acceptance and usability of the FLSEC model. Understanding user experiences and potential challenges can help refine the model's implementation and improve its performance.
- Economic Analysis: The case study should also include an economic analysis to assess the cost-effectiveness of implementing the FLSEC model. This analysis should consider both the upfront implementation costs and the long-term energy savings generated by the model.

The Fuzzy Logic Smart Energy Control (FLSEC) model offers several advantages, including flexibility, real-time decision-making, reduced energy consumption, and improved energy efficiency. However, the model also has limitations, such as complexity in rule development, interpretability challenges, and data requirements. In a case study, careful consideration of application-specific factors, data collection, model calibration, and comparison with baseline strategies is essential to assess the FLSEC model's effectiveness and potential for energy savings in real-world scenarios.

5. Conclusions and future research

The current study has been carried out to determine an energy-efficient heat pump system by investigating the effect of outdoor unit air to water heat exchanger and a developed FLSEC method parameters. LabVIEW's graphical programming language, modular approach, extensive libraries, and system integration capabilities make it an ideal tool for rapid prototyping of SCADA systems for smart home applications. It can help to stream-line the development process and reduce time-to-market for new systems. In a real world test scenario with underfloor heating system, the developed FLSEC method was tested. Improving energy efficiency with FLSEC, authors developed a newer technology that improves energy efficiency even further and this improves the algorithm of the FLSEC technology. In a comparative test, carried out in a fair climatic chamber, FLSEC technology was tested against the classical controller. This concluded that FLSEC technology was able to save a further 6 - 8% of energy and reduce the equivalent coefficient of consumption. The main objective of all model predictive control approaches is to obtain future solutions for a problem based on actual and future data performed by a model. These solutions should be provided within a reasonable time and to a certain level of quality. In this context, an FLSEC optimization with a detailed energy model has been performed. Through a specific case study, a novel methodology to measure the convergence time and accuracy of the solution has been demonstrated.

Possible future development strategies for the energy-efficient smart home heating system using a renewable energy source with fuzzy control design includes a continuous research and development of advanced fuzzy control algorithms that can lead to more efficient and precise control of the heating system. These algorithms should take into account additional factors such as occupant behavior, weather patterns, and energy demand fluctuations, to further optimize energy consumption and indoor comfort. Incorporating energy storage technologies, such as batteries or thermal storage systems, can enhance the system's ability to store excess renewable energy for later use during peak demand periods. This would ensure a consistent supply of heating even when renewable sources are not available. Integrating the smart home heating system with the smart grid infrastructure would enable demand-response capabilities. This would allow the system to adjust heating operations based on real-time electricity pricing and grid conditions, contributing to a more stable and efficient energy grid. Utilizing artificial intelligence and machine learning techniques can enhance the system's predictive capabilities, enabling it to learn from historical data and optimize heating schedules based on occupants' preferences and weather patterns. By implementing these future development strategies, the energy-efficient smart home heating system using a renewable energy source with fuzzy control design can become even more effective, sustainable, and user-friendly, contributing to a greener and more energy-efficient future.

Author Contributions: Conceptualization, J.S.; methodology, J.S.; validation, J.S.; formal analysis, J.S.; investigation, R.S.; resources, R.S.; writing—original draft preparation, J.S.; writing—review and editing, J.S.; visualization, J.S.; supervision, R.S.; The author has read and agreed to the published version of the manuscript.

Funding*:* This research received no external funding.

Data Availability Statement*:* The related resources are addressed in the references.

Conflicts of Interest*:* The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abraham, D. S., Chandrasekar, B., Rajamanickam, N., Vishnuram, P., Ramakrishnan, V., Bajaj, M., Piecha, M., Blazek, V., & Prokop, L. (2023). Fuzzy-Based Efficient Control of DC Microgrid Configuration for PV-Energized EV Charging Station. Energies, 16(6), 2753. https://doi.org/10.3390/en16062753

Alowaidi, M. (2022). Fuzzy efficient energy algorithm in smart home environment using internet of things for renewable energy resources. Energy Reports, 8, 2462-2471. https://doi.org/10.1016/j.egyr.2022.01.177

Aprea, C., Mastrullo, R., & Renno, C. (2004). Fuzzy control of the compressor speed in a refrigeration plant. International Journal of Refrigeration, 27(6), pp. 639–648. https://doi.org/10.1016/j.ijrefrig.2004.02.004

Arfaoui, J., Feki, E., & Mami, A. (2015). PID and fuzzy logic optimized controller for temperature control in a cavity of refrigeration. In Proceedings of the IREC2015 The Sixth International Renewable Energy Congress, Sousse, Tunisia, pp. 1–6. https://doi.org/10.1109/IREC.2015.7110951

Barelli, L., Bidini, G., & Arce, R. (2003) Fuzzy Logic Regulator for the Performance Improvement and the Energy Consumption Reduction of an Industrial Chiller.

Proceedings of the ASME 2003 International Mechanical Engineering Congress and Exposition. Dynamic Systems and Control, Volumes 1 and 2. Washington, DC, USA. November 15–21, pp. 1215-1224. https://doi.org/10.1115/IMECE2003-41910

Belman-Flores, J. M., Ledesma, S., Rodríguez-Valderrama, D. A., & Hernández-Fusilier, D. (2019). Energy optimization of a domestic refrigerator controlled by a fuzzy logic system using the status of the door. International Journal of Refrigeration, 104, pp. 1–8. https://doi.org/10.1016/j.ijrefrig.2019.04.025

Chu, C. M., Jong, T. L., & Huang, Y. W. (2005). Thermal comfort control on multi-room fan coil unit system using LEE-based fuzzy logic. Energy Convers. Manag., 46(9–10), pp. 1579–1593. https://doi.org/10.1016/j.enconman.2004.08.002

Derrouazin, A., Aillerie, M., Mekkakia-Maaza, N., & Charles, J. P. (2017). Multi input-output fuzzy logic smart controller for a residential hybrid solar-wind-storage energy system. Energy Conversion and Management, 148, 238-250. https://doi.org/10.1016/j.enconman.2017.05.046

Duhui J., Hongshe C., Rui S., & Wei L., (2020). Study fuzzy variable supplied water temperature control for air-to-water heat pumps connected to a residential floor heating, IOP Conf. Series: Earth and Environmental Science 467(1), 012192. https://doi.org/10.1088/1755-1315/467/1/012192

Duhui, J., & Cui, H. (2020). Study on Fuzzy Control for Air-To-Water Heat Pumps Connected to a Residential Floor Heating System, Mathematical Problems in Engineering Volume 2020(11), https://doi.org/10.1155/2020/3861824

Durur, H., & Yokuş, A. (2021). Exact solutions of (2 + 1) - Ablowitz-Kaup-Newell-Segur equation. Applied Mathematics and Nonlinear Sciences. 6 (2), 381–386. https://doi.org/10.2478/amns.2020.2.00074

Ekren, O., & Kücüka, S. (2009). Energy saving potential of chiller system with fuzzy logic control. International Journal of Energy Research., 34(10), pp. 897–906. https://doi.org/10.1002/er.1621

El Zerk, A., & Ouassaid, M. (2023). Real-Time Fuzzy Logic Based Energy Management System for Microgrid Using Hardware in the Loop. Energies, 16(5), 2244. https://doi.org/10.3390/en16052244

Fujitsu (2020). Design and Technical Manual, Fujitsu General Limited, DA_SHP001EF_01.

German, R. R., Eva, L. S., & Carlos, F. B. (2019). Model predictive control optimization via genetic algorithm using a detailed building energy model, Energies, vol. 12(1), p. 34. https://doi.org/10.3390/en12010034

Gozuoglu, A., Ozgonenel, O., & Karagol, S. (2019). Fuzzy Logic Based Low Cost Smart Home Application. In 2019 11th International Conference on Electrical and Electronics Engineering (ELECO) (pp. 64-68). https://doi.org/10.23919/ELECO47770.2019.8990409

Jafari, M., Malekjamshidi, Z., Zhu, J., & Khooban, M. H. (2018). A novel predictive fuzzy logic-based energy management system for grid-connected and off-grid operation of residential smart microgrids. IEEE Journal of Emerging and Selected Topics in Power Electronics, 8(2), 1391-1404. https://doi.org/10.1109/JESTPE.2018.2882509

Jiang, D. H., Cui, H. S., Jiang, K. D., & Yang, J. L. (2019). Study building heat storage operation strategy for air-to-water heat pumps connected to a residential floor heating system, IOP Conf. Ser.: Earth Environ. Sci., vol. 227, p. 4. https://doi.org/10.1088/1755-1315/227/4/042054

Khayyam, H., Nahavandi, S., Hu, E., Kouzani, A., Chonka, A., Abawajy, J., Marano, V., & Davis, S. (2011). Intelligent energy management control of vehicle air conditioning via look-ahead system. Applied Thermal Engineering, 31(16), pp. 3147–3160. https://doi.org/10.1016/j.applthermaleng.2011.05.023

Killian, M., & Kozek, M. (2018). Implementation of cooperative Fuzzy model predictive control for an energy-efficient office building, Energy and Buildings, vol. 158, pp. 1404–1416. https://doi.org/10.1016/j.enbuild.2017.11.021

Lin X., Longjie W., Chenlei Z., Xiao L., & Bo F., (2022). Research on Fuzzy Control Strategy of Heating Condition Based on Electric Vehicle Heat Pump Air Conditioner, Academic Journal of Science and Technology 3(3), 175-181. https://doi.org/10.54097/ajst.v3i3.2932

Marín, L. G., Cruz, N., Sáez, D., Sumner, M., & Núñez, A. (2019). Prediction interval methodology based on fuzzy numbers and its extension to fuzzy systems and neural networks. Expert Systems with Applications. 119, 128–141. https://doi.org/10.1016/j.eswa.2018.10.043

Miao, Z. (2023). Intelligent control system for the electric vehicle heat pump air conditioner based on machine learning. Frontiers in Energy Research. 11. https://doi.org/10.3389/fenrg.2023.1142243

Mraz, M. (2001). The design of intelligent control of a kitchen refrigerator. Math. Comput. Simul., 56(3), pp. 259–267. https://doi.org/10.1016/S0378-4754(01)00281-6

Nasution, H. (2008). Development of fuzzy logic control for vehicle air conditioning system. Telkomnika, 6(2), 73. https://doi.org/10.12928/telkomnika.v6i2.553

Nguyen, A. T., Taniguchi, T., Eciolaza, L., Campos, V., Palhares, R., & Sugeno, M. (2019). Fuzzy control systems: Past, present and future. IEEE Comput. Intell. Mag. 14 (1), 56–68. https://doi.org/10.1109/MCI.2018.2881644

Nilpueng, K., Ahn, H. S., Jerng, D. W., & Wongwises, S. (2019). Heat transfer and flow characteristics of sinusoidal wavy plate fin heat sink with and without crosscut flow control. International Journal of Heat and Mass Transfer. 137, 565–572. https://doi.org/10.1016/j.ijheatmasstransfer.2019.03.114

Nyers, A., Pek Z., & Nyers J. (2018). Dynamical behavior of a heat pump coaxial evaporator considering the phase border's impact on convergence, Facta Universitatis Series: Mechanical Engineering, 16(2), pp. 249-259, https://doi.org/10.22190/FUME180424019N

Nyers, A., & Nyers, J. (2023). Enhancing the Energy Efficiency—COP of the Heat Pump Heating System by Energy Optimization and a Case Study. Energies, 16(7), 2981. https://doi.org/10.3390/en16072981.

Parameshwaran, R., Karunakaran, R., Kumar, C. V. R. & Iniyan, S. (2010). Energy conservative building air conditioning system controlled and optimized using fuzzy-genetic algorithm. Energy Buildings, 42(5), pp. 745–762. https://doi.org/10.1016/j.enbuild.2009.11.014

Sahin, A.Ş., Kılıç, B., & Kılıç, U. (2011). Optimization of heat pump using fuzzy logic and genetic algorithm. Heat Mass Transfer 47(12), pp. 1553–1560. https://doi.org/10.1007/s00231-011-0818-4

Santa, R. (2021). Investigations of the performance of a heat pump with internal heat exchanger, Journal of thermal analysis and calorimetry 147(15), 8499–8508. https://doi.org/10.1007/s10973-021-11130-5

Santa, R., Bošnjaković, M., & Čikić, A., (2022). Experimental and numerical testing of heat pump evaporator, Applied Sciences-Basel 12(23), 11973. https://doi.org/10.3390/app122311973

Schmitz, J. E., Silva, F. V., Neves Filho, L. C., Fileti, A. M. F., & Silveira, V. (2014). Multivariable fuzzy control strategy for an experimental chiller system. Journal of Food Process Engineering., 37(2), pp. 160–168. https://doi.org/10.1111/jfpe.12071

Suganthi, L., Iniyan, S., & Samuel, A. A. (2015). Applications of fuzzy logic in renewable energy systems–a review. Renewable and sustainable energy reviews, 48, 585-607. https://doi.org/10.1016/j.rser.2015.04.037

TeGrotenhuis, W., Butterfield, A., Caldwell, D., Crook, A., & Winkelman, A. (2017). Modeling and design of a high efficiency hybrid heat pump clothes dryer. Applied Thermal Engineering, 124, pp. 170-177. https://doi.org/10.1016/j.applthermaleng.2017.05.048

Vivas, F. J., Segura, F., & Andújar, J. M. (2022). Fuzzy logic-based energy management system for grid-connected residential DC microgrids with multi-stack fuel cell systems: A multi-objective approach. Sustainable Energy, Grids and Networks, 32, 100909. https://doi.org/10.1016/j.segan.2022.100909

Wang, A., Cao, F., Fang, J., Jia, F., Yin, X., & Wang, X. (2022). Research on efficient defrosting control logic for transcritical CO2 electric vehicle heat pump airconditioning system. International Journal of Refrigeration. 138, 13–22. https://doi.org/10.1016/j.ijrefrig.2022.03.028

Wang, Y., Ye, Z., Song, Y., Yin, X., & Cao, F. (2021). Experimental analysis of reverse cycle defrosting and control strategy optimization for transcritical carbon dioxide heat pump water heater. Applied Thermal Engineering. 183, 116213. https://doi.org/10.1016/j.applthermaleng.2020.116213

Wang, Z., Yang, R., & Wang, L. (2010). Multi-agent control system with intelligent optimization for smart and energy-efficient buildings. In IECON 2010-36th annual conference on IEEE industrial electronics society (pp. 1144-1149). https://doi.org/10.1109/IECON.2010.5675530

Xi, Z., Yao, R., Li, J., Du, C., Yu, Z., & Li, B. (2021). Experimental studies on hot gas bypass defrosting control strategies for air source heat pumps. Journal of Building Engineering. 43, 103165. https://doi.org/10.1016/j.jobe.2021.103165

Xie, Y., Liu, Z., Liu, J., Li, K., Zhang, Y., Wu, C., Wang, P., & Wang, X., (2020). A Self-learning intelligent passenger vehicle comfort cooling system control strategy. Applied Thermal Engineering, 166, p.114646 https://doi.org/10.1016/j.applthermaleng.2019.114646

Xie, Y., Yang, P., Qian, Y., Zhang, Y., Li, K., & Zhou, Y. (2022). A two-layered ecocooling control strategy for electric car air conditioning systems with integration of dynamic programming and fuzzy PID. Applied Thermal Engineering. 211, 118488. https://doi.org/10.1016/j.applthermaleng.2022.118488

Yuan, Y., Lin, W., Mao, X., Li, W., Yang, L., Wei, J., & Xiao, B. (2019). Performance Analysis of Heat Pump Dryer with Unit-Room in Cold Climate Regions. Energies. 12(16), 3125. https://doi.org/10.3390/en12163125

Zangeneh, M., Aghajari, E., & Forouzanfar, M. (2022). Design and implementation of an intelligent multi-input multi-output Sugeno fuzzy logic controller for managing energy resources in a hybrid renewable energy power system based on Arduino boards. Soft Computing, 26(3), 1459-1473. https://doi.org/10.1007/s00500-021-06288-x

Zheng, S., Wei, M., Song, P., Hu, C., & Tian, R. (2020). Thermodynamics and flow unsteadiness analysis of trans-critical CO2 in a scroll compressor for mobile heat pump air-conditioning system. Applied Thermal Engineering. 175, 115368. https://doi.org/10.1016/j.applthermaleng.2020.115368