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SURVEY AND STATE OF THE ART

Fuzzy cognitive maps in systems risk analysis: a comprehensive review

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Abstract

Fuzzy cognitive maps (FCMs) have been widely applied to analyze complex, causal-based systems in terms of modeling, decision making, analysis, prediction, classification, etc. This study reviews the applications and trends of FCMs in the field of systems risk analysis to the end of August 2020. To this end, the concepts of failure, accident, incident, hazard, risk, error, and fault are focused in the context of the conventional risks of the systems. After reviewing risk-based articles, a bibliographic study of the reviewed articles was carried out. The survey indicated that the main applications of FCMs in the systems risk field were in management sciences, engineering sciences and industrial applications, and medical and biological sciences. A general trend for potential FCMs' applications in the systems risk field is provided by discussing the results obtained from different parts of the survey study.

Keywords System risk · Error · Fault · Failure · Fuzzy cognitive map

Abbreviations

BBN	Bayesian belief networks
ERP	Enterprise resource planning
FCMs	Fuzzy cognitive maps
FGCMs	Fuzzy grey cognitive maps
HFCMs	Hesitant fuzzy cognitive maps
NFCMs	Neuro-fuzzy cognitive map
FIS	Fuzzy inference system
FMEA	Failure mode and effects analysis
GA	Genetic algorithm
MS-FCMs	Multi-stage fuzzy cognitive maps
NHL	Nonlinear Hebbian learning
PSO	Particle swarm optimization
TOPSIS	Technique for order of preference by similarity to ideal solution
MOORA	Multi-objective optimization on the basis of ratio analysis
PROMETHEE	Preference ranking organization method of enrichment evaluation
ISM	Interpretative structural modeling
DEA	Data envelopment analysis
SEM	Structural equation model

Introduction

The modern world relies on sophisticated human systems and new technologies to make decisions in the presence of uncertainty. As a result, decision-makers attempt to control the risks that arise from the complexity of those systems when making decisions [69]. Exposure to risks is inevitable in fields such as management, engineering, medicine, etc. Decision-makers use techniques to assess potential risks within the scope of risk assessment and to analyze the causes and effects associated with them [101]. Therefore, a variety of qualitative and quantitative techniques have been developed and applied in various sciences and industries [155]. However, the complexity of a technique for analyzing the relationships between risks and risk factors, the completion time of analysis, the level of robustness, and the reliability of the risk analysis techniques are potential features to be taken into account [77].

In the meantime, fuzzy cognitive maps (FCMs) can simultaneously analyze risk-based factors in a system by considering the causal relationships between them. An FCM

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can therefore be used as an effective decision-making tool in systems risk analysis and management. Time can be saved by using the FCM methods, especially in modeling complex systems when many variables interact and there are some restrictions with the expert interactions [49, 53, 105]. FCMs help decision-makers to consider cognitive mechanisms that affect the decision-making process in risk management, and to provide corrective/preventive measures for system performance improvement [27]. Other features of the FCM method are the ability to model complex systems with limited and missing data or in the case of high costs for data collection [103], the ability to display what may be happening in the system due to causal relationships and their initial states [21], and the ability to reduce dependence on expert opinions in comparison with the majority of decision-making techniques [24, 123]. Therefore, in the field of systems risk analysis, the current and future status of a system can be analyzed and predicted using FCMs along with other analytical and scenario-making techniques. To put it differently, applying the FCM method enables decision-makers to monitor the future status of the system through scenario making technique and using learning algorithms as well as analyzing the current state of it. Moreover, this method enables decision-makers to provide preventive or corrective measures to control the adverse effects of risks. Thus, identifying the features of the FCM and the way of implementing this method in dealing with various problems in the field of risk analysis such as decision making, modeling and forecasting can demonstrate the importance of this method as a useful tool.

In recent decades, several researchers, especially Papageorgiou, Salmeron, Groumpos, and Stylios, and their research groups have developed FCMs and learning algorithms with different applications. Their attempts have led many research groups to develop and apply FCMs in various fields. The main review papers on FCMs are described as following. One of the first review papers on FCMs was done by Stach et al. [142] to investigate algorithms designed to improve the accuracy of causal relationship weights and map structure. In other words, the main purpose of this study was to investigate FCMs learning algorithms and classify them into two categories including Hebbian learning rule-based methods and genetic algorithm (GA), which is one of the population-based algorithms. In the following, Papageorgiou [110] reviewed research work that represented and developed learning algorithms related to FCMs. They categorized them into three groups based on population, Hebbian, and hybrid algorithms. Papageorgiou [111] reviewed research work with the trends and applications of FCM in a decade. They attempted to outline the growth trend of FCM applications to improve its applicability in various fields. In addition, Papageorgiou and Salmeron [112] surveyed studies with FCM applications in different fields over a decade. They summarize the knowledge state of FCM to provide a clear understanding of that for future works.

Furthermore, Felix et al. [44] reviewed software and solution tools based on FCM methods. In this study, learning algorithms, basic FCM concepts, and their properties have been investigated with a focus on time series forecasting and classification application of FCMs. Amirkhani et al. [7] reviewed recent decision-making studies with FCM applications in the medical field. They categorized these applications into the areas of decision-making, classification, prediction, and diagnosis. The existing review papers in the field of FCM can be classified into two categories including the introduction of the FCM (the structure of the method and learning algorithms) and its applications. Accordingly, the present study, unlike most previous studies that have focused on the theoretical concepts of the FCM, has tried to examine its applications in dealing with real-world problems to guide researchers and professionals in the path of future studies. Besides, due to the pervasiveness of the systems risk analysis concept in various fields, especially engineering and medicine, as well as the high uncertainty of the related problems, this topic has been considered for the study.

This paper reviews articles published in the field of risk-based analysis that used FCMs as an analytical or decision-making tool. The main aim is to provide a framework for how the applications of the FCM methods can be increased in the case of systems risk analysis. Therefore, the concepts that refer to conventional or systemic risks in a system are focused. To this end, articles published with the keywords “cognitive map” and “failure”, “accident”, “incident”, “hazard”, “risk”, “error” or “fault” are considered. A search of the Web of Science database to the end of August 2020 resulted in 261 articles found. After reviewing these articles and removing unrelated ones, 89 articles remained for further investigation. This review not only studies the applications of this method in systems risk analysis, but it also provides recent trends and future research paths for researchers in the field of FCMs-based risk analysis.

The remaining contents of this review are as follows. Section "Background" studies the background of systems risk analysis and FCMs in two separate sub-sections. In Sect. "Systems risk analysis applications", the applications of FCMs in the field of systems risk analysis are reviewed. In Sect. "Results", a bibliographic study of the reviewed articles is carried out. Section "Future trends" discusses the limitations and suggestions for future research in the field of systems risk analysis using FCMs. Conclusions are presented in Sect. "Conclusions".

Background

Risk analysis

Various terms such as objective uncertainty, the effect of uncertainty on objectives, probability of an (undesirable) event, uncertainty potential/possibility of a loss, the expected value (loss), consequences/damage/severity of consequences with uncertainty, and event or consequence have been used to express risk definitions in different fields [13]. In the layout of risk management, risks should be analyzed and addressed by making decisions to effectively control them [15]. Risk management systematically applies management policy processes to determine, identify, control, and minimize the effects and consequences of potential events. Risk identification and assessment are the main core of a risk management system [69].

Risk identification is the process of searching for and recording risks to recognize what might happen or what situations may occur that can influence the achievement of the goals of the system. Risk assessment is used to determine quantitative and qualitative risks and to investigate the potential consequences of accidents on individuals, materials, equipment, and the environment [3, 140]. Risk assessment in three stages of identifying, analyzing, and measuring risks is aimed at reducing the negative impacts of identified risks in developing activities and improving the performance of decision-makers [62, 154]. To this end, risks can be ranked to assist managers in identifying and evaluating areas with high risks, the necessary controls, and then adjusting techniques for those required controls [23]. After identifying risks, analysis, and assessment of the risks can be done based on three factors: occurrence probability, severity, and detection using the conventional failure mode and effects analysis (FMEA) method [20, 69].

Risk analysis considers the sources and causes of risk, consequences, and the probability of these consequences for identified risk events, assuming their occurrence or non-occurrence and the effectiveness of each available control. In this situation, the level of risk can be determined by integrating the consequences and probabilities of the risk. Risk measurement determines the importance of the level and type of risk by comparing the estimated risk levels with defined risk criteria. Risk measurement utilizes the risk perception established during the risk analysis process and determines when a decision should be made on future actions by taking ethical, legal, and financial considerations into account. These decisions may include the need to address risk, prioritizing how it is addressed, undertaking the necessary activities, and selecting an appropriate course of action [63].

Fuzzy cognitive maps

Tolman [150] introduced the term "cognitive map" for the first time, and since then many researchers have represented and developed this subject. Axelrod [14] developed a cognitive map in the field of social sciences. The materials developed by him are close to the dynamics of systems. In general, regarding the structure of the FCM, this method can have various applications, especially decision-making and modeling. Furthermore, the capabilities of this method, such as the ability to model complex systems with limited and missing data or in the situation in which the data collection process is expensive, has increased its application domain [103]. Although this subject has been introduced in the field of psychology, its applications have been developed in other disciplines such as geography [87], education [37], systems control [51, 52], transportation [18], medicine [10], supply chain [6], banking [17], engineering [22], energy [5], and environment [117].

Kosko [76] developed an FCM based on the fuzzy logic introduced by Zadeh [163]. Following that, several researchers have conducted FCMs in various fields. FCM is a soft computing method that can be used to recognize, describe, and model complex systems [147, 166]. FCM is a general term for a set of methods that helps the decision-maker to obtain a graphical description of the person's perception in relation to a particular discussion or problem that is easy to understand and can provide a suitable insight into the structure of information [78, 141]. FCM is a process in which a network of elements and relationships of a complicated phenomenon is represented as a graph or map, and as a qualitative model it can show how a system operates [12, 25]. The FCM method does not predict any numeric, but it shows what happens in the system based on the relationship between concepts and the initial state of concepts [124].

An FCM is introduced by the basic features of concepts and causal links [142]. Concepts are represented as nodes and causal links in the form of arcs between nodes in FCMs [92]. The nodes or concepts indicate the information of the system under investigation, such as attributes, characteristics, qualities, variables, and states [1, 108]. Concepts can have direct or indirect relationships with each other or have no relationship [66]. The relationships between nodes can be in states of positive, negative, and neutral, which express the type of relationship between concepts and the degree of causality [107]. In Fig. 1, a sample of the FCM method with its components is shown.

Where, C_i expresses nodes or concepts associated with the weighted arcs [114, 133]. Each relationship between the concepts C_i and C_j have a weight of W_{ij} (the weight between ith node and jth node), which might be positive, negative, or neutral (indicates that two concepts under consideration have no relationship) [36, 128]. Based on the

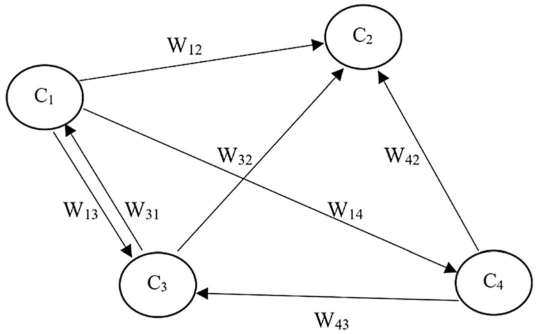

Fig. 1. Sample cognitive map

FCM developed by Kosko [76], the relationship between concepts is changed from the state {0,1} or {− 1,0,1} to a set of states by a number in the interval [0,1] or [− 1,1] or fuzzy linguistic terms [129, 130, 135].

After drawing the map, mathematical formulas are used for modeling. Although different mathematical calculations of FCMs have been developed by researchers [54], the basic formulas are focused in the current study. By finding the values of a node, other nodes associated with this node must be determined through Eq. (1) [146]:

$$A_i^{(k+1)} = f\left(A_i^{(k)} + \sum_{\substack{j=1 \\ j \neq i}}^{n} W_{ij} A_j^{(k)} \right) \tag{1}$$

where $A_i^{(k+1)}$: the value of concept C_i in iteration, $A_i^{(k)}$: the value of concept C_i in iteration, $f\ (x)$: the transformation function.

The matrix system is given in Eq. (1) can be re-written as Eq. (2).

$$A_{\text{new}} = f(A_{\text{old}} + \sum W \cdot A_{\text{old}}) \tag{2}$$

where A the matrix of concept values ($1 \times N$ vector), W the weights between concepts of the system (an $N \times N$ matrix).

Transformation function (f) returns the resultant values to defined ranges, while the product of two matrices is greater than the defined value for variables. This action assigns a significance level to each number. Several functions such as sigmoid function with different coefficients. λ ($\frac{1}{1+\exp(-\lambda x)}$) and hyperbolic tangent (Tan$h(\lambda x)$) can be used to explain the transformation function [24, 134]. Finally, FCM calculations can be continued through Eq. (2) to reach one of the following states [107]:

- Until A_{new} is equal to A_{old} or there is a slight difference (stable state).
- Reveals a limit cycle behavior in the case of concept values going down in a loop of values in a specific period.
- Reveals chaotic behavior in the case of each value getting a variety of values in a random way.

Historical data and the opinions of experts can be used to draw FCMs. In a calculation-based FCM, time-series data is utilized as input and a neural network serves to approximate the weights of a map. This opinion is categorized into automated and semi-automated groups [142]. The semi-automated category is often used to draw a map. In this category, some inputs are required to draw an FCM that derives from the knowledge and experience of an expert in the related field. Accordingly, concepts and the causal relationships between them can be drawn [124]. In the automated category, numerical vectors are converted to fuzzy sets, which are introduced by Zadeh [163], and the degree of similarity between the vectors and the type of relationship (direct and inverse) between them is determined using fuzzy logic. To determine the weight of relationships based on the similarity between the vectors related to the two concepts under study, the relations presented in Schneider et al. [139] research are used,in which, the way of addressing the direct and inverse relationships has been distinguished from each other. The automated type of drawing is based on historical data only and does not require human inference [139, 142]. Given that FCMs can model a variety of simple and complex systems with an infinite number of concepts and links, they have become a useful tool in modeling,therefore, a variety of FCMs has been developed.

After drawing FCMs, estimating the precise weights of the map is a very important problem [124]. The opinions of experts are the basis of most of the FCMs [2]. Human knowledge is an important tool in the design process of different kinds of maps, but in some cases, there is no expert opinion or the stated opinions are subjective and imprecise [136]. As well, there might be many more variables and components [7]. Therefore, it is necessary to present a mechanism to address these problems. Learning algorithms have been recently proposed to increase weight accuracy, decrease the dependence on expert opinions, and improve maps' performance by producing a learned weight matrix [111, 120]. Therefore, applying these algorithms contributes to solving the problem of the map's convergence and making reliable decisions [123].

Learning algorithms can be supervised or unsupervised [105] These algorithms have different training patterns,in supervised algorithm labeled patterns are used, and in unsupervised algorithms, unlabeled patterns are used [40]. Learning algorithms are divided into four categories: Hebbian-based, population-based, hybrid algorithms, and other algorithms [136]. Each category has its own characteristics and consists of some algorithms. One of the main unsupervised learning algorithms is the Hebbian-based algorithm [153], which was introduced by [76] to modify the weights of FCM during several iterations, to achieve desired value based on unsupervised Hebbian learning rules [58].

In the first category, Hebbian rules-based learning algorithms, such as Differential Hebbian [41], Nonlinear Hebbian [104], Balanced Differential Hebbian [60], and Active Hebbian [105], work intending to update the weights of causal relationships using available data and Hebb rule amendments in multiple iterations. The main disadvantages of this category are the high volume of calculations and low search power [136]. In the second category, population-based learning algorithms can decrease the effects of experts' opinions in ascertaining the initial weighting matrix and provide the ability to use different objective functions in the learning process based on the type of problem [7]. Several population-based algorithms, such as multi-local and balanced memetic algorithms [134], asexual reproduction optimization and its modified version [136], etc. have been developed. Hybrid learning algorithms as the third category are based on Hebbian-based and population-based algorithms, which can employ human knowledge together with historical data to adjust the weighting matrix. One of the main algorithms in this category is a combination of Nonlinear Hebbian and differential evolution algorithms [106]. In the last category, there are new algorithms that are not in the main three groups and have been introduced to solve some of the problems of the previous algorithms. For example, an extended Delta rule algorithm has been introduced by Rezaee [124] to solve the problem of non-convergence in the Hebbian rules-based learning algorithms.

Systems risk analysis applications

In this section, published articles related to FCM applications in the systems risk analysis domain to the end of August 2020 are reviewed. To follow these studies simply, the problems which are solved through FCMs are described in six application subjects: decision-making (28 articles), modeling (14 articles), analysis (19 articles), prediction (7 articles), systematic learning (3 articles), and classification (2 articles). The decision-making subject includes identification, evaluation, diagnoses, and prioritization. Furthermore, 16 articles considered more than one mentioned subject simultaneously using FCM. These studies are included in subsection (4.7) as *hybrid*.

Decision making

Based on the literature, the first application of FCMs in the case of systems risk analysis belongs to the research by Choi et al. [35]. They evaluated risk communication strategies in the nanotechnology field using a risk cognitive map to identify nanotechnology risks and benefits, and to prepare for its application in products to the public. Lee et al. [79] used FCM to diagnose the on-line fault of the system and implemented it in a tank-pipe system. In a similar study, [73] proposed an FCM-based fault diagnosis scheme and used a fuzzy set theory and a neural network to find out the root causes of faults and to make the diagnosis scheme robust in the face of changes. In another study, [74] offered a fault diagnostic approach using FCM and applied principal component analysis to enhance the diagnostic results. He estimated target values by fuzzy inference rules and used fuzzy gradation to tune FCM. Then, [80] adopted a multi-agent FCM to analyze the risks of an information systems project and applied the PSO algorithm to calculate their causality coefficient.

Xiao et al. [161] combined FCM and fuzzy soft set to evaluate suppliers and select the best ones considering risk. They used FCM to weight evaluation criteria/attributes and consider dependence and the feedback effects among them. Also, the learning process of FCM was done using a PSO algorithm. Lee et al. [81] surveyed a group decision-making problem and presented an integrated approach based on an agent-based model, FCM, and PSO. In this study, FCM was used to represent experts' knowledge of the target problem [90] provided a decision-making tool using FCM in the healthcare field to analyze meningitis risk in children and infants. Augustine et al. [11] identified system interaction failure modes through FCM simulation and implemented it in an electric water heater system.

Brito et al. [39] identified body dysmorphic disorder risk in cosmetic surgery using FCM. Mouna and Anis [99] designed an FCM to extract causal knowledge and identify the failure factors and implemented it in stock market evaluation. Lee et al. [83] proposed a decision-making system to assess the lifetime of a rubber fender using FCM, fuzzy inference system (FIS), and the certainty factor method. They applied FCM to determine key factors that might affect a rubber fender's lifetime. Buck et al. [30] utilized the conceptual content FCM approach to identify patients' cognitive representations in heart failure self-care.

Recently, Mendonca et al. [94] studied reliability centered maintenance issues and used FCM to identify faults and defects in electric motors. They also provided maintenance actions to correct them and improve the system's performance. Rezaee et al. [124] developed the FCM and presented multi-stage fuzzy cognitive maps (MS-FCMs) to calculate a new score for risk prioritization. Also in this approach, they used the process failure mode and effects analysis to identify important risks in each subsystem. Han and Deng [57] presented a hybrid approach to recognize critical factors in a high-risk emergency system based on FCM. Firstly, they applied an affinity diagram to select potential critical factors and used the Dempster–Shafer evidence theory to combine experts' opinions. Finally, a decision-making trial and evaluation laboratory was applied to calculate the adjacent matrix of FCM. Rezaee et al. [125] applied process failure mode and effects analysis to identify risks in systems, including some sub-sections and prioritized determined risks using MS-FCMs. They verified this approach by implementing it in the food industry.

Rezaee et al. [127] proposed an approach to identify root barriers and prioritize improvement solutions in renewable energy resources management. They applied interpretative structural modeling (ISM), FCM, and data envelopment analysis (DEA) to this end. Dabbagh and Yousefi [38] carried out a study to determine and prioritize occupational health and safety risks. They presented a hybrid approach based on the FMEA, FCM, and multi-objective optimization on the basis of ratio analysis (MOORA) method, and implemented this approach in a manufacturing company. Bakhtavar and Shirvand [21] applied the FCM based on fuzzy weights so as to prioritize critical drilling and blasting factors in tunneling. Liu et al. [85] proposed a hybrid approach using FCM and Pearson's product-moment correlation coefficient to find critical factors affecting emergency management and enhance efficiency of which [61] studied the interaction between human and natural systems in water resource management. They integrated the FCM, agent-based model, Bayesian inference mapping, and cost-loss model. Trostianska and Semencha [151] employed FCM to diagnosing the reputational bank risks and used impulse modeling and scenario analysis to determine better risk management strategies. Khodadadi et al. [72] conducted a study using FCM with the aim of diagnosing the strike. They used the Non-linear Hebbian learning algorithm for FCM training. Ziolo et al. [168] presented a hybrid method using the FCM and preference ranking organization method of enrichment evaluation (PROMETHEE) method to prioritize environmental, social, and governance factors in financial decisions and rank financial systems based on these criteria. Amirkhani et al. [9] introduced neuro-fuzzy cognitive maps (NFCMs), an extended version of FCM based on the neuro-fuzzy inference system, to diagnose autoimmune hepatitis. They substantiated the NFCMs has high convergence speed and accuracy. Yousefi et al. [162] identified and prioritized critical logistics risks using sequential MS-FCMs and process FMEA and implemented them in an automotive spare parts company. Dursun and Gumus [42] employed FCM so as to determine the best supply chain configuration for studied companies, and evaluate supply chain risk factors, strategies, and performance criteria.

Modeling

Lee and Han [82] carried out a study in the information science field by applying FCM to model electronic data interchange. Glies et al. [47] modeled the thinking of Canadian aboriginal and conventional science on the causal determinants of diabetes through FCM to provide a framework for health management. Walshe and Burgman [156] analyzed the risks of emerging diseases so that FCM was used to model the problem, Bayes nets determined probabilistic relationships, and multi-criteria analysis was utilized to evaluate the consequences and effects of alternative decisions [118]. modeled animals' navigation through FCM considering environmental fields for that and used geometric techniques to predict error patterns in navigation. In modeling environmental issues, [137] used FCM with the purpose of mitigating natural hazards. They also applied a self-organizing map to improve FCM processing. Giordano et al. [48] proposed an approach to assess the impacts of drought at Lake Trasimeno. They used FCM to model the drought phenomenon and applied Bayesian belief networks (BBN) to analyze stakeholders' understandings of drought impacts. In a similar study, [59] presented a BBN-based knowledge management reliability approach to assess the reliability of the bank's knowledge management. In this approach, FCsM was used to model the knowledge management system and measure failure likelihood.

Ravasan and Mansouri [121] surveyed critical failure factors in enterprise resource planning (ERP) systems and modeled risks' interrelations in ERP implementation projects using FCM. Mezei and Sarlin [96] presented a hybrid approach to measuring systemic risk in a financial system. They used FCM to model the system and the Choquet integral method to aggregate the expert assessments of risk. Zhang et al. [165] evaluated the safety performance of oil and gas production plants using the combination of a relative degree analysis model, fault tree analysis, FCM, and fuzzy comprehensive evaluation. In the proposed approach, after determining critical risk factors by fault tree analysis, they modeled the system by the FCM relative degree analysis, and the overall safety level was calculated using a fuzzy comprehensive evaluation. Kang et al. [67, 68] evaluated oil-spill emergency response capability to reduce pollution and accidents. Their proposed approach includes FCM to model the system and calculate weights in the first level, analytic hierarchy process to find the weights in the second level of the distribution model, and fuzzy comprehensive evaluation to measure oil-spill emergency response capability level. Štula et al. [143] developed a self-adjusting FCM to apply in the case of reducing errors between values generated by FCM and real system data. Pourreza et al. [119] assessed the factors of health, safety, environment, and ergonomics in the energy area by integrating the FCM and Bayesian network.

In this study, FCM was utilized to construct a graphical model of the Bayesian network based on experts' opinions. Conditional probability tables of the Bayesian network were elicited by the noisy-OR method, and finally, important factors were determined by the Bayesian network. Mital et al. [97] constructed the decision-makers' mental model and provided a framework of a supply chain risk using FCM. Also, they used the analytic hierarchy process to find the importance of the criteria and evaluate them.

Analysis

In this field [116], used FCM to analyze failure modes and effects [88]. drew an FCM of a keyboard to analyze typing errors [160]. applied FCM to study depression and analyze the hypothesis of the depression occurrence. Medina and Moreno [93] used FCM to assess the risks of the electricity market as regulatory risk, electric risk, and social-political risk. Also, they applied FIS in designing FCM. After that [28], explored the application of FCM in analyzing the accidents at work in industrial plants. Mohagheghi [98] used graph theory concepts of FCM to analyze causal relationships and vulnerabilities of an automation system, as well as to show weak links in the system [4] combined a system based on human factors analysis and classification with FCM to evaluate the human factors in marine accidents. Papageorgiou et al. [113] applied FCM in medical science to analyze familial breast cancer among family members.

Park et al. [115] analyzed the root causes of the sentiment using FCM with relation to determining the main causes of faults in a system and applied fuzzy formal concept analysis to consider sentiment relations. Bağdatlı et al. [18] evaluated the cost and benefits of highway projects. Due to the inherent uncertainty of these projects, they utilized FCM including risk parameters to deal with such uncertainties and to assess the highway cost–benefit analysis. Bakhtavar and Yousefi [22] studied workplace accidents in the mining industry and proposed an integrated approach using multi-goal FCM and technique for order of preference by similarity to ideal solution (TOPSIS). They analyzed underground collieries accidents using FCM based on multiple goals and risk effects and did a sensitive analysis by TOPSIS to improve the safety of the workplace. Bevilacqua et al. [27] analyzed the risks of the drug administration process to ameliorate the quality of healthcare services using FCM. Rezaee and Yousefi [123] analyzed airport risks by presenting a hybrid approach based on FCM slack-based data envelopment analysis so that the former was used for risk analysis and the last method was applied to risk prioritization.

Wang et al. [158] applied FCM and FIS to analyze ship navigation safety status and used the Non-linear Hebbian learning algorithm to taring the FCM. Efe et al. [43] analyzed the interaction of hazards in a construction firm using the FCM. In the other study, FCM applied by Hamilton et al. [56] to analyze the wildfire risk in the American regions. Rezaee et al. [126] studied causal relationships among delay risk factors in construction projects. They used ISM, FCM, and DEA to analyze the impact of these factors on project performance. Onari et al. [102] considered concepts of uncertainty and reliability simultaneously in the systems risk analysis process by integrating MS-FCMs and Z-number theory. Besides, they presented a new learning algorithm based on the PSO and S-shaped transfer function. Chen et al. [46] proposed an approach using FCM and structural equation model (SEM) to analyze performance risks in public–private partnership projects.

Prediction

Salmeron and Lopez [131] used FCM to predict risk effects on enterprise resource planning maintenance goals. Azadeh et al. [16] took advantage of the prediction feature of FCM to predict housing market fluctuations. They also used fuzzy linear regression in their approach to deal with imprecise and fuzzy data in the studied problem. Wang et al. [157] implemented FCM to predict configuration errors in psychological issues. Tang et al. [149] proposed a novel genetic algorithm FCM path prediction approach to solving the problem of the risk of wireless disconnection between mobile terminals and access points. Li et al. [84] applied a simple FCM for the prediction of possible faults in using the internet, to ensure the reliability of transmission in hierarchical environments. Turner et al. [152] carried out a study to survey animals' navigation and used FCM to predict spatial patterns of initial orientation errors [55]. proposed a novel interval-valued FCM with real-coded GA to predict corporate financial distress, and they showed this approach has better performance than adaptive neuro-fuzzy systems, traditional FCMs, and fuzzy grey cognitive maps (FGCMs) in terms of root mean squared error.

Systematic learning

Wee et al. [159] analyzed start-up failure in the automobile industry, combining BBN and FCM. In their study, an approach was proposed to migrate BBN to FCM to describe causal strength intuitively. Brennan et al. [29] drew an FCM to provide a residential population's spatial perception of flood risk as an environmental issue. They also applied a spatial analytical method for the first time to recognize the boundaries of risk perception. Nagayoshi and Nakamura [100] studied organizational learning from failure and used the techniques of "unlearning," "media richness," and "FCMs and framing" to accelerate information interpretation and prevent recurring failures.

Classification

Considering FCMs' ability to deal with classification problems [7], studies have recently been conducted with this specific aim. Zhao et al. [167] assessed the impacts of membership in socially withdrawn peer groups and used social FCM to classify peer groups. Amirkhani et al. [8] proposed a hybrid approach integrating FCM and possibilistic fuzzy C-means to grade and classify Celiac disease. They used the nonlinear Hebbian learning (NHL) learning algorithm to train the proposed FCM.

Hybrid

Here, FCM was used to solve multiple subjects simultaneously, including *decision-making, modeling*, *analysis, prediction, and classification.* For example, to solve the *decision-making* and *modeling* problems simultaneously, some studies have used FCM in different scopes, such as engineering and management to model the evaluated system and determine the failures [144, 145] and risks [50] associated with the system. Büyükavcu et al. [31] utilized decision-based cognitive maps to determine the effective risk factors in breast cancer occurrence based on oncologists' knowledge, modeling the problem, and finally analyzing the defined risks. In addition, to solve *decision-making* and *analysis* problems simultaneously [95], used FCM to determine key factors that have the most effect in an environmental health impact assessment and evaluated the framing assumptions in this process.

Furthermore, there are some other studies that have solved both *modeling and analysis* problems simultaneously. Kontogianni et al. [75] implemented FCM in the marine industry for the first time, with the aim of modeling and analyzing the risks related to the Black Sea. To construct FCM, they used augmented individual FCMs for the Black Sea resilience. Salmeron and Gutierrez [132] applied FGCMs to model failure causes and analyze the failure defined through FMEA and the reliability of the system. Mago et al. [91] used simple FCM with the purpose of modeling homelessness as a social problem and analyzing the impact of social factors on it. Zaccaria et al. [164] studied agricultural issues and applied FCM to formulate the perception of water use in the agricultural field as well as to assess the risk of aquifer degradation related to intensive groundwater pumping. James et al. [65] identified failures in automobiles considering maintenance errors using an event tree diagram and determined their causes through the Fishbone diagram. After that, they modeled the maintenance error-caused relationship and analyzed the failures using FCM. Khanzadi et al. [70] modeled the causes of change orders in construction projects and analyzed them [86] presented a new version of the FCM based on the hesitant fuzzy sets called hesitant fuzzy cognitive maps (HFCMs). They aimed to model and analyze the impact of risks on the security of the electric power system by considering the intrapersonal hesitancy and the interpersonal hesitancy simultaneously. Jalilian et al. [64] applied intuitive fuzzy FMEA and intuitive FCM to model and analyze credit banking risks to reach acceptable financial stability.

To solve *modeling and prediction* problems simultaneously, [89] carried out a study about enterprise resource planning maintenance projects and modeled the dynamic risks of such projects using FCM. They also applied FCM to predict the impact of risks on the outcomes of these projects. Sarala et al. [138] utilized FCM to predict multi-stage attacks and to model the causally dependent events in the field of computer science-related problems.

Finally, to solve prediction and *classification* problems simultaneously, [148] proposed a two-level FCM to predict the post-screening risk of developed breast cancer and to classify tumor grading. In each level of FCM, different Hebbian-based algorithms have been used.

Results

In this section, the distribution of the reviewed articles with applications of the FCM method in the field of systems risk analysis studied up to the end of August 2020, is discussed. The articles were assessed based on publication year, publisher journals, and the organizational affiliations of authors. As illustrated in Fig. 2, the publication of these articles has been an ascendant trend in recent years. Among the 89 investigated articles, 54 articles (about 61%) were published from 2015 to the end of August 2020, which indicates an increasing application of FCMs in the subject of risk-included problems. In detail, the number of articles published from 2012 onwards has been increased dramatically. The reason for this growth can be attributed to the publication of review papers in this field, including [110] and [111] studies, which have provided more information about the main advantages of the FCM method. As summarized in Table 1, the maximum number of published articles in each journal is only 3. Notably, investigations indicate that 89 identified articles have been distributed among 75 different journals, which points out the widespread application of FCMs in the field of systems risk analysis in various sciences.

The 89 articles reviewed in this paper are categorized into 16 categories according to their application scope, as summarized in Table 2. Among the 89 articles, 7 articles are taken in two distinct categories according to their subject. Table 2 indicates that 19.79% of the articles are in the field of engineering, 13.54% are in medical sciences, and 10.41% are in financial management. The high number of articles in these three categories is due to the existential

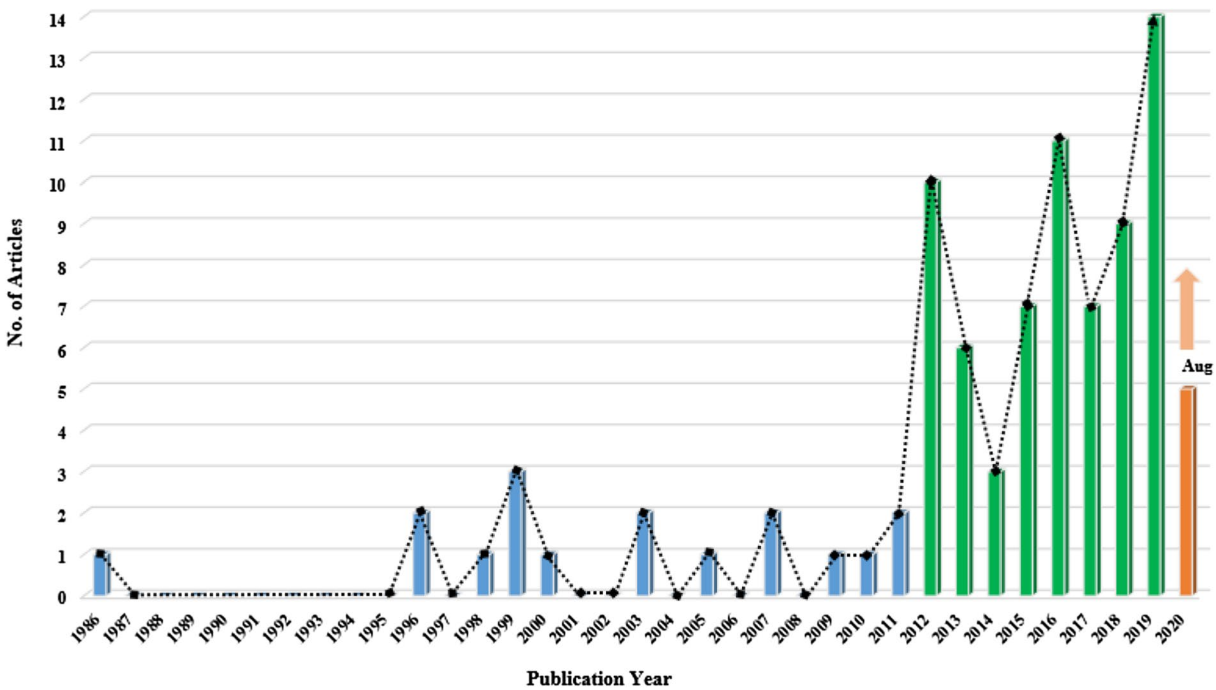

Fig. 2 Distribution of the reviewed articles based on the publication year

Table 1 Distribution of the reviewed articles based on the journals

Row	Journal	No. of articles
1	Applied Soft Computing	3
2	International Journal of Fuzzy Systems	3
3	Safety Science	3
4	Bmc Medical Informatics and Decision Making	2
5	Computer Methods and Programs in Biomedicine	2
6	Expert Systems with Applications	2
7	Information Sciences	2
8	Journal of Loss Prevention in the Process Industries	2
9	Journal of Theoretical Biology	2
10	Neurocomputing	2
11	Technological Forecasting and Social Change	2
12	Other Journals*	64

*Each journal published one paper

nature of the FCM method and the predicted application objectives of this method from its introduction. According to Table 2, FCM independently or dependently has been used as a tool for managers in the cases of financial, crisis, safety and health, maintenance, human resources, supply chain, transportation, and construction management. Therefore, in another view, it can be concluded from Table 2 that the total portion of all management sciences is 37.51%. Furthermore, engineering sciences and industry, medical and biological sciences, and other scientific fields have 25%, 15.62%, and 21.87% of the applications of FCMs, respectively. Notably, the marine industry (4.17%) and biotechnology (1.04%) are added to engineering (19.79%) in the section of engineering and industry.

By the end of August 2020, 2416 scientific citations had been made to the articles under review. Table 3 lists the top 10 articles in terms of the most citations reviewed at the end of August 2020. Among them, the article by Peláez and Bowles [116] in the field of engineering had 265 citations, indicating around 11% of total citations, making it the most cited article. Articles by Stylios and Groumpos [145] and Xiao et al. [161] in the field of engineering and supply chain management had been cited 126 and 117 times and take the second and third ranks, respectively. Investigations indicate that 742 citations (30.71% of total citations) were made to the articles published in the field of engineering.

Table 4 summarizes the top 10 articles in terms of the average annual citations reviewed in the last week of August 2020. As a result, the articles by Han and Deng [57], Lopez and Salmeron [89], and Xiao et al. [161] which had an average of 21.7, 14, and 13 citations per year, respectively, are identified as the three top articles based on this indicator.

Table 5 summarizes the top 10 researchers (contributing authors) in the field of FCM-based applications for systems risk analysis based on publication quantity, total citation, and average citation indicators. More analysis and insights are provided through the information summarized in Table 5. It can be understood from the table that the ranking

Table 2 Distribution of the reviewed articles based on the scope

Application scope	Literature	Total number
Engineering (19.79%)	[79, 116, 73, 144, 145, 74, 132, 11, 98, 159, 115, 164, 124, 143], Rezaee et al. (2018b), [21], [86], [127], [102]	19
Medical Science (13.54%)	[47], [156], [90], [39], [95], [148], [30], [113], [31], [27], [8], [72], [9],	13
Financial Management (10.41%)	[50], [93], [16], [99], [96], [18], [55], [64], [151], [168]	10
Information Science (9.37%)	[82, 50],Chang [80], Lee et al. (2012); [149], [84], [59], [138], [100]	9
Environmental Science (7.29%)	[48, 95, 137, 67][68], [22], [56], [61]	7
Social Science (5.21%)	[88], [160], [157], [91], [167]	5
Crisis Management (5.21%)	[48, 29, 67][68], [57], [85]	5
Safety and Health Management (5.21%)	[28], [165], [119], [22], [38]	5
Marine Industry (4.17%)	[75], [4], [83], [158]	4
Supply Chain Management (4.17%)	[161], [97], [162], [42]	4
Construction Management (4.17%)	[70], [46], [126], Efe et al. (2019)	4
Maintenance Management (3.13%)	[89], [94], [65]	3
Enterprise Resource Management (3.13%)	[131], [89], [121]	3
Biology (2.08%)	[118], [152]	2
Transportation Management (2.08%)	[18], [123]	2
Biotechnology (1.04%)	[35]	1

Table 3 Top 10 articles based on the total citations

Row	Title	Authors	All citations
1	Using fuzzy cognitive maps as a system model for failure modes and effects analysis	[116]	265
2	Fuzzy Cognitive Maps: a model for intelligent supervisory control systems	[145]	126
3	An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation	[161]	117
4	Forecasting risk impact on ERP maintenance with augmented fuzzy cognitive maps	[131]	106
5	A soft computing approach for modeling the supervisor of manufacturing systems	[144]	105
6	Dynamic risks modeling in ERP maintenance projects with FCM	[89]	98
7	Integrating conventional science and aboriginal perspectives on diabetes using fuzzy cognitive maps	[47]	77
8	Analyzing the impact of social factors on homelessness: a Fuzzy Cognitive Map approach	[91]	72
9	Fuzzy cognitive map for the design of EDI controls	[82]	67
10	Utilisation of cognitive map in modelling human error in marine accident analysis and prevention	[4]	66

Table 4 Top 10 articles based on the average annual citations

Row	Title	Authors	Average citations
1	A hybrid intelligent model for assessment of critical success factors in high-risk emergency system	[57]	21.7
2	Dynamic risks modeling in ERP maintenance projects with FCM	[89]	14
3	An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation	[161]	13
4	Comparing supply chain risks for multiple product categories with cognitive mapping and analytic hierarchy process	[97]	11.3
5	Forecasting risk impact on ERP maintenance with augmented fuzzy cognitive maps	[131]	10.6
6	Using fuzzy cognitive maps as a system model for failure modes and effects analysis	[116]	10.6
7	Risk analysis of sequential processes in food industry integrating multi-stage fuzzy cognitive map and process failure mode and effects analysis	[125]	9.7
8	Utilization of cognitive map in modeling human error in marine accident analysis and prevention	[4]	9.4
9	Analyzing the impact of social factors on homelessness: a Fuzzy Cognitive Map approach	[91]	9
10	A dynamic ERP critical failure factors modelling with FCM throughout project lifecycle phases	[121]	8.6

Table 5 Top 10 contributing authors

Row	Authorss	Publication quantity	Authors	Total citation	Authors	Average citation
1	Yousefi S	9	Salmeron JL	280	Bowles JB	265
2	Papageorgiou EI	7	Bowles JB	265	Peláez C	265
3	Rezaee MJ	7	Peláez C	265	Chen WJ	117
4	Salmeron JL	4	Groumpos PP	231	Li L	117
5	Li X	3	Stylios CD	231	Xiao Z	117
6	Groumpos PP	2	Papageorgiou EI	209	Groumpos PP	115
7	Stylios CD	2	Mago VK	117	Stylios CD	115
8	Mago VK	2	Chen WJ	117	Lopez C	98
9	Karmegam A	2	Li L	117	Findlay CS	77
10	Papandrianos N	2	Xiao Z	117	Glies BG	77

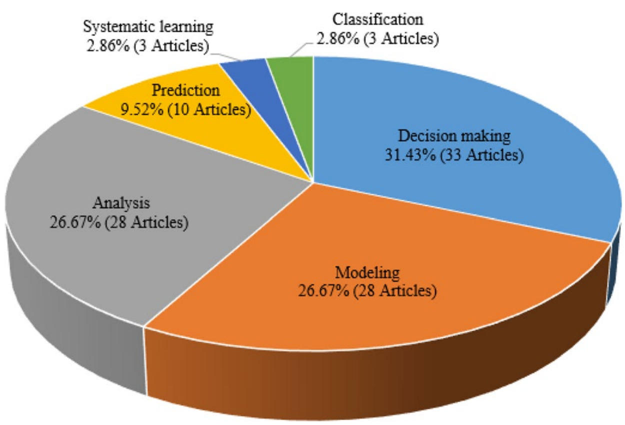

Fig. 3 Distribution of the reviewed articles based on the application tasks

of the authors changes with respect to different indicators. All top authors have published less than 10 papers in this field. Yousefi S (with 9 papers) and Rezaee MJ (with 7 papers) have been among the most productive researchers in the field since 2017. Papageorgiou EI and Salmeron JL have 7 and 4 papers, respectively. These two authors as well as Groumpos PP and Stylios CD have been known as the top researchers in the field of FCMs in general. Based on the total citations, Salmeron JL, Bowles JB, and Peláez C with 280, 265, and 265 citations rank the top three, respectively. However, Bowles JB, Peláez C, and Chen WJ with 173, 153, and 153 citations are the top three authors with respect to the average citation indicator, respectively. It is worth noting that regarding publication quantity indicator, some other authors have published 2 papers in addition to the authors indicated in Table 5. One of them is Subramanian J with 95 and 47.5 total and average citations, respectively. Notably, Haas G, La France B, Laughing W, and Pembleton S are four more authors with an average citation of 77.

As shown in Fig. 3, reviewing the studies in the six main application subjects reveals that the key focus is on modeling, decision making, and analysis. The reviewed articles indicate that 31.43% of articles have used FCMs in the decision-making area, making this the most popular application of FCMs (Fig. 3). Notably, in some of these articles, FCMs have been used for modeling alongside decision making or system analysis. Figure 3 indicates that the applications of FCMs in two areas of analysis and modeling, separately, account for 26.67% of total articles. It can be inferred from this figure that researchers would apply FCMs to the decision-making problems compared to the other areas under investigation.

In the subject of decision making, researchers mainly applied FCMs along with analytical and decision-making methods to analyze risks in various systems. In some applications, systems risk analysis was done in the form of identification and prioritization. In some cases of this subject, faults, failures, and errors of systems were assessed using FCMs. A variety of application fields has appeared in nanotechnology, information systems, piping systems, supply chain, children's health care, mental disorders, stock market, heart failure, and emergency systems.

In the modeling subject, FCMs were applied to model various systems in terms of evaluation and assessment of risk, hazard, failure, health, safety, accident, and error. The main applied fields were diabetes health management, diseases, natural hazards, knowledge management, enterprise resource planning, financial systems, oil and gas production plants, electronic data, supply chain, and health, safety, and the environment in energy.

In the analysis subject, researchers used FCMs to analyze undesirability in cases of failure, fault, error, risk, accident, and vulnerability. These undesirable issues were analyzed in problems such as breast cancer, depression, the drug administration process, mining, and industrial workplaces, marine, highway projects, airport, construction industry, automation system, and typing by the keyboard.

Future trends

One of the risk management objectives after identifying critical risks is to provide corrective or preventative strategies for improving the status of the system or organization under review. As reviewed in this study, FCMs can be used to study the impact of each strategy on the system status in the forms of modeling, analysis, prediction, systematic learning, and classification. To this end, some concepts can be considered evaluator nodes using multi-objective fuzzy cognitive maps [22], based on management's discretion or organizational goals. In this way, risks that are directly affected are considered active nodes and can be determined after running each scenario as a solution. After performing FCM calculations for each scenario using learning algorithms, the effects of that scenario on the system can be measured. Accordingly, solutions with high priority in the running can be identified. This issue can lead decision-makers to improve systems by implementing the most effective solutions, especially in the case of limited resources [26]. The future trend of FCMs in solving risk-based problems can be derived from the following discussions, given the applications of FCMs in the risk area, FCMs categories, and learning algorithms.

Applications of FCMs in systems risk analysis in terms of the prediction (9.52%), systematic learning (2.86%), and classification (2.86%) subjects are new (Fig. 3). The reviewed literature indicated that FCMs have been mostly applied to address these subjects in recent since 2015. However, the first applications appeared in 2012 when three different groups of researchers applied FCMs for the prediction of housing market fluctuations, configuration errors in psychological issues, and risk of wireless disconnection. As the database of the study indicated, other studies in the prediction subject were about faults and errors in financial issues, spatial patterns, and the internet of things. FCM applications in the systematic learning subject were used to analyze failures in the automobile industry, flood risk, and information interpretation based on the database. The analyzed literature revealed that there are only two studies in the classification subject based on FCMs, which classified celiac disease and socially withdrawn peer groups. The use of data mining techniques such as fuzzy C-means can be seen in this case, which is one of the useful methods for feature selection [122].

There are several studies using FCMs for simultaneous subjects, including decision-making, modeling, analysis, prediction, system learning, and classification. The majority of FCM applications addressed modeling and analysis subjects and were focused on fields such as the marine industry [4, 75], homelessness as a social issue [91], water policy in agricultural [164], automobile maintenance [65], and construction projects [70, 126] based on the analyzed database. Breast cancer risk and system failures and risks were evaluated using FCMs in decision-making and modeling subjects simultaneously [31, 113, 148]. In the simultaneous case of modeling and prediction subjects, dynamic risks of enterprise resource planning and attacks in computer science were studied. The only application of FCMs in prediction and classification subjects simultaneously was in breast cancer as resulted from the analyzed database. Critical factors in environmental health [119] were studied in the subject of analysis along with decision making.

More risk-based studies are needed to be done based on all the above-mentioned subjects, especially in decision-making and the combination of subjects. In the meantime, multi-criteria decision-making techniques are one of the most popular methods because of their ability in applying experts' preferences in the decision-making process [19]. Additionally, FMEA, Bayesian networks, FIS, and artificial neural networks are among other most useful methods used along with FCMs for systems risk analysis. The purpose of most of these combinations is to achieve a decision support system to take into account time constraints and use resources to find a compromise solution between several options [71].

Type of risk data, the application subject and problem, and experts and their knowledge are the most important factors in selecting an appropriate learning algorithm and FCM method. If experts enforce some structural constraints on a cognitive map, the FCMs in the semi-automated category are suggested [110]. In the cases of a specific type of data and the availability of knowledge-based experts, the NHL algorithm by Papageorgiou [104] is preferred due to better performance and fewer iterations to reach a solution. Hybrid algorithms, however, are shown to be more useful [24, 102]. A useful hybrid algorithm is a combination of NHL and differential evolution presented by Papageorgiou and Groumpos [106], which can employ human knowledge along with historical data to adjust the weights of the initial matrix.

The reviewed literature indicated that the majority of the risk-based problems follow a dynamic concept. Hence, time-based FCMs should be applied amongst all FCMs. However, some risk-based problems consider a qualitative representation of causal relationships. In this case, rule-based FCMs presented by Carvalho and Tomè [32] are preferable. It is worth noting that rule-based FCMs use fuzzy rules based on fuzzy linguistic variables and support time dimension in a qualitative system [33], which can be applied by non-specialists [34]. The reviewed and analyzed database indicated that FCMs have been majorly applied to analyze risk-based concepts by following decision-making forms. Since a certain kind of decision-making concept usually prevails in systems risk analysis and assessment problems, case-based reasoning FCMs are preferred based on [45]. In all cases, the augmented fuzzy cognitive map by Papageorgiou [109] is a suitable alternative to extract the opinions of experts and the information of various datasets through fuzzy rules. As the literature analysis revealed, some risk-based problems may follow a complicated process with too many components. These problems should be divided into sub-problems with fewer components and complexity. Accordingly, MS-FCMs [124] can perform relationships among different stages in the complex system. As examined by Bakhtavar and Yousefi [22], multiple objectives of a system should be considered in some risk-based problems. To this end, multi-objective FCMs can address multiple objectives in the forms of maximization and minimization in the analysis and decision process.

Conclusions

FCMs have been developed and used in a variety of scientific fields, especially in the recent decade. One of the main applications of FCMs is in risk-included systems. Therefore, this study focused on the FCMs' applications in the risk area based on the concepts of failure, accident, incident, hazard, risk, error, and fault. By reviewing the studies in the cases of the various risk-based concepts using FCMs can be seen that this method is a useful tool in solving complex risk-based problems in a wide range of fields. Most applications of FCMs in systems risk analysis have been done to address such problems in the domains of engineering, medicine, and management sciences. FCMs can help researchers to analyze and prioritize risk-based concepts in the forms of decision-making, modeling, analysis, prediction, systematic learning, classification, and a combination of them. Based on the outputs of this study, decision-making is the most widely used application, when decision-makers face a risk-based problem.

Briefly, by simultaneously examining the previous research and the applicability of the FCM method in real-world problems, it can be stated that the focus of future studies will be on both engineering and medical fields along with management issues. To put it precisely, due to the importance of analyzing the potential risks in the industry sector and assessing medical failures, these areas will be of interest to more researchers. On the other hand, most of the problems arisen in these fields have a decision-making nature in which decision-makers or policymakers attempt to provide preventive actions by simulating and analyzing the system to reduce the imposed cost of some risks and failures. In this regard, in addition to using the intrinsic features of the FCM, researchers can combine this method with other ones, especially decision-making techniques and analytical models, to increase its effectiveness and applicability to an acceptable level. Besides, to deal with the inherent uncertainty of the problems related to the risk management field, extending this method in different fuzzy environments makes this method more adaptable with real-world problems. To do this, it is proposed to consider uncertainty in the definition of concepts and causal relationships between them, and maintain this uncertainty until reaching the final output of the model through the development of FCM learning algorithms.

Compliance with ethical standards

Conflict of interest There is no conflict of interest.

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