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Review

Survey of Applications of Machine Learning for Fault Detection, Diagnosis and Prediction in Microclimate Control Systems

Nurkamilya Daurenbayeva [1,*], Almas Nurlanuly [2], Lyazzat Atymtayeva [3] and Mateus Mendes [4,5,*]

1 Department of Computer Engineering, International Information Technology University, Almaty A15H7X9, Kazakhstan
2 Department of Aviation Equipment and Technology, Academy of Civil Aviation, Almaty A35X2Y6, Kazakhstan
3 Department of Information Sciences, Suleyman Demirel University, Kaskelen 043801, Kazakhstan
4 Polytechnic Institute of Coimbra, Coimbra Institute of Engineering, Rua Pedro Nunes-Quinta da Nora, 3030-199 Coimbra, Portugal
5 Institute of Systems and Robotics, University of Coimbra, Rua Silvio Lima-Polo II, 3030-290 Coimbra, Portugal
* Correspondence: n.daurenbayeva@iitu.edu.kz (N.D.); mmendes@isec.pt (M.M.)

Abstract: An appropriate microclimate is one of the most important factors of a healthy and comfortable life. The microclimate of a place is determined by the temperature, humidity and speed of the air. Those factors determine how a person feels thermal comfort and, therefore, they play an essential role in people's lives. Control of microclimate parameters is a very important topic for buildings, as well as greenhouses, where adequate microclimate is fundamental for best-growing results. Microclimate systems require adequate monitoring and maintenance, for their failure or suboptimal performance can increase energy consumption and have catastrophic results. In recent years, Fault Detection and Diagnosis in microclimate systems have been paid more attention. The main goal of those systems is to effectively detect faults and accurately isolate them to a failing component in the shortest time possible. Sometimes it is even possible to predict and anticipate failures, which allows preventing the failures from happening if appropriate measures are taken in time. The present paper reviews the state of the art in fault detection and diagnosis methods. It shows the growing importance of the topic and highlights important open research questions.

Keywords: microclimate control systems; fault detection and diagnosis; prediction methods; machine learning

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Citation: Daurenbayeva, N.; Nurlanuly, A.; Atymtayeva, L.; Mendes, M. Survey of Applications of Machine Learning for Fault Detection, Diagnosis and Prediction in Microclimate Control Systems. *Energies* **2023**, *16*, 3508. https://doi.org/10.3390/en16083508

Academic Editor: Gheorghe-Daniel Andreescu

Received: 14 February 2023
Revised: 22 March 2023
Accepted: 12 April 2023
Published: 18 April 2023

1. Introduction

Microclimate control is a very important feature for different types of buildings. Fault prediction and detection is an important challenge for the optimal performance of microclimate control systems.

1.1. Microclimate Control as a Global Problem

Over the past decade, the rapid growth in energy consumption and the associated Carbon Dioxide (CO_2) emissions, with a reduction in the amount of the planet's fuel and energy resources, have led research scientists to pay special attention to finding energy efficiency solutions. According to reports by the United States Department of Energy (DOE), among all sectors of the economy that consume significant amounts of energy, buildings, and residential complexes use more than one-third (up to 40%) of the total world energy consumption. In addition, more than 60% of the electricity consumed goes to the sector of residential and commercial buildings [1]. On a global scale, commercial buildings use approximately 41% percent of primary energy consumed worldwide, including the United States, Europe, and Asia. Those numbers are still expected to will rise over the next 20 years [2].

About 90% of the total energy consumption by the housing and communal services sector of the Republic of Kazakhstan is spent on building exploitation. Residential buildings are characterized by the highest energy consumption: 50–55% . Industrial buildings use somewhat less, 35–45% and civilian buildings account for about 10% [3]. In housing and civil engineering, energy efficiency reserves reach up to 40%. In this regard, measures to reduce heat and energy waste are of great importance for the Republic [4]. In general, the state of a microclimate system is described mainly by the environment air parameters: air temperature, relative humidity, amount of carbon dioxide, as well as air mobility, NH_4 (ammonia) content, H_2S (hydrogen sulfide) and bacterial contamination.

To cope with increasing demand, different control strategies are being incorporated into the existing infrastructures, to sustain the demand for electricity in residential and commercial buildings. Currently, the most widely used automated microclimate control systems with provide just temperature regulation. That increases people's comfort and modern intelligent control allows energy consumption optimization. Nonetheless, there are still other variables for optimal comfort and well-being. Hence, a good microclimate control system goes beyond temperature, namely controlling also humidity and speed of moving air.

1.2. Importance of Microclimate Control for People

Indoor microclimate conditions depend on a number of the factors, such as climate zone; season of the year; type equipment used; type of facilities; air exchange conditions; size of the room to be climatized; and number of people inside the room.

Zhitov [5] studied the microclimate of dwellings in a harsh climate and proved that both regional and seasonal differentiation of the thermal state of a person is necessary to create thermal comfort in a residential room. Naturally, in winter, a higher air temperature is needed in the room. Such a temperature indicator relieves the physiological fatigue of people coming from low ambient temperatures. For this reason, in the winter season in hygienists recommend maintaining indoor air temperatures within 23–24°. Human thermal comfort is also highly correlated to the local temperature in which individual parts of the body are located, and in particular, the head and legs. The floor temperature affects the thermal state of a person most strongly. Direct contact with the cold floor leads to colds. In this regard, in residential premises, the temperature on the floor surface can be lower than the average air temperature, but should not be lower by more than two degrees. With an increase in the difference of temperature between the air and the interior surfaces, the radiant cooling of a person increases. That can cause a violation of the thermoregulation of the human body. According to physiological observations [5], thermal comfort in a residential room is considered to be achieved only when the air temperature is not higher than the interior surfaces by more than 2–3°. The normalized difference for residential premises determines the dew loss on the wall surface to a greater extent than the thermal comfort of a person. The comfortable values of indoor air mobility depend on the combination of air temperature, humidity, radiation situation in the room, type of work and season of the year. The totality of the considered characteristics of the microclimate and their permissible ranges, established by hygienists, describe the conditions that need to be created in the room so that a person experiencing a thermal state of neutrality (that is, could not determine whether he is warm or cold), which is usually assessed as comfortable. The microclimate in the premises is formed due to the disturbing effects of the external environment and the technological process inside the building, which is countering outer effects by heating or cooling, as well as controlling other microclimate variables. The peculiarity of microclimate systems is that they consume a large amount of energy resources, including thermal and electrical energy and sometimes tap water.

1.3. Importance of Fault Detection Methods

Fault detection and diagnosis play a key role in high-cost and safety-critical processes, such as in microclimate systems. Early detection, or even prediction, of process faults is very important to plan and execute maintenance interventions to help avoid abnormal event progression [6]. Early interventions can help maximize equipment availability and minimize maintenance costs [7].

Fault detection can be accomplished through various means. With the growing demand for smart building infrastructure and organization maintenance, automatic fault detection has attracted attention from both academia and industry [8]. Industry 4.0 proposes models that place a growing emphasis on automation, namely deployment of automated systems such as smart buildings, to maximize equipment availability and reduce energy demands, contributing to increased efficiency, sustainability and cost-effectiveness. As the hardware becomes more powerful and cheaper, automatic fault detection and diagnosis methodologies have been proposed. They implement modern data analysis methods, namely data mining (DM) and machine learning (ML) techniques. Modern data analysis algorithms are sound and powerful methods capable of learning and adapting themselves to different patterns and levels of operation. They can, therefore, be trained to identify patterns of failure, overload, or different malfunctions which can affect the consumption, performance, safety, or availability of the microclimate control systems.

1.4. Paper Structure

The present paper is a survey of the latest fault detection and diagnosis methods in the area of microclimate systems, focusing especially on the latest methods based on machine learning approaches. Section 2 describes the most common types of microclimate control systems. Section 3 describes relevant work about fault detection and diagnosis methods. Methods of fault detection and diagnosis, such as the Quantitative Model, Rule-Based Model, and Process History Based Model types are mentioned. Section 4 is about Fault Prediction Methods, focusing on prediction with Machine Learning. This section mentions prediction models such as ARIMA. Section 5 is a conclusion and highlights of possible future research.

2. Types of Microclimate Control Systems

This section discusses the types of microclimate control systems, such as microclimate control in greenhouses, Microclimate control in hospitals, and microclimate studies in monuments and art galleries. Indoor climate control is a complex task, within which it is necessary to consider continuously changing influencing conditions. To accomplish this task, many different management methods have been developed and are being applied. Different strategies are chosen for use, depending on the building, operating conditions, resources available, goals, and other relevant criteria.

2.1. White and Black Box Models

The models that are known as the so-called "white box" have a narrow focus, and among them can be distinguished as the most versatile, the Fanger model, based on Predicted Mean Value/Predicted Percentage Dissatisfied (PMV/PPD). The most traditional thermal comfort model is the PMV model. The two-node model and the multi-node model are also frequently employed in addition to the PMV model. [9], it reduces the human body to a two-layer structure with a skin and core, which is symbolized as a concentric cylinder. It is crucial to start with the person who came up with the predictions—Povl Ole Fanger—to comprehend the model that generates figures for the projected mean vote and the predicted percentage of dissatisfaction. He postulated that a person could only be said to be "comfortable" if their skin temperature and sweat production were balanced within a specific range of acceptable levels. Human thermal comfort, according to his theory, is based on these two parameters. Fanger's model is one of the most classical models, but it is not applicable to nonuniform environments or outdoor environments. Currently, the most cited standards of thermal comfort are ASHRAE 55-2016 [10] and ISO 7730 [11], which are based on the Fanger model.

The ”black box” models based on the methods of intelligent computing usually rely on large amounts of data and variables, and they allow achieving the required balance between providing an acceptable level of comfort and reducing energy consumption.

“Black box” models based on intelligent computing methods are usually based on large amounts of data and variables, and make it possible to achieve the required balance between providing an acceptable level of comfort and reducing energy consumption. Such models have a number of disadvantages, including the need for a large amount of data and the complexity of the configuration with a larger number of parameters and variables, which can lead to a long learning process. Additionally, those models are becoming more and more popular, due to their good performance, which includes high accuracy, robustness to dynamically changing external conditions, reliable forecasting, flexibility in management and adaptation over time, among other reasons. Thus, those models have the capabilities and properties necessary to run a microclimate control system, maintaining warmth and other variables within the required ranges. The most effective nowadays tend to be models based on machine learning.

Below is presented a review of some important methods and applications of microclimate control systems. A selection of the most relavant papers that were published since 1989 was considered for the review.

2.2. Microclimate Control in Greenhouses

A greenhouse is a building that protects vegetation from bad weather while letting sunlight in. Despite the fact that greenhouses are often simple structures, they are still very complex systems. The main function of a greenhouse is to maintain the internal climate within desired parameters. The climate within a greenhouse is influenced by many outside factors, such as wind speed, solar radiation, temperature and humidity. The function of the microclimate control system is to counter those factors and, thus, protect vegetation, optimizing the growth and reducing the probability of sickness and pests. Two main problems have limited the expansion of greenhouse agricultural production. One is that the method for controlling and adjusting the air temperature inside the greenhouse is diffuse. Temperature is the main climatic variable that affects crop yield, so it receives particular attention in greenhouse microcontrol systems. Another problem is that the use of multiple actuators for controlling ventilation, heating and humidification/dehumidification systems, requires generous amounts of energy and makes the greenhouse an energy-intensive consumer. Therefore, efficient energy systems should be used to reduce operating costs.

Today, there are many works devoted to greenhouse microclimate control models. All these models aim to ensure the right conditions for vegetation during photosynthesis. The proposed climate models serve as the basis for the development of climate models in greenhouses. The main proposed models are based on continuous time. A solution to the problem of adaptive multiple inputs of multiple outputs of air temperature, air humidity, and carbon dioxide concentration for greenhouses is proposed by Choab et al., [12]. The controller synthesis is based on a parametrically uncertain model of the greenhouse microclimate represented by a system of nonlinear differential equations and on the method of controlling cascading systems. Controller parameters are adjusted online by an identification algorithm with an integral cost function and fast parametric convergence. Verification of the properties of the closed-loop system is accomplished with the use of Matlab/Simulink environment.

In [13], the authors classify existing greenhouse climate models into two types: (1) the principal models using data on the physical processes of heat and mass transfer taking place in a greenhouse. The processes are described by differential equations with parameters having a physical interpretation; and (2) cybernetic, when the greenhouse microclimate is seen as a “black box”, and examined the relationship of input and output values. The parameters of these models are determined experimentally.

Ganzhur et al., [14] propose the Arvanitis 1999 model as a basis for a dynamic model of an experimentally validated agricultural greenhouse to create a suitable microclimate with appropriate drives installed in the greenhouse.

2.3. Microclimate Control in Hospitals

For many years, especially from the mid-1990s to the present, significant funds have been invested in the development of air cleaning technologies, starting with the disinfection of air and indoor surfaces, the use of Moderna technological solutions and the introduction of the latest equipment in the field of microclimate. Modern technologies have emerged that can provide and maintain the necessary air conditions. Designing engineering systems in medical institutions has always been a more difficult task than designing many other facilities. Medical facilities and other public buildings are among the most demanding environments. The characteristics of the design methods of heating, ventilation and air conditioning systems in these buildings are directly related to the characteristics of the medical institution itself. These include general and specialized clinical hospitals, maternity hospitals, and perinatal centers. Medical complexes include infectious disease hospitals, polyclinics and clinics, diagnostic and rehabilitation centers, various medical centers, dental clinics, laboratories, clinics and sanatoriums, ambulance substations, as well as kitchens and sanatoriums, and other services. These diverse but specific facilities require the use of various medical technologies related to the operation of the buildings. Medical technologies have developed rapidly in recent years. New and very complex processes are being carried out in operating rooms, laboratories, and other facilities. Sophisticated and very sensitive Moderna equipment is used. On the other hand, the improvement of medical technologies requires new technical and engineering solutions that are directly relevant, but which are often unknown without the support of technical experts. This creates difficulties in design, and even engineers with extensive experience in the healthcare field often face the fact that new construction projects present new problems and require solving research, technical, and engineering tasks. Another feature of medical institutions is special hygienic requirements for the indoor air environment. Indoor air is characterized by the presence of mechanical, chemical, and gaseous pollutants, as well as microbiological pollutants. The standard criterion for the purity of indoor air in public buildings is the absence of excess heat, humidity, and carbon dioxide in it. In medical institutions, the main indicator for assessing air quality is nosocomial infections, the risk of which is especially high. The source of nosocomial infections is usually the staff or the patients themselves. The peculiarity of pathogen groups is that they accumulate, multiply quickly, and spread throughout the building premises, regardless of the planned disinfection measures. In addition, in 95 percent of cases, the spread occurs through the ventilation system [15]. The next feature is the nature of architectural and planning solutions for healthcare facilities, which has changed qualitatively. In the past, hospital buildings provided for the presence of various groups of buildings located at a distance from each other, each of which was divided by air between the buildings. This made it possible to divide medical and technical processes and patient flows into clean and dirty ones. Clean and dirty rooms were located in different buildings, which helped to reduce the transmission of infectious diseases. Nowadays, savings on the area of project buildings have led to a trend towards more compact floors and hospital plans and greater throughput, which leads to a reduction in the length of communication lines and, of course, to greater economies of scale. On the other hand, rooms of different cleanliness classes are closely intertwined with each other, creating the possibility of contamination from dirty rooms to clean ones, both vertically and according to the layout. The specifics of medical activities that are carried out in buildings and premises of medical organizations require a serious approach to meeting sanitary requirements regarding microclimate, air environment, ventilation, and heating. This is due to the nuances of the functioning of the MO, which, in turn, are associated with the treatment, rehabilitation, and care of sick patients. Strict compliance with the numerous sanitary requirements imposed by the legislator for the microclimate, air environment, ventilation, and heating, is often complicated due to the variety of medical and technological purposes of premises located in the same medical complex.

In hospitals, requirements related to comfort, thermohygrometry, lighting, and air quality play a major role and are related to the characteristics of the building and equipment system and the activities that take place in it. Climate control of the environment is a major issue in the field of hospitals and affects not only the implementation of new facilities, but also maintenance and repair. This is easy to do in the case of new buildings, but more difficult in the case of renovation. The system must be designed to be fully integrated into the overall design, as it must interact with the limiting constraints that cause such a complex and articulate distribution of space.

When designing the systems of a hospital building, two fundamental aspects must be ensured: total control of the thermo-hygrometric parameters (temperature, humidity, and air velocity), and the possibility of the control and adjusting for the single areas of flows and air changes within individual rooms.

The conditioning systems of the hospitals are supposed to represent the state of the art, in terms of technological research and energy savings, maintaining overall the highest level of safety and comfort, for operators and users. In fact, less than half of modern health facilities are newly built and only 34 percent have been completed after 1971 [15].

In 2019, Fabbri et al. [16] published an article on the microclimate in hospitals, where they noted the importance of following step-by-step protocols provided by standards and literature for other buildings, typologies such as offices, schools or residences. They study whether the metabolic values obtained for patients (especially for pregnant women) are valid in any climatic or cultural environment, or whether they may depend on local conditions.

Ferrante et al. [17] assessed the compliance of the staff and management of the medical service with the proposals received as a result of monitoring. According to the results of the study, all the parameters of the microclimate were beyond acceptable values. The authors of this work also noted that constant monitoring of the environment is an important element for maintaining optimal living conditions in the working environment. The study was done in the Sicily region, Italy. In the overall rating of microclimatic welfare (PMV and PPD) with reference to the operators and to the patients inside the examined operating rooms, a significant difference in the percentage of comfort to the detriment of the patients was found. Although a tolerance of 20 percent in the data of the operator was permitted, a remarkable discomfort concerning the thermo-hygrometric wellbeing of the patient was found at 79.5 percent for the PMV and 78.8 percent for the PPD. This gap should be minimized, as also pointed out by the literature.

In addition, from specific regulatory perspective, for air-conditioning systems in hospital buildings, in Italy there is no real legislative/regulatory corpus. In [15] the authors state that the legislation is very limited. The paper reports studies carried out at a hospital in the city of Messina, for evaluating the indoor global comfort conditions through the feedback of appropriate quality indices: temperature, humidity, and air velocity, lighting, and air quality. For the evaluation of hygrothermal comfort conditions is used the model suggested by the ISO 7730 standard.

The authors of article [18] took the example of the city of Berat, in Albania, which is well-ventilated, and the air is cleaner thanks to the greenery inside the city and the surrounding hills. Berat Hospital plays a very important role in the entire region, and even recently it has been visited by patients from other cities to receive some of the highly specialized services it offers. For this reason, he must have studied all the factors of the hospital's internal environment to meet the standards of the hospital building, as well as better manage the resources of the physical infrastructure. The purpose of this study was to study the most important microclimate parameters for proper management of microclimatic environmental conditions in the Berat Regional Hospital.

Czarniecki et al. [19] describe studies of the microclimates in several patients' rooms in a Convalescent hospital during the period May–December. Psyhrometric and thermohygrographic measurements were made to analyze the temperature and air humidity conditions. The findings include that the temperature-humidity conditions in the rooms were bad, with major deviations from comfort parameters. In particular, there were observed excessive air temperature fluctuations over 24 h. The conclusions are that patient discomfort after a long period in the enclosed and heated rooms was not caused by too-low humidity but by a too-high or too-low temperature.

2.4. Microclimate Studies in Monuments and Art Galleries

Monuments and art galleries are other types of buildings that may need special microclimate control to preserve paintings, old structures, and other art or antique relics.

In 2010, Garcia-Diego et al. [20] published an article describing a system for monitoring the microclimate surrounding frescoes for preventive conservation. The developed system in this paper consists of temperature and humidity sensors. During the restoration process, some of these sensors were placed inside the paintings, while others were placed outside. The aim of the paper was to analyze the data obtained during the first months of monitoring to evaluate the effectiveness of the system in detecting anomalous conditions that could damage photographs at an early stage. To further stimulate research in the field of monitoring the microclimate of cultural heritage, the authors of the work created a database of temperature and humidity measurements, which became available to the scientific community through a website.

Camuffo et al., [21] described the evolution of the internal climate in some of the rooms of the Uffizi Gallery (Florence). The major parameters of microclimate such as air temperature, relative humidity, specific humidity, dew point, and atmospheric stability were measured automatically for some years, and also manually, with seasonal measuring surveys. Measurements were started in 1997 and are still continuing. The use of heating, air conditioning, ventilation, lighting, and the daily flux of a huge number of visitors produce rapid changes and marked thermo-hygrometric gradients in the rooms. Sharp variations are found when the system is switched on in the morning, and switched off in the evening, instead of operating day and night, which is desirable for the preservation of the paintings. The humidifying system in the Pollaiolo room was found to be much too powerful, so that, instead of mitigating the relative humidity drop that is expected after a daily rise in air temperature, it increases it, forming an undesired excess of moisture. In the long run, all these cycles risk becoming harmful to the exhibits if air temperature and air humidity control are not regulated in accordance with the results of the study. These problems and the possible approaches to the installation of a new plant and the mitigation of these negative effects are discussed.

2.5. Automatic Microclimate Control Methods

Microclimate is considered to be a combination of the characteristics of the air in a given room, namely, temperature, humidity, and air velocity. The microclimate of a room directly depends on a combination of certain factors. First of all, there are climatic conditions, that is, the climate of the area in which this building is located. Secondly, there is the degree of protection of the premises from the influence of external conditions (wind, low or high temperatures, and humidity). In addition, lastly, there are internal factors, such as the release of moisture, heat from people or other sources in most indoor airflows. In addition to moisture, heat, and carbon dioxide, products of household and industrial activities of a person can be various gases and aerosol dust. Increasing the concentration of harmful substances in the air of a closed room negatively affects the quality of the microclimate in it and, accordingly, on the health of people. Heat loss can be carried out through windows, walls, doors, roofs, floors, and so on. In [8], air exchange is determined and ventilation equipment operation mode is calculated. In [22] the authors provide information about microclimate standards. This paper contests the claim that technical standards for comfortable temperatures are not applicable to all regions due to different climatic conditions and clothing traditions. The authors have proposed a combined machine for controlling microclimate parameters. The developed system is designed for climate control of the building and relative humidity, as well as for raising or lowering the temperature. In addition, the Program is developed in ladder logic language based on OMRON software and hardware. The control system takes into account the internal and external environmental factors associated with the regulation process.

Figure 1 shows a room and the variables that are important to monitor. The variables considered are:

- Qceil—Heat loss through the ceiling
- Qd—Heat loss through door;
- QEo—Heat loss through exhaust openings;
- Qh—Human heat dissipation;
- Qwin—Heat loss through windows;
- Qw—Heat loss through walls;
- tR—Radiation temperature;
- +t—Room temperature;
- −t—Outside temperature;
- +fi—Room humidity;
- −fi—Outside humidity;
- −v—Outside air velocity;
- +v—Room air velocity;
- Qfl—Heat loss through the floor;
- 1—Heating system;
- g—Building structure thickness;

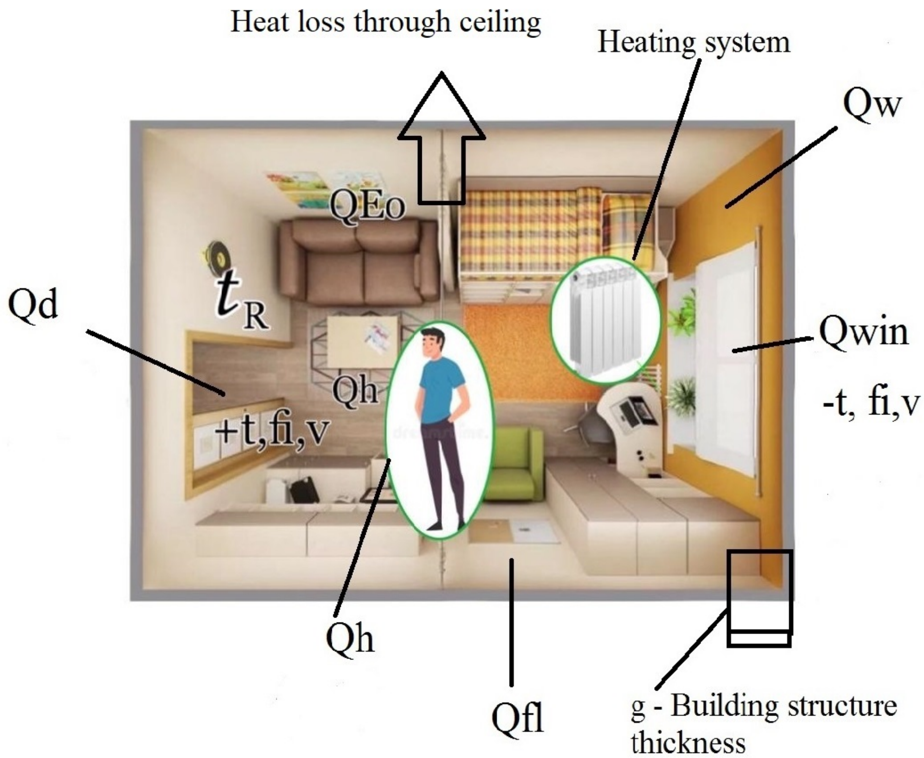

Figure 1. Room microclimate variables. Diagram based on [5].

There are smart thermostats that help monitor and control electromechanical equipment in buildings. In [4], the authors consider intelligent thermostats as one of the types of Building Energy Management Systems (BEMS). One of the types of BEMS systems is the increasingly popular intelligent thermostat aimed at room-by-room control of Heating, Ventilation, and Air Conditioning (HVAC) systems in a building. Analysis of research in the field of energy saving of buildings proves the possibility of reducing energy consumption to 20–30 percent, due to the reduction (shutdown) of heating or air conditioning of buildings during the absence of residents or even at night. The authors conclude that the location of the thermostat in the room, the sensitivity level of the built-in sensor, and the power supply are critical for making effective management decisions.

2.6. Summary

Table 1 shows a summary of the main approaches cited in Section 2. As the table shows, among the variables or parameters of the microclimate, temperature plays a key role. It is monitored and processed in all the approaches. Humidity is also very important. All approaches control directly or indirectly, relative or absolute humidity. Ventilation and light are not monitored in all the approaches, but they are also deemed important variables especially for care facilities, such as in hospitals. Carbon dioxide is monitored in greenhouses, but it is not deemed so important for other environments.

Table 1. Comparison of methods/approaches in microclimate control systems.

Author/Year	Variables Monitored	Method/Approach	Main Contribution
Nemanja Radojević et al., 2014 [23]	heating, ventilation, fogging, lighting and shading, fertigation, CO_2 injection	practical approach to the real-time control system in a greenhouse	An effective mechatronic system for large greenhouses. The monitoring concept is based on a centralized main block and distributed local blocks and censorship in neighboring assets.
Moin Rezvani et al., 2020 [24]	temperature, humidity, light, concentration of carbon dioxide	Crop growth model, Functional-structural plant model	Greenhouse process (KASPRO) model is constructed from modules describing the physics of mass and energy transport in the greenhouse enclosure and the modules that simulate the greenhouse climate controllers.
Giovanna Deiana et al., 2021 [25]	air temperature, relative humidity, mean radiant temperature, airspeed	Evaluation of thermal comfort using Fanger indices, standards required by current legislation and specific guidelines	Non-compliant values for at least one parameter were found in 98.8% of the examinations. A condition of thermal discomfort was calculated for 3.6% of healthcare professionals and 98.3% of patients.
Adrian Hoxha et al., 2014 [18]	temperature, relative humidity, lighting, and air movements	Monitor air temperature, humidity, lighting (lux), air speed	Method to control internal temperature and relative humidity compared to the norms
Mauro Cannistraro et al., 2017 [15]	air temperature, absolute humidity or moisture, a minimum flow of outdoor air	Use the model suggested by the ISO 7730 standard	Full control of thermohygrometric parameters (temperature, humidity, and airspeed), as well as the ability to control and regulate large areas of flow and air exchange in individual places.

3. Fault Detection

3.1. Methods of Fault Detection

Determining if there are faults in the control system that need to be eliminated is the main task of the Fault Detection (FD) system in microclimate control systems. Complete detection of all system failures is almost impossible. Therefore, already at the design stage, the requirements of safety and reliability are the main characteristics of modern complex systems and technologies. To use it, the monitoring and fault diagnosis capabilities are installed in the control systems. Thus, we should consider the impact of any faults on the potential behavior of future systems during the process of detecting and predicting faults. In particular, today's applications rely on fast and efficient hardware/system troubleshooting resulting in increased productivity and reduced downtime.

Abid et al. presented developments in fault detection and diagnosis (FDD) techniques and reviewed research in this area. The review covers the description of both traditional, model-based, and relatively new signal processing-based FDD approaches, with a special focus on artificial intelligence methods. The authors present systematic steps for the design and development of current automatic FDD systems, including system information presentation, data acquisition, and signal processing, fault classification, and maintenance-related decision-making activities. It also provides perspectives for future research directions, challenges, and potential solutions. In ref. [26], researchers classify fault detection methods according to the following criteria:

- Initial fault detection;
- Detection of multi-faults ;
- Uncertainty control;
- Compatibility;
- Requirements for real-time computing;
- Justification and output response

Table 2 summarizes the various approaches identified in the literature review for FDD methods. ML stands for machine learning; WV stands for weighted voting.

Table 2. Comparison of fault detection methods in microclimate control systems.

Reference	Classification	Approach	Detection Approach	Topology Dependent	Threshold Based
Panda et al., 2014 [27]	Centralized	Statistic	Active	Yes	No
Warriach et al., 2012 [26]	Centralized	ML	Active	No	No
Park et al., 2020 [28]	Centralized	Statistic	Passive	No	No
Lau et al., 2006 [29]	Centralized	ML	Active	No	Yes
Chen et al., 2018 [30]	Distributed	Hybrid	Active	No	Yes
Ning et al., 2017 [31]	Distributed	WV	Active	Yes	Yes
Panda et al., 2015 [32]	Distributed	Self detection	Active	Yes	Yes
Yu et al., 2015 [33]	Distributed	Statistic	Active	Yes	Yes
Lazarova-Molnar et al., 2017 [34]	Centralized	ML	Active	No	No

In [27] the authors show that such influences as battery discharge, environmental influences, or sensor aging can affect the inaccuracy and erroneousness of the collected data. The efficiency of the sensor network depends on the earlier detection of such faults. In this paper, the researchers propose a hybrid approach to fault detection and illustrate its effectiveness with data coming from actual sensor deployments. This proposal is the first step towards creating a hybrid method for real-time automatic detection and classification of failures in a context-sensitive WSN (Wireless Sensor Network) middleware environment. This approach covers traditional methods for detecting and diagnosing non-bugs to check for a trend or pattern. It determines whether the given process variable is behaving normally or not. However, there are some hidden characteristics that may not be revealed due to the nature of the process dynamics. The main function of fault detection and diagnosis (FDD) for industrial processes is to create an effective indicator that can identify a fault condition and then take appropriate action to handle future failures or adverse accidents. To improve many process characteristics (such as quality and productivity), FDD is attractive to various industries. Therefore, in the current work, we consider FDD approaches for process monitoring.

In [26], the authors consider a centralized reliable fault detection algorithm for identifying a faulty network sensor node. The simulation results demonstrate high detection accuracy and false positive rates, which exceed those of conventional algorithms under the same conditions.

Recently, the study of individual classes of faults and the conditions for their detection has been fundamental for many studies. Based on the current assumptions, if no more than one type of fault occurs in the software under test, then the conditions for its detection can be used in two cases: (1) to develop a strategy for selecting test cases when appropriate classes of faults are detected. (2) to study the hierarchy of failure classes, where some other types of failures can be detected on a test example, corresponding to a certain class structure. In [29], the authors study the conditions for detecting double faults. In addition to developing strategies for selecting test cases and exploring a new hierarchy of failure classes, this analysis provides additional information about the impact of failures among themselves. The authors suggest that we can consider the cases of double faults not embedded in the software and include them in special strategies for test case selection, then check the effectiveness.

In the article [30], the authors propose the fastest algorithm for fault detection in the case of photovoltaic systems within a detection base with sequential changes. They used several meters to measure the various output parameters of the photovoltaic system. The time correlation of the faulty signal and the signal correlation between different counters are used in modeling the signal after changing by means of the AR vector model. To solve the problem associated with the lack of prior knowledge about the malfunction, the authors developed a change detection algorithm with a general local likelihood ratio test. The results of the simulation show high adaptability and fast detection during the process of eliminating the various types of faults in photovoltaic models. Troubleshooting the failure in the flight control system needs to have subsequent reconfigurable management for the stability of the system [35]. Authors claim that due to good knowledge of malfunctions of sensors and actuators, the small unmanned aerial vehicle (SUAV) is usually not taken into consideration.

The paper [31] presents the state of the art in fault detection and diagnosis for air dynamics by specifying the methods for SUAV pneumatics parameters and properties determining as well as the key FDD technologies analysis. Another effective method for detecting faults in a sensor network concerns the distribution of faults. This method is based on information from neighboring sensor nodes that influence the node's own fault status.

The paper [32] presents a new distributed algorithm for detecting failures in sparse wireless sensor networks. The authors distinguish them as sensory nodes with soft failures. The principle of algorithm operation is based on reducing communication overhead by collecting node information only from the nearest neighboring nodes. Node failure state prediction is based on the Neyman-Pearson testing method, where a voting scheme is considered to obtain the final data for each sensor node. Circuit performance evaluation (analytical and simulation-based) includes considering general parameters such as accuracy of detection, false positive rate, the complexity of time, message complication, detection latency, network battery life, and power consumption. The result shows that the proposed scheme makes significant improvements in terms of all mentioned characteristics. The sensor networks' failure vulnerability is the result of long-term monitoring under adverse conditions. The reason for the generation of erroneous sensor data and, as a result, an incorrect assessment of the environment and resource consumption is often a functional failure and failure of the sensor network node. Therefore, continuous detection of erroneous data in real-time mode is necessary. The paper [33], proposes a new algorithm based on the temporal and spatial correlation of sensor data for distributed fault detection. Localization of detection of erroneous data and their rejection minimize the consumption of network resources and reduce the load on the processing terminal. It is shown that the accuracy of fault detection is improved by considering various parameters such as conditions, environment, mode, test cases, and software used for various devices. There are different types of real-time fault detection methods. They include Model-based Systems, Rule-based Systems, Semantic Networks, Decision Trees, Fuzzy Logic, Bayesian Networks, and Neural Networks.

Statistical analysis methods are also often used. Traditional signal processing techniques can also be applied to fault detection systems, including Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Least Squares (PLS). The main idea of PCA is to use the direction of multivariate data without correlation in different orthogonal directions with the largest variance as the main feature. Together with multivariate time series (MTS), this will allow efficient fault detection. For example, Li et al. [35] combined several methods such as PCA, ICA, and PLS with the Kalman filter to improve the accuracy of fault detection by projecting a subspace along the fault area. When using the ICA algorithm, the authors accounted for the data as linear combinations of statistically independent components during the stratification process. For PLS, which includes the ideas of PCA and canonical correlation analysis, they considered the limitations in processing non-linear MTS and unbalanced data.

Figure 2 shows a hierarchy of possible approaches to the main issue of FDD, according to [36]. History of processes may affect all methods as well as the different approaches such as data-driven, statistical, or machine learning-based.

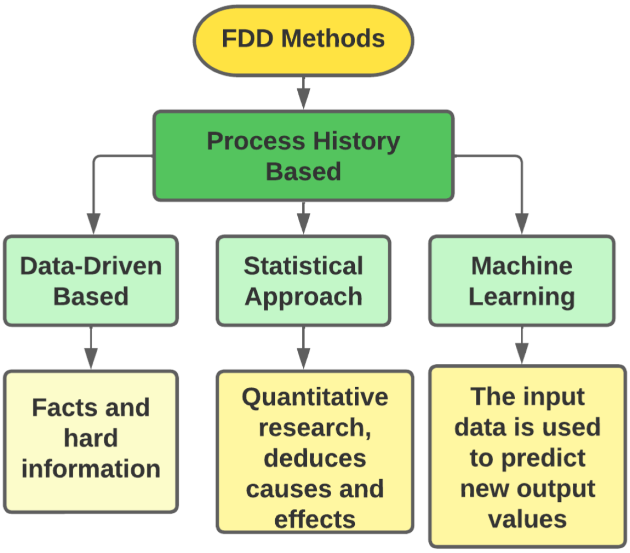

Figure 2. Approaches for fault detection and diagnosis methods. Based on [36].

Figure 3 shows the hierarchy of fault detection and diagnosis (FDD) methods according to [5]. As shown in the figure, there are methods based on quantitative models, methods based on the history of processes, and methods based on rules. Quantitative model-based methods are divided into two types: detailed physical model and simplified physical model. The next method, Process History Based, also includes two types: knowledge-based and data-driven-based methods. The two types presented consist of six main categories. One branch includes systems based on knowledge—(Expert system (ES)), pattern classification (PC), and casual analysis (CA). Another branch contains methods driven by data—a statistical approach, feature extraction, and machine learning) [36]. Finally, in the third main branch there are rule-based methods, which are often simple but effective if-then rules, limits, and alarms based on predefined thresholds, and first principles. Finally, in the third main branch there are rule-based methods, which are often simple but effective if-then rules, limits, and alarms based on predefined thresholds, and first principles.

There are various fault detection methods. For example, Zeng et al. [37] used several types of fault detection methods based on information fusion, artificial intelligence (AI), neural networks, fuzzy algorithms, and genetic algorithms. The authors note that different fault information can serve as a good source for processing different fault detection methods. Thus, it is possible to reduce the influence of the interfering signal, eliminate the limitations of a single protection circuit, and improve the accuracy and reliability of fault detection by integrating and combining all kinds of fault information.

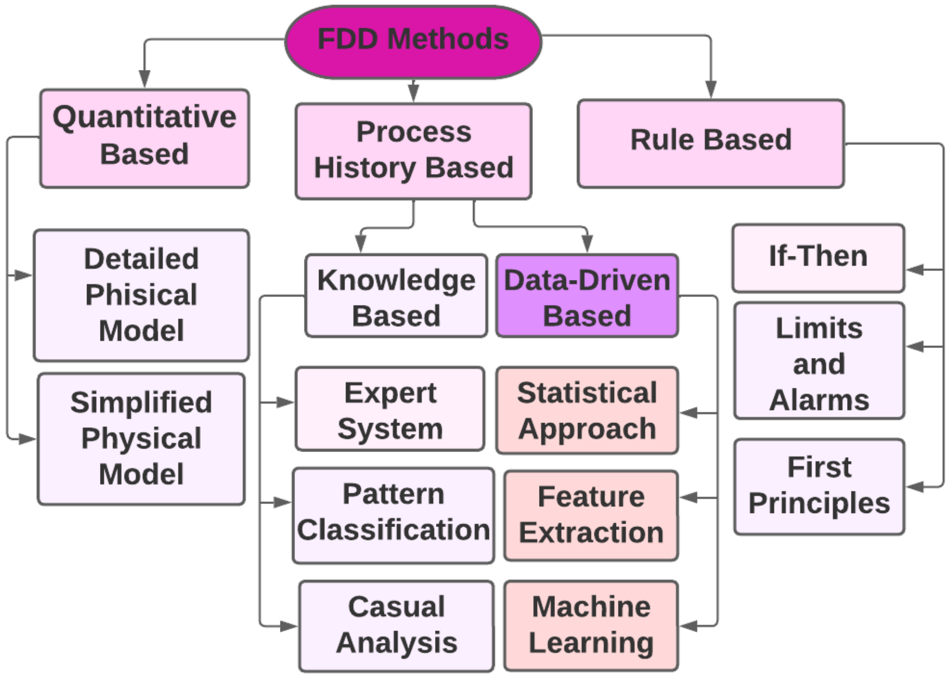

Figure 3. Fault detection and diagnosis methods. Based on [5].

3.2. Quantitative Methods

Statistical data on defects and faults in the system under study imply the use of quantitative methods. These data are usually collected or already exist in the system. One of the pros of Quantitative Model-based methods is that they do not require historical data. They are simple ways to diagnose the cause of detected faults. On the other hand, cons are next: They can be difficult to calibrate and expensive due to reliance on sensors. In addition, they are computationally demanding and need to be tailored to specific system structures. We can use a wide range of quantitative models of varying complexity for fault detection tasks. By applying dynamic models, we create a set of calculations that are repeated several times, while the initial values of the variables in the current set are taken from the results of the previous set of calculations. Whereas static models imply getting the result immediately and independence from previous calculations. This applies to stochastic static models as well.

3.3. Rule Based Methods

Fault detection models can also use rule-based methods that traditionally involve human participation in the evolution of the system. Therefore, if we need to consider human needs in the functioning of the system, and the system has special requests for microclimate control with a focus on human factors, the use of rule-based methods becomes important. In such systems, by writing a request, the user can always check whether the system can process it and how it will all happen. Any found faults are easy to localize and fix by changing the rules in the appropriate module. We can use rule-based models if it is necessary to correctly decipher the linguistic relationships between words to interpret a sentence and classify the failures found. Any request in the system made by the user can be analyzed at the level of parsing and retrieval. The analysis of situations and faults that occur in the system at the level of human needs can be represented as a mechanism of expert systems, including facts and IF-THEN rules, as well as modus ponens, as the main inference method for drawing new conclusions from existing knowledge. These rules are called production rules and allow us to directly encode experience in a particular area. Using “situation-action” pairs, it is possible to define aspects of the situation (IF) that lead to one or more actions (these are described in the THEN part). When applied to fault detection systems, rule-based models have several advantages and disadvantages (Pros and Cons).

Pros:

- Economy and relative accuracy of results;
- The output is stable and non-random, as it depends on the rules;
- The coverage is fair under different scenarios and circumstances as the accuracy of the results is high. The error rate of the results is low due to the predefined rules, in the case if the rules are well defined;
- Optimizing system speed is easy because all parts of the system are well-known;

Cons:

- Too much data and deep knowledge of the subject area, as well as too much manual work;
- Difficulty in writing and maintaining rules, time-consuming;
- Minimal capacity for self-learning;
- Difficulty in identifying complex patterns since the coding rules requires a lot of time and analysis.

3.4. Process History Based Model

As shown in Figure 3, one class of fault detection and diagnosis methods is the process history-based one. Data-driven methods, including statistical approach, feature extraction, and machine learning, are one important branch of this class of methods, while the other branch includes knowledge-based systems such as expert systems, pattern classification methods, and casual analysis. A process history-based FDD method can be implicitly defined. The method is based on available data and expert knowledge. It leads to the possible identifying the patterns and developing decision-making models. Not requiring the explicit system model is very beneficial in combination with the large amounts of data that have become available as a result of recent developments in monitoring systems. Therefore, this class of systems is very attractive for modern industry, where sensors are becoming more accurate and affordable, and the computing power of computers is going to be cheaper and more accessible for storing and processing large amounts of data. If the system consists of different structures, then this approach can also be easily applied. However, the method is data-driven and requires the use of a large amount of training data [38]. In this case, the efficiency of the method may deteriorate due to unknown operations of the system.

In paper [39] the authors describe the use of non-intrusive load monitoring (NILM) techniques for smart buildings and highlight their effectiveness and limitations. According to the authors' opinion, this method can be implemented to evaluate the efficiency of the microclimate system or detect various types of faults. They also mention that using of NILM methods can reduce the energy consumption and costs of remote monitoring of complex HVAC systems, especially in commercial buildings. In spite of the analysis of climate system performance being in real-time mode, more effort is needed to detect and calculate faults. Machine learning methods make it possible to predict potential malfunctions before they are actually detected and to monitor and avoid them in a planned manner. Building owners who invest in machine learning-assisted fault detection are enjoying lower energy bills, extending equipment life, and improving occupant comfort. In another paper [40], the authors proposed an automated fault detection method based on a top-down model that can detect abnormal power consumption by building ventilation systems. After conducting a series of experiments, the authors [39] identified some time spans of suspicion with a high degree of urgency during the study period. At the same time, faults were diagnosed manually by using sensor data at the room level. The result shows the discovery of a faulty busy counter. According to the authors of [40], the proposed method has promising prospects in the field of automated fault detection methods in terms of identifying periods with anomalous behavior. Comparing these methods with machine learning methods, several advantages can be noted. An ML-based FDD method should identify problems, notify operators, and recommend solutions when equipment is operating outside of expected performance criteria. Smart building software with machine learning makes it the best possible way. The smart building platform, which uses machine learning for fault detection, defines rules and automatic responses to limit false alarms. Building owners are minimizing reliance on contractors to identify the root cause of alarms, and maintenance visits are becoming more targeted and cost-effective. False alarm limitation also prevents premature upgrades or replacements of related equipment, eliminating unnecessary labor and material costs. ML methods can also allow to classify the alarms and abnormal situations, detect their importance and significance and then provide the prediction with consideration of the defined situation.

4. Fault Prediction

Prediction is necessary for many situations. For instance, making a decision to build a power plant in five years requires predicting future demand. Or, the scheduling of call center employees for the upcoming week requires a formal or informal preliminary assessment of the expected workload for this week. Prediction methods are also useful in software engineering for predicting effort, safety, quality, failures, costs, and reusability. Failure prediction is the process of detecting and predicting deviations from the normal or expected behavior of the monitored equipment or system. Therefore, quantitative prediction methods can also be applied to this area.

4.1. Prediction Methods

Prediction is a method of making reasonable estimates using historical data as input data and making forecasts when choosing the direction of observation. Figure 4 shows the most popular types of prediction methods. They include informal qualitative and also quantitative methods. There are also modern Artificial Intelligence (AI) techniques, such as random forest, shallow, and deep neural networks.

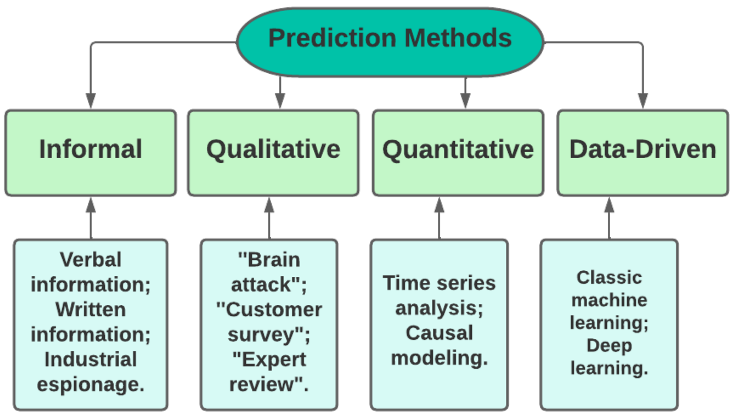

Figure 4. Types of traditional prediction methods.

Informal methods, such as verbal information or written information, may be important on the industrial floor. They may also be important sources of information for knowledge-based systems and fine-tuning of more sophisticated computer models. Nonetheless, they are not automatic prediction systems themselves. The informal type of prediction method refers to the intuitive process by which humans make predictions. Qualitative methods, such as Customer surveys or Expert reviews, can be useful formal methods for better understanding and as a basis for more formal models, such as quantitative or machine learning methods. Qualitative prediction method is based on information that can't be measured. It is especially important when a company, machine, or process are just starting out since there is a lack of past (historical) data. Quantitative predicting relies on historical data that can be measured and manipulated.

Quantitative methods include Time series analysis and Causal modeling. They played the most important role in formal prediction before the development of modern data-driven models. The most promising methods for fault prediction, however, are based on modern AI methods, which can in general abstract patterns from time series signals and predict longer in the future [41].

4.2. Quantitative Methods

A time series is a sequence of observations carried out continuously for a certain time. Many data sets are presented in the form of time series, for example, monthly changes in shipments at factories, weekly changes in the number of road accidents, daily precipitation, hourly observations of the output of the chemical process, etc. Quantitative prediction methods use historical data to predict future data, especially numerical data and continuous patterns. This method is usually used for short-term forecasting. It is based on mathematical models and is objective.

General prediction methods are still at a rudimentary stage. Experiments and research are currently being conducted to create more reliable models. Software Fault Prediction (SFP) is the process of developing models that software developers can use to detect faulty classes or modules prior to the testing phase. Predicting faulty modules before the testing stage can help the heads of the software development team to allocate resources more optimally and reduce the complexity of testing [42]. A similar process was applied to industrial equipment [7,43].

The prediction model ARIMA is one of the most popular quantitative models. ARIMA is an acronym for AutoRegressive Integrated Moving Average, which is used in statistics and econometrics to measure events that happen over a period of time. The model is used to understand past data or predict future data in a series. It is used when a metric is recorded at regular intervals, from fractions of a second to daily, weekly, or monthly periods. ARIMA is a type of model known as the Box–Jenkins method. The Box-Jenkins method proposes a methodology for time series prediction [44]. Figure 5 illustrates the main steps of the methodology. The first step is to explore the data and process it to make it suitable for modeling. The second step consists of estimating model parameters and assessing the quality of the models obtained. The third method is the actual use of the model, after it has been developed and assessed.

ARIMA is the simplest model of Boxing–Jenkins. It is a widely used statistical method for predicting time series. This is a model that reflects a number of different standard time structures in time series data. The abbreviation is descriptive and reflects an important aspect of the model itself. Namely, it is an autoregression, that is, a model that uses a dependent relationship between an observation and a certain number of delayed observations. In addition, it is integral that uses the difference between the raw observations (for example, by subtracting an observation from the observation of the previous time step) to stationarize the time series. In addition, the moving average. This is a model that uses the relationship between observations and residual errors from a moving average model applied to lagged observations. Each of these components is explicitly specified in the model as a parameter. The standard ARIMA notation (p, d, q) is used, and the parameters are replaced with integer values to quickly indicate the specific order of the ARIMA model used. The parameters of the ARIMA model are defined as follows: p is the number of lag observations included in the model, also called the lag order; d is the number of times the original observations differ, also called the degree of difference; q is the size of the moving average window, also called the order of the moving average.

A linear regression model is constructed that includes a certain number and type of terms, and the data are prepared according to the degree of difference to make it stationary, that is, to remove trend and seasonal structures that negatively affect the regression model. A value of 0 can be used for the parameter, indicating that this element of the model is not used. Thus, the ARIMA model can be configured to perform the functions of the ARMA (autoregressive moving average) model and even simple AR (autoregression), I, or MARK models. Using the ARIMA model for a time series assumes that the main process that generated the observations is the ARIMA process. This may seem obvious, but it helps to motivate the need to test the model's assumptions with the help of leftovers from raw observations and predictions from informal methods.

The ARIMA model cannot learn seasonal patterns. Therefore, SARIMA variation was developed to deal with seasonal patterns. The SARIMA has an extra parameter, which is the period of the seasonal pattern.

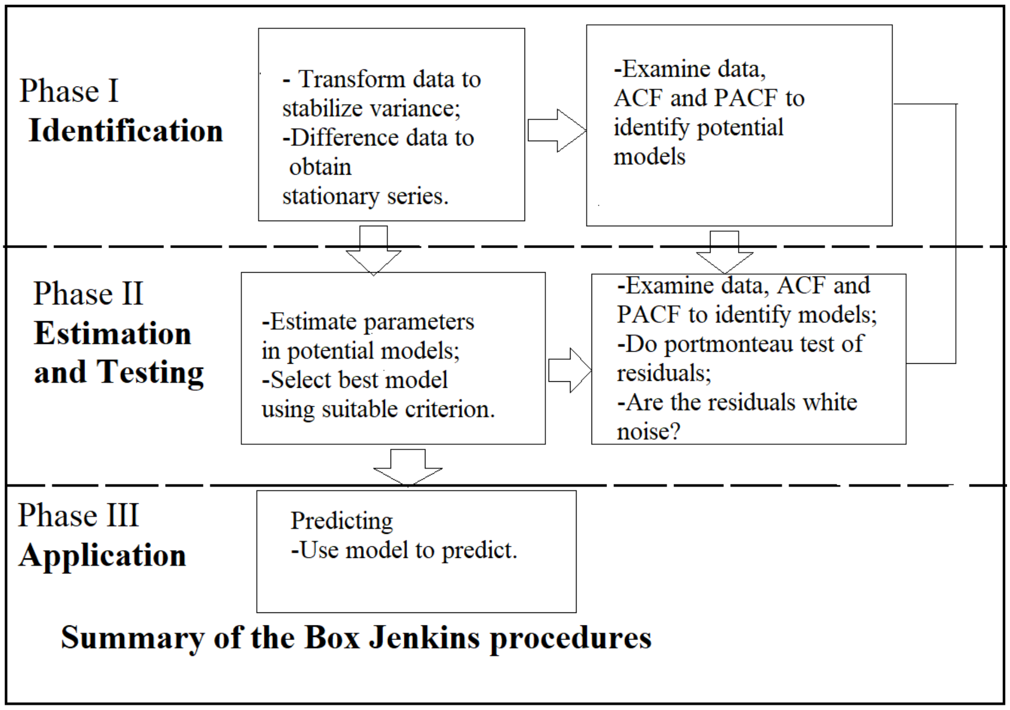

Figure 5. The Box–Jenkins method.

4.3. Machine Learning Approach

The modern AI approach to the problem of prediction is mostly based on neural networks, shallow and deep. Figure 6 illustrates a typical modern approach.

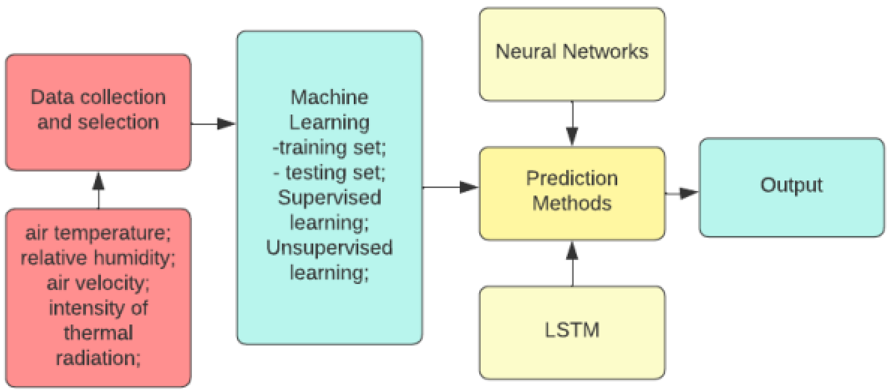

Figure 6. Prediction with Machine Learning.

When applying modern AI techniques, the process is different. While ARIMA methods work with as little as 50 samples, machine learning methods require large datasets for training and testing the learning process. After receiving a suitable data set, the data research specialist transmits them to the ML algorithm. Each ML algorithm produces a model whose internal parameters are adjusted at the training stage to be able to predict new results. Data developers can fine-tune the learning algorithm using different regulators to produce different models. The model that gives the best results is used in production. The use of ready-made models is similar to what is used in traditional software solutions.

It takes input data and outputs results that are forecasts of a time series at a certain point in the future. In general, for fault prediction, the values predicted for the time series are then fed to a classifier that has been trained to recognize patterns of failure. Thus, the complete pipeline is (i) the sensory readings of an equipment or system at time t are fed to the predictor module; (ii) the predictor module outputs the probable state of the system at time $t + g$, where g is a gap which can be from seconds to days or months; and (iii) the probable state that comes from the predictor module is fed to a classifier which calculates the probability of failure of the system. This approach is being used for example in [7] and [41]. Martins et al. also use a predictive model based on a Hidden Markov Model and an artificial neural network as classifier [45].

Figure 7 illustrates the approach that is commonly followed in fault prediction and detection systems.

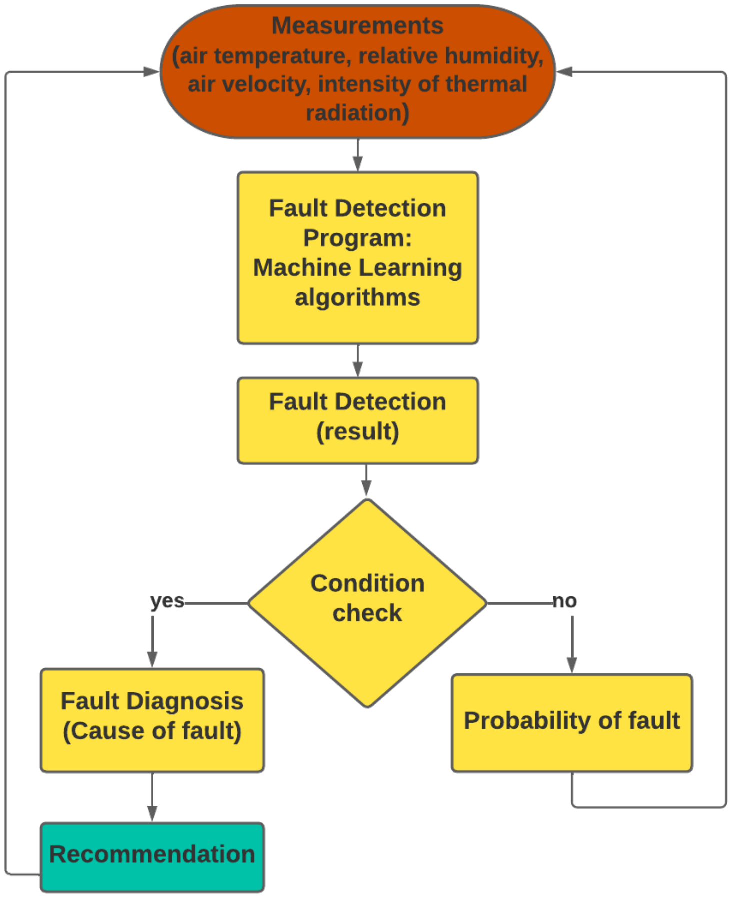

Figure 7. Fault detection and diagnosis in microclimate system.

4.4. Discussion

Table 3 summarises the most common predictive models and the advantages and disadvantages of each of them. As the table shows, in general the neural models are the most powerful. They work better on long-term predictions, are scalable, can model non-linear processes, and adapt to a large number of processes.

Table 3. Summary of advantages and disadvantages of prediction methods.

Methods	Advantages	Disadvantages
Regression models	Speed of obtaining results; Availability of intermediate calculations; Simplicity of models; The heterogeneity of the tasks being solved.	Complexity of determining parameters; Possibility of modeling only linear processes; Complexity of determining the type of functional dependence.
Autoregressive models	Speed of obtaining results; Availability of intermediate calculations; Simplicity of models; Heterogeneity of the tasks being solved.	Complexity of determining parameters; Possibility of modeling only linear processes.
Exponential smoothing models	Simplicity of models; Speed of getting results;	Lack of flexibility.
Neural network models	Solving long-term prediction problems; Possibility of modeling nonlinear processes; Adaptability; Scalability; Heterogeneity of the tasks being solved.	Complexity of software implementation; Lack of intermediate calculations; High requirements for consistency of the training sample.
Models based on Markov chains	Simplicity of models;	Narrow applicability of models. Impossibility of solving prediction problems with a long memory.

5. Conclusions

Microclimate control plays a very important role in humans' healthy and comfortable life. That is also important in contexts such as to protect cultures in greenhouses, hospitals, monuments art in art galleries and other applications.

This paper reviewed different methods for detecting faults in microclimate systems, namely quantitative, rule-based, and process history-based models. Prediction methods were also reviewed, namely quantitative and machine-learning-based approaches.

The main aim of this study was to review and analyze methods for detecting, diagnosing and if possible predicting problems before they happen. Relevant information on the topic was used, from relevant scientific sources. The main methods and models that can be used in further research were enumerated, as well as some examples of application from the state of the art. It was also possible to identify that most of the approaches are based on a limited set of variables, namely air temperature, relative humidity, air velocity and intensity of thermal radiation. The authors believe that other variables, such as voltage, electrical current, and equipment vibration, could play an important role in fault prediction.

Author Contributions: Conceptualization, N.D., L.A. and M.M.; writing—original draft preparation, M.M. and L.A.; writing—review and editing, N.D., M.M. and A.N.; supervision, L.A. and M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This work received financial support from the Polytechnic Institute of Coimbra within the scope of Regulamento de Apoio à Publicação Científica dos Professores e Investigadores do IPC (Despacho n.º 12598/2020).

Conflicts of Interest: The authors declare no conflict of interest.

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