

Review Article

A Systematic Review of Greenhouse Humidity Prediction and Control Models Using Fuzzy Inference Systems

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Cultivating in greenhouses constitutes a fundamental tool for the development of high-quality crops with a high degree of profitability. Prediction and control models guarantee the correct management of environment variables, for which fuzzy inference systems have been successfully implemented. The purpose of this review is determining the various relationships in fuzzy inference systems currently used for the modelling, prediction, and control of humidity in greenhouses and how they have changed over time to be able to develop more robust and easier to understand models. The methodology follows the PRISMA work guide. A total of 93 investigations in 4 academic databases were reviewed; their bibliometric aspects, which contribute to the objective of the investigation, were extracted and analysed. It was finally concluded that the development of models based in Mamdani fuzzy inference systems, integrated with optimization and fuzzy clustering techniques, and following strategies such as model-based predictive control guarantee high levels of precision and interpretability.

1. Introduction

Relative humidity has a great impact on the development of greenhouse crops, and it is important to comprehensively understand how it is currently being approached from the perspective of fuzzy inference systems. The objective is to determine the various relationships within fuzzy inference systems and their variations through optimization algorithms currently used for modelling, prediction, and control of humidity in greenhouses. Their degree of interpretation and precision will be considered, as well as how it has changed over time to be able to develop more robust and simpler to understand models for the modelling and control of the variable in greenhouses.

1.1. Greenhouse Cultivation. Facility agriculture consists of using certain engineering facilities and technology, according to particular requirements for plant growth and

development, in order to enhance or create environmental meteorological factors by providing a good environment for plant growth conditions and thus eliminate, to some extent, dependence on the natural environment [1]. Greenhouse cultivation then has the fundamental objective of protecting plantations from bad weather and diseases. It is a complex system that in recent years has become a means to achieve controlled agricultural production by providing a strictly controlled climate [2–5].

The practice of controlling climatic environments through the use of greenhouses has lately received considerable attention due to agronomic and financial interests: extending the growing season and potential yield, managing climate in order to achieve higher levels of quality and develop low-cost production systems compatible with the scarcity of resources and the low capacity of producers to invest, aiming towards food self-sufficiency [5–8]. Therefore, agricultural greenhouses must be profitable, depending on

the nature and type of production, insofar as its structure is improved, wall materials are correctly selected, and technical facilities and equipment that constitute it are precisely defined [8].

Some of the advantages of the use of agricultural greenhouses are the satisfactory production and yield, the production of offseason fruits, vegetables, and floral species, the significant reduction of plant pests thanks to air conditioning and of land use, and the quality and precocity of crops contributing greatly to the development and future strategy of the sector [7]. Agricultural production is very sensitive to a series of factors such as climatic conditions, water resources, and the exploitation of energy resources, which is why the expansion of the agricultural sector requires the introduction of new technologies that emphasize economic efficiency and optimal use of scarce resources and which minimally impact the environment [9].

On the other hand, the production of plants is affected by the climate generated by greenhouses, influenced in turn by external climatic conditions such as wind speed, solar radiation, external temperature and humidity, the structure of the greenhouse, the type and the conditions of the crop, and activation control signals, such as ventilation and heating and CO₂ injection to influence photosynthesis and evaporative cooling for enriching humidity and lowering air temperature [2–4].

Taking into account the different approaches associated with the structure of greenhouses, its main factors are as follows: physiological, technical, and socioeconomic. At a physiological level, it requires total care and extensive scientific and experimental treatment, allowing to characterize the plant's behaviour during its evolution, from growth to the end of its cycle, and to establish an operating model. Its technical aspect involves the large amount of data, decisions, and actions to which greenhouse systems are subjected to and which must be executed in the immediate climatic environment of the plant, together with the complexity of managing this environment which requires approaching the system from an analytical, digital, computerized, and operational perspective. Socioeconomically, social evolution will be legitimized by the urgent demand for fresh products throughout the year. This state of affairs leads all socioeconomic agents to form part of a scientific, technological, and culinary dynamic that requires a high degree of expertise [7, 8].

Guaranteeing automatic climate control becomes fundamental. It is mainly used to maintain a protected environment despite fluctuations in outdoor climate, committing to energy conservation and better plant productivity [2]. In this aspect, the relevance of computing for greenhouse management continues to increase even in countries where environmental conditions favour the growth of crops [9, 10]. Thus, modern greenhouses and computerized climate control modules have become inseparable today [6], allowing crops to be maintained in conditions compatible with agronomic and economic objectives, favouring competitiveness [7]. However, although the application of computer technology and especially artificial intelligence in the industry has extended considerably, its application in the field of agricultural greenhouses remains incipient [8].

1.2. Variable Modelling and Prediction in Greenhouses. Greenhouse climate is a time-varying, nonlinear system with distributed parameters. There are therefore many challenges in modelling and controlling it due to the interaction between the inputs and outputs of the system, the nonlinear relationship between the producer of heat and humidity, and the air outlets built in the greenhouse [7, 10–12]. In addition, climate behaves dynamically: it is defined as a combination of physical processes that involve energy transfer (radiation and heat) and mass transfer (water vapour flows and CO₂ concentration) and that take place in the greenhouse and from the greenhouse to the outdoor air [1, 12–14].

Physical processes depend on external climatic conditions, the structure of the greenhouse, the type and condition of the crop, and the activation of control signals—normally ventilation and heating—in order to modify internal temperature and humidity conditions, shade and artificial light for changing internal radiation, and CO₂ injection that influence photosynthesis and evaporative cooling for enriching humidity and lowering air temperature [6, 13, 15].

Thus, some effects such as the greenhouse effect can occur, caused by the suppression of the wind and the reduction of air convection, making the soil and plants located under the shelters that receive the sun's rays become much hotter than out in the open air. The trapping effect of solar radiation is likewise generated: the physical properties of the greenhouse cover allow an absorbing surface of the infrared rays emitted by the soil. During the summer, these effects generate a dangerous natural overheating, making mechanical ventilation essential in order to cool down the greenhouse; during the winter, heating is required and used the following biotechnological procedures or energy sources [7].

Based on the described physical behaviour, modelling a greenhouse from a physical point of view requires great computing efforts due to the intrinsic complexity of the system and the phenomena involved [10, 16]. The software tools proposed must be suitable for predicting the climate inside the greenhouse, achieving its adequate regulation, as well as reducing pollution and energy consumption in order to optimize production [13].

Some have proposed approaching the greenhouse climate model using differential equations for air temperature, humidity, and CO₂ concentrations, differentiating the appropriate mass and energy balances for indoor temperature and indoor humidity [2, 4, 6, 9, 13, 17, 18]. However, many processes related to greenhouse climate are difficult to describe mathematically, especially when the structure of the system and the relationship between variables are not well known or are too complex [17].

Taking into account the complexity of its modelling using traditional techniques, black box models are proposed. These attempt to approach the behaviour without a priori information, for example, polynomial fitting, neural networks, fuzzy sets, etc. It is difficult to select a priori the most useful type of model between these two: those based on linear equations are more understandable, but they are difficult and expensive to develop; those based on black boxes do not have a high degree of physical significance, but are easier to obtain [6].

Models related to the horticultural industry and especially to agricultural greenhouses often require considerable additional programming efforts in order to make them easy enough to be used [19], since, in addition to nonlinearity, they present fluctuation of the variables of state, coupling between the different variables, fluctuations of the system over time, variation of meteorological parameters, and uncontrollable climatic disturbances. Together, these lead towards studying and developing an intelligent controller and regulation, and control and domain models of the climatic environment of the internal atmosphere of the greenhouse [7].

Greenhouse modelling then becomes one of the keys for greenhouse control. Nonetheless, building a complete and perfect model is also very difficult because the environment of greenhouses involves more variables that present mutual influences and limitations both in physical phenomena and in the phenomenon of plant physiology [1]. These models must reproduce the essential properties of the mechanisms and the interactions between different compartments, which must be specific enough in order to obey the dynamic and real behaviour of the greenhouse system and small enough to easily adapt to the simulation phases [8].

1.3. Variable Control in Greenhouses. The study and design of efficient environmental controllers for greenhouses require a priori knowledge of greenhouse climate models. The quality of the model is a fundamental aspect to achieve high-performance controllers [15]. These models must be related to the external influences of outdoor climatic conditions (such as solar radiation, outdoor air temperature, wind speed, etc.) and to the actions carried out (such as ventilation, cooling, heating, among others) [6, 13, 19, 20].

The control of the internal climate is thus of utmost importance for optimal performance. The management of production in a greenhouse requires decisions on several timescales and also needs a rapid and frequent response so that the system adapts to the alternative climatic conditions, seeking greater efficiency in energy consumption and therefore reducing production costs [7, 8]. This is how the control of indoor environments is one of the key factors that drive the commercial production of greenhouses [19].

Likewise, due to prevailing environmental conditions such as high humidity, the great difference between daytime and night-time temperatures, especially in summer, and the risk of proliferation of different pests and diseases require the development of advanced control strategies to ensure the protection of crops [14].

The precise control of greenhouse climate could provide the right conditions for plant growth, improving the greenhouse's climatic performance [11]. Therefore, the control processes are inclined to regulate the most relevant variables: temperature and humidity. Temperature is controlled by regulating the water temperature within an appropriate set of pipes evenly distributed in the greenhouse or by using a halogen or heating lamp system; humidity is controlled by regulating the rate of ventilation and air exchange inside the greenhouse, which affects both

temperature and humidity, and humidification that depends mainly on the sprinkler system [10, 15, 21, 22].

Implementing a control system in a greenhouse is a complex process due to the number of variables involved and the dependence between them. The internal control of the microclimate can be automated using, for example, a fuzzy controller only if a physical model of the greenhouse is available [3, 21]. The main objective then becomes to design an economical and reliable greenhouse climate controller. Computerized climate control is an intrinsic part of current modern greenhouses whose functions are, among others, to maintain a protected environment despite outdoor climate fluctuations and to act as a program memory, which can be operated by producers as a tool to control their crops [6].

Main improvements in computer-based climate control are in data recording, the determination of climate set points, monitoring, and alarm functions [10]. Among its main advantages are energy conservation, better plant productivity, and reduced human intervention [6]. Currently, greenhouse climate computers solve regulatory problems and ensure compliance with the climatic limitations required by plants [8].

Furthermore, it is observed that greenhouses were originally controlled by on-off control techniques or PI controllers, conventional PIDs, and natural cooling systems. However, these control strategies have certain limitations to guarantee the desired performance because they do not take into account the relationship between the different variables and components in a greenhouse [9, 14, 16]. To overcome these limitations, some techniques were developed for the monitoring and control of the climatic management of agricultural greenhouses through the application of AI such as artificial neural networks (ANNs), fuzzy logic (FL), and genetic algorithms (GAs). Various control techniques, computation, and different structures related to them are developed. These techniques are widely applied in the world of modern industry, robotics, automation, and especially the food industry [7].

1.4. Relative Humidity in Greenhouses. The main environmental factors that affect crops are humidity, temperature, and shade, which is why the proper management of these edaphoclimatic conditions can result in an increase in the degree of vitality of the plants [9, 23].

Humidity balance in greenhouse air is determined by the transpiration of the cover's surface, the evaporation of the soil, and the exchange of free and forced ventilation with outdoor air. It thus depends on the exchange of water vapour with the air outside and the transpiration rate of the crop, and therefore on humidification and heating systems [1, 7, 9, 13, 16].

Humidity control plays an important role in the optimal economic management of greenhouse climate and has a great effect on the growth and production of crops [4, 14]. Controlling air temperature alone can lead to poor greenhouse management mainly due to the important role relative humidity plays in biological processes such as transpiration and photosynthesis [7]. Greenhouse humidity control then

becomes a complicated and difficult job, since it demands a lot of knowledge and depends on the number of agricultural experts available [22, 24].

1.5. Fuzzy Inference Systems in Greenhouse Prediction and Control. Due to the physical dynamics involved in a greenhouse, the synthesis of a climate controller becomes a complicated task if using traditional control techniques [10]. Fuzzy modelling provides a framework for modelling complex nonlinear relationships. Compared to traditional mathematical modelling, fuzzy modelling possesses some distinctive advantages, such as an understandable reasoning mechanism, the ability to take linguistic information from human experts and combine it with numerical data, handling numerical and linguistic information in the same context, the ability to execute complex nonlinear functions with simple models, and representation in linear time-invariant local models [2, 5, 7, 10, 12, 13, 20].

Expert systems, and in particular fuzzy rule-based systems, are essential in implementing and optimizing knowledge from human experts within computerized greenhouses to avoid major damage to plants. Such expertise is adopted either through direct interaction or the collection of relevant data for the establishment of fuzzy rules [16, 22].

Fuzzy modelling can provide an alternative way of describing the process. It can be easily interpreted by a non-specialist using a representation of the relationship that is modelled by a collection of IFTHEN fuzzy rules where the natural language of the discipline is incorporated as linguistic variables or fuzzy membership functions [5, 13, 25].

In addition, many studies have concluded that fuzzy and physical models have adequate and similar performances. Fuzzy modelling methodology provides additional benefits from the point of view that the dynamic greenhouse climate can be described by linguistic models without the need to analyse the thermodynamic laws involved in the process [13, 17, 21].

Fuzzy clustering techniques also allow the automatic generation of fuzzy models and can be used to model and predict the behaviour of key greenhouse parameters. K-means, C-means fuzzy clustering, and subtractive fuzzy clustering are useful techniques to describe complex dynamic systems and provide an automated way to generate robust fuzzy systems [20].

The use of fuzzy logic controllers (FLCs) for the regulation of climatic variables such as temperature and humidity in artificially conditioned greenhouses represents a powerful way to minimize cost and energy loss and guarantee the stability of the greenhouse system [4, 6, 9, 10, 12, 16]. Compared to traditional controllers, the fuzzy controller system has more capacity compared to other systems, it is very inexpensive to implement, and fuzzy membership functions are simple, thus making the system attractive to all kinds of farmers [1, 6, 8]. This suggests a balanced interest in complexity, human experience, the systems domain, the realism of the model, the configuration mode, and the robustness of the control method for predictive performance [8].

It can be thus said that the fuzzy controller has structures of different types and several parts, like number, kind, the position of the entry and exit membership functions, entry and exit revenues, and the rules. These variations in the controller structure have significant effects on fuzzy controller performance, which is why difficulties arose when trying to design a fuzzy controller for general use [7]. Likewise, it becomes a powerful way to optimize and facilitate the global management of modern greenhouses, while providing an interesting and encouraging simulation that translates into an optimization of the values of the state variables favourable for the growth and development of protected cultures [4, 6, 8, 17].

The complex processes and interactions of greenhouse environment make this type of control a powerful, efficient, and successful tool for the precise control of greenhouse system management or in combination with GAs and ANNs [18]. It is currently used to provide a larger scale between different sizes of production systems, handling loads in ventilation control, heating, and ventilation systems, and providing intelligent real-time management decisions to control greenhouse environment and hydroponics [7,22].

Taking into account the global vision previously presented, having overviewed greenhouse cultivation, the relevance of modelling and the prediction of the variables for their correct control and the importance of humidity in the balance of the system and the subsequent application of fuzzy inference systems as a solution to provide better models, and therefore better control actions, this article is divided into the following sections: Methods, Results and Discussion, and Conclusions. It will offer some conclusions about the use of the fuzzy inference in the prediction and control of relative humidity in greenhouses.

2. Methods

The proposed methodology for reviewing follows PRISMA guidelines [26], according to the flow diagram for new systematic reviews which included searches of databases and registers only as shown in Figure 1. It is divided into 3 phases: identification, screening, and included. This last one does not present any development since an exhaustive search methodology which avoided adding any extra missing records was preferred.

The main limitations for this review are the use of the databases available for the search, which in this case are 4; in addition, only the results generated by the formula oriented to the pillars of this review are considered. The review does not intend to generate a model to predict and control humidity in greenhouses, but to give indications of which are the most suitable to be able to develop more robust and simpler to understand models for the modelling and control of the humidity in greenhouses.

2.1. Identification. In the identification stage, the academic databases Scopus, Web of Science, ScienceDirect, and Google Scholar were selected as the repositories of the studies to be analysed in this review, as observed in Table 1,

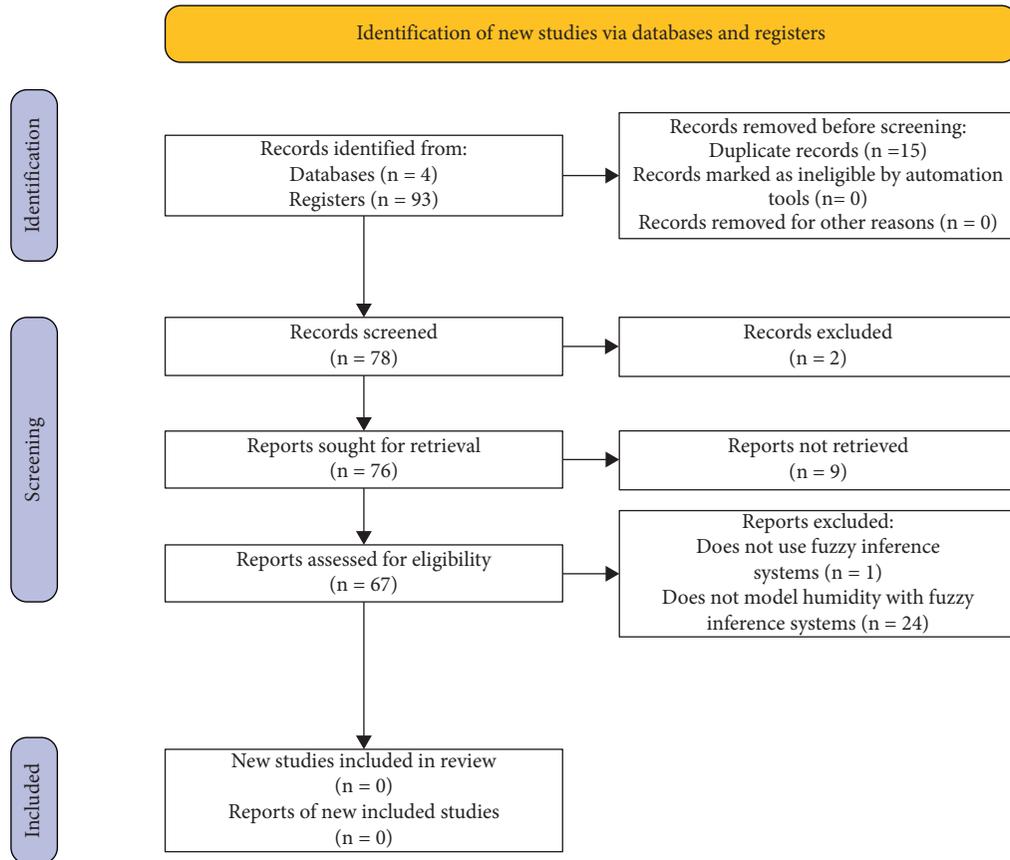


FIGURE 1: Flowchart for the identification of new studies for the review process. Adapted from [26].

TABLE 1: Consulted databases and their search formula.

Databases	Formula	Registers
Scopus	TITLEABSKEY ("Climate Model*" OR "Humidity Prediction*" OR "Humidity Estimation*" OR "Mathematical Model*" OR "Computer Simulation*" OR "Humidity Forecasting*" OR "Prediction Model*" OR "Parameter Estimation*" OR "Parameters Estimation*") AND TITLEABSKEY ("humidit*" OR "Atmospheric Humidit*" OR "Relative Humidit*" OR "Air Humidit*" OR "Ambient Humidit*") AND TITLEABSKEY (greenhouse*) AND TITLEABSKEY ("fuzzy" OR "ANFIS" OR "Membership Function*") TS= ("Climate Model*" OR "Humidity Prediction*" OR "Humidity Estimation*" OR "Mathematical Model*" OR "Computer Simulation*" OR "Humidity Forecasting*" OR "Prediction Model*" OR "Parameter Estimation*" OR "Parameters Estimation*") AND TS= ("humidit*" OR "Atmospheric Humidit*" OR "Relative Humidit*" OR "Air Humidit*" OR "Ambient Humidit*") AND TS=(greenhouse*) AND TS= ("fuzzy" OR "ANFIS" OR "Membership Function*")	31
Web of Science	Find articles with these terms: ("Climate Model" OR "Humidity Prediction" OR "Humidity Estimation" OR "Mathematical Model" OR "Computer Simulation" OR "Humidity Forecasting" OR "Prediction Model" OR "Parameter Estimation")	4
ScienceDirect	Title, abstract or author specified keywords: (("greenhouse") and ("fuzzy" OR "ANFIS" OR "Membership Function") and ("humidity" OR "Atmospheric Humidity" OR "Relative Humidity" OR "Air Humidity" OR "Ambient Humidity"))	13
Google Scholar	("fuzzy" OR "ANFIS") AND ("greenhouse") AND ("prediction" OR "model" OR "estimation" OR "forecasting" OR "simulation") [title], ("humidity")	45

which shows the search formula used to get the results according to the syntax of each repository. The information from the databases was originally extracted in April 2021 and updated in November 2021, obtaining a total of 93 records. Search formulae were designed in such a way that they

contain the fundamental pillars of this review: modelling or prediction, relative humidity, greenhouses, and fuzzy inference systems.

Of the 93 records obtained, a total of 15 records corresponding to duplicate data between the databases were

eliminated, having a total of 78 distributed among 31 records in Scopus, 1 in Web of Science, 10 in ScienceDirect, and 36 in Google Scholar.

2.2. Screening. In the screening stage, 2 records corresponding to references to two collections of articles from scientific popularization congresses were excluded. Furthermore, it was not possible to access the content of 9 additional articles.

Of the 67 selected documents, 1 article was excluded because its content did not refer fuzzy inference systems in any section. It was rather oriented towards an integration model of a membership model for growth response to measure the degrees of optimization of the membership function. The optimization degrees of air temperature and relative humidity in a tropical greenhouse planted with tomato *Lycopersicon esculentum* [27] were measured. This was not included in this research due to the use of the phrase "Membership Function." On the other hand, 24 articles were excluded because although their content presented information about greenhouses, fuzzy inference systems, and modelling, they did not show a description or detail of the fuzzy inference systems in the humidity variable, which is the present study variable. However, these will be considered and accumulated for the bibliometric reports and classification of the publications.

2.3. Synthesis Methods. For each of the documents reviewed, the following data were obtained, divided according to their potential purpose for the review:

- (i) Bibliometric
 - (i) Authors: used for collaborative analysis and author relevance among each other
 - (ii) Title, Abstract: used for the analysis of repetition of terms
 - (iii) DOI, search platform, Journal, and ISSN
 - (iv) Keywords: used for word analysis
 - (v) Publication year: used for reviewing publication tendencies on the matter
 - (vi) Article citation index, quartile, H journal index, and relevance according to the repository: used to classify and order the articles according to their relevance, impact, and visibility
- (ii) Research
 - (i) University or affiliation of the first author, country of the institution, and type of financing: used for the analysis of entities that promote research on this subject
 - (ii) Methodological observation: it corresponds to information on the methodology used and the variables analysed
 - (iii) Prediction it indicates if the article corresponds to prediction models
 - (iv) Control: it indicates if the article corresponds to control models

- (v) Fuzzy set type: it indicates the type of fuzzy set used
- (vi) Optimization type: it indicates the type of optimization that was applied
- (vii) Model: it indicates the description of the developed model.

3. Results and Discussion

The results of the review are divided into two sections according to the proposed methodology: in the first instance, the results obtained from the analysis of the bibliometric data are reviewed and, later, the research results, where only the documents that contain fuzzy inference information systems are considered, describing relative humidity.

3.1. Bibliometric Results. The objective is to analyse trends, relevant aspects, among others, based on the bibliographic characteristics observed in the documents.

3.2. Authors. A coauthorship analysis was carried out for the 66 documents reviewed as shown in Figure 2. Coauthors with equal ponderation were equivalent to 12 authors presenting 2 or more coauthors. It was observed that there are 4 collaboration clusters, and also that there are currently three of these that are producing academic documents as seen on a timescale by colour.

3.3. Analysis of the Title and Abstract for Co-Occurrence of Terms. In order to determine the most relevant terms both in the title and in the summary of the reviewed research, an analysis was carried out using a co-occurrence map of terms as shown in Figure 3. By means of a binary count that considered the presence of a term and a minimum number of 11 occurrences per each, 60% of the terms that meet the criterion were selected giving a total of 11 elements. After observing through the timescale, the most relevant today are study, simulation result, humidity, parameter, temperature, and model. They are intrinsically related to technological advances and the use of computational tools for model simulation and the study of humidity in them.

3.4. Keywords. The co-occurrence of the keywords was determined through the analysis evidenced in Figure 4. Words repeated more than twice are identified and analysed, totalling 36 words. The words with the most relevance are greenhouse, fuzzy logic, modelling, ANFIS, fuzzy control, and fuzzy clustering, and within the most important variables, humidity and temperature. Presently, the most relevant are humidity, greenhouse, ANFIS, modelling, and fuzzy logic.

The analysis presented in Figures 3 and 4 evidences that humidity is a variable that has gained great interest at the moment since there is a great co-occurrence in its use in the investigations carried out.

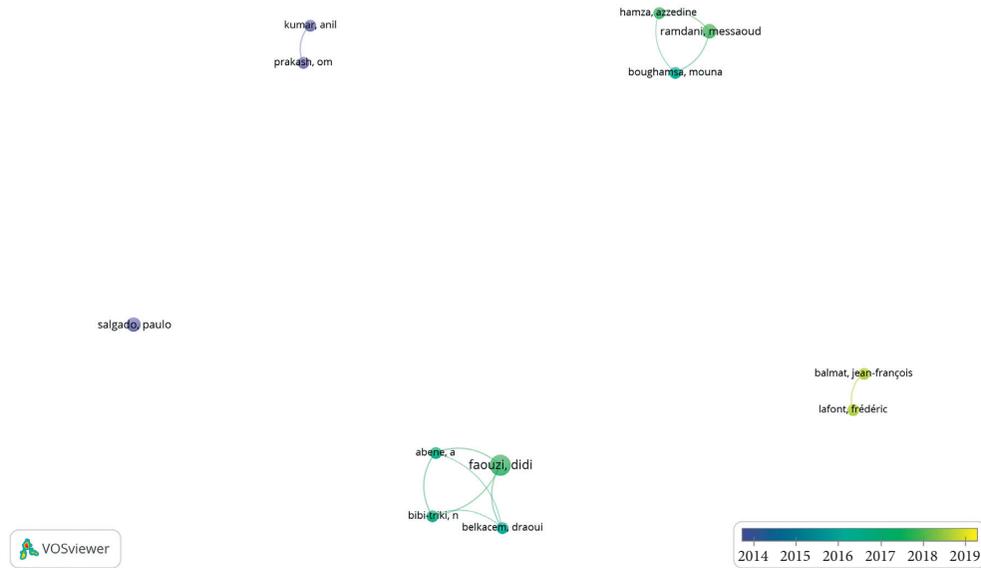


FIGURE 2: Co-authorship map analysis.

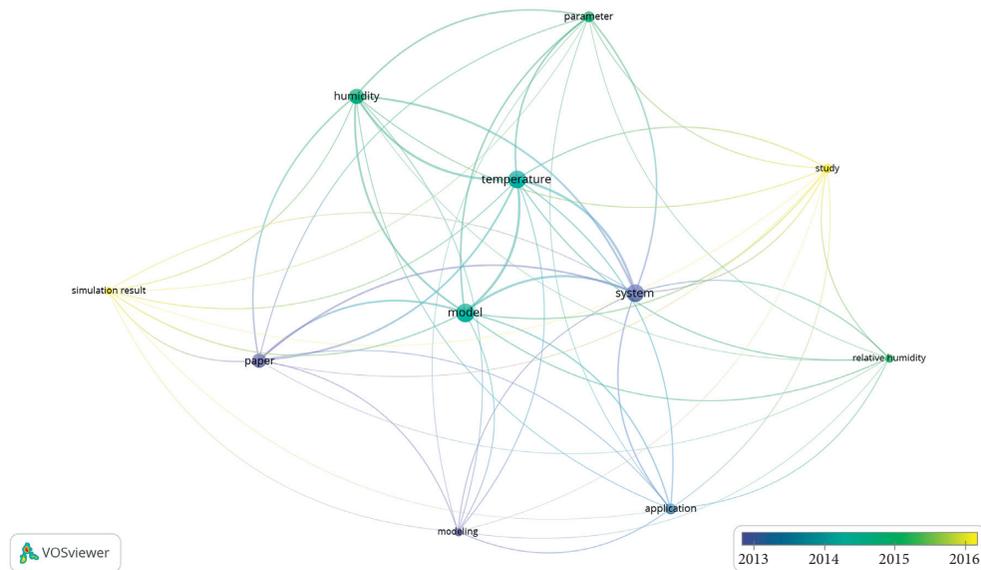


FIGURE 3: Title and abstract co-occurrence map analysis.

3.5. *Temporal Analysis of Investigations.* The analysis of the number of researches on humidity modelling or prediction in greenhouses using fuzzy inference systems is shown in Figure 5. Starting with a first publication in 1996 [16], an upward and stable trend is shown as time moves on, which is in line with the technological advance that has been developed during the last two decades and drives the development of the models.

3.6. *Research Results.* Several analyses were performed in order to solve the proposed objective of determining what are the various relationships in fuzzy inference systems and their variations with optimization algorithms currently used

for the modelling, prediction, and control of humidity in greenhouses. Some elements considered were their degree of interpretation and precision and how it has changed over time in order to develop more robust and easier to understand models for the modelling and control of the variable in current greenhouses.

3.7. *Analysis of Entities That Promote Research.* In order to perform an analysis of the entities which the authors are affiliated to, Table 2 is drawn. It identifies the 42 researches analysed and the university or institution that they relate to, its nature—that is, public or private—and the country to which it belongs.

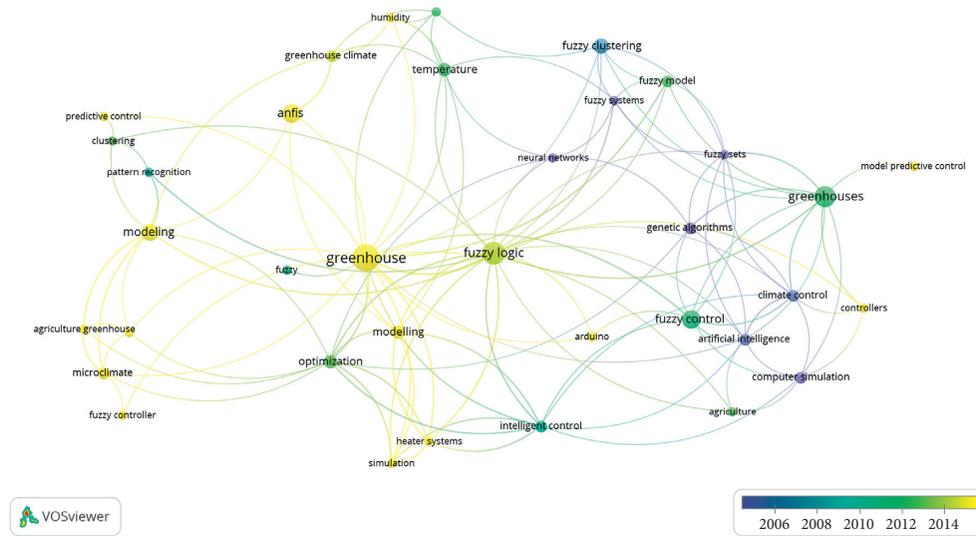


FIGURE 4: Keyword’s co-occurrence map analysis.

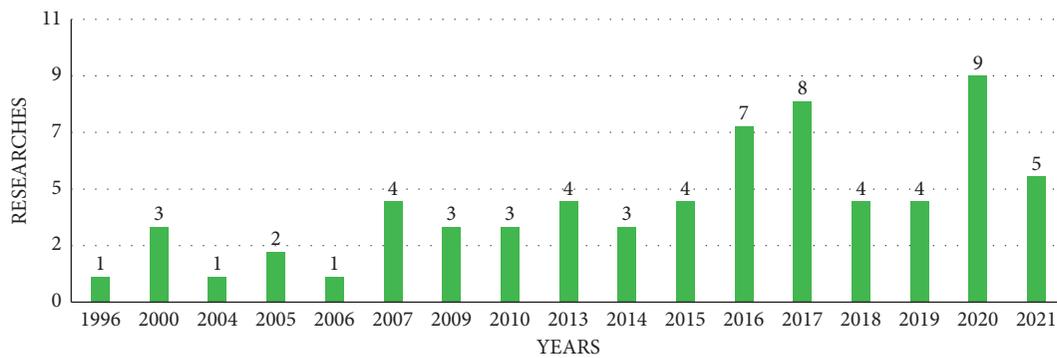


FIGURE 5: Frequency of investigations through the years.

Table 2 shows that institutions are predominantly public, with a total of 37 in contrast to 5 which are private. This can be attributed to the fact that the development of greenhouses in conjunction with prediction and control models is a problem of character public and general, to which governments have also paid attention [7].

On the other hand, as shown in Figure 6, countries that present more than two publications were analysed, obtaining that 36% of the research is led by China, 18% by Algeria, 14% in India, 11% in Mexico, and 7% for each Morocco, Tunisia, and Iran. These data can be related to the economic activity and the level of industrialization of the countries, observing that an industrial and agronomic power such as China leads the research. In addition, Mexico stands out as a representative of Latin America in this field of research.

3.8. Analysis of Prediction and Control Models Based on Fuzzy Inference. It is observed that the models start from a basic structure of the greenhouse environment as shown in Figure 7. This scheme shows the outside weather conditions and the control mechanisms that affect the internal climate;

within the greenhouse, the crop development is related to energy balance, CO₂ concentration, and air humidity, and these are affected by the outside variables.

It is obtained that the models developed for humidity control and prediction using fuzzy inference systems generally follow a block diagram as shown in Figure 8. This model is based on outside weather conditions such as external temperature, external humidity, global radiation, and wind speed, and control mechanisms such as ventilation, heating, shading, artificial light, CO₂ injection, and fogging/cooling, their interaction is defined by fuzzy rules, and the output of the fuzzy system is the value of the internal humidity.

Finally, to address the prediction and control models based on fuzzy inference, Table 3 presents a relationship between each investigation (I) and whether or not it corresponds to a prediction (P) or control (C) model, the type of fuzzy inference system used, whether or not some type of optimization was applied, and a description of the proposed model.

Taking into account the information presented in Table 3, 24 of the 42 researches reviewed and analysed present

TABLE 2: Details of the institution promoting the research.

Authorship	University or institution (first author)	Type	Country
[23]	School of Science and Engineering, UNESP	Public	Brazil
[11]	Islamic Azad University	Private	Iran
[20]	Universidad Autónoma de Querétaro	Public	Mexico
[13]	Universidade de TrásosMontes e Alto Douro	Public	Portugal
[2]	University BadjiMokhtar	Public	Algeria
[3]	Don State Technical University	Public	Russia
[4]	Universidad de Valladolid	Public	Spain
[21]	Universidad del Magdalena	Public	Colombia
[6]	University of Tehran	Public	Iran
[7]	URERMS	Public	Algeria
[18]	Universidad Autónoma Chapingo	Public	Mexico
[14]	University BadjiMokhtar	Public	Algeria
[9]	Tunis El Manar University	Public	Tunisia
[19]	Birla Institute of Technology and Science Pilani	Private	India
[15]	Zhejiang Univesity City College	Public	China
[12]	University of Water Resources and Electric Power	Public	China
[22]	Shenyang University	Public	China
[1]	Zhejiang University of Technology	Public	China
[24]	Suzhou Institute of Industrial Technology	Public	China
[28]	Ehime University	Public	Japan
[29]	Beijing Institute of Technology	Public	China
[30]	Sichuan Agricultural University	Public	China
[31]	China Jiliang University	Public	China
[32]	University BadjiMokhtar	Public	Algeria
[33]	École nationale d'ingénieurs de Sfax	Public	Tunisia
[34]	Menoufia University	Public	Egypt
[35]	University of Toulon	Public	France
[36]	St John's University	Private	Taiwan
[37]	Universidad Tecnológica de Querétaro	Public	Mexico
[38]	King Abdulaziz University	Public	Saudi Arabia
[39]	Technological Educational Institute of Crete	Public	Greece
[40]	Maulana Azad National Institute of Technology	Public	India
[41]	Atish Dipankar University of Science and Technology	Private	Bangladesh
[42]	Birla Institute of Technology	Private	India
[43]	University BadjiMokhtar	Public	Algeria
[44]	Zhejiang University of Technology	Public	China
[45]	University Sidi Mohamed Ben Abdellah	Public	Morocco
[46]	Addis Ababa Science and Technology University	Public	Ethiopia
[47]	University of Technology Baghdad	Public	Iraq
[48]	Shenyang Agricultural University	Public	China
[49]	Bhagat Phool Singh Mahila Vishwavidyalaya	Public	India
[50]	Moulay Ismail University	Public	Morocco

prediction models, while 26 present control models. This shows a fair behaviour for both aspects of interest. On the other hand, only 8 of the investigations—that is, around 19%—combine both approaches, which indicates that both characteristics have been vaguely explored together. In addition, it is observed that 75% of these cases use some configuration of the Mamdani inference system, ensuring great interpretability of the system.

Regarding the fuzzy inference systems used, Table 3 shows 38% of implementations with Mamdani fuzzy inference systems and 21% both for the Takagi–Sugeno (TS) and for adaptive neuro-fuzzy inference systems (ANFISs). This indicates that around 42% of the investigations revolve around fuzzy inference systems that provide great precision, but reduce the interpretability in their output. In addition, only in one of the Mamdani fuzzy inference systems [28] its

precision is increased by artificial intelligence techniques, obtaining good results.

In the aspect of prediction-only models, it is observed that 50% of the cases use ANFIS, followed by 18.75% for both Mamdani and TS. On the other hand, in the control-only models, it is observed that 38.88% of the cases use Mamdani fuzzy inference systems, 27.77% use TS, and 5.55% use ANFIS.

Taking all this into account, it is possible to acknowledge how prediction models have been mainly oriented towards increasing precision in the output without losing interpretability in the input. This suggests that models seek to present easily understandable inputs and in a common language for the farmer, making the outputs of the variables only exact numerical figures to facilitate their subsequent manipulation. On the other hand, the approach of the

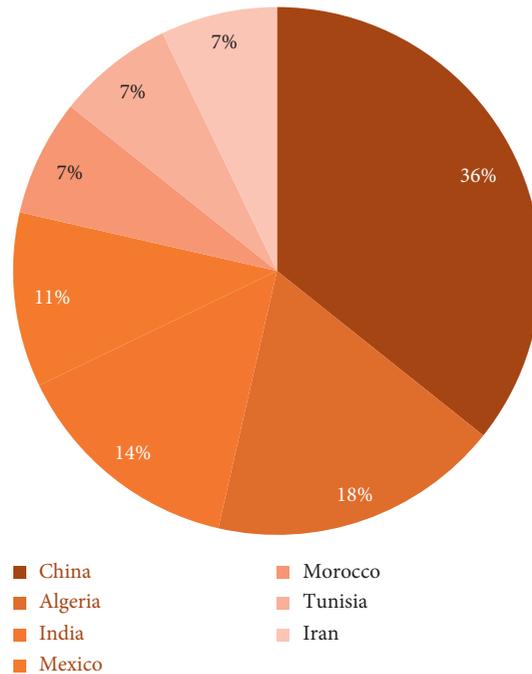


FIGURE 6: Research distribution by countries with more than one publication.

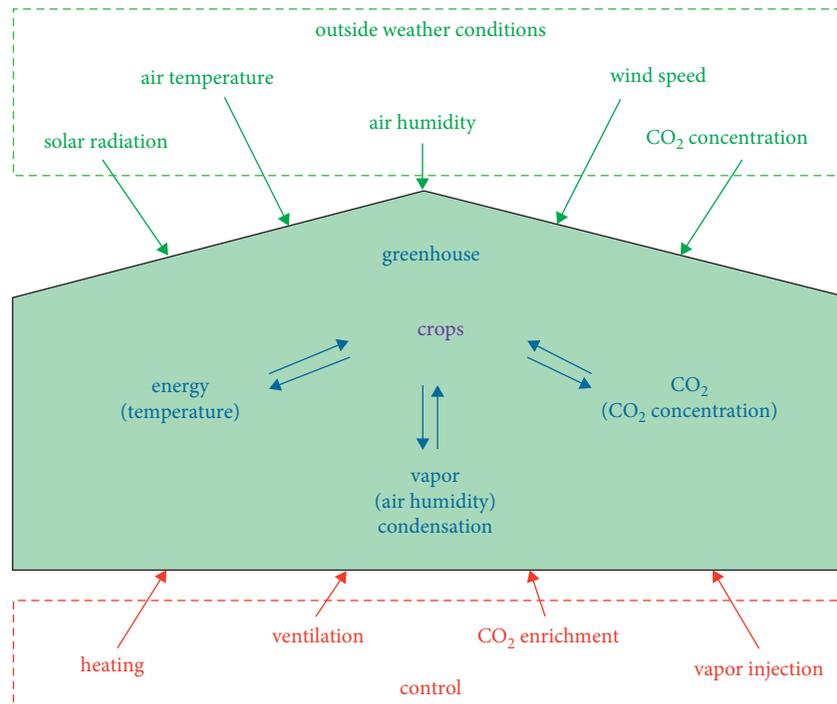


FIGURE 7: Scheme of greenhouse climate model (adapted from [2, 13, 14, 17, 32, 45, 46, 51]).

control models shows a tendency towards the increase of interpretability both in the input and in the output, that is, of easily understandable inputs and outputs expressed in terms of fuzzy sets, which allows the controller to act more flexible, in contrast to activation paradigms such as on/off and PID.

The monotonicity relationship in the fuzzy inference system for the humidity prediction and control models shows a better performance in the Takagi–Sugeno fuzzy systems due to the use of consequents of linear types, and the fuzzy partition with various membership functions for each climatic variable, so it is possible to obtain a monotonous

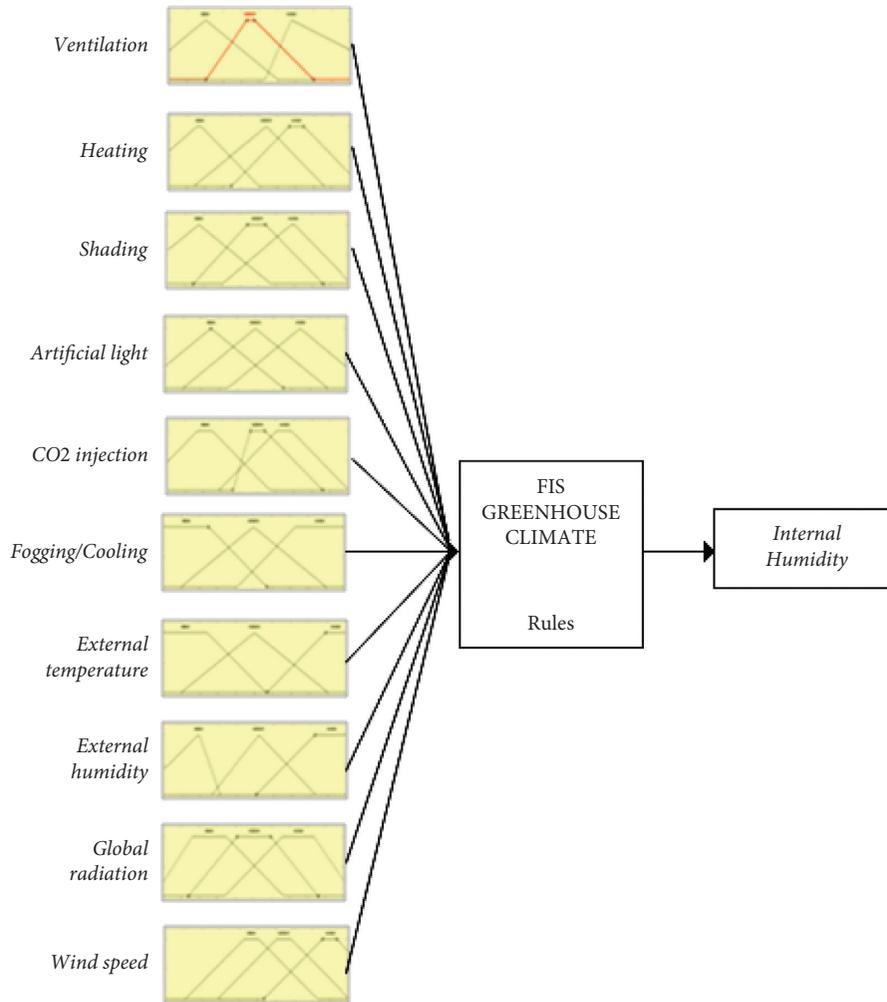


FIGURE 8: Block diagram of the fuzzy inference system for greenhouse humidity prediction and control (adapted from [32]).

model to calculate the control actions and have the least fuzzy rules possible [52].

It is also interesting to observe that, in the cases where both approaches are combined, 75% of the cases use Mamdani fuzzy inference systems. This means that the prediction model presents in its both input and output a value corresponding to a set fuzzy which, according to the previous analysis, serves as the perfect gear to be the input of the control systems used. That is why it can be inferred that if both approaches are combined, Mamdani fuzzy inference systems must be used.

Regarding the use of fuzzy clustering techniques, it is only present in 11.91% of the studies analysed, which is why it is evident that it has not been an extensively used tool but which helps define both the topology of fuzzy sets and the clustering and establishment of better rules in the system.

Regarding optimization to increase the precision of the models, it is observed that only 16.66% of the studies analysed present some optimization technique or algorithm where both heuristic methods or those developed by AI and exact or traditional ones are equally found. The optimization of this type of solutions is therefore not an issue that has been worked on in great depth but that, on the contrary, and

according to the observed models, greatly improves the performance of the models [14, 15, 28, 32–34, 43].

3.9. Performance of the Models and Technical Checks. The performance of the models was obtained by various methods as it is shown in Figure 9, the most common is the use of the value of the prediction error through metrics such as mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and error sum of squares (SSE), having values less than 10% in all the models where they were used. On the other hand, another way to measure performance is graphically by comparing the predictions and the expected values; finally, the use of correlation coefficient or variance accounted is also common.

The methods of technical check of the models are shown in Figure 10, where the most common is the computer simulation used in 43% of the cases, followed by the verification by experimentation in 40% of the models and, finally, checked by other simulation methods such as mathematical simulation in 12% of the cases.

TABLE 3: Prediction and control models based on fuzzy inference.

I	P	C	Fuzzy inference system	Optimization	Fuzzy model
[23]	X		Mamdani	NA	Prediction of vitality based on humidity, temperature, and shade
[11]	X	X	Mamdani	NA	Control based on error and its derivatives, uses k-means, c-means, and subtractive fuzzy grouping
[20]	X		Takagi–Sugeno–Khan (TSK)	NA	Base algorithms for temperature and humidity modelling
[13]	X		Hierarchical collaborative fuzzy system	NA	Diffuse models of air temperature and humidity comparing regularized NRLS vs. SLIMHCS vs. physical model
[2]	X		Takagi–Sugeno (TS)	NA	A predictive controller based on diffuse hybrid wave model (MBPC) is proposed to regulate the temperature and humidity inside the greenhouse using Gustafson–Kessel (GK) clustering algorithm
[3]	X		Mamdani	NA	Control of ventilation speed and heating rate taking into account humidity and temperature
[4]	X		Takagi–Sugeno (TS)	NA	Control from a dynamic nonlinear model
[21]	X		Mamdani	NA	Control based on optimal ranges of the crop for monitoring and control
[6]	X		Mamdani	NA	Control with a design based on thermodynamic equations
[7]	X		NA	NA	Definitions of identification and control models. Heuristic, global, and (GA) optimization techniques are addressed
[18]	X		ANFIS	NA	Humidity and temperature prediction from census data
[14]	X	X	Takagi–Sugeno (TS)	Recursive least squares algorithm (RLS)	Analytical greenhouse model with model-based predictive controller using C-means clustering
[9]	X	X	Mamdani	NA	Physical model of a greenhouse based on the interaction of variables and actuators
[19]	X	X	Mamdani	NA	Mamdani PID control using a multivariable nonlinear model of transfer functions based on the thermodynamic laws of greenhouse behaviour
[15]	X	X	Fuzzy neural network (FABPMBP)	ANN three-layer fuzzy optimization feedforward	Fuzzy model for actors, which serves as an input for the three-layer feedforward neural network optimized prediction
[12]	X		ANFIS	NA	Greenhouse environment based on Simulink block diagram, humidity, and thermal balance equations combined with ANFIS ventilation controller
[22]	X		Mamdani	NA	Expert fuzzy control based on sensor readings to activate certain actuators and a literature review of their effects
[1]	X		Fuzzy PID	NA	Fuzzy PID smart greenhouse control
[24]	X		Fuzzy numerical conversion algorithm	NA	PTZ control based on MSP430 chip
[28]	X	X	Mamdani	ANN, GA	Two optimizers are established; the first one uses an ANN to identify the responses of the fruits, affected by the environment, and a GA to find the optimal set points of the environment. In the second optimizer, the ANN is used to identify the environmental responses, affected by a fuzzy controller, and a GA to find the optimal membership functions and the control rules in a fuzzy controller
[29]	X		Fuzzy GA	NA	Tomato growth model based on modified Elman lattice and fuzzy GA
[30]	X		Node fuzzy controller ZigBee	NA	ZigBee network mushroom greenhouse control with intelligent fuzzy control algorithm as core
[31]	X	X	Mamdani	NA	Greenhouse multimodel adaptive fuzzy control built on a toggle mechanism that can consider and handle multiple greenhouse climate variables
[32]	X		ANFIS	Back propagation, least squares algorithm	Model of the growing process of tomato plants inside the greenhouse using the ANFIS system to predict the effect of meteorological variables and control actuators
[33]	X		Takagi–Sugeno (TS)	Recursive weighted least squares algorithm (RWLS)	Temperature and humidity description model based on Gustafson–Kessel (GK) fuzzy grouping techniques to determine both the premises and the consequent parameters of the fuzzy rules and subsequently optimizing their parameters
[34]	X		Fuzzy pseudo derivative feedback (FPDF)	GA	Fuzzy pseudo derivative feedback (FPDF) controller

TABLE 3: Continued.

I	P	C	Fuzzy inference system	Optimization	Fuzzy model
[35]	X		ANFIS	NA	Prediction of the level of pest risk in a greenhouse rose by applying ANN and an ANFIS
[36]		X	Takagi–Sugeno (TS)	NA	Temperature and humidity control of a greenhouse that integrates ZigBee WSN to design and build an intelligent air conditioner
[37]	X	X	Mamdani	NA	ANN prediction for temperature in greenhouses. Its purpose is to start a sprinkler irrigation system using a fuzzy expert system (FES) that controls the activation of a water pump to protect against internal freezing
[38]	X		ANFIS	NA	Observe the ozone concentration level
[39]	X	X	Mamdani	NA	Model based on thermodynamic equations for two controller design
[40]	X		ANFIS	NA	Modified active greenhouse dryer without load using ambient temperature, relative humidity, global radiation, and experimentation time as inputs
[41]		X	Mamdani	NA	Control of GHS parameters such as temperature, humidity, light, soil humidity, and plant irrigation system using fans, heaters, humidifiers, motors, lamps, and irrigation
[42]	X		Mamdani	NA	Prediction of natural and forced convection moisture evaporation rate of jaggery in a controlled environment
[43]		X	Type 2 Takagi–Sugeno (TS) interval	Linear matrix inequality (LMI)	Model to represent the nonlinear dynamics of the plant subject to uncertainties of the parameters, which are effectively captured by the interval membership functions
[44]	X		ANFIS	NA	Greenhouse temperature model based on an adaptive fuzzy logic system with inputs: previous temperature, external temperature, humidity, wind speed, and solar radiation
[45]	X		Takagi–Sugeno (TS)	NA	Internal temperature and humidity prediction. The proposed algorithm is based on the decomposition of the fuzzy relationship into subrelationships, through a process of developing fuzzy rules with cluster c-means.
[46]	X		Takagi–Sugeno (TS)	NA	Predictive control to regulate the temperature and humidity of the greenhouse
[47]	X		Mamdani	NA	Greenhouse ventilation and shutter control
[48]	X		ANFIS	NA	Model the greenhouse climate in its values of temperature, hygrometry, and internal radiation
[49]	X		Mamdani	NA	Greenhouse rose yield prediction using temperature, solar radiation, humidity, nitrogen, phosphorus, and potassium concentration and leaf area
[50]	X		ANFIS	NA	Prediction of humidity and internal temperature

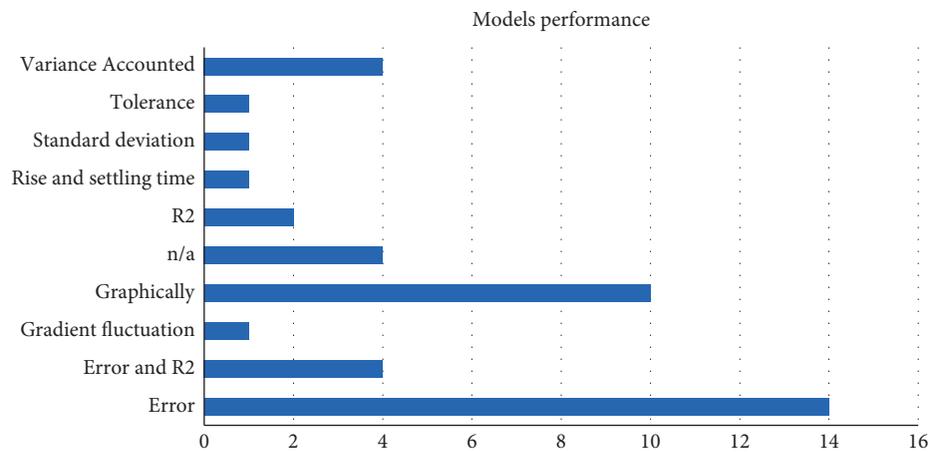


FIGURE 9: Models performance by analysed research.

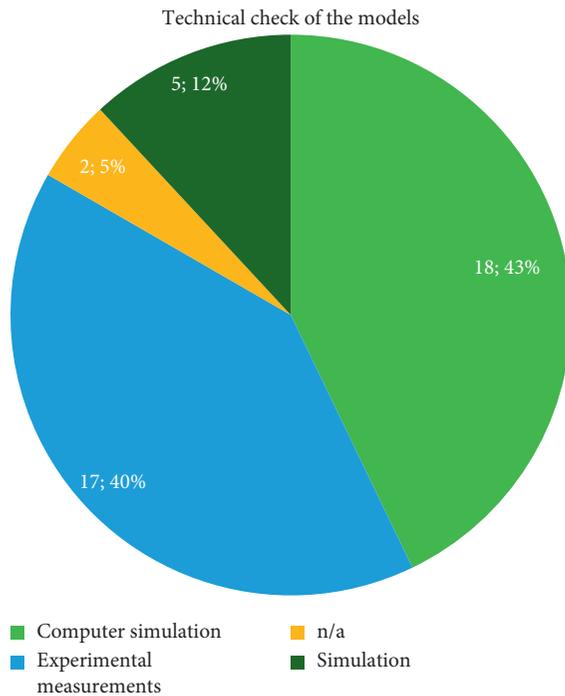


FIGURE 10: Research distribution by countries with more than one publication.

3.10. Model Proposals for Greenhouse Humidity Prediction and Control Using Fuzzy Inference Systems. One of the most particular proposals in terms of control is model-based predictive control (MPC), an advanced technique with several applications in the industry, characterized by the use of nonlinear system models in prediction for control complex processes [2]. The MPC design is based on three basic elements at each sampling time: a model of the process to predict its future behaviour based on past and current values; an objective function; and an optimization procedure that calculates the optimal control sequence. It is thus a model that describes the dynamic behaviour of the system and that can be treated as a black, grey, or white box model [2].

As seen earlier, many fuzzy modelling approaches focus on the accuracy of the model, that is, on fitting the data as accurately as possible, paying little attention to the simplicity and interpretability of the model, such as the “black box model,” which is considered a main merit of fuzzy inference systems [7]. Desired solutions should maintain both the precision of the system and its interpretability, guaranteeing better performance and greater understanding of the modelled system.

The desired solution must have a high degree of precision, represented by the evaluation of the success of the numerical prediction and the deviation from the control point measured through the error obtained, and a high level of interpretability, evidenced in the calculation by qualitative description structures used in common language and classes of objects without sharp but clearly defined limits.

4. Conclusion

Currently, very little attention has been paid to the optimization of fuzzy inference systems for the prediction and control of humidity in greenhouses. It is a tool that guarantees better performances for models, as well as high degrees of precision. Hence, its use should be increased and promoted in the future research.

Mamdani fuzzy inference systems are the most recommended for models that involve control and prediction actions. Likewise, they are the most used for control models, but they are replaced by ANFIS, which guarantee great precision in prediction models.

The use of fuzzy clustering techniques presents a low use rate, but it is a valuable tool for defining the topology of fuzzy sets as a way of establishing better rules in the inference system used.

The use of strategies similar to model-based predictive control allows to integrate prediction and control models in conjunction with optimization techniques. In this specific case, it would allow the development of models based on more robust fuzzy inference systems that also guarantee high levels of precision integrating them with optimization techniques and high levels of interpretability when using fuzzy clustering techniques and Mamdani systems.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

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