Papageorgiou *et al. J Smart Environ Green Comput* 2023;3:18-36
DOI: 10.20517/jsegc.2022.21

Journal of Smart Environments and Green Computing

Review

Open Access

An overview of energy management using fuzzy cognitive maps

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How to cite this article: Papageorgiou EI, Groumpos P. An overview of energy management using fuzzy cognitive maps. *J Smart Environ Green Comput* 2023;3:18-36. https://dx.doi.org/10.20517/jsegc.2022.21

Received: 30 Nov 2022 **First Decision:** 22 Feb 2023 **Revised:** 19 Mar 2023 **Accepted:** 20 Apr 2023 **Published:** 18 May 2023

Academic Editors: Witold Pedrycz, Francisco Javier Cabrerizo **Copy Editor:** Ke-Cui Yang **Production Editor:** Ke-Cui Yang

Abstract

Soft computing, especially fuzzy cognitive maps (FCMs), has become increasingly applicable to energy management and policy-making. In recent decades, there has been a worldwide effort to minimize energy consumption and manage energy flow in private and public buildings. We present a critical overview of today's applications of FCM-based methods in the energy domain. We analyzed FCM methods related to energy planning, efficiency, sustainability, transition, forecasting, energy policy, and scenario analysis. We highlight FCM's applicability in the energy domain, especially its contribution to the academic and research communities. Specific drawbacks and limitations were identified while using FCM methods on several challenging applications, primarily when learning algorithms are used. A new approach addressing these issues is provided and defined as the advanced fuzzy cognitive maps (AFCM) approach. These drawbacks are considered when providing future research challenges of FCMs for building energy management and efficiency. Finally, research gaps are identified, and we suggest solutions, especially AFCM is advanced fuzzy cognitive maps.

Keywords: Fuzzy cognitive maps, energy management, energy efficiency, forecasting, optimization, policy-making, energy planning

INTRODUCTION

Humans have been using energy since the dawn of civilization. Today, we use it everywhere in our daily activities. Most essential activities depend on access to "modern" energy. Indeed, manufacturing, health, construction, communications, agriculture, computing, transportation, space, business, tourism, marine, government, and social services cannot function properly if they lack the appropriate amount of energy. The way people use energy directly affects the environment and lives positively or negatively.

Energy consumption by buildings (residential and commercial) has steadily increased over the last 30-40 years. International studies and surveys show that energy consumption is 30%-40% in developed countries. In some developing countries, it is between 50% and 60%. The arrival of COVID-19 has changed energy consumption and has shown a slight decrease. Nevertheless, the rise of energy demand will increase shortly due to the effects of COVID-19 on our daily life. Energy efficiency resulting in energy savings for buildings is a primary concern. Automated meter reading and smart metering systems have been employed to collect building energy data to provide insights into how individuals consume energy and identify improvements likely to reduce consumption[1].

Unfortunately, every year, the power crisis escalates[2-8]. Thus, energy-efficient building (EEB) design has become a high priority. EEB design is challenging for multi-disciplinary technology. Developing an EEB design involves the knowledge of computer scientists and civil, mechanical, electrical, environmental, and architectural engineers. The evidence for climate change and the impact of greenhouse gas emissions is becoming increasingly evident. In most countries, "buildings" (state and private) are responsible for 47% of national energy consumption. Scientists and environmental professionals are trying to develop advanced technologies, use renewable energies, and design practical control strategies to reduce carbon dioxide emissions[2].

When dealing with energy in buildings, the concept of energy management (EM) is critical. EM is the process of tracking and optimizing energy consumption in a building or a "typical plant." More precisely, EM is the means of controlling and reducing buildings' energy consumption. This process enables owners and operators to minimize costs, reduce carbon emissions, monitor equipment performance, and reduce the associated risks. The most common approach to meet these objectives is the energy management system (EMS). When referring to buildings, the term building energy management systems (BEMS) is often used.

Commercial building owners worldwide spend 30%-35% of their operating budget on energy. Improved building EM practices can reduce total operating costs. BEMS represent an automated system that studies the contribution of certain blocks of standard building equipment for energy efficiency following optimization. Modern, cloud-based EM systems can control heating, ventilation, air-conditioning (HVAC), and other energy-consuming devices while collecting real-time data for these devices. Hence, EMS can offer explicit, valuable real-time guidelines for achieving cost-effectiveness[3].

This paper addresses EM and energy savings using the soft computing methodology of fuzzy cognitive maps (FCMs). FCMs model complex systems for decision-making tasks[9-12], in which they represent the cognitive state of a system graphically in the form of cognitive maps. Although FCMs are applicable in diverse domains, The literature lacks a review of utilizing FCMs in the energy domain. To our knowledge, there has not been a systematic review on this topic in the last 6-7 years. Two previous reviews by one of the authors were conducted seven years ago[13,14]. The present study covers 2016 without disregarding previous reviews[13,14]. This study also covers the period before 2016 in a novel systematic manner.

This paper aims to provide a concrete and critical review of FCMs and their applicability to EM and efficiency. The paper does not present any new results. On the contrary, it reviews studies that cover the aspects of EM and energy savings of human-made energy systems while using the recent theories of FCMs. For the reader to appreciate this review study, it is necessary to comprehend the FCM theories and their drawbacks. For this reason, the paper provides a detailed analysis of these issues in Sections “FCM” and “Some drawbacks and new challenges for FCMs”. The primary goal is to provide the academic and scientific communities with information from other studies and not to run simulation studies that produce concrete results. The discerning reader can select studies in this review paper to perform their research using FCMs. Sections “FCM”, “Some drawbacks and new challenges for FCMs” and “Future research challenges of FCMs in EM and efficiency” provide the academic and scientific communities with straightforward procedures on how to study aspects of EM and energy savings in any residential and commercial buildings. The advanced FCM method (AFCM) outlined in Section “Some drawbacks and new challenges for FCMs” is unique in the existing literature and is an innovative approach that has been used very little recently.

The outline of the paper is as follows. In Section “Basics of energy management and efficiency”, the basics of EM and efficiency are reviewed. Section “FCM” details the fundamentals of the FCM methodology. A critical overview of EM and efficiency approaches and methods is provided in Section “A critical overview of energy management and energy efficiency: the case of FCMs”. All related studies are reported when FCM methods are used in the same section. Section “Some drawbacks and new challenges for FCMs” highlights several drawbacks of the classical FCM methods and provides several solutions. Section “Future research challenges of fcms in em and efficiency” catalogs future challenges and research directions. Conclusions are given in Section “Conclusions”.

BASICS OF ENERGY MANAGEMENT AND EFFICIENCY

Cost analyses usually follow energy analyses. In some cases, the performances of alternative packages are compared[5,6]. EM is a generic term for all societal applications. It includes planning and operating energy production and consumption units[15]. When renewable energy sources are used, EM covers energy distribution and storage. EM is critical for sustainable development. Given the world’s energy situation, economic growth, social development, conflicts, and deterioration of resources and the environment have been explored. The primary objectives of EM are energy savings, resource conservation, climate protection, and cost savings[16]. A recent volume describes how decision-makers can improve system safety and reliability performance using advanced decision-making methods to utilize EM concepts better[17]. This volume provides several methodologies for government officials, company decision-makers, and society analysts and is suited to the complexity of decision problems related to EM.

The electrical energy consumed in a power system is examined to assess costs. Where several sources are available, all sources must be evaluated separately to estimate the total cost applying common standards. This method determines whether the selected conditions are optimum or whether there is a need to adjust them in favor of cost-effectiveness. Two common examples are when power is imported from another system or is generated locally. The cost of electrical energy produced in the second case differs from that provided by the supply authority and cannot have a direct connection to it. Thus, because increased supply reliability leads to the installation of local generation, it is reasonable to compare imported electrical energy and local generation costs on account of fuel costs, maintenance costs, and possible deterioration or replacement costs. To address these issues, we turn to automation, and new methods have been developed, including EMS.

EMS are automation systems that collect, analyze, and display energy-related characteristic values such as energy usage, waste, depletion, expenditure per unit, costs, and other inputs. They provide a comprehensive understanding of the energy performance of a building that is critical for companies. All businesses seek the most effective and efficient actions to optimize energy. To meet these objectives, there are eight basic steps that an EMS must address[6]:

1. Collect and analyze continuous data. Evaluate long- and short-term use of continuous energy supply and energy-efficient energy system use.

2. Identify optimizations in equipment schedules, set points, and flow rates to improve energy efficiency.

3. Identify and incorporate energy-efficient process technologies and devices.

4. Identify and incorporate energy-efficient operating practices and methods.

5. Improve energy productivity of the energy system using smart metering and intelligent control; combine them with flexible process automation and optimal control.

6. Calculate return on investment. Determine the lifecycle costing of all aspects of the processes (hardware and software).

7. The primary objective of EM is not to reduce total energy costs. Issues of compromising productivity and product quality must be considered. In addition, attention must be paid to increasing the involvement and awareness of all team members associated with the activity and the relevant process.

8. Repeat any of the above steps until optimal energy efficiency is obtained.

The most significant challenge is reducing the facility costs of a building - especially for larger ones like hospitals, government buildings, residential apartments, schools, and factories - using EM methods. An EMS is an advanced automated system to control and monitor energy-consuming devices, including HVAC, fans, air conditions, pumps, dampers, and lighting.

Investing in a fully functional EMS is ideal for individuals or companies. Here are some benefits of such an investment[5-7].

● Reduce operational costs - energy represents 25%-35% of all operating costs in a building. The most obvious of all benefits is the EMS's ability to reduce electricity costs by monitoring and optimizing energy used for lighting, heating and cooling, and ventilation.

● Improve overall well-being and productivity - If an individual is uncomfortable in their environment, they will not feel well and would not like to work. Thus, temperature, humidity, and lighting regulation are critical to productivity. With an EMS, one can regulate indoor temperature while minimizing energy usage and keep the area well-lit with minimal lights. This adjustment improves overall well-being and boosts productivity. Similarly, maintaining optimal ventilation, lighting, and temperature to limit mold and bacteria reduces the risk of illnesses.

• Reduce carbon emissions to meet internal sustainability goals and regulatory requirements.

• Build a positive brand image - By optimizing energy consumption and minimizing waste, companies can send a positive image about themselves to society. This move improves relationships with customers, partners, and potential investors.

• Increase property value - If one owns their space and sees the prospect of selling it someday, EMS substantially increases the value. This fact is actual for private residences and commercial structures.

• Increase return on investment - EMS guarantees these increases.

• Reduce risk to affect oner profitability - Intelligent EM solutions can help reduce the risk of efficient operation of a system. This goal can be achieved by reducing energy demand and controlling it to make it more predictable.

Theories and practices for EM, efficiency, and savings have been used for some time[5-7,15-17]. Several studies have been related to the broad issue of EM and efficiency. One group presented an intelligent decentralized EM strategy for optimal electric vehicle charging in low-voltage islanded microgrids[18]. Another study asked whether EM was critical for energy-efficient investments[19]. Similarly, a Swiss National Science Foundation study addressed the issue of EM as a driver of energy performance[20]. A survey of Malaysian manufacturing firms revealed the impacts of EM practices on energy efficiency and carbon emissions[21]. Another study provided information regarding EM and its relation to industrial energy efficiency[22]. A study from 1998 studied whether investments in energy efficiency would consider industry characteristics[23].

Several studies addressing other issues regarding EM and efficiency have been conducted in the last 30-40 years[6,24-34]. To the best of our knowledge, these studies do not consider EM and efficiency from the perspective of FCM. The present review focuses on EM and efficiency using FCMs and does not cover other theories and technologies.

FCM

Kosko introduced FCM in 1986[35]. Their goal was to combine theories of fuzzy logic and neural networks. Since then, FCM has been used to model complex systems. A detailed presentation of FCM was described previously[15-16]. FCM investigates complex situations and deals with fuzzy or uncertain environments through reasoning[36,37]. FCM methodology is the appropriate tool for decision-making systems and (as will be shown in this paper) differs from statistical methods.

To model the system's operation, FCMs encapsulate accumulated knowledge and experience of the system's behavior in various circumstances. The knowledge is converted into linguistic variables and then numerical values through defuzzification. In other words, the process denotes the system's parameters with a modeling process consisting of an array of interconnected and interdependent nodes Ci (variables) and the relationships between them (weights, W). Concepts take values in the interval[0, 1], and weights belong in the interval[-1, 1]. Figure 1 shows a representative diagram of an FCM.

The entire procedure of the development of an FCM follows the steps below:

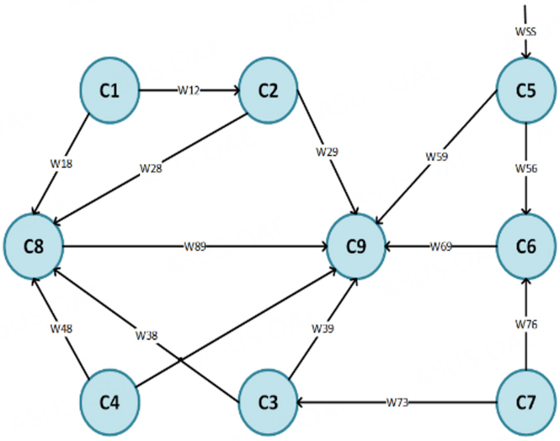

Figure 1. An illustration of a simple FCM.

Step 1: Experts select the system's critical attributes, like the number and the kind of concepts C_i that constitute the FCM.

Step 2: Each expert defines the relationship between the concepts of the system.

Step 3: Experts define the kind and the value of the relationship between the two nodes.

Step 4: Experts describe the existing relationship in a fuzzy way, assigning initially a negative or positive sign and then a degree of influence using a linguistic variable, such as low, medium, or high.

There are three types of interconnections between two concepts C_i and C_j and their weighted relationship w_{ij}:

- $w_{ij} > 0$, an increase or decrease in C_i causes the same result in concept C_j.

- $w_{ij} < 0$, an increase or decrease in C_i causes the opposite result in C_j.

- $w_{ij} = 0$, there is no interaction between concepts C_i and C_j.

The absolute value w_{ij} is the degree of influence from C_i to C_j. During the simulation, the value of each concept is calculated using the following rule:

$$A_i(k+1) = f(k_2 A_i(k) + k_1 \sum_{j=1, j \neq i}^{N} A_j(k) W_{ji}) \tag{1}$$

where N is the total number of the system's concepts, $A_i(k+1)$ is the calculated value of the concept C_i at the iteration step $(k+1)$, $A_j(k)$ is the value of the concept C_j at the current iteration step k, w_{ij} is the weight of interconnection from concept C_j to concept C_i, and f is the sigmoid function. k_1 expresses the influence of the interconnected concepts on the configuration of the new value of the concept A_i and k_2 represents the proportion of the contribution of the previous value of the concept in computing the new value. The sigmoid function f is defined as:

$$f = \frac{1}{1 + e^{-\lambda x}} \tag{2}$$

Where λ > 0 determines the steepness of function *f*. The initialized values of the FCM's concepts are re-calculated after each iteration step, depending on their weighted relationship. A steady state must be achieved to stop the calculations, with no (or below a threshold) changes in concept values. A more comprehensive mathematical presentation of FCMs with application to real problems with valid results has been described[36].

Since 2000, several studies examined the Non Linear Hebbian (NLH) learning method providing results and solutions to this issue[38,39]. This learning algorithm triggers the nodes of the system simultaneously interact with their values in the same iteration step so they are updated. The initial weights defined by experts are modified using the following relationship:

$$w_{ij}^{(k)} = g \cdot w_{ij}^{(k-1)} + h \cdot A_j^{(k-1)} \cdot \left(A_i^{(k-1)} - \operatorname{sgn}(w_{ij}) \cdot w_{ij}^{(k-1)} \cdot A_j^{(k-1)} \right) \tag{3}$$

coefficients *g* and *h* are essential to control parameters with values *g* $ [0.9, 1] and *h* $ [0, 0.1], called the weight reduction and learning parameters, respectively.

The weights w_{ij} are updated for each iteration step, and then the updated values are imported in Equation (1) to compute the new values of concepts at the current iteration step. The update procedure (learning) ends when the following criteria are met. The first concerns the minimization of a loss or cost function F_1 which is the sum of the square differences between each desired output concept *i* (DOC_i) and a target value T_i. T_i is defined as the mean value of the range of $DOC_i = [T_{imin}, T_{imax}]$.

$$F_1 = \sqrt{\sum_{i=1}^{m} (DOC_i - T_i)^2} \tag{4}$$

$$T_i = \frac{T_i^{\min} + T_i^{\max}}{2} \tag{5}$$

The second criterion is the minimization of the variation of two subsequent values of desired output concepts:

$$F_2 = \left| DOC_i^{(k+1)} - DOC_i^{(k)} \right| \tag{6}$$

At the termination of the learning procedure, the new final weight matrix w_{ij} with the DOCs returned. Proposed methodologies, drawbacks, and limitations of the updated FCM theories are described in the following section. A detailed demonstration of FCMs methods and algorithms has been described[40].

Numerous diverse domains, including engineering and medicine, have exploited Hebbian-based learning when dealing with decision-making and prediction tasks[41-44]. Moreover, there are critical research studies applying FCMs accompanied by learning algorithms in diverse domains[40] and research works emphasizing the significant contribution of FCMs in energy[11,45-48], environmental sustainability, and health[41,49-52].

A CRITICAL OVERVIEW OF ENERGY MANAGEMENT AND ENERGY EFFICIENCY: THE CASE OF FCMS

Although smart and energy-efficient buildings have recently become a trend, EM and efficiency have been prevalent since the early 1980s. This concept was needed for space exploration[53]; the US National Aeronautics and Space Administration established an environmental management division responsible for water management and set policies and guidelines to ensure the success of each mission while using energy and water resources as efficiently as possible. The substantial dependency on fossil fuels and the continuous increase in fuel prices over time (especially during shortages) led to a need for alternatives such as renewable energy sources (RESs). The US Department of Energy has projects for space application technologies [e.g., photovoltaics (PVs) and other RESs] to meet societal needs[4]. The survival and development of emerging communities, especially in developing countries, depend heavily on the availability of electricity[54,55]. For example, in Egypt, several rural areas are without access to electricity as the grid cannot reach distant locations. RES is promising because developing nations have high irradiation levels and other weather conditions that favor RESs for generating electricity. Nevertheless, this is a challenging task. In the case of PV systems, designing and installing a stand-alone system according to the daily electrical needs is challenging for a small village or remote dwelling where weather data (i.e., solar irradiation, temperature, and wind patterns) are needed. The sizing of each system component (e.g., the PV array/panels, mechanical structure, battery, maximum power point tracker, inverter, and charge controller) must be carefully designed. The energy efficiency of each component must be considered, and energy load management must be developed as part of a stand-alone energy system. An energy load management system was developed to provide energy to a village that depends solely on RES, implementing classical energy efficiency methods[5-7,56-58]. Several stand-alone PV villages have been developed worldwide[54-56,58,59].

FCM theories emerged after 1986[14]. All EM and its impact on energy efficiency used classical control methods[5-8,57,58,60]. Since the late 1990s, the first studies of fuzzy systems appeared in power and energy applications. The first study was reported in 1999, in which the FCM approach was proposed to model a steam boiler mill fan[61]. A year later, a two-level power system was modeled using for the first time using FCMs[62]. Papageorgiou *et al.* used a two-level hierarchical structure to model first-time radiotherapy for breast cancer, obtaining very high accuracy results[63]. Doukas *et al.* used fuzzy ruled sets to study for the first time an "intelligent building"[64].

Investigators reported the emergency management of a nuclear power plant as a challenging problem[65]; they applied FCM for the first time as early as 2008, when FCM theories had not yet identified their limitations and drawbacks. To model abnormal situations in a nuclear power plant, the authors used FCM to determine the decision-making process. This procedure is a complex multivariate process that requires experts with a fundamental background and substantial experience. The process is analyzed by nuclear reactor operators based on a set of instructions and flow charts. These instructions mitigate the consequences of operation failures, whose primary characteristic is linear representations of events within a scenario, even though this process is not linear. An FCM approach was introduced by the authors for the emergency operating procedures (EOPS), simulating different cases, such as the loss of coolant accident scenario in a boiling water reactor) with the Mark II containment. The proposed methodology designed and based on experts in nuclear power represents the experts' reasoning with high fidelity and provides an efficient decision-making tool for reactor operators. The simulation results show that the FCM correctly predicted the phenomenon in the reactor vessel and primary containment.

In December 2012, Kyriakarakos *et al.* used the term FCM for Petri Nets EM system for autonomous poly-generation microgrids[66]. Petri Nets and FCM were used to optimize an energy grid in that study. As an optimization algorithm, a platform consisting of TRNSYS, TRNOPT, and GenOPT software packages was used for the simulations and *Particle Swarm*. The authors designed an FCM-Petri Nets EM system and a simpler two-state (on/off) microgrid. The former method produced an effective energy distribution, which led to a considerable decrease in the sizing of the microgrid's components.

Two studies demonstrated the use of FCMs for modeling the highly nonlinear and challenging problem of modeling wind energy systems[67]. Scenario analysis identifies alternatives for the future state of technologies, needs, policies, and environment. Scenario planning helps to overcome thinking limitations by presenting multiple futures. FCMs are based on causal cognitive maps and combine the benefits of qualitative and quantitative analysis uniquely for wind energy studies and actual system design for real applications. Around the same time (2012-2014), the Laboratory for Automation and Robotics of the University of Patras was extensively researching energy and power systems using FCMs.

In 2013, FCMs were for the first time used to model hybrid energy systems[68]. Hybrid energy systems produce energy with a combination of more than one source (e.g., solar and wind) and are ideal for applications where some sources are periodically unavailable. FCMs perform well even with missing data and despite existing nonlinearities in the system. The obtained simulation results verified the effectiveness and reliability of the proposed FCM hybrid energy system[68].

Fuzzy control was used to study the energy efficiency of a building[69]. A performance comparison of fuzzy control *vs.* FCM theories was performed, and compelling results were obtained. An increase in the energy efficiency of a building was obtained using multi-level intelligent controllers to manage the various components of a building's automation. Simulation studies were performed using actual environmental conditions in Western Greece in 2014 and data from a large building at the University of Patras. The results were beneficial, demonstrating an increase in energy efficiency of 20%-25%.

The well-known BEMS was modeled using FCM theories[70]. That study used FCM to model the total energy dynamic behavior of an autonomous building for residential or commercial use. To construct the FCM controllers, energy requirements for two buildings in southern Greece were analyzed. Simulations were conducted using the building's actual and weather data for three years.

The findings revealed some interesting conclusions. (1) The benefits offered by FCMs in complex dynamic problems (CDS) involving many parameters. For example, the CDS parameters can be increased or decreased without having to model the system from the beginning. (2) The method obtained rapid and accurate results regarding how to use the building automation when the parameters and other related data of the CDS are constantly changing without wasting time in the mathematical modeling of the problem. (3) The model suggested implications for energy savings. (4) Energy engineers and technicians unfamiliar with mathematical modeling and simulation studies can easily use the proposed FCM approach. These individuals do not need to understand thoroughly the theories of energy efficiency and savings and controlling concepts of building automation. (5) The simple and innovative proposed FCM approach enables control of the automation of the building based on the actual needs of buildings while saving energy.

A national-level wind energy roadmap for Pakistan was developed through scenario planning[71]. Multiple future scenarios were developed using the FCM approach. This research extended technology road mapping using FCM-based scenario analysis. Scenarios with FCM were developed for the wind energy sector in Pakistan. If these scenarios were implemented, an estimated 15%-20% energy savings would be obtained for

Pakistan[71]. Using linguistic relationships and FCM methods, dynamic environmental factors were identified that are essential for energy production by photovoltaic and wind technologies or other RESs[72]. Such a model is helpful for governments and investors to make decisions regarding future energy investments.

A study examined how FCMs can affect buildings' energy efficiency[73]. Advanced automation control systems for intelligent buildings were analyzed to minimize the energy needed in buildings for better efficiency without sacrificing comfort. The approach demonstrates how an FCM can make an energy-efficient decision based on climate data and an expected operation. FCM methodology was also used to increase the energy efficiency of buildings[14]. Other studies using FCMs methods present interesting and useful results in obtaining energy savings and increasing building energy efficiency[74,75]. Three expert intelligence tools were developed for EM, improving decision-making related to fault detection and diagnostics and intelligent predictive maintenance of essential building equipment. Surveys on energy efficiency in buildings with FCM methods were published in 2020[76,77]. In one of these studies, control systems for EM and comfort in buildings were presented with recommendations for controlling parameters by implementing FCM architectures[76]. Presenting new equations for the concept values calculations in FCMs; other authors focused on modeling a nearly-zero-energy building[77]. Using this advanced FCM method and considering environmental variables, methods of energy production, and consumptions in a few concepts established a robust base for the importance of the FCM theory.

Two studies reported FCM in characteristics and scenarios of solar and the root barriers in energy development in Iran[46,78]. The FCM approach was implemented to examine how the system's parameters dynamically interact. A survey and two workshops with the participation of several multidisciplinary stakeholders led to a participatory stepwise framework[46]. A semi-quantitative model was formed in an integrated FCM model comprising 31 interwoven concepts. The study suggested that FCM in many activities of Iranian daily life would benefit the energy policies for energy savings annually while simultaneously achieving a profound reduction in CO_2 emissions. Based on lack-based data envelopment analysis and FCM, their integrated approach proposes solutions to improve development and provides a clear view of the effects of each improvement solution and their causal relationships[78].

A review of control techniques for HVAC Systems - nonlinearity approaches based on FCM - shows that the FCM approach is the only method that can address challenging problems associated with nonlinear systems and has characteristics of uncertainties, ambiguity, and fuzziness[79]. A novel control strategy for EM in plug-in hybrid electric vehicles based on FCM demonstrates the usefulness of the approach[80]. A suitable FCM controller for air-conditioning systems to reduce energy consumption was investigated[81]. This FCM methodology for controlling the direct expansion air-conditioning system accurately tracked the set point while maintaining appropriate temperature and humidity values, despite disturbances in heat and moisture.

FCM theories were applied to healthcare centers, and the influence of maintenance operations on energy consumption and emissions was investigated[82]. The qualitative analysis of this work shows the effect of maintenance intensity on energy consumption, energy costs, and emissions in healthcare centers. FCM theories were used for the first time to determine how many and which specific relevant variables are involved in the maximization of the building efficiency of the healthcare centers. Twelve variables were observed to show a direct connection to energy and environmental efficiency and its maintenance condition.

Investigators proposed a methodological framework with FCMs, a semi-quantitative modeling application to evaluate different strategies in the energy efficiency sector[83]. The authors implemented an open-source MATLAB-based application for modeling FCMs and tested it in an application for enhancing energy efficiency based on Greece's national plan. Their findings suggest that long-term energy efficiency measures focus on behavioral changes in the residential sector.

An exciting approach to solar-based energy transition for the case of Greece was presented[84]. The authors considered the barriers and consequences and employed an FCM model to identify this transition's most critical implementation and substantial risk. The model simulated several scenarios, comparing the relative performances of the different policy strategies.

Quantitative evidence for urban energy conservation focused on policies provided by implementing an FCM[85]. The authors developed a framework that integrates urban residential expenditure and sectoral energy consumption and clarifies how these indicators influence each other. Using data from Beijing revealed that policies regarding controlling resident spending contribute to reducing Beijing's sectoral energy consumption.

Scenarios for PV solar energy development in Brazil with the help of FCM were presented[86]. Barriers in the Brazilian energy sector with the potential for solar energy utilization due to the country's geographic location were explored with FCM development, providing a quasi-quantitative model for scenario planning. The online tool FCMWizard was used in a dynamic and complex system of the renewable energy sector. The findings highlight the economic and political influence on development.

Investigators employed FCMs to semi-quantitatively explore different scenarios of wind energy deployment in Iran[87]. Through participatory workshops and a subsequent questionnaire survey, authors identified 26 influential factors as the dynamics of their FCM-based framework. As different scenarios were analyzed, one showed optimistic results in wind energy development.

An FCM for indoor temperature forecasting was implemented, and an evolutionary learning algorithm was developed to select the most significant concepts, sensors, and the weights of causal influence between them[88]. The findings suggested reducing the number of concepts by selecting the most important ones and high forecasting accuracy. Another interesting approach was introduced by the authors[89] in forecasting solar energy with fuzzy time series using high-order FCMs. The proposed hybrid method combines weighted high-order fuzzy time series with high-order FCMs. Public data from solar stations in Brazil from 2012 to 2015 for their solar energy forecasting demonstrated that their method achieves the best results with few concepts.

This overview of FCM in EM and efficiency demonstrates that FCM use is severely limited. Nevertheless, FCM is beneficial in several applications. A reference study presented FCMs for decision-making and prediction in optimization processes[11]. This proposed methodology is clustering concepts using k-means and popular evolutionary algorithms for learning. This case study demonstrated their approach's functionality to analyze an energy prediction dataset, with energy data recorded for four and a half months from a low-energy house[11].

Other applications and helpful studies were also described[12,90,91]. An FCM approach to energy-efficiency policies for decarbonizing residential heating demonstrated the usefulness of FCM in Spanish residential sectors[92]. A review of theories and applications of FCMs for the decade before 2013 was also performed[44].

Investigators employed FCMs to semi-quantitatively explore the scenarios of wind energy deployment for energy savings in Iran[87]. The findings highlight the possibilities for government decisions in complex macroeconomic and political settings for economic benefits for the country.

An FCM technique was proposed for web effort estimation, which is a critical challenge in software engineering when they are developed for EM and energy savings in any building[93]. A master's thesis generated a decision support tool based on an FCM software tool focusing on households as the users with the objective of energy savings of the building[94]. The practical use of this FCM technique is toward the residents' attitude toward the transition, and the data for the evaluation of the attitude were collected from an online survey using the concept of the technology adoption model.

Another study proposed a fuzzy logic control EMS for commercial loads with a hybrid grid-solar PV/battery energy system[95]. The obtained results show the applicability of FCM methods on EM tasks. A recent chapter from an edited volume described FCMs as computing frameworks to assist cities in becoming smarter and more resilient[96]. In this experimental research work, the study area was confined to a portion of a housing estate, and the data acquisition tools were in the public domain. The objective was to test the algorithmic process to capture urban environments built in an augmented reality model within the FCM framework.

SOME DRAWBACKS AND NEW CHALLENGES FOR FCMS

FCM theories existed only for 40 years, while approaches such as artificial intelligence are more than 80 years old. FCMs have not been used as extensively as other theories. Several drawbacks and limitations were identified while using FCM on challenging applications despite the beneficial results obtained[97-100]. Thus, FCM theories and methods must be re-examined on a scientific basis. FCM theories take seriously the human values embedded in a process, seeking knowledge while exploring the causality of the processes of CDSs.

The FCM model is a promising and innovative approach for studying and controlling a CDS. This model can determine the most significant structural elements and the dynamic behavior of a CDS. Frequently, FCM methods constitute an efficient, comprehensive, and practical mechanism for analyzing and predicting the evolution of CDS data. For years, numerical data have been considered crisp, with exact values. By contrast, most data are fuzzy, uncertain, or challenging to mine, and therefore their exploitation needs an exact mathematical model, which may be costly, complex, or even impossible. Considering the lack of formal models, humans should introduce knowledge and rely on natural language arguments.

An FCM has qualitative rather than quantitative attributes. FCM methods are not statistical approaches in modeling and analyzing complex systems. They are based on causality and not correlation. This is a significant scientific statement that must be stressed and clearly understood. The FCM approach can model a complex system with dynamic behavior that comprises various components in a simple, flexible, and straightforward way. An FCM model can explore any characteristics of a CDS with the help of the following six characteristics:

1. They define the causality between all subsystems/components of the CDS. This causality must indicate a positive, zero, or negative relationship.

2. The nature of the causal relationships between the subsystems always assumes fuzzy values.

3. The causal links between the subsystems/components are always dynamic and never static.

4. The history of the CDS model should always be available, well-defined, and reliable. If not, search for it.

5. Human-like reasoning must always be taken seriously.

6. Experts with a solid knowledge of the overall behavior of the CDS are always available. If not, seek them.

Considering these characteristics, one can always model, analyze, and control any natural or human-made CDS. As in all cases of new theoretical methods, there are always drawbacks and limitations[14,67,72]. The first major drawback lies in the fact that the concepts of an FCM model are investigated altogether. All equations of the mathematical model of FCM include all concepts[98]. However, this should be avoided in any scientific approach. For example, in early FCM theories, some concepts did not affect others, which remained static throughout the iteration process. However, due to Equations (1) and (2), all concepts are updated immediately after the first iteration. This is not true; consequently, the model sometimes leads to incorrect results. This outcome depends, of course, on the nature of the problem each time.

Another drawback is in the "concept vector" C, which includes all variables/concepts, defining the same iteration step k in Equation (1) for all concepts. Concerning actual problems, the question is why the inputs and outputs of a CDS when considered as concepts, must change simultaneously at every iteration step k? For instance, on a health problem while treating a patient: the inputs (concepts) (e.g., the dose of a drug given to a patient every morning) and the outputs (concepts) (e.g., X-ray or biopsy results) monitored once a month are updated simultaneously, taken every time the health conditions (concepts) are monitored every hour or every six-hours. Why does one calculate using Equation (1), which is the case using FCM theories, especially Equations (1) and (2)? The same question holds for Equation (3), which updates the weights of all concepts at the same iteration time. However, this approach cannot be taken seriously.

Even the calculation method of the values of the concepts, Equation (1) has a severe drawback problem. It considers the change that each concept causes separately instead of the total change caused by the concept C_i. This fact leads to a significant increase in the value of the concept C_i that extends far beyond the interval[0, 1]. Thus, the sigmoid function [Equation (2)] is needed to suppress the estimated result to the interval[0, 1]. However, due to the shape of the sigmoid curve, any concept value beyond 3 leads the sigmoid function to correspond to the value 1, which is problematic as the final output corresponds to the linguistic variable "high".

However, continuing with the sigmoid function [Equation (2)], there is another drawback that leads to high output values. This is because the center of the sigmoid curve, instead of being on the (0, 0) point on the XY axis is on the (0.5, 0) point. This means that each concept's lowest value can be 0.5. This drawback has been considered, and a solution to overcome it has been provided[97].

Similarly, the learning algorithms of FCM theories are subject to other drawbacks and limitations. Having conducted several simulations using non-Hebbian learning methods and Equation (3), we observed the following: considering the way weights are calculated [Equation (3)], the causality reverses, and all or some of the w_{ij} become positive in the case that the number of iterations of the algorithm is increased to reach a steady state. The causality between concepts changes as it was initially given by the experts, making it a significant drawback. Thus, on several occasions, instead of reaching the correct values of the concepts, the obtained results were unacceptable. This drawback significantly complicates interpreting the results correctly. Finally, maintaining a stable running system is difficult when the problem has predetermined stability.

For these reasons, the early FCM methods have been referred to as the classical theories of FCM or simply the classical FCM methods[13,97,100]. Groumpos addressed several of these drawbacks and provided some solutions[98].

Let us readdress the problem of the concepts being considered as one vector.

Even when a CDS is described using fuzzy characteristics through an FCM approach, the primary mathematical idea is the same. Each system has its states, inputs, outputs, and other parameters and constraints. Representing such a system, FCM should consider these fundamental characteristics. On this basis and following the classic control theory methods[99], the concepts of an FCM are classified into the following three categories:

A. State concepts, x

B. Input concept, u

C. Output concepts, y.

In this way, a better understanding of the overall behavior of the CDS is gained. This classification offers insight into the system's operation and contributes to calculating the values of states, inputs, and outputs in their physical nature, representing the concepts of the real system. This categorization of the FCM concepts was first proposed by Groumpos[44]. This new approach is referred to as the AFCM method. More specifications and definitions of these AFCM theories were described[13,14,43,69,73,77,100-102].

FUTURE RESEARCH CHALLENGES OF FCMS IN EM AND EFFICIENCY

Based on the presentations over only 40 years and the findings of FCMs, the future research directions are many and open in all aspects. A challenging and promising research area is the development of the new AFCM models, as proposed[70-73,97]. In this effort, concepts associated with EM and energy efficiency must carefully be separated by energy experts jointly with control engineers to state input and output concepts. AFCM can investigate system characteristics such as controllability, observability, stability, and reachability. New learning algorithms are needed for the AFCM models. New software tools must be developed.

When FCM theories are used methodologically and extensively, intensive studies in this research direction can achieve new and higher levels of energy efficiency for residential and commercial buildings. Developing AFCM models for energy management-energy savings of buildings (especially large ones) appears promising. A challenging research area is applying FCM (classical and advanced) methods to several real applications of large buildings (e.g., schools, hospitals, government buildings, manufacturing plants, ports, and public buildings). The recent topic of nearly-zero-energy buildings offers many opportunities to investigate the use of classical and advanced FCM models.

Causality must be investigated, and its difference from correlation needs to be studied. Another challenging future research direction is specific real-life applications and results to be compared with other today's methods, especially statistical studies. Another challenging research topic is defining the concept of intelligent buildings[13,14,102]. How can a building be made intelligent? Intelligence does not always come with technologically advanced systems. For example, there are cases in which intelligent buildings do not incorporate information and communication technology tools or not-so-intelligent buildings that integrate state-of-the-art technology. Hence, efficiently managing a building's components is essential in defining its state of intelligence. The building is a high energy cost and environmentally hazardous machine without efficiently managing its components. Energy efficiency is achieved through the contribution of building automation components, and using RES is an essential and promising research field[103,104]. The challenging research topic is to use AFCM in developing realistic, intelligent buildings.

CONCLUSIONS

EM is the process of monitoring, controlling, and conserving energy in a building or organization. Much of the importance of energy saving stems from the global need to save energy. Different methods and approaches have been implemented to provide EMS. FCMs were introduced only in 1986[35]. Their use in EM and energy efficiency has been minimal. Studies have only reported on these essential energy systems issues in the last ten years. The importance of causality in these systems has not been well understood or sufficiently utilized. This review is the first comprehensive EM and efficiency survey using the new FCM theories. It is critical to realize that the few limited studies reported in this paper demonstrate the potential of FCM models and theories in energy savings in many aspects of everyday life; this is especially true in energy buildings.

FCMs provide a tool for capturing the system behavior from available information. Proper vertex selection is critical because the relevant concepts of the system should be identified, and their activation must be modeled so that causal relationships are properly identified. The FCM provides a new strategy for predicting effects and causes in an energy system.

This paper provides for the first time an overview of FCM theories for EM and building efficiency, with information for the reader to understand this essential scientific topic. This review shows that the FCM approach was used only in the last 15 years and obtained excellent results. We also highlighted the drawbacks of classical FCM theories and provided concepts for dynamic AFCMs that solve some of these problems. Finally, this paper discusses future challenges and research directions.

DECLARATIONS

Authors' contributions

Conceptualization, methodology, review analysis, and investigation: Groumpos P, Papageorgiou EI
New challenges: Groumpos P
Writing - original draft preparation: Groumpos P, Papageorgiou EI
Writing - review and editing: Groumpos P, Papageorgiou EI

Availability of data and materials

Not applicable.

Financial support and sponsorship

None.

Conflicts of interest

Both authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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