IoT Control Systems base on Fuzzy Inference

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Relevance

- Range of devices connected to the Internet is huge and that number continues to grow.
- Among the devices connected to the Internet, which are quite popular in household use, are smart ventilation systems.
- The world aims to improve effective methods of intelligent control for IoT ventilation systems

Problem Statement

- IoT systems, in addition to the higher advantages, have disadvantages, one of which is energy consumption. Heating, ventilation, and air-conditioning systems predominate in energy usage in commercial buildings. The numbers variate between 40 percent and 70 percent of the total building electricity consumption

- Therefore, the development of IoT-based platforms in the field of smart ventilation needs to be improved in terms of resource consumption. We must develop new techniques for improving the energy efficiency of ventilation systems to achieve the reduction in overall building energy consumption and as a result decrease operating electricity costs.

Fundamentals of fuzzy control systems and the Takagi-Sugeno algorithm

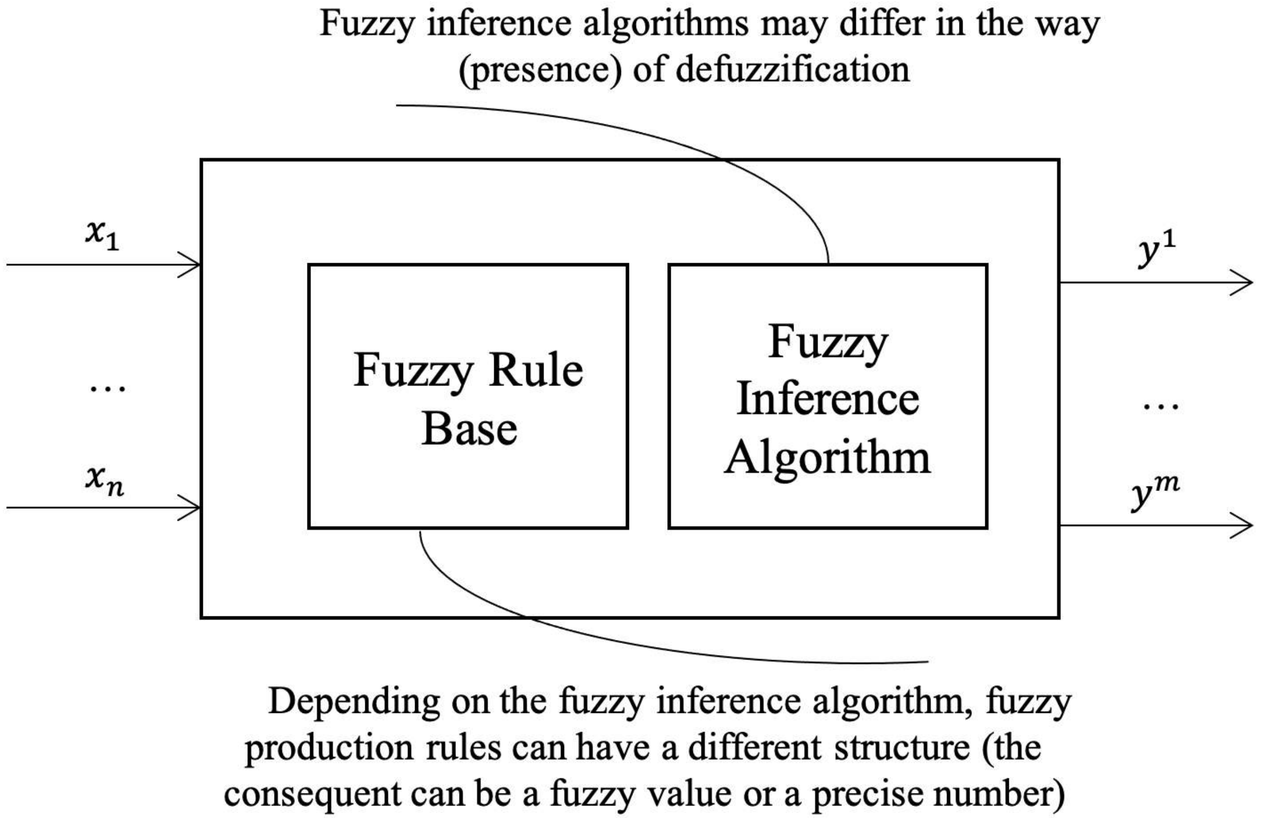
Intelligent fuzzy systems are actively used to solve a wide class of problems in many areas of industry and life (medicine, production, safety, management, etc.). Belonging to the class of intellectual, fuzzy systems are designed to solve highly specialized tasks of the creative direction. Such tasks may include decision-making systems, expert systems, artificial intelligence systems, testing, assessment, classification systems, etc.

Control systems based on fuzzy converters of input data into output data are used in cases where the following features take place:

- The system operates with qualitative values and characteristics
- There is incomplete data about the modeled object and its environment
- The investigated object is extremely difficult to model and find ideal solutions
- There is a non-linear dependence of the input-output data
- Decision making by the system is based on the knowledge and experience of experts in a specific problem area

Fuzzy inference

General scheme of a fuzzy inference system



The functioning of fuzzy systems consists of the following stages:

- Fuzzification of input variables
- Activation of fuzzy production rules
- Aggregation of rule subconclusions (in consequent)
- Accumulation of sub-conclusions of the consequent of fuzzy rules (carried out only for those systems, the consequents of which are fuzzy values)
- Defuzzification of output values (or a procedure similar to defuzzification, if the consequents of the rules are clear numbers)

The Takagi-Sugeno fuzzy rule is:

$$R_w^j: \ IF \ \ \mathrm{x}\ is\ A_w^j \ \ \ THEN \ \ \ y_w^j = k_{w0}^j + \sum_{i=1}^{n} k_{wi}^j x_i,$$

where j – system-generated output number, w – fuzzy rule number, n – number of input variables, – free coefficient. The consequent of a rule is essentially a weighted summation of non-fuzzified input prerequisites.

An output conclusion for every according to the Takagi-Sugeno algorithm, it is the finding of the weighted average of rule subconclusions in a fuzzy knowledge base:

$$y^j = \frac{\sum_{w=1}^{L}\left[\Lambda_{i=1}^{n}\mu_w^j(x_i)\right]\left(k_{w0}^j + \sum_{i=1}^{n}k_{wi}^j x_i\right)}{\sum_{w=1}^{L}\left[\Lambda_{i=1}^{n}\mu_w^j(x_i)\right]} = \frac{\sum_{w=1}^{L}\mu_w^j(\mathrm{x})y_w^j}{\sum_{w=1}^{L}\mu_w^j(\mathrm{x})},$$

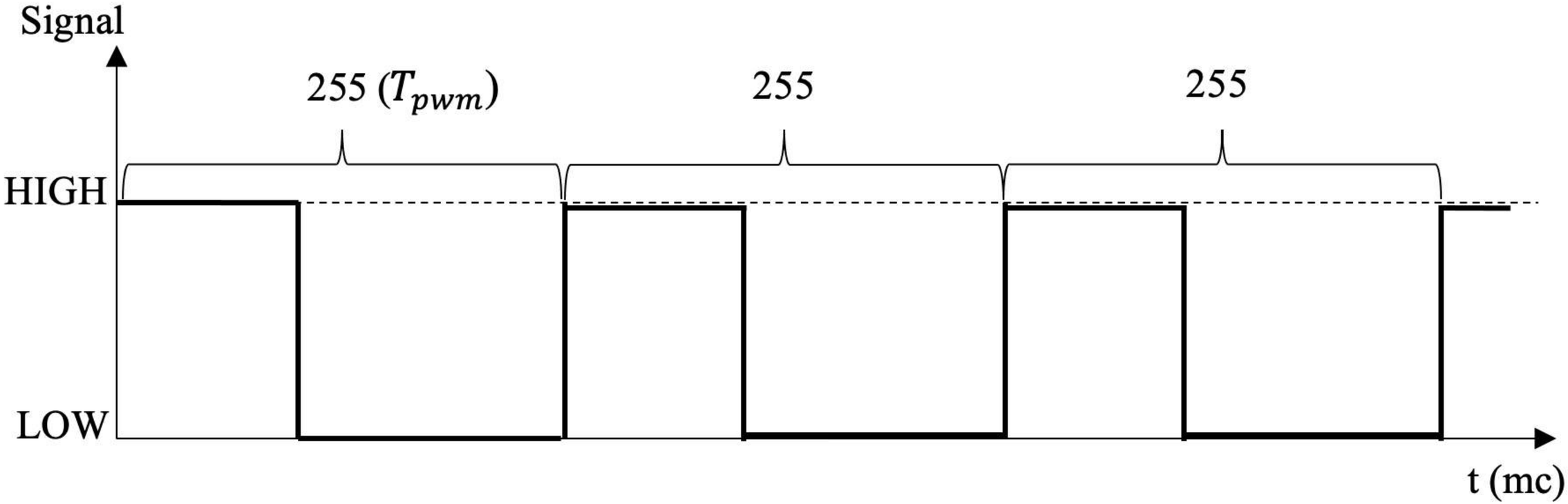
where is the operation of taking the minimum, – is the membership function of the input value to a fuzzy term.

Control of the output PWM signal in IoT systems based on intelligent fuzzy converters

The total power consumption at the PWM output is calculated as:

$$P_{out} = \frac{E_r + E_{dr} + E_f + E_{rc}}{T_{pwm}},$$

where – the energy consumption during the time of transition from Low to High mode, the energy consumption during the current supply time to maintain High mode, the energy consumption during the time of transition from High to Low mode, – the energy consumption during the time for current regeneration in order to maintain Low mode, total operating time of the PWM signal (0..255).



Scheme of the digital PWM output signal

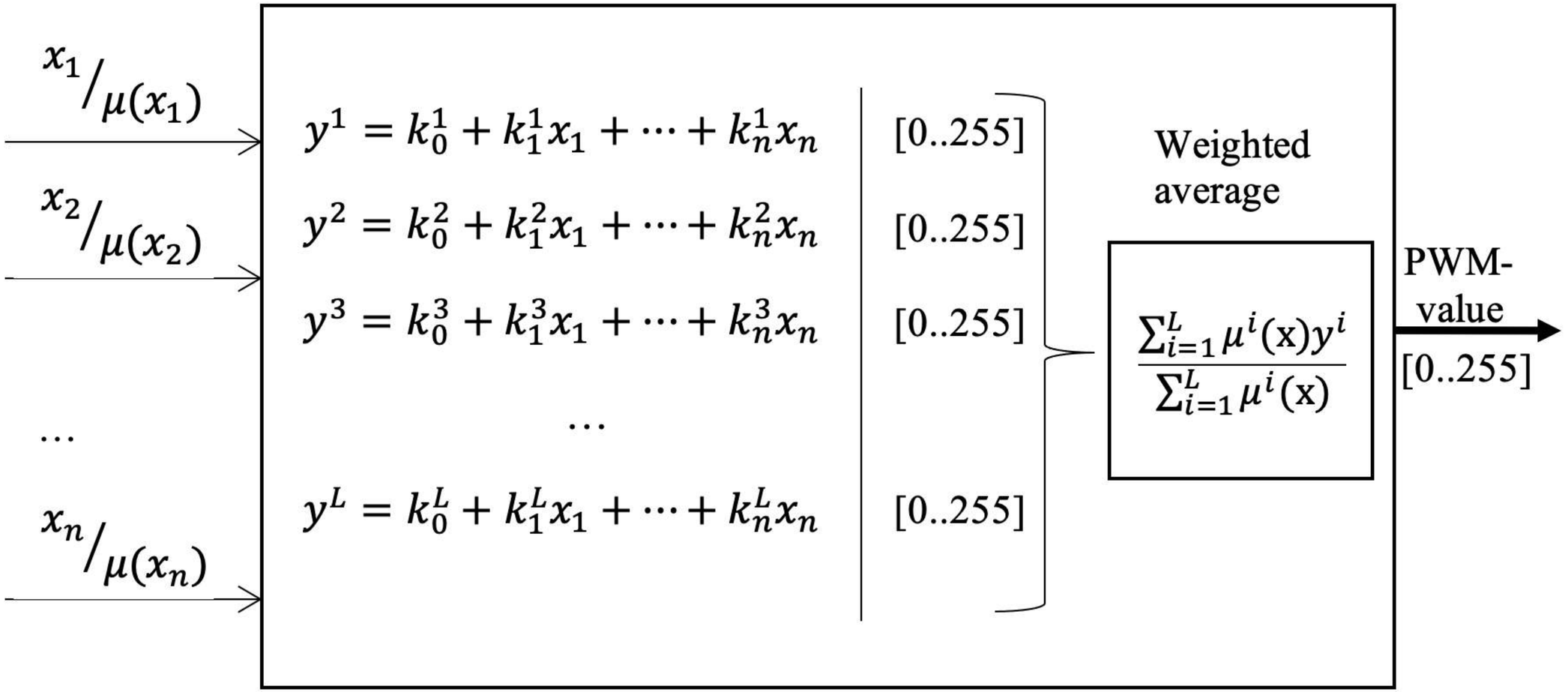
The input parameters are represented by a vector of fuzzy (fuzzified) values, which are qualitative characteristics read from the sensors:

$$\tilde{X} = \{\tilde{x}_i, i = \overline{1,n}\},$$

$$\tilde{x}_i = \left\{ \frac{x_i}{\mu_{term\,1}(x_i)} + \frac{x_i}{\mu_{term\,2}(x_i)} + \cdots + \frac{x_i}{\mu_{term\,Q}(x_i)} \right\},$$

where is a union operation, – vector of fuzzy input values.

Subconclusions of fuzzy rules (Takagi-Sugeno fuzzy rules), form the weighted values of the PWM output signal from 0 to 255, which then go through the procedure for finding the weighted average value, which, accordingly, will also lie in the range [0..255].



Model of the converter of fuzzy (quality) data from sensors to a PWM signal (range of values [0..255])

Smart fan based on the fuzzy converter of quality indicators into PWM signal

The architectural design of the Smart ventilation system

Basic fuzzy-based architectural model of smart ventilation system consists of (Figure 4):

1. Sensor components:

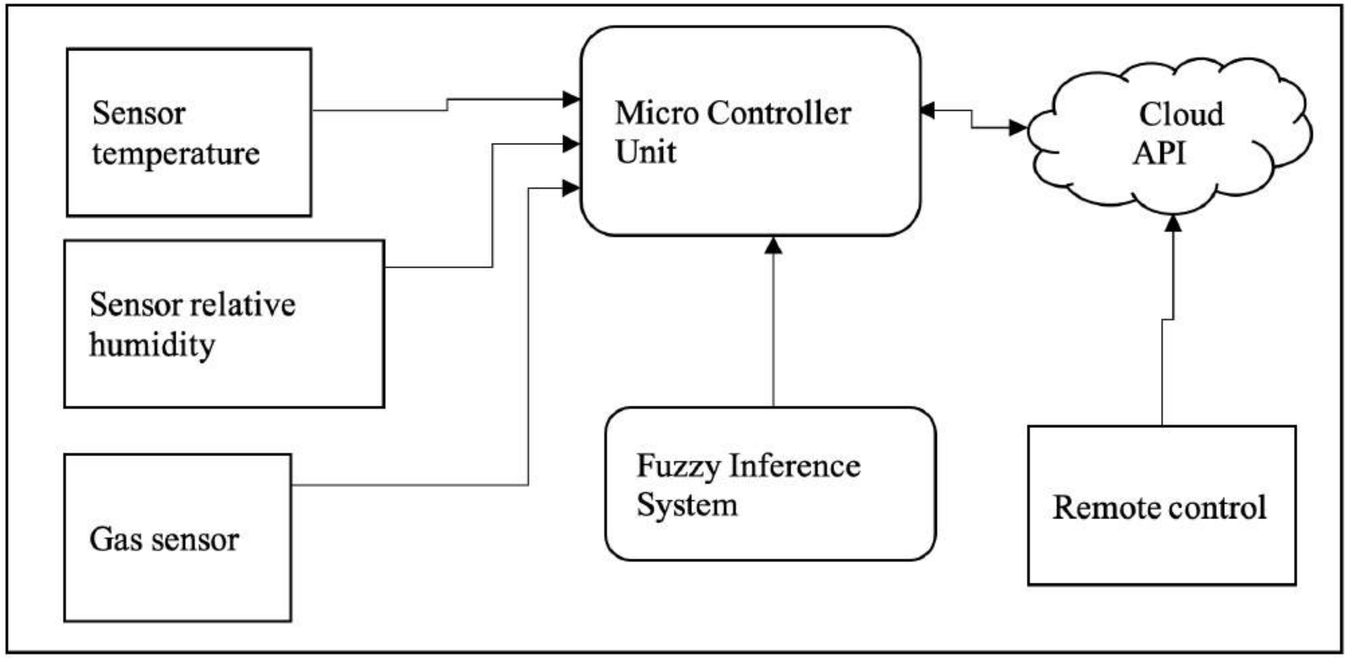
1.1. Sensor temperature

1.2. Sensor relative humidity

1.3. Gas sensor

2. Micro Controller Unit – intermediate component, which receives transmitted information from the sensors for processing of the collected data

3. Cloud API



Block diagram of the fuzzy-based smart ventilation system

Fuzzy Smart Fan Controller Model

To model the edge values (terms) of linguistic variables, we use sigmoidal membership functions:

$$\mu(x) = \frac{1}{1 + \exp\left[-b(x - c)\right]},$$

where – the number characterizing the slope of the graph (the larger the , the greater the slope), –inflection point of the function $(\mu(c) = 0{,}5)$.

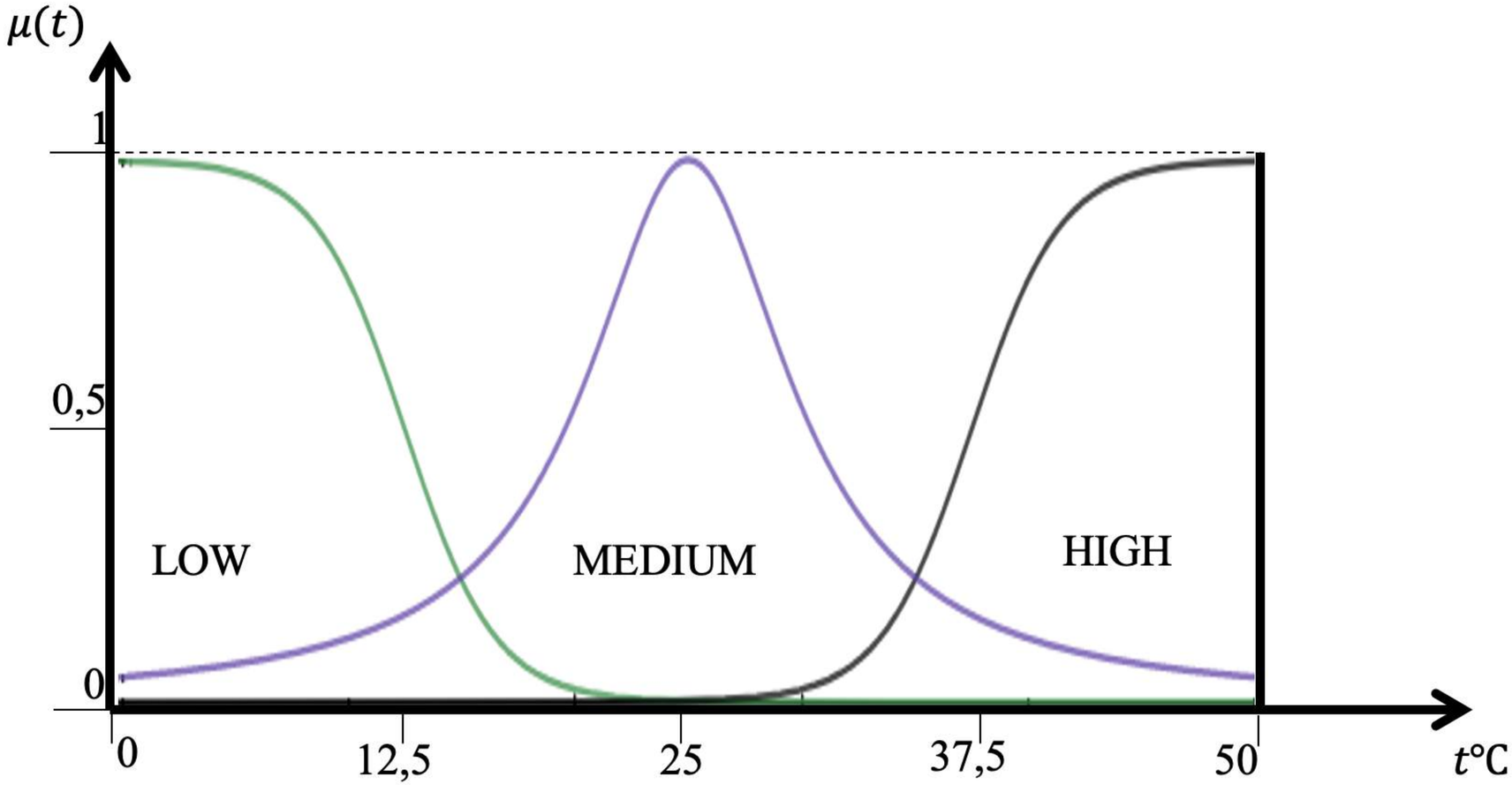
Furthermore, we will use the bell-shaped membership functions to model the mean values of fuzzy terms:

$$\mu(x) = \frac{1}{1 + \frac{|x - c|^{2b}}{\alpha}},$$

where c – central (modal) value at which $\mu(c) = 1$, $b \geq 0$– number characterizing the slope of the graph (similar to sigmoidal membership functions), $\alpha > 0$ – the distance from the center c to the inflection points of the function, where at $b = 0{,}5$ the $\mu(c \pm \alpha) = 0{,}5$ is fulfilled.

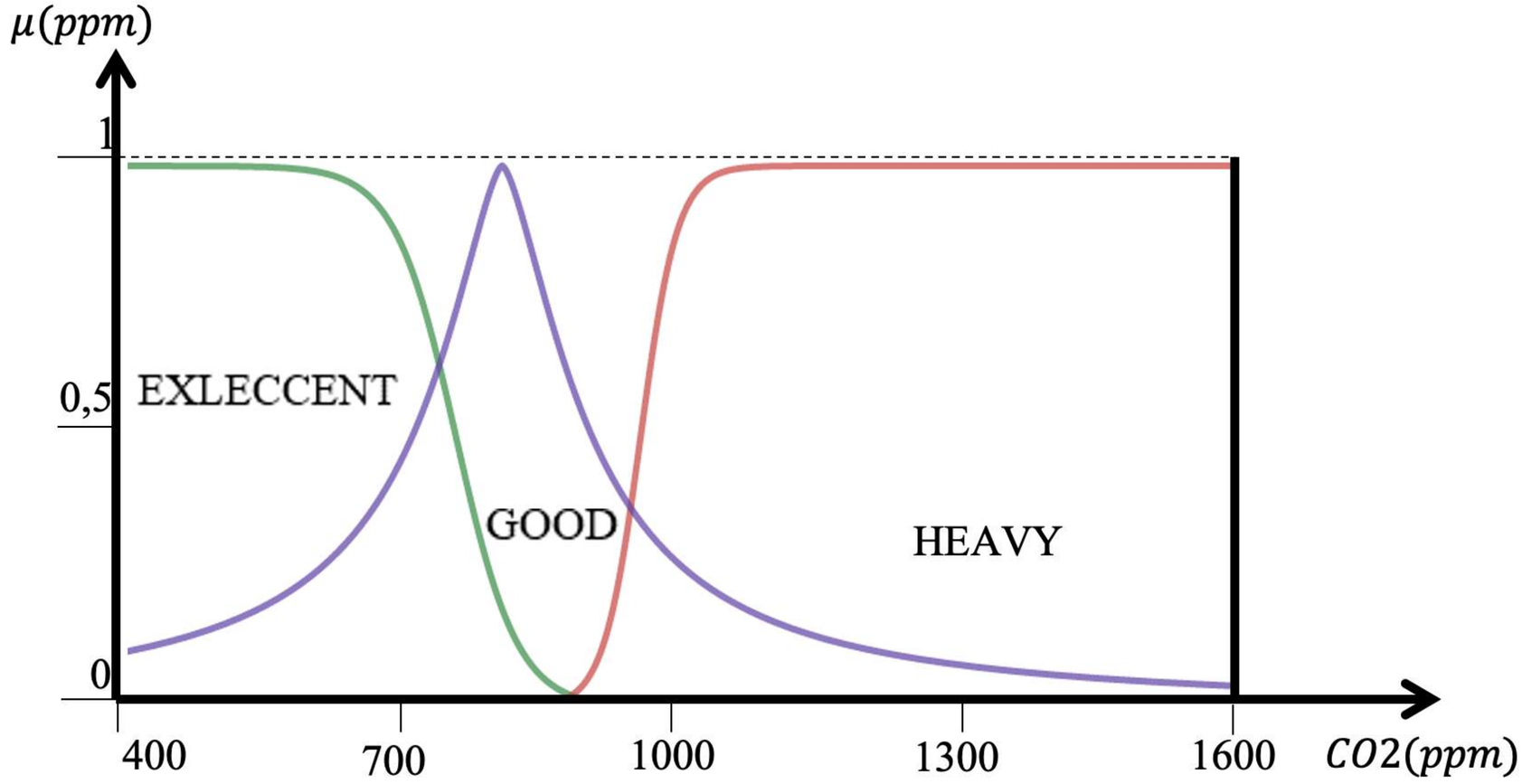
Linguistic variable "temperature" and its membership function graph

$$T = \left\{ \mu_{LOW}(x) = \frac{1}{1 + e^{0,5x-6,25}} + \mu_{MEDIUM}(x) = \frac{1}{1 + \frac{|x-25|^2}{30}} + \mu_{HIGH}(x) = \frac{1}{1 + e^{-0,5x+18,75}} \right\}.$$



Linguistic variable "carbon dioxide concentration" and its membership function graph

$$CO2 = \left\{ \mu_{EX}(x) = \frac{1}{1 + e^{0,03x-24}} + \mu_{GOOD}(x) = \frac{1}{1 + \frac{|x-850|^{1,5}}{1000}} + \mu_{HEAVY}(x) = \frac{1}{1 + e^{-0,05x+50}} \right\}.$$



Linguistic variable "relative humidity" and its membership function graph

$$RH = \left\{ \mu_{LOW}(x) = \frac{1}{1 + e^{0,1x-5}} + \mu_{HIGH}(x) = \frac{1}{1 + e^{-0,1x+5}} \right\}.$$

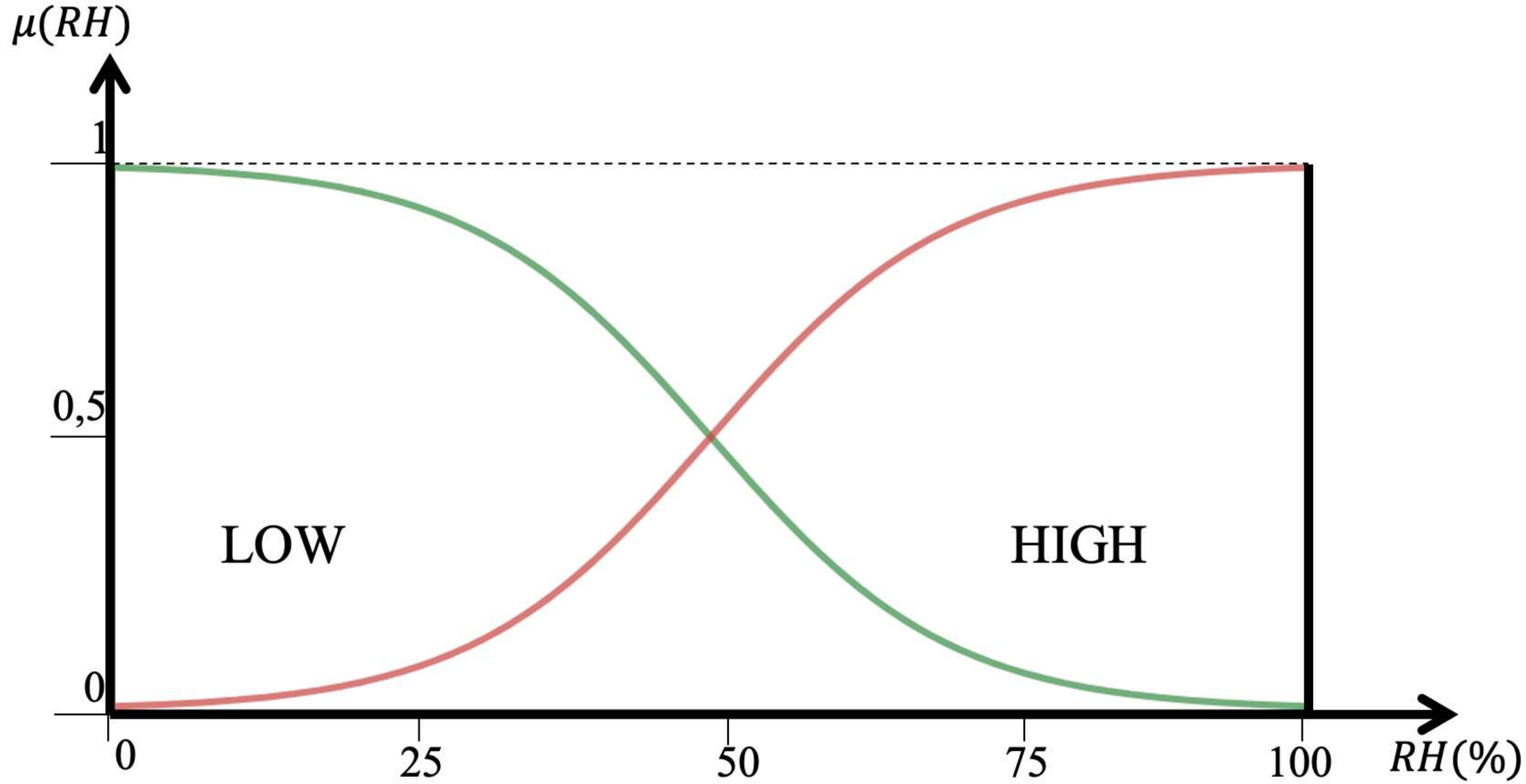


Table 1 presents a block of Takagi-Sugeno fuzzy production rules for controlling fan power through a PWM signal, consisting of 18 fuzzy rules.

Table 1

Takagi-Sugeno fuzzy rule block for Smart fan control

R_i	x_1 (t°C)	x_2 (ppm)	x_3 ($RH(\%)$	y_i (PWM)
R_1:	LOW	EXCELLENT	LOW	$y_1 = 0{,}5x_1 + 0{,}1x_2 + 1{,}5x_3$
R_2:	LOW	EXCELLENT	HIGH	$y_2 = 0{,}25x_1 + 0{,}1x_2 - 0{,}15x_3$
R_3:	LOW	GOOD	LOW	$y_3 = 0{,}6x_1 + 0{,}15x_2 + 1{,}7x_3$
R_4:	LOW	GOOD	HIGH	$y_4 = 0{,}5x_1 + 0{,}12x_2 + 0{,}2x_3$
R_5:	LOW	HEAVY	LOW	$y_5 = 0{,}7x_1 + 0{,}1x_2 + 1{,}6x_3$
R_6:	LOW	HEAVY	HIGH	$y_6 = 0{,}5x_1 + 0{,}1x_2 + 0{,}7x_3$
R_7:	MEDIUM	EXCELLENT	LOW	$y_7 = 0{,}6x_1 + 0{,}15x_2 + 1{,}4x_3$
R_8:	MEDIUM	EXCELLENT	HIGH	$y_8 = 0{,}3x_1 + 0{,}12x_2 - 0{,}1x_3$
R_9:	MEDIUM	GOOD	LOW	$y_9 = 0{,}7x_1 + 0{,}17x_2 + 1{,}7x_3$
R_{10}:	MEDIUM	GOOD	HIGH	$y_{10} = 0{,}4x_1 + 0{,}14x_2 + 0{,}3x_3$
R_{11}:	MEDIUM	HEAVY	LOW	$y_{11} = 0{,}7x_1 + 0{,}11x_2 + 1{,}8x_3$
R_{12}:	MEDIUM	HEAVY	HIGH	$y_{12} = 0{,}8x_1 + 0{,}1x_2 + 0{,}9x_3$
R_{13}:	HIGH	EXCELLENT	LOW	$y_{13} = 0{,}8x_1 + 0{,}2x_2 + 1{,}7x_3$
R_{14}:	HIGH	EXCELLENT	HIGH	$y_{14} = 0{,}7x_1 + 0{,}15x_2 + 0{,}8x_3$
R_{15}:	HIGH	GOOD	LOW	$y_{15} = 0{,}9x_1 + 0{,}14x_2 + 2x_3$
R_{16}:	HIGH	GOOD	HIGH	$y_{16} = 0{,}7x_1 + 0{,}14x_2 + 0{,}5x_3$
R_{17}:	HIGH	HEAVY	LOW	$y_{17} = x_1 + 0{,}11x_2 + 1{,}7x_3$
R_{18}:	HIGH	HEAVY	HIGH	$y_{18} = 0{,}95x_1 + 0{,}11x_2 + 0{,}34x_3$

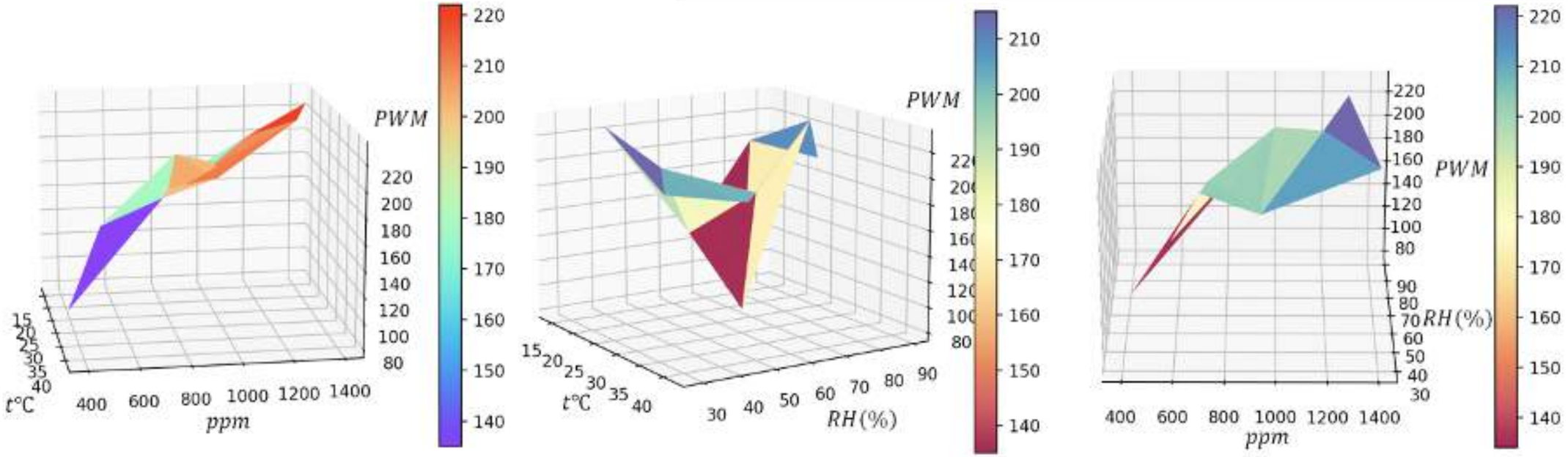
It is also important to note that the maximum number of rules of a fuzzy system can be found according to

$$RuleMaxNum = \prod_{i=1}^{N} terms(L_i),$$

Experimental results

Table 2
Experimental results of operation of the Smart Fan fuzzy control system

№	t°C	ppm	$RH(\%)$	PWM
1	23	400	70	77
2	28	820	40	208
3	14	1200	85	198
4	37	940	29	203
5	40	730	50	201
6	15	570	65	130
7	25	1000	90	195
8	30	1300	80	234
9	42	700	45	198
10	21	1400	33	234



Graph of dependencies between input and output variables of a fuzzy Smart fan controller

Conclusion

An IoT system of an intelligent fan has been developed based on the approach of converting fuzzy input parameters read from sensors into a PWM signal to control the fan screw rotation speed. A mathematical model of an intelligent fan based on fuzzy control has been developed, as well as its hardware architecture. In this approach, the model operates with three input parameters, namely, temperature, relative humidity and carbon dioxide concentrations (CO2) under different operating conditions vis-à-vis the PWM signal output.

Experimental studies have been carried out that demonstrate the characteristics of the proposed methods for intelligent control of Internet of Things devices that support a PWM signal, using the example of a Smart Fan.

Thank you for attention!