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TOPICAL REVIEW

Fuzzy Theory in Fog Computing: Review, Taxonomy, and Open Issues

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ABSTRACT Geographically dispersed Fog Computing architecture ubiquitously connected to a range of heterogeneous nodes at the edge of the network can provide cooperative flexible, and variable computations, communications, and storage services. Several fog computing methods, models, and techniques have been used to solve cloud issues. The fuzzy theory has also been used in many aspects of fog computing. Objectives: This work presents a systematic literature review of the use of fuzzy theory in Fog Computing, highlighting the main practical motivations, classification types in research approaches, fuzzy methods used, popular evaluation tools, open issues, and future trends. Methods: The investigations were systematically performed using fuzzy theory in fog computing, and four databases which are ScienceDirect, Web of Science (WoS), Scopus, and IEEE Xplore Digital Library from 2015 to 2022, were used to analyse their performance evaluation, architecture, and applications. Results: 94 articles were selected based on fuzzy theory in fog computing using different methods, models, and techniques, based on the proposed exclusion and inclusion criteria. The results of the taxonomy were divided into five major classes: task and resource management, intrusion detection systems, trust management, and healthcare services. Discussion: Applications requiring real-time, low latency, and quick responses are well suited for fog computing. These studies show that resource sharing improves the fog computing architecture by delivering reduced latency, distributed processing, improved scalability, better security, fault tolerance, and privacy. Conclusion: The majority of the time, research areas on fuzzy theory in fog computing are crucially significant. We conclude that this review will enhance research capacity, thereby expanding and creating new research domains.

INDEX TERMS Fog computing, fuzzy logic, healthcare, resource management, task management, intrusion detection system.

I. INTRODUCTION

In 2012, Cisco introduced a new architecture called Fog Computing (FC) to address the limitations of Cloud Computing (CC). FC is a geographically distributed paradigm that expands from the cloud, provides networking and processing to the edge of the network, is closer to IoT devices and users, and is supported by several fog nodes [1], [2], [3]. Future applications and services can be provided because of FC's planned ability to enable computation straight at the network's edge [2]. The FC paradigm is designed to reduce CC issues, such as [4] scalability [5], security [6], latency [7], and response time [8]. FC is used by scholars in several fields like task and resource management [9], intrusion detection [10], [11], [12], [13], trust management [14], [15], [16], healthcare services [17], [18], [19], [20], and many other fields as well. However, FC still suffers from a few issues; [15], [21], [22], [23], [24], [25], [26], [27], [28]. Hence, to solve these issues, many models, techniques, theories, and methods have been proposed, including fuzzy theory [29].

The fuzzy theory was used for the first time in this study [30]. Since then, the fuzzy theory has been used in many areas. At the end of the '80s and early'90s, fuzzy logic

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was used in computers to improve several methods, such as clustering [31] and decision-making [32]. Recently, the fuzzy theory has been used to improve FC in many fields, such as resource management, fog security, and attack detection and prediction.

This paper presents a Systematic Literature Review (SLR) of fuzzy theory in FC in many fields and analyzes previous studies on FC improvement. The criteria and characteristics taken into account to increase comprehension of relevant components of this topic in the literature include motivation, limitations, and recommendations to analysts and advance this crucial research area. This study highlights fuzzy theory's issues, problems, and challenges in FC.

Based on our search and knowledge, there are no reviews, surveys, or systematic literature reviews on fuzzy theory in FC, making it difficult to develop and determine the issues of implementation and proposition, especially the future directions of fuzzy theory in FC. There is a need to examine and emphasise the value of applying fuzzy theory in FC, given the growing variety of methodologies, techniques, and theories employed in FC. An SLR can determine, categorise, and synthesise a comparative analysis of state-of-the-art studies. It enables knowledge transfer within the scientific field [5], [33]. The SLR was conducted to identify, perform taxonomic classification, and systematically compare existing studies on planning, executing, and validating the fuzzy theory in fog systems. Specifically, by performing a methodological review of the existing studies, we aim to provide answers to the following questions:

- What are the main practical motivations for fuzzy theory in FC?
- Which type of classification in research approaches can be applied to fuzzy theory in FC?
- What are the fuzzy methods used in FC?
- What popular evaluation tools are applied for fuzzy theory in FC?
- What are the open issues and future trends of fuzzy theory in FC?

The guidelines in [1], [17], and [34] were followed in this study. We aim to have a comprehensive comparison to examine the limitations and possibilities of previous research and to have a systematic determination and taxonomy classification of the evidence on fuzzy theory in FC. The SLR of this work was created by focusing on the proposed solutions, techniques, and algorithms for fuzzy theory in FC. Therefore, 94 studies were selected, classified, and compared by applying characterisation taxonomy. The characterisation taxonomy based on these fields comprises five groups: task and resource management, intrusion detection, trust management, healthcare services, and others. Furthermore, open issues and future directions related to fuzzy theory in fog systems are also presented.

The remainder of this paper is organised as follows: Section 2 provides an overview of the FC. In Section 3, an overview of fuzzy theory is presented. Section 4 presents the research methodology. Section 5 presents the fuzzy theory of the FC taxonomy, and Section 6 describes the analysis results. Section 7 presents the limitations and open issues, and section 8 represents the conclusion.

II. FOG COMPUTING

FC is a paradigm with constrained abilities that uses distributed computing, storage, and networking services across several endpoints and traditional CC [2]. This presents a potential solution for latency-sensitive IoT applications. [35]. FC is an extension of CC but is more closely related to systems that handle IoT data. It also serves as a bridge between the devices and CC, bringing networking, processing, and storage capabilities closer to the end devices, as shown in Figure 1. The fog devices are known as Fog Nodes (FNs). The FN could be installed anywhere there is a network connection. A fog node can be any device capable of computations, storage, and networking, including an embedded server, industrial controller, switch, router, or security camera [35], [36].

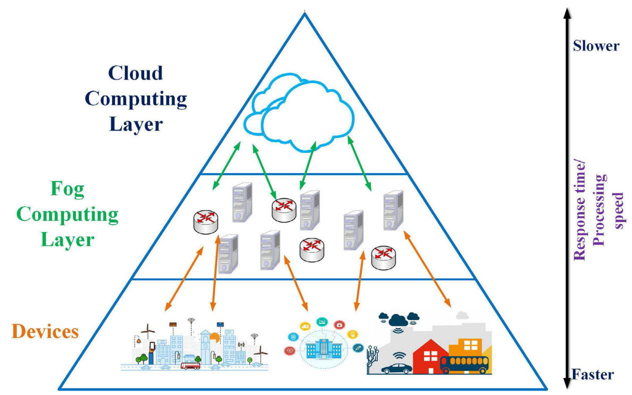

FIGURE 1. Fog computing architecture [37].

FC is used in three network layers: 1) the data collected from the edge's nodes, 2) a large number of nodes connecting to the network and sending data, and 3) the collected data should proceed within a second with the decision-making [38]. FC is used to switch the services of the cloud close to the users and to provide communications, and computations, and store in the edge's devices in which mobility, privacy, protection, low latency, or bandwidth can be enhanced and improved by fog, enabling perfect matching of the latency-sensitive or in real-time applications [7]. The fog layer provides ample computing resources and supports both the performance of the sensor nodes and system data transmission.

A. FOG COMPUTING CHARACTERISTICS

The FC can provide connections to the cloud. Fog architectures shift control, calculation, decision-making, and storage to the network's edge, where data are collected to overcome infrastructure constraints and enable mission-critical dense data consumption [39]. The main features of FC are as follows.

1) LOCATION AWARENESS AND LOW LATENCY
Insufficient support at the edge of a network highlights the importance of FC in terms of quality services. The FC, which is located at the edge, provides less latency and geographical variety, reducing the distance between the devices and the cloud and conditions control, storage, and computation locally [40]. In other words, FC matches the abilities of low-latency applications such as emergency and healthcare services [2].

2) GEOGRAPHICAL DISTRIBUTION
A fog provides a geo-distributed environment using fog devices, in contrast to a centralised cloud. Owing to its widely dispersed deployments, the network can supply basic yet crucial services because of the fog layer's ability to distribute analytics and data processing throughout the system, and high-quality services can be delivered by locally controlled distribution systems [2].

3) LARGE-SCALE SENSOR NETWORK
FC covers large-scale networks of sensors and end devices and manages professionally by providing storage resources and distributing computing and elasticity by adding or removing nodes when required to minimise latency and support faster response time [2].

4) MOBILITY
The FC architecture supports mobility techniques in many applications, particularly mobile sensors, to enable direct communication. The fog facilitates mobility and does not require any device reconfiguration. The computation of the edge network provides a high degree of mobility [2].

5) HETEROGENEITY
A virtualised FC platform offers storage, networking, and computational services between the end devices and the CC. FC heterogeneity features work as blocks that exist in many forms and are widespread in wide-ranging environments [41].

6) REAL-TIME INTERACTION
Different FC applications, like monitoring systems, require real-time processing and interactions [2].

7) PREVALENT TO WIRELESS ACCESS
FC supports wireless communication, mobile cellular gateways, and access points as examples of fog node networks [2].

8) INTEROPERABILITY
To guarantee services in a wide range, such as streaming data, FC must be able to collaborate and integrate services from other areas [2].

B. FOG COMPUTING APPLICATIONS
In this section, FC's usefulness and services are highlighted to show the importance and significance of FC. As mentioned above, FC has many important characteristics, such as mobility, low latency, real-time interaction, heterogeneity, wireless access, large-scale sensor networks, location awareness, and geographical distribution, which play a role in FC in many applications.

1) SMART CITIES
FC is used in smart cities, in which they offer many services, such as monitoring climate and plant growth through sensor nodes [42]. Vehicle tracking in smart cities can be achieved by implementing an FC-based system that provides real-time tracking. The FC also perfectly supports location awareness in smart cities by providing real-time responses [43].

2) SMART ENERGY MANAGEMENT
Energy management is crucial for stabilising power generation and usage in industrial, commercial, and residential domains [44]. Applications such as home energy management (HEM) of low-cost energy and advanced management systems identify the main challenges of energy management implementation, such as:

- Interactivity, interoperability, and performance between heterogeneous devices.
- The capability to modify the services, flexibility, and scalability of various types of energy management, such as applications, homes, and buildings.
- Energy management platform implementation cost.

3) REMOTE GAMING
Because mobile gaming applications are demanding, FC can offer Gaming-as-a-Service. Remote gaming is a common application in which users can play games immediately by connecting to the server over the Internet without having to install them on their device [45].

4) INDUSTRIAL WIRELESS SENSOR NETWORKS
A substantial volume of data is produced by real-time monitoring, manufacturing, and production processes [46]. Data centres are used to centrally store and handle widely dispersed industrial device-collected data. The exchange of IoT data will use communication resources as the number of connected devices increases; however, FC can overcome the bottleneck caused by data processing, traffic overhead, and latency [47].

5) INTELLIGENT TRANSPORTATION SYSTEM
It would be useful to implement FC in intelligent transportation systems (ITS). CC is not considered suitable for applications that require high response times. FC provides the mechanism of local decision-making, load balancing in real-time, and geo-distribution deemed suitable for ITS [48].

6) HEALTHCARE
FC supports many healthcare applications. Healthcare applications demand real-time processing, low latency, mobility, and many other features that the FC can offer. Monitoring is an important healthcare application requiring a high response time. ECG, EEG, body parameters, emergency systems, brain

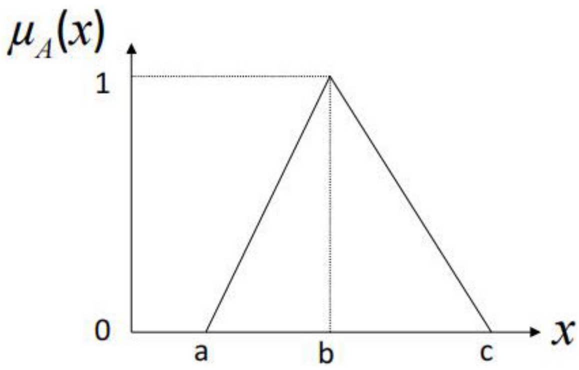

FIGURE 2. The triangular membership function for a fuzzy set.

storks, and fall detection are healthcare monitoring applications that require FC features [49]. FC is an innovative technique for improving emergency healthcare monitoring by allowing users to use only the resources they need and those that are closest to them [50], [51].

III. FUZZY THEORY

Research in the fuzzy sciences originated over 50 years ago, with a seminal paper [30] published in Information and Control [52]. This study analysed the fuzzy theory concept, enabling multivalued logic to be used with traditional Boolean sets. Since then, the fuzzy theory has been used in many aspects, particularly in computer science.

Having a role as the extension of the classical notion of set, fuzzy can be defined as human thinking and reasoning that involves fuzzy information to make a decision. Because most of the questions are not reliably answered, the fuzzy theory is designed to help make a decision by transforming the data into the linguistic language to make it easily interpreted. Many types of linguistic languages have been widely used, such as low, medium, high, small, medium, big, and many more. These linguistic languages are chosen depending on the type of data and are most compatible with the study. A fuzzy set is also described as a collection of objects with varying degrees of membership [53], [54]. Mathematically, a fuzzy set is a pair (A, μ_A) where A is a set, and $\mu_A : A \rightarrow [0, 1]$. For all $x \epsilon A$, $\mu_A(x)$ is the membership grade of x. This membership function is specified by three parameters $\{a, b, c\}$ where a, b, and c represent the x-coordinates of the three vertices of $\mu_x(x)$ in a fuzzy set A (a: lower boundary and c: upper boundary where membership degree is zero, b: the centre where membership degree is 1).

They can also be described mathematically as shown in equation (1) [55], [56].

$$\mu_x(x) = \begin{cases} 0 & if\ x \leq a \\ \dfrac{x-a}{b-a} & if\ a \leq x < b \\ \dfrac{c-x}{c-b} & if\ b \leq x < c \\ 0 & if\ x \geq c \end{cases} \tag{1}$$

A fuzzy set with membership function $A: [a, b] \subseteq R \rightarrow [0, 1]$ is called a fuzzy number if it is normal. Because the membership function of a triangle is derived from a fuzzy set, A, where it is characterized using the triple (a, b, c), $a \leq b < c$, it is denoted by $A \triangleq (a, b, c)$. Hence, the set of all fuzzy numbers of R is denoted by E_1 or otherwise, it can also be represented as a pair of functions of L^μ, R^μ), $o \leq \mu < 1$ by satisfying the following conditions:

- L^μ is a bounded, non-decreasing, left-continuous function in (0,1], and it is right-continuous at $\mu = 0$.
- R^μ is a bounded, non-decreasing, left-continuous function in (0,1], and it is right-continuous at $\mu = 0$.
- $L^\mu \leq R^\mu$.

The fuzzy theory has been improved over the years to be used in many fields of computer science [57], leading to many method inventions based on fuzzy set theory. The following section presents an overview of fuzzy methods.

A. FUZZY LOGIC

Introduced by Zadeh in 1965, fuzzy logic was derived from fuzzy set theory [58]. They have been successfully used in many applications. Human reasoning uses both true and false to describe a decision that can sometimes be insufficient. Hence, the idea of fuzzy logic is to help decision-making by constructing a different degree of membership, called the membership function. Known as fuzzy logic derived from a fuzzy set, fuzzy logic is a method to compute depending on the 'degrees of truth' compared to 'true or false' (1 or 0) that the computers are based on it. This membership function is used in the linguistic language with an interval [0,1].

The application of fuzzy logic can be widely seen in our daily life activities because it is intended to address issues by taking into account all relevant data and reaching the right decision possible based on the given output [59]. For example, in a washing machine, there are a few fuzzy logic applications: foam detection, compensation imbalance, and water level adjustments. According to the quantity and type of laundry, the fuzzy automatic water level adjustment adjusts the water and energy usage to meet the specific needs of each wash program. Evidently, fuzzy logic has helped many operations in daily life.

Four main components of designing fuzzy logic are as follows:

Fuzzification
Fuzzy rules/ knowledge base
Fuzzy inference method
Defuzzification

Figure 3 presents the flow of these components, which is important to ensure that fuzzy logic provides the right output based on the given input. First, the fuzzification technique involves taking certain input values and turning them into various degrees of membership in fuzzy sets according to their synchronisation. The second concerns the fuzzy rules. These are if-then rules, which can be found in many researchers. It is frequently produced by decision-makers or through more

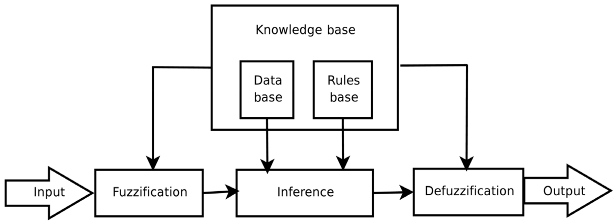

FIGURE 3. The flow of components for Fuzzy logic systems.

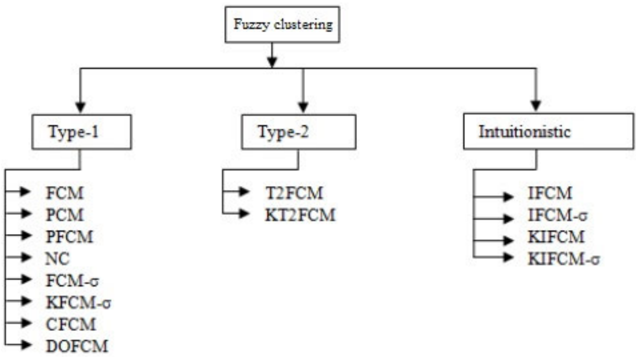

FIGURE 4. Fuzzy clustering algorithms [65].

quantitative methods. The third approach is the inference method, which bases its consideration of the final fuzzy conclusion on the extent to which the input variables belong to fuzzy sets and specific fuzzy rules. Finally, the defuzzification components emphasize the procedure for turning vague conclusions into precise output values. These conclusions can be used in decision-making processes [60], [61].

B. FUZZY CLUSTERING

In 1968, a study [62] presented a technique for creating clusters and a hierarchy of fuzzy subsets. However, one year later, a fuzzy clustering bellwether appeared [63].

If the crisp clustering that characterizes every data belonging to exactly one cluster is utilised, a datum may have uncertainties or fuzziness, which will make it difficult to determine the cluster. Fuzzy clustering analysis enables the degree in [0, 1] of gradual membership from the data to the cluster to be measured [64]. Fuzzy clustering uses many algorithms, as shown in Figure 4.

Bezdek's famous fuzzy clustering algorithm, namely the fuzzy C-means (FCM) algorithm and many other algorithms like possibilistic C-means (PCM), possibilistic fuzzy C-means (PFCM), and fuzzy C-means with a new distance metric (FCM-σ) derived from the FCM algorithm, has been useful in several research fields, such as image analysis and pattern recognition [66], [67], [68], [69], [70]. While the noise clustering (NC) algorithm was proposed [71] for robust clustering, credible fuzzy C-means (CFCM) was proposed by [65], and density-oriented fuzzy C-means (DOFCM) [72], [73].

Type-2 fuzzy C-means (T2FCM) and Kernelized Type-2 Fuzzy C-means (KT2FCM) algorithms are depending on Type-2 fuzzy sets; Consequently, some data items have a greater impact on determining the correct cluster centroids [74], [75]. Depending on intuitionistic fuzzy c-means (IFCM), robust intuitionistic fuzzy c-means (IFCM-), kernel version of intuitionistic fuzzy c-means (KIFCM), and kernel fuzzy c-means with a novel distance metric (KIFCM-), a new concept of hesitation degree was combined with the membership degree are used to develop the clustering algorithms [65].

C. FUZZY DECISION MAKING

Making decisions is becoming increasingly important in today's world, despite the prevalence of many different types of updated technologies and tools. In some cases, technology fails to provide decisions without considering the mental capacity of humans [76]. Humans with valuable insights should be able to use effective decision-making to approach a very acceptable decision. Fuzzy decision-making is a promising decision-making method.

Fuzzy logic remains a decision-making area among numerous theoretical and practical developments. Experiments on fuzzy decision-making arose from research into the fuzzy sets [30], fuzzy environments [77], approximate reasoning [55], [56], [78], and fuzzy decision systems applications [79], being worked on by a significant number of scientists from all over the world [80].

Decision-making research focuses on handling with issues of multiple-criteria-decision-making (MCDM), which considers the decision-subjectivity maker in selecting, prioritising, and organising various actions and observing the feasibility of an alternative option based on available resources. Consequently, the fuzzy theory is combined with MCDM to study issues in situations involving subjective ambiguity, as objectives and limitations might include linguistic variables and fuzzy variables [81].

Fuzzy multi-criteria-decision-making (FMCDM) is a popular decision-making approach in engineering, technology, science and management, and business [82]. The FMCDM methods aim to enhance the decisions' quality by making their evolution more reasonable, efficient, and explicit.

According to a study [83], FMCDM algorithms can be classified into four types: pairwise comparison, outranking, distance, and others, as shown in Figure 5. Pairwise comparison methods include the analytic hierarchy process (AHP), analytic network process (ANP), and measuring attractiveness using a categorical evaluation technique (MACBETH). Outranking-based methods include fuzzy elimination and choice expressing reality (ELECTRE) and the fuzzy preference ranking organisation method for enrichment evaluation (PROMETHEE). Distance-based methods include the technique for order preference by similarity to the ideal solution (TOPSIS) and fuzzy multi-criteria optimisation and compromise solution (VIKOR). Other method categories include

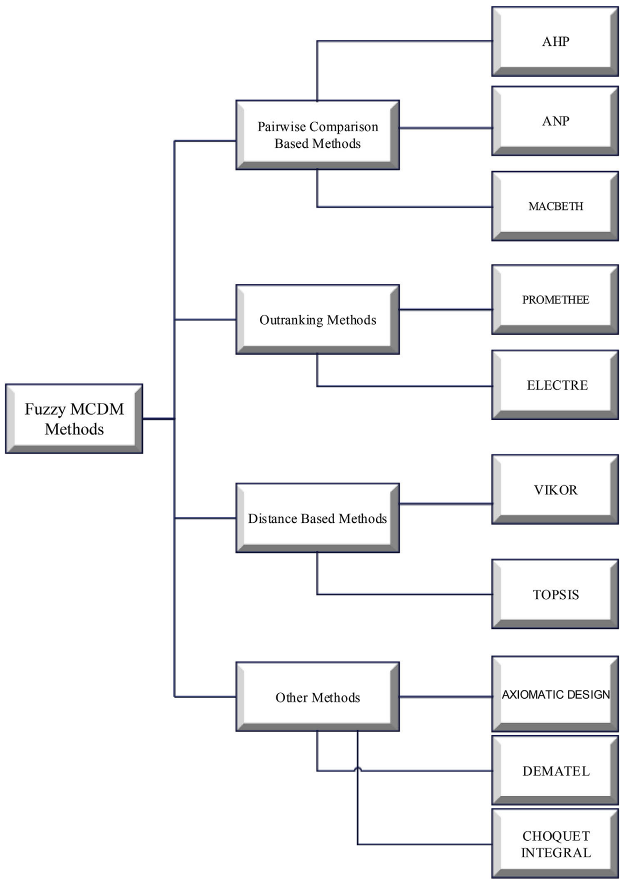

FIGURE 5. FMCDM methods classification [83].

the fuzzy decision-making trial and evaluation laboratory (DEMATEL), axiomatic design, and Choquet Integral.

D. FUZZY INFERENCE SYSTEM

A fuzzy inference system (FIS) is a nonlinear mapping whose output is derived from fuzzy theory and fuzzy if-then rules. The mapping domain and range correspond to fuzzy sets or points in multidimensional space.

Over the past 30 years, research on FIS that was started by [58] has drawn the interest of various fields. [84]. FIS is divided into three types depending on the consequence of the fuzzy rules required for the inference procedure: [85] Mamdani FIS, Takagi Sugeno Kang FIS, and Tsukamoto FIS.

In general, FIS consists of a few steps that involve a fuzzifier unit that fuzzifiers the data input. A knowledge base (KB) unit that contains fuzzy rules of the form IF-THEN, i.e., IF a set of conditions (antecedent) is acceptable, THEN a set of conditions (consequent) can be inferred, and then an inference engine module that computes the rules firing strengths to infer knowledge from KB; and finally, a (crisp output), as shown in Figure 4 [86].

IV. FUZZY THEORY IN FOG COMPUTING

Fuzzy set theory approaches are used in different models, techniques, and frameworks to improve the ability of these models, techniques, and frameworks. Many researchers have recently used fuzzy theory in FC to solve fog issues. The following sections review recent studies on fuzzy theory in FC.

A. RESEARCH METHODOLOGY

A systematic literature review was based on determined and assessed review protocols for extracting, analysing, and documenting the results. We obtained the guidelines [1], [17]with three-stage study procedures, including planning, conducting, and documenting.

The first stage is the planning review process of fuzzy theory in FC. The following steps are followed: (1) highlight the necessity and requirements for a literature review of the fuzzy theory in FC; (2) describe and investigate the research gaps, questions, and problems faced by the previous research; and (3) improve/assess the procedure to perform a systematic literature review on the subject of fuzzy theory in FC. The actions related to directing the systematic literature review of fuzzy theory in FC involve the following steps: (1) identifying the fuzzy theory in FC research, (2) selecting the literature, and (3) extracting information for fuzzy theory in FC. The documenting review phase implements the outcomes of the systematic literature review of fuzzy theory in FC and examines how to select studies.

B. PLANNING THE REVIEW

Review planning begins with gaining insights into the motivations for systematic work and the results of a review protocol as follows:

1) MOTIVATION OF THE REVIEW

A systematic review results from identifying, categorising, and comparing current evidence on fuzzy theory in an FC environment. It focuses on categorising and contrasting fuzzy theories in the FC. Concerning the importance of fuzzy theory in fog networks, it is necessary to consolidate the existing evidence on fuzzy theory in fog systems.

2) IDENTIFY THE RESEARCH QUESTIONS

The research questions shape the research motivation; the answers give us an evidence-based review of fuzzy theory. Six research questions were developed to define the basis for obtaining the search strategy for deriving literature, as shown in Table 1. The aim of investigating each question was motivated by motivation. On the other hand, comparative analysis permits an analysis of the collective influence of the research, which is presented in terms of comparative features.

3) STUDY SELECTION

The investigations were systematically performed using four databases which are: Web of Science (WoS), ScienceDirect, Scopus, and IEEE Xplore Digital Library. The study was chosen based on an index demonstrating a simple and complex computer science journal and conference research publications. Technical considerations were therefore considered during the selection process, offering a wider perspective

TABLE 1. Research questions.

No	Question
RQ1	What are the main practical motivations for fuzzy theory in FC?
RQ2	Which kind of classification in research approaches can be applied in fuzzy theory in FC?
RQ3	What the fuzzy methods are used in FC?
RQ4	What popular evaluation tools are applied for fuzzy theory in FC?
RQ5	What are the open issues, and future trends of fuzzy theory in FC

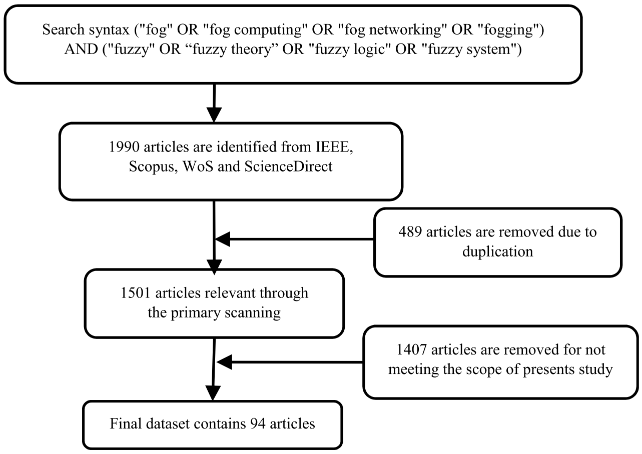

FIGURE 6. The protocol for a systematic literature review.

on research studies and taking into account many scientific domains.

The query used in the search was divided into two parts. The first was about the FC ("fog" OR "fog computing" OR "fog networking" OR "fogging"), whereas the second part was about the fuzzy ("fuzzy" OR "fuzzy theory" OR "fuzzy logic" OR "fuzzy system"). These parts of the query were combined by "AND." In each database, we selected two types of articles, namely, research articles and review articles, as shown in Table 2.

TABLE 2. Included and excluded articles.

Criteria	Type of data
Included	Research articles (Framework, Model, Architecture, Review, and Survey) that are related to fuzzy theory in FC.
Excluded	Books, Book Chapters, Theses, and Non-English articles.

The next step was to identify related articles. The selection process is divided into three steps, as shown in Figure 6. First, duplicates were excluded. In the first step, we aimed to remove duplicates. We found 1990 articles between 2015 and 2022, and there were 489 duplicates. In the second step, titles and abstracts were scanned to find related and unrelated articles. Out of the 1501 articles, 94 used fuzzy theory in FC.

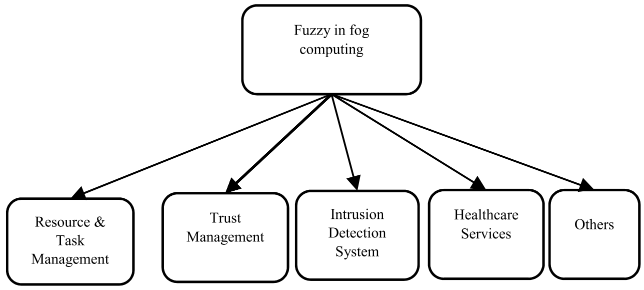

FIGURE 7. Literature classification.

V. FUZZY THEORY IN FOG COMPUTING CLASSIFICATION

A structured classification of related literature is defined here. The classification was performed based on the area that used fuzzy logic in FC, as shown in Figure 7.

A. TASK AND RESOURCE MANAGEMENT

The FC is a distributed computing system that offers local data processing and storage capabilities for IoT applications rather than transporting data externally to the cloud. FC provides computation, networking, and storage capabilities like the cloud. Making FC a reality requires task and resource management mechanisms owing to the fog environment's dynamic, heterogeneous, and uncertain nature [87]. Task and resource management can be classified into two categories: scheduling and load balancing for both tasks and resources, where offloading and allocation fall under these two main categories. In other words, enhancing offloading or allocation enhances scheduling and load balancing. In recent years, fuzzy methods have been used to improve tasks and resource management. Table 3 shows the previous studies on fuzzy logic in task and resource management in recent years.

1) SCHEDULING

Scheduling is one of the solutions to the main challenge of efficiently managing limited resources. Two forms of scheduling are possible, namely resource scheduling and task scheduling [122]. The former is the process of dynamic allocation of the workload, whereas the latter is the process of scheduling tasks based on appropriate available resources [123]. The fuzzy theory has recently been used to improve task and resource scheduling. In this section, previous works are unfolded. Most studies use fuzzy logic to improve scheduling, as shown in Figure 8.

In recent years, fuzzy logic has been used to solve scheduling issues. A study [93] presented a ranking-based task scheduling technique that combines user preferences and fog node attributes by rating fog nodes from the most to the least pleasant one using language and fuzzy quantified propositions. The fuzzy reinforcement learning (FRL) approach has been proposed [88] for task allocation of fog vehicles. The FRL merges fuzzy logic and greedy heuristic with on-policy reinforcement learning to reduce the learning

AQ:5 **TABLE 3.** Fuzzy task and resource management in FC.

Authors	Proposed	Fuzzy type	Tool	Type	Advantage	Disadvantage
[88]	Energy efficient vehicle scheduling	Fuzzy logic	Monte Carlo simulations	Scheduling	The energy consumption and local processing tasks have been improved	The total service time is still high
[89]	Produce software-defined traffic splitting	Fuzzy logic	Not mentioned	Load balancing	Reduce the latency, cost, energy, and response time	Reduced IoT service delay can be used to quantify the quality of service.
[90]	Propose a Fuzzy Deep Q-learning base Offloading scheme (FDQO)	Fuzzy logic	Not mentioned	Offloading – load balancing	Maximize the Quality of Experiences (QoE)	The authors did not calculate the cost and energy consumption
[91]	A real-time task scheduling	Fuzzy logic	iFogSim	Scheduling	Improved task-scheduling for the fog broker	It does not support large-scale networks
[92]	Combine fuzzy clustering with PSO to divide the resources	Fuzzy clustering	MATLAB	Scheduling	Improve the used satisfaction	The cost and energy are not considered to be calculated
[93]	Ranking based task scheduling	Fuzzy logic	Not mentioned	Scheduling	Improve energy consumption, and execution time	Did not consider calculating the cost
[94]	Fuzzy logical offloading strategy	Fuzzy logic	C language	Offloading - scheduling	Reduced search space	It does not support large-scale networks
[95]	Joint fuzzy particle swarm optimization mobility-aware approach to fog task scheduling algorithm (FPFTS)	Fuzzy logic	iFogSim	Scheduling	Reduce network utilization and delay	- The used data sets are not explained - No fog gateways fault tolerance
[96]	Fuzzy Logic-based Resource Management scheme (FLRM)	Fuzzy logic	VanetMobiSim	Load balancing	Improve the average throughput	Focused only on throughput
[97]	Fuzzy-Based Dynamic Time Slot (DTS) Allocation	Fuzzy logic	NS2	Allocation – load balancing	Enhance delay and energy consumption	The cost and execution time are not considered
[98]	A new mathematical fuzzy-based method	Fuzzy logic	OPNET modeller	Allocation – load balancing	Reduce the overheads of applying multiple techniques in Fog	The dynamic resources are not considered
[99]	Integrated virtualization (IV) fog	Fuzzy logic	Apache JMeter	Load balancing	- Reduce error rate - Reduce delay rate	Human parameters are used for scaling, not machines.
[100]	Data Allocation Mechanism	Fuzzy logic	FogBus and Matlab	Allocation – load balancing	Improves usage, storage, and delay and reduces energy consumption.	Heavy security measures that hinder authorised access to application services and resources have not been taken into account.
[101]	Task Offloading system	Fuzzy logic	Matlab	Offloading – load balancing	Enhance the energy consumption and delay	The dataset is not explained
[102]	Task scheduling scheme	Fuzzy logic	iFogSim	Scheduling	Improve the processing time	Did not consider calculating the cost and the energy consumption
[103]	Resource provisioning model	Fuzzy clustering	Matlab	Load balancing	Improved the clustering accuracy	Cost and energy consumption are not calculated
[104]	Scheduling algorithm depending on the Priority Queue	FDM	Not mentioned	Scheduling	Decrease the delay, waiting time, and energy consumption	The delay is still high
[105]	Virtual Network Function (VNF) placement approach	Fuzzy logic	Not mentioned	Load balancing	Reduce the energy consumption and execution time	The energy is still high
[106]	an intelligent approach to managing resources	Fuzzy logic	Not mentioned	Load balancing	Time-sensitive applications are never executed in the cloud, only on the edge or fog layer.	Cost and energy consumption are not calculated
[107]	Dynamic Resource Scheduling Process (RSP) based on fuzzy control theory	Fuzzy inference system	Not mentioned	Scheduling	Reduced task execution time and decreased overall task computation costs	Energy consumption is not calculated
[108]	Multi-criteria Mamdani fuzzy algorithm	FDM	Visual Studio	Scheduling	Improve overall application scheduling success rate	Cost and response time are not considered
[109]	Feedback-based optimized fuzzy scheduling approach (FOFSA)	Inference fuzzy system	iFogSim	Scheduling	Decrease the makespan of time	In the waiting queue, the lower priority tasks must wait for a very long time.
[110]	Distribution-Map-Transfer-Combination (DMTC)	FDM	Not mentioned	Allocation – load balancing	Improve Energy Consumption	Cost is not calculated
[111]	Fuzzy replication algorithm	Fuzzy inference system	OptorSim	Scheduling	It can deal with large-scale networks	The average response time is high
[112]	Vehicular fog gateways selection	Fuzzy logic	NS3	Scheduling	Minimize latency	Energy consumption and cost are not collected

TABLE 3. ***(Continued.)*** **Fuzzy task and resource management in FC.**

[113]	Fuzzy Reinforcement Learning Data Packet Allocation (FRLDPA)	Fuzzy logic	Not mentioned	Allocation – load balancing	Using the resources besides the criticality of the task	The cost and energy consumption are not calculated
[114]	Effective Load Balancing Strategy (ELBS)	Fuzzy inference system	Matlab	Load balancing	Reduce the cost and response time	The dataset is small
[115]	A bipartite graph task allocation approach	Fuzzy clustering	CloudSim	Allocation – scheduling	Improve the cost and makespan	Calculation complexity does not take communication costs into account
[116]	intelligent approach for resource management in SDN-VANET	Fuzzy logic	C language	Load balancing	Use the application priority to make a decision	The delay will be increased if the vehicle moves relatively much slower/faster than neighbouring
[117]	The priority-based traffic scheduling mechanism	FDM	OMNET++	Load balancing	Can deal with large-scale networks	The delay is high
[118]	Fuzzy Logic-based Resource Management scheme (FLRM)	Fuzzy logic	VanetMobiSim	Load balancing	Fulfil the demand of the users in case of dynamic topology	The cost and energy consumption are not calculated
[119]	Fuzzy-based System for Resource Coordination and Management (FSRCM)	Fuzzy Logic	Not mentioned	Load balancing	Use the application priority to make a decision	The delay will be increased if the vehicle moves relatively much slower/faster than neighbouring
[120]	bipartite graph with fuzzy clustering task allocation	Fuzzy clustering	CloudSim	Allocation – load balancing	Reduce the cost	The execution time is not calculated
[121]	Fuzzy multi-objective particle swarm Optimization approach	Fuzzy logic	Not mentioned	Scheduling	The average response time is low	The CPU and RAM usage is high

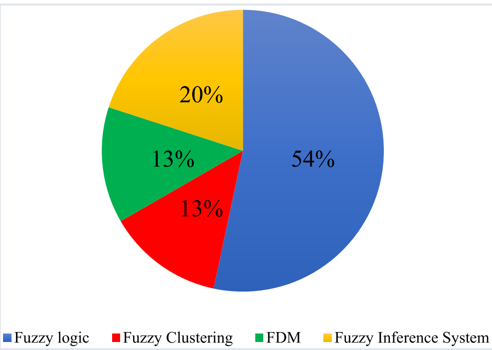

FIGURE 8. **Fuzzy scheduling classification.**

process and optimize the selection of optimal fog vehicles to reduce energy and response time. By taking into account the task deadline, the resource requirements, availability, and the workload of the fog nodes, a real-time task scheduling method was proposed by [91] at the fog broker. The authors created a fuzzy-logic decision method in the fog-cloud architecture to divide tasks across the fog and cloud layers. Clustering and tiering of various application task types were accomplished using a fuzzy logic-based partition method [94]. A suitable DAG task offloading technique is developed using this algorithm. Tasks are delegated to a specified tier, which saves a significant amount of computing and scheduling capacities. PSO and fuzzy theory are combined in the FPFTS fog task scheduler [95], which uses data on application loop latency and network utilisation. This study also employed a Mamdani fuzzy inference system to take advantage of fuzzy logic in parameter prioritisation. In IoT-fog networks, FUPE [121] has been presented as a security-conscious task scheduler. To combine the best computing resources and provide an adequate level of security safety, a fuzzy-based multiobjective PSO approach is proposed. The Mamdani fuzzy inference system takes advantage of the correlation between metrics and IoT demand priority to enhance the scheduler. A fuzzy logic task scheduling method was presented in [102] to choose tasks from the task set and offload them to a fog node in an ordered list. Each task in the task set was assigned depending on the lambda value, calculated every task in the taskset by the RSU using the fuzzy logic. On the Internet of Vehicles, a multiaccess edge-based vehicular FC architecture was introduced by [112], where the vehicles operate as fog nodes. The gate selection module was the focus of this study. To decrease the connection costs, the function of this module is to choose the best fog nodes for accessing the MEC servers and the traditional cloud. The proposed selection method consists of two parts. The first part involves choosing a group of potential gateways using fuzzy logic, whereas the second part optimises the chosen gateways number.

Fuzzy inference systems have also been used in recent years to improve scheduling. A FOFSA model was proposed in [109]. The proposed technique automatically decreases end-to-end latency by drastically reducing the transmission between IoT devices and clouds. If all rudimentary realities produced by fog devices are sent to a single cloud, feedback-based optimal fuzzy assists in resource management and alleviates bottlenecks. A fuzzy replication was proposed in [111], which aims to prevent delays by considering a wide range of important aspects to enhance performance. The proposed technique uses a hierarchical approach to choose the best replica while considering transmission cost, queue delay, and failure probability. The approach uses a fuzzy inference system to decide where to replicate data while considering queue workload, future access count, last access time, and communication capacity. One study [107] proposed two types of scheduling: RSP and FCERS, for task scheduling. When compared to the baseline, fuzzy control is primarily responsible for lowering the average total cost of computing, execution time, and energy usage.

Fuzzy clustering has also been used in scheduling. A study [92] standardised and normalised the resource characteristics and combined fuzzy with PSO to divide resources, thereby reducing the scale of the resource search. The resources and tasks are also matched in accordance with weight matching to obtain the final resource scheduling results. A two-tier bipartite graph with a fuzzy clustering task allocation methodology is a new method for allocating tasks, as proposed in [115]. It employs a hybrid DAG to perform both dependent and independent activities. To solve the uncertain execution issue and determine the maximum bipartite matching, fuzzy clustering and bipartite graphs are used in the first layer. The second layer allows it to select the ideal virtual machine for every task inside the designated processing node.

FDM is also used in scheduling, and a study [104] presented a scheduling algorithm based on the priority queue, fuzzy, and AHP, called PQFAHP. The PQFAHP was used in this study to integrate several priorities and prioritise using multiple criteria. A comparison and analysis of the system overhead and cost for the proposed schemes, as well as alternative schemes, follow the presentation of a priority-scheduling model based on the fuzzy AHP approach. A module for long-term memory parallel neural network prediction was used [108] to analyse the workflow graphs using the multicriteria Mamdani fuzzy method. The fuzzy inference system group-based priority assignment schema gives workflows a priority value to denote the relative precedence of the requests. The workflows are then sent to the target locations based on their current workloads by distributed schedulers. Decentralised operations were used throughout the process to avoid bottlenecks.

2) LOAD BALANCING

Load balancing is a fundamental technique, especially in FC, owing to its distributed structure. Tasks should be distributed efficiently according to available resources [124]. Load balancing and prioritisation are the main issues in FC [114]. The fuzzy theory was used to improve the load balancing issues in FC, as shown in Figure 9.

Fuzzy logic was used by most articles to solve load-balancing issues. By utilizing various designs and tuning stages for fuzzy controllers, fuzzy load balancing is introduced [89]. The fuzzy logic technique has been used to analysis as an interconnection for traffics management.

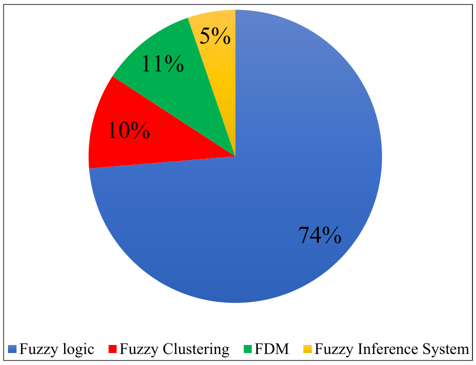

FIGURE 9. Fuzzy load balancing classification.

To reduce performance uncertainty, fuzzy representation was used in [90] deep reinforcement learning. Specifically, a real-time offloading approach for a delay-constrained car FC system was proposed, leveraging the complementary strengths of deep Q-learning and fuzzy logic. Considering the fact that the resource list contains the time tag, the source ID, the resource ID, and the resource metadata, a study [96] proposed FLRM. This study slightly alters them and collects data sets based on the length of time it takes to request and download each resource using the intended V2I connection protocol. Another study [97] suggested a fuzzy logic based DTS allocation technique that can improve packet delivery and decrease the delay. Each node receives a time slot that is dynamically assigned based on factors such as energy availability, buffer availability, and packet arrival rate. The appropriateness of a node's neighbours was assessed using a novel mathematical fuzzy-based method presented in [98]. A fuzzy method based on XGBoost integrates the parameters and calculates the score. The fuzzy approach analyses eight using three membership functions for each. There were 3^8 states available in total, requiring 6156 rules. A hybrid strategy combining fuzzy and reinforcement learning can reduce the latency in IoT healthcare, and the cloud was presented by [113]. The fog services using the FRLDPA algorithm are used to interface healthcare devices and the cloud. A fuzzy real-time auto-scaling (FRAS) mechanism was proposed in [99] and implemented in the IV FC. Service auto-scaling can be resolved quickly, simply, affordably, and dynamically using the FRAS method. A new context-aware data-allocation system was suggested by [100] that determines the on-chain allocation of every IoT data request by a rating of allocation (RoA) value calculation utilizing a variety of context criteria. To calculate the RoA value, the mechanism is based on the fuzzy logic data controller that collects context factors from every data request, such as data, quality, and network, which is used as a threshold to determine which data requests should be allocated off-chain or to a cloud database for storage. An offloading system for tasks based on fuzzy logic was developed in [101], allowing the administrator to choose an appropriate computer network for the task while avoiding high latency and the energy consumption. To save energy and time, fuzzy logic systems have chosen the best computing system for a variety of real-world scenarios and factors. A new Fuzzy-FCA (fuzzy formal concept analysis) strategy for VNF placement was proposed by [105] depending on the FCA and the fuzzy logic in a mixed environment facilitated by CC and multiple access edge computing (MEC) architecture. Fuzzy-FCA was used in this study to the group and classify the VNF obtained by FCA based on their support value; this must be set at the relevant VM and must be larger than or equal to the confidence value specified. Fuzzy-FCA is primarily based on a confidence value to prevent uncertainty in the data. To flexibly and effectively manage resources in networks, an integrated system for resource management and cooperation based on fuzzy logic (IFS-CMR) was presented in [106]. The proposed method uses an integrated fuzzy logic system to determine which resources are best for vehicles to use under various conditions. Another study [116] suggested employing fuzzy logic, which is an intelligent technique, to control resources in SDN-VANETs. In SDN-VANETs, a tiered cloud-fog-edge architecture is introduced and managed by the SDN controller (SDNC). To decide on the application data processing layer for the VANETs, SDNC has created a fuzzy-based system. Prioritising the application requirements and considering the connections that are available helps make the choice. A fuzzy logic-based resource management system (FLRM) for FC in VANETs was suggested in [118]. Using the planned vehicle-to-infrastructure (V2I) connection protocol, they first gathered and recorded the request and download times for every resource in the scheme. Using an aforementioned information and the proposed fuzzy logic, the authors calculated a survival period for each resource that was saved. In response to the set survival time, the local server can update the resource list in real-time. Finally, simulations were run to check the FLRM performance. The FSRCM for VANETs was proposed in [119]. The suggested system chooses the processing layer of the VANETs application data by taking into account vehicle movement, data size, time sensitivity, and remaining storage capacity.

In addition, fuzzy clustering was used to solve load-balancing issues. A bipartite graph with a fuzzy clustering task allocation approach was suggested in [120]. Both independent and dependent tasks were represented using a hybrid DAG. To overcome the problem of unpredictable execution and determine the maximum bipartite matching, the authors employed fuzzy clustering and bipartite graphs. As a resource provisioning paradigm for FC, a study [103] developed a unique clustering with a flower pollination technique known as FCM-FPA. Resource properties were standardised and normalised at an earlier stage. The development of fuzzy clustering with FPA, which is used to divide resources and reduce the scalability of resource searches, follows. Finally, an optimised fuzzy-clustering-based resource-provisioning technique was developed.

FDM is also used for load balancing. For a dynamic wireless sensor network, two computational distributions were presented by [110]. In this fog-based system, optimistic and blind methods were used to spread the computing burden among fog networks. Based on the proposed distribution methods, FMCDM is also utilised for network clustering and routing. An RRAHB protocol was presented in [117]. An FDA is proposed for the nodes to choose the next node for every message. To ensure network load balancing, For the hotspot impact and forwarding scheduling problem, the authors also proposed a random selection and hotspot avoidance mechanism (RSHAM) and a priority-based traffic scheduling mechanism (PTSM) based on FDA.

Only one study has used a fuzzy inference system for load balancing [114]. It proposes a new, deemed appropriate for use in healthcare applications called an ELBS for FC environments. Real-time scheduling and caching methods are used by ELBS to accomplish efficient load balancing in an FC. To achieve dependable linkages between fog servers, several criteria have been introduced. The process priority was determined by a study using a fuzzy inference approach. The following consecutive steps were used to carry out the fuzzy inference process: fuzzification of the inputs was followed by the use of fuzzy rules and defuzzification.

B. INTRUSION DETECTION SYSTEM

As the use of FC increases, devices used for computing may run into security problems due to FNs' proximity to end users and their limited capabilities. Some of these issues might destroy the entire network and fog nodes; therefore, an intrusion detection system (IDS) is one of the most effective solutions that can overcome this concern or mitigate its impact [10], [125].

An intrusion is an unauthorised or illegal activity to obtain entry into computer system information or to harm the functionality of the system. An IDS is a security software that intents to detect a variety of security violation, spanning from planned break-ins through outsiders to system abuses and insider penetrations [126], [127], [128]. IDSs' major functions of IDSs are monitoring hosts and networks, evaluating computer system behaviour, producing alerts, and responding to suspicious behaviours. IDS is often located near protected network nodes because they monitor linked hosts and networks (e.g., switches of key network segments) [129]. The fuzzy theory used in recent years to improve the intrusion detection of FC is shown in Table 4. In this section, previous studies on fuzzy theory in intrusion detection in FC are presented.

Fuzzy logic was used to improve the IDS. FLFSIoT, which works in real-time, was proposed [130]. To reduce the uncertainty of an edge node belonging to a crisp cluster and to identify different conventional attacks, the proposed framework utilises fuzzy logic. Additionally, by eliminating latency and other problems, FLFSIoT is fundamentally more secure than cloud-supported IoT due to the Fog-supported IoT architecture which has been utilized. For recognizing dangerous behavior in uncertain IoT systems, a general and lightweight security technique based on fuzzy logic and fog technology was proposed [133]. (GLSF2 IoT). It is based

TABLE 4. A fuzzy intrusion detection system in FC.

Authors	Proposed	Fuzzy type	Tool	Advantage	Disadvantage
[130]	Fuzzy Logic and Fog-based Secure Architecture for IoT (FLFSIoT)	Fuzzy logic	COOJA	Increase the true positive rate	- The attack detection accuracy is low
[131]	Phishing detection	Fuzzy inference system	Not mentioned	The detection accuracy is high	The detection does not perform well with unfamiliar attack
[132]	Intruder Detection for Smart Home	Fuzzy inference system	iFogSim	The detection time is better than ANN, KNN, and SVM	The accuracy is low It records over 93%
[133]	Detecting malicious behaviour	Fuzzy logic	COOJA	Achieve high and real-time detection	The accuracy of detecting Collusion Attacks is low
[134]	FC-based security approach	Fuzzy inference system	COOJA	This approach provides self-protection	The prediction time is high
[135]	Fog-based attack detection framework	Fuzzy clustering	Not mentioned	The detection time is low	The detection accuracy is not high

on the idea of ''zero trust or on the idea that everything should be viewed with suspicion. Although fuzzy logic was utilised to eliminate uncertainty, GLSF2IoT is fundamentally superior to IoT cloud, owing to its IoT fog architecture. When a malicious activity is discovered, GLSF2IoT automatically restricts network access to the offending IoT device, preventing it from attacking other devices.

In addition, a FIS was used to improve the detection methods. Based on a developed neuro-fuzzy framework, unified resource locator attributes and web traffic characteristics were reported in a study [131] to determine phishing websites (dubbed Fi-NFN). This study developed an anti-phishing method based on FC to transparently monitor and defend FC users from phishing accidents. For a home security system, [132] proposed an intelligent framework of a foot-mat-based intruder monitoring and detection system. In order to determine individuals, the model utilizes the real-time measurement of foot pressure, size, and motion using FC technology. Utilizing an ANFIS, which handles the prediction problem, the proposed model may assess the possibility of an intrusion. To protect IoT applications using FC, an autonomous technique has been developed [134]. The proposed system is thought to be appropriate for IoT applications, including weather forecasting, smart homes, and environmental monitoring, which link to and process data from end devices in the cloud. The reaction module employs fuzzy logic to generate defences that can successfully repel an onslaught.

Fuzzy clustering has also been used in IDS. Using the FC paradigm and the recently proposed ELM-based semi-supervised fuzzy C-means (ESFCM) approach, a study [135] introduced a fog-based attack detection system. FC is an extension of CC that allows and supports distributed attack detection and network edge attack detection. In the ESFCM method, the issue of labelled data was addressed using a semi-supervised FCM method, and an extreme learning machine (ELM) algorithm was employed to give superior generalization performance at a higher detection rate.

C. TRUST MANAGEMENT

Trust management plays the main role in fostering relations depends on prior interactions between FNs and edge devices, fog nodes, cloud data centres, and even between the fog nodes themselves. The most important part is an FN, which is in charge of assuring end users' anonymity and privacy [136]. To ensure that the FN performs the global concealing mechanism on its released data and only conducts legal actions, this component must also be trusted for delegation [137]. In this case, a certain degree of mutual confidence between all nodes in the fog network is necessary [138]. Fuzzy theory is used in trust management to improve the security of the FC, as shown in Table 5. This section covers the use of fuzzy theory to improve trust management in FC in recent years.

A bidirectional fuzzy logic based TMS was presented [138] that enables both a service requester (SR) and service provider (SP) to assess the level of trust of the other party. The SP can also assess the SR's level of trustworthiness. Both the safe offloading and fog-to-fog cooperation applications can benefit from the distributed trust propagation provided by the proposed TMS. A three-layer framework for the IoT was developed in [141], where the users of the first layer are supposed to receive information from the sensors of the third layer by the fog devices of the second layer. To conserve energy, resource-constrained sensors are freed from verifying the legitimacy of the users. As a result, fog devices, such as high-capacity nodes, are used to verify user authentication. Using fuzzy logic, users are rated as high-, moderate-, or low-trustworthy. By employing a simple two-phase authentication technique, the authentication of low- and medium-trusted users is also explored. A physical unclonable function (PUF) is utilised to produce challenge–response pairs and give each user a distinct identity (CRPs). A study [144] developed a methodology for broker-based trust evaluation that focused on finding a reliable fog to fulfil user requests. This study considers the availability and cost of fog and bases its evaluation on fuzzy logic. To detect a user request and match it with

TABLE 5. Fuzzy trust management in FC.

Authors	Proposed	Fuzzy type	Tool	Advantage	Disadvantage
[138]	Bi-directional trust management system (TMS)	Fuzzy logic	NS3	The TMS allows an SR to determine the trustworthiness of an SP before service offloading	- The accuracy is still low - The weighting of both direct and indirect trust are assigned statically
[139]	Identify and prioritize trust formation criteria in FC services	FDM	Not mentioned	They prove that QoS is the best metric that can be used to determine the trust level	Did not address the malicious behaviour of interacting entities
[140]	Secure the vehicular network	FDM	Not mentioned	Tackles the uncertainty and imprecision of data in the vehicular network in both line of sight (LOS) and non-line of sight (NLOS).	Does not consider the dynamic characteristics of traffic flows.
[141]	User Categorization using Fuzzy Logic (UCFL)	Fuzzy logic	Python	Used to phases of authentication scheme	Use single a factor solution and the associated enrolment process is complex
[142]	Construction trust authentication scheme	Fuzzy inference system	NS3	Reduce message delay	Cannot guarantee data confidentiality
[143]	A novel trust model	FDM	Not mentioned	The accuracy of finding trusted node is high	It depends on the delay if no nodes are qualified
[144]	Trust evaluation framework	Fuzzy logic	MATLAB	By preventing underutilization or overutilization of fog resources based on a threshold of fog nodes, the framework's dynamic operation also ensures the effective exploitation of fog resources.	Conceives only QoS trust metrics, and it is unidirectional

one of the predetermined sets developed and controlled by a broker, the authors suggested a request-matching algorithm and fuzzy-based filtering method.

Fuzzy AHP was used [139] to prioritise the specified criteria and ascertain the contribution of each criterion and its categories to the trustee's overall trust score. To protect automotive networks, a fuzzy trust model that depends on knowledge and plausibility was presented in [140]. To ensure the accuracy of the data received from authorised cars, the proposed trust model performs several security checks. Fog nodes were also used to assess the accuracy of an event's location. Another study [143] proposed an algorithm aimed at mitigating the security and trust concerns associated with choosing a node in a fog network. For FC, the authors used weighted weakest links (WWL) and fuzzy neural networks (FNNs). The crux of the proposed approach is to train, validate, and use fog nodes to be classified based on their trust scores.

By utilising blockchain technology and the neuro-fuzzy machine learning technique, a compact and privacy-preserving certificateless authentication scheme in fog-assisted VANET was suggested by [142]. Before being authenticated by a validator, fake requests were detected and filtered using a neuro-fuzzy machine-learning technique. Consequently, the authentication procedure is significantly improved, and the scheme becomes resistant to DoS attacks.

D. HEALTHCARE SERVICES

Healthcare services are a vital aspect of life, providing different resources, including counselling, diagnosis, and prevention of disease, sickness, injury, and mental health. Healthcare and technology have a long history of connections. Numerous medical applications have been created because of the technology's ability to improve human lives [21]. Remote monitoring is an important feature of healthcare services which has several applications such as mobile health (mHealth) and electronic health (eHealth) [145]. These applications provide monitoring and patient tracking for people who live alone, stay in hospitals, and live in rural areas [146].

To overcome the challenges of today's healthcare, such as delay in patient care, core CC alone is not the best solution [147]. In addition, healthcare services and existing applications on CC do not fulfil the needs of the Healthcare 4.0 environment. However, they have their own drawbacks, such as slow response times and delays. In healthcare, a small delay can cost the patient's life. Thus, to enhance services and applications, FC has come into the fore. FC empowers on-time service delivery with high consistency and overcomes difficulties such as delays or jitter and cost overhead while transmitting information to the cloud [147], [148]. Using fuzzy theory, FC has been used by many researchers to enhance disease detection and patient health monitoring, as shown in Table 6.

Fuzzy inference systems have been used by several authors. A study [149] proposed a decentralised patient–agent-controlled blockchain healthcare system. They used a fuzzy interface system to determine the fog node ratings. The system is divided into three levels: fuzzier, interface engine, and defuzzier.

For the COVID 19 pandemic conditions, the IoT used for physical distance monitoring and healthcare was presented in [150]. A lightweight and inexpensive IoT node, smartphone application (app), and fog-based machine learning (ML) tools for data analysis and diagnosis constitute the framework. A fuzzy inference system, called the decision-making system, is employed in the FC to predict the likelihood that the virus will spread. A study [158] enhanced the quality of service over a heterogeneous network utilising

TABLE 6. Fuzzy in healthcare services in FC.

Authors	Proposed	Fuzzy type	Tool	Advantage	Disadvantage
[149]	Remote patient monitoring (RPM) system	Fuzzy Inference System	Java	Use blockchain to avoid reliance and provides better security	The fuzzy inference engine use three parameters only
[150]	Automated Health Monitoring	Fuzzy inference system	Not mentioned	Use 6 symptoms for covid 19	Low scalability Low privacy
[151]	FC architecture and FDPA algorithm	Fuzzy inference system	Cloud Analyst	Reduce the latency	Doesn't provide early warning
[152]	Healthcare monitoring systems	Fuzzy logic	Not mentioned	Increase accuracy, monitoring ratio, and prediction ratio	The processing speed is high
[153]	Remote diagnosis of Encephalitis (ENCPH)	Fuzzy clustering	MATLAB	Improve the latency and delay	Cost and energy consumption are not considered
[154]	Physiological parameter detection	Fuzzy logic	iFogSim	Improve latency, execution time, and detection accuracy	The complexity is high
[155]	Nasogastric Tube Dislodgment Detection	Fuzzy inference system	C language	The results indicated a hit rate of 100% under possible situations of complications	The cost is not calculated
[156]	Enhanced FC 3-tier architecture	Fuzzy logic	iFogSim	Reduce the network latency	The cost and energy consumption are not considered
[157]	Diagnose the possibly infected by Zika virus	Fuzzy clustering	Amazon EC2 cloud	The dataset is large, and the accuracy is high	The decision tree is used instead of a k-nearest neighbour algorithm for better result
[158]	Classify the health care data	Fuzzy inference system	Matlab	Provide better QoS	Use only three parameters to identify the criticality
[159]	Blockchain-based secure healthcare services for disease prediction	Fuzzy inference system	Java	Use multi-layer of FIS	The diabetic prediction accuracy still low
[160]	Parkinson's disease prediction	Fuzzy inference system	MATLAB	Use large dataset	The detection accuracy is still low
[161]	Various mosquito-borne diseases	Fuzzy clustering	Not mentioned	Improve the accuracy	Improvement is needed in the Real-time monitoring process.
[162]	Parkinson disease detection	Fuzzy clustering	MATLAB	Improve the accuracy and sensitivity	The dataset is not large
[163]	Lung cancer diagnosis	Fuzzy clustering	MATLAB	High accuracy and sensitivity	The computation time need to be improved
[164]	Privacy- Aware Disease Prediction Support System (PDPSS)	Fuzzy clustering	Java	Improve the accuracy and sensitivity	The complexity is high because of the mathematical computational
[165]	Coronary Heart Disease prediction	Fuzzy inference system	Not mentioned	Used three level of evaluation steps	The cost is not calculated
[166]	Chikungunya virus (CHV) detection	Fuzzy clustering	MATLAB	Improve the execution time	It cannot trigger and support the decision making for modifying care plans when the health of the elderly deteriorates.
[167]	Cancer diagnosis	Fuzzy clustering	Not mentioned	High accuracy	The dataset is small which contain 143 cases only

the computing QoS in a medical information system using the fuzzy (CQMISF) method and reinforcement learning-based multimedia data segregation (RLMDS) algorithm in FC. The fuzzy inference method uses three parameters—heart rate, electrocardiogram, and blood sugar—to classify the health data and detect critical cases. To decrease the significant network latency when processing and acting upon device data, a fuzzy-based FC architecture was developed in [151]. High network latency, high service delay, and huge data transmission from IoT devices have been reduced. The ability of fog nodes to make decisions can be automated using fuzzy inference systems. Using learning algorithms to create accurate decision support systems, [160] a novel model was developed to extract clinically valuable information for Parkinson's disease (PD) assessment. By combining PSO and grey wolf optimisation (GWO), they developed a model for ANFIS's parameter optimisation of ANFIS. The proposed optimisation model uses the exploitation and exploration capabilities of PSO and GWO. A cloud-based cyber-physical localisation system was presented [165] using an adaptive neuro-fuzzy inference system to identify the risk level of CHD early. ANFIS was used to categorise the risk of CHD into several risk levels. This method has been used on a regular basis to monitor and analyse changes in a user's CHD risk level.

To identify nasogastric (NG) tube dislodgment over several days or weeks for ongoing insertion of the NG tube, a digital warning tool was developed [155]. The proposed assistance tool was built using a fuzzy Petri net (FPN) and dexter-to-sinister light-controlled sensors on the foundation of the FC. For disease prediction in FC, efficient blockchain-based secure healthcare services were presented [159]. Diabetes and cardiovascular conditions were considered while making the predictions. The patient's health data were initially gathered from fog nodes and stored on a blockchain. An adaptive neuro-fuzzy inference system based on feature selection was used to predict the occurrence of diabetes and cardiovascular diseases (FS-ANFIS).

Fuzzy logic has also been used for health monitoring. F-AMLF with an FC architectural framework has been suggested [152] to track patient conditions using IoT devices. A basic estimation approach can be used to forecast the effectiveness of a health-monitoring program. The framework developed fuzzy mathematical calculations for several essential output parameters. To detect the physiological parameters, a new tri-fog health architecture was proposed in [154]. The wearable, intelligent fog, and cloud layers are the three layers that represent the overall system. The study suggests using the fuzzy aided objective optimisation by ratio analysis (FaMOORA) approach to eliminate redundant data. [156] presented a 3-tier architecture and a hybrid technique using fuzzy logic and reinforcement learning in an FC environment for the IoT in healthcare.

Fuzzy clustering was used [153] to create a fog-based model for the remote diagnosis of ENCPH based on patient health symptoms and surrounding environmental factors. The classification of a patient was determined by the FCM classifier using parameters from health-related data. To effectively manage medical resources for health-oriented decision-making and information distribution to consumers, a prediction model based on spatiotemporal data is being used. In one study [157], a fuzzy k-nearest neighbour method was employed to identify people who might be infected with the Zika virus. The FKNN classifier uses fuzzy set theory, which blends fuzzy set theory with KNN, to solve classification issues across a range of domains more accurately. As a function of the vector's distance from its KNN and its memberships in potential classes, the FKNN determines the class membership of the vector. FC is utilised [161] to evaluate, classify, and exchange medical information between users and healthcare service providers. Wearable and IoT sensors were used to collect the necessary information. The authors used the FKNN approach to classify the user into infected or uninfected classes and the similarity coefficient to differentiate the various mosquito-borne diseases according to the patient's symptoms [162]. The proposed method uses a combinatorial FKNN and case-based reasoning classifier to more accurately distinguish between people with Parkinson's disease and healthy people. To increase accuracy in the FC environment as well as to detect lung cancer nodules early, a suitable diagnosis method was presented in [163]. For high-volume CT-scanned image storage, a fog environment is used to achieve high privacy, low latency, and mobility support. The strategy employs a hybrid of FCM and region-growing segmentation algorithms for precise segmentation of the region of interest (ROI). In [164], a hybrid-reasoning-based model for disease prediction was presented. Improved prediction outcomes were produced according to the combinatorial advantage of fuzzy set theory, KNN, and case-based reasoning. Although the DPSS supports healthcare services, data security and privacy remain important and difficult problems that need to be addressed. To locate and stop the spread of CHV, a healthcare system based on IoT and fog was suggested [166]. In the fog layer, FCM is utilised to assess potentially infected users and promptly produce diagnostic and emergency alerts. It is [167] suggested to diagnose cancer early and to begin treatment. In addition, an enhanced semi-supervised tumour detection technique was suggested. The clustering process is guided by a modified semi-supervised FCM algorithm that introduces labelled samples as supervised information. The algorithm can also employ a similar distance-labelled sample membership to lead the unlabelled samples.

E. OTHERS

In addition to task and resource management, intrusion-detection systems, trust management, and healthcare services are crucial. Many papers face difficulties in categorising them within the primary topic, therefore, we combine them and categorise them as "Others," as shown in Table 7. This section discusses related studies.

Several researchers have used fuzzy methods for different aspects of security. For Fog-IoT technology, one study [168] developed a contextual risk-based access control model that takes into an account real-time data request for IoT devices and provides automatic feedback. To measure risk, two different types of risk estimation methods, risk assessment and fuzzy models, have been developed. To rank the elements at both levels in an edge-fog-cloud context, a study [169] used AHP based on interval-valued intuitionistic fuzzy sets (IVIFS). The Fog-IoT security factors and their subfactors are prioritised and ranked using this integrated approach. For efficient and optimal economic dispatch in microgrids, a distributed multi-agent-based framework was proposed in [170]. It is structured as a three-layer FC architecture. This framework monitors load variations throughout the day while considering the sudden entrances and exits of the units. The optimisation approach of this model is a quick consensus-based algorithm modified by a fuzzy adaptive leader technique that may be applied by utilising the FC. In a fog-cloud IoT scenario, a study [171] presented a safe compute offloading approach (SecOFF-FCIoT). The study achieved efficient and secure offloading in a Fog-IoT context using machine-learning techniques. To secure the data specifically at the smart gateways, the IoT devices first choose a suitable node in FC to which they may offload its task through PSO via the smart gateway.

Other researchers have used fuzzy FC to detect and predict disasters. For example, the fuzzy logic model was proposed in [172] as a three-level hierarchical system with seven inputs and one output. Six fuzzy-logic subsystems constitute the proposed fuzzy-logic system. Every subsystem of fuzzy logic has two inputs and one output. The output of the fuzzy logic system is produced by the sixth subsystem. Additionally, [173] suggested an IoS-based sensing network for flood forecasting and prediction that is driven by mobile edge computing (MEC), FC, and CC following analysis through a modified multi-ANFIS architecture called OFFM-ANFIS. The OFFM-ANFIS consists of seven modified ANFIS models that analyse the sensory data received and trained data

TABLE 7. Other papers classifications.

Authors	Proposed	Fuzzy type	Tool	Type	Advantage	Disadvantage
[168]	Contextual risk-based access control mode	Fuzzy inference system	Not mentioned	Risk assessment	Used 6 factors as an input to the fuzzy risk model	It includes past risk factor which might not be provided
[169]	Interval-Valued Intuitionistic Fuzzy Set (IVIFS)	FDM	Not mentioned	Security ranking	Prioritizing the security factors of Fog-IoT scenario	The dataset is small
[170]	Distributed multi-agent-based framework	Fuzzy inference system	Not mentioned	Privacy	The framework accuracy against sudden changes is high	Only focus on the power
[171]	Secure computation offloading scheme in Fog-Cloud-IoT environment (SecOFF-FCIoT).	Fuzzy inference system	NS3	Secure offloading	Improve the response time	The tested network is too small
[172]	Drone capability analysis on disaster risk assessment	Fuzzy logic	MATLAB	Disaster monitoring and prediction	Use multi-level of fuzzy	The system has not been evaluated and tested
[173]	Flood prediction model	Fuzzy inference system	Microsoft Azure cloud	Disaster monitoring and prediction	The accuracy is high	The timeframe needs to be improved
[174]	An IoT-fog-cloud paradigm for evaluating the academic environment	Fuzzy Inference System	Not mentioned	Education sector	Use 4 large datasets	Doesn't focus on academic ranking
[175]	E-learning recommendation system	Fuzzy logic	Not mentioned	Education sector	The accuracy has been improved	The contexts are not considered in analysis
[176]	Monitoring pond water quality	Fuzzy logic	Not mentioned	Water monitoring	Provide recommendation response	Use three parameters as an input
[177]	Intelligent driving-support system	Fuzzy logic	Visual studio	Driver monitoring	Use 9 factors	The ECG is not considered while calculating the driver health
[178]	A fuzzy fog cloud approach	Fuzzy logic	Not mentioned	Human activity recognition	The timeline's space dedicated to providing information on the activity's evolution is reduced by the fuzzy model	Cost and energy are not calculated
[179]	Wildfire monitoring	Fuzzy clustering	Amazon EC2	Disaster monitoring and prediction	The accuracy, specificity, sensitivity, and precision are high	There are more attributes can increase the accuracy are not used
[180]	Wildfire monitoring	Fuzzy inference system and fuzzy clustering	Not mentioned	Disaster monitoring and prediction	Sends early warning signals	False-positive fire detections negatively affected the validity of targeted sensory system
[181]	Fuzzy-based feature selection	Fuzzy logic	Not mentioned	Electrical monitoring	Provides the lowest error value	Feature selection technique is applied to a small set of features (five)
[182]	Automatic detection and analysis of solar panel-affecting variables	Fuzzy logic	Not mentioned	Electrical monitoring	The transmission time has been improved	The cost is not considered
[183]	Early fire detection system	Fuzzy inference system	Matlab	Disaster monitoring and prediction	Provides high accuracy	The cost is not considered
[184]	Image segmentation comparison between Fuzzy C-Means and Fuzzy K-Means	Fuzzy clustering	Python	Image segmentation	Prove that fuzzy C-means can produce better segmentation	The dataset is too small
[185]	Energy trading for prosumers in smart grid infrastructure.	Fuzzy inference system	Matlab	Electrical monitoring	Maximize energy trading profits while reducing electricity consumption	Can use more parameters as an input
[186]	Automatic traffic light control system	Fuzzy inference system	Not mentioned	Traffic light system	Reduce the load	Need to use more parameters in the rule based
[187]	Planet growth control	Fuzzy inference system	Not mentioned	Planet greenhouse	Reduce the death risk	Use only 4 parameters
[188]	Intersection vehicle fog (IVF) model	Fuzzy logic	OMNeT++	Intersection-based stable routing	Improve the end-to-end delay	The cost is not considered

TABLE 7. ***(Continued.)*** **Other papers classifications.**

[189]	Hierarchical Pythagorean fuzzy deep neural network (HPFDNN)	Fuzzy logic	OpenCloud	Cloud Resources Demand	Reduce the cost of purchase of the cloud services	The accuracy needs to be improved
[190]	SDN-based MEC framework	Fuzzy logic	OMNeT++	MEC	Improve the latency	The complexity is high
[191]	Feature selection-based ranking (FSBR)	Fuzzy inference system	Paython	Electrical monitoring	Improve the accuracy	Didn't consider electricity consumption
[192]	Fuzzy Based Aggregator selection in Energy-efficient	Fuzzy inference system	Matlab	Disaster monitoring and prediction	Improve energy consumption	Cost is not calculated
[193]	Fuzzy-based Driver Monitoring System (FDMS)	Fuzzy logic	Visual studio	Driver monitoring	It is not complex	Use only 4 parameters
[194]	MEC based vehicular fog architecture	Fuzzy logic	NS3	MEC	Doesn't require high memory capacity	The QoS is not considered

to forecast floods. Using soft computing techniques, [179] presented a collaborative IoT-fog-cloud system for in-the-moment wildfire monitoring, forecasting, and prediction. The system provides suggestions for categorising forest terrain into the proper wildfire proneness class using a fuzzy KNN classifier by examining the variables that influence and contribute to wildfires. An efficient Fog-IoT-centric architecture for rapid wildfire detection was proposed in [180]. The proposed methodology provides a practical and immediate remedy to reduce the wildfire's damages. K-means clustering was first utilised to identify the start of a wildfire at the fog layer, and then real-time alerts were sent to the authorities and the local population. Additionally, the forest fire vulnerability index is employed by the cloud layer-based adaptive neuro-fuzzy inference system to classify a forest block into one of the five risk zones and determine the vulnerability to forest fires. An early fire-detection system using distributed fuzzy logic was proposed in [183]. The recommended general architecture is supported by a three-level data management paradigm consisting of dew, fog, and cloud computing for efficient data flow in IoT-based homecare systems. In addition, another study [192] proposed fuzzy-based aggregator selection in energy-efficient RPL for a region, thereby forming DODAG for communicating to Fog/Edge. Fuzzy inference rules were developed for selecting the aggregator based on strength which takes residual power, node degree, and expected transmission count (ETX) as input metrics. The fuzzy aggregator energy-efficient RPL (FA-ERPL) based on fuzzy inference rules is analysed against E-RPL in terms of scalability, energy consumption, and aggregator node energy deviation.

Fuzzy methods have also been used in the education sector. To determine the education quality assurance index (EQAI) element for an education quality-oriented smart recommender system, a study [174] recommended formulating an ANFIS based framework for efficient decision-making (SRS). The fog-based recommendation system (FBRS), which aligns objects (courses) to the learner's enquiry, was proposed in [175]. According to the user's enquiry revealing his/her interests and wants, FBRS provides recommendations for resources or courses relevant to specific subjects. The class identification module (CIM), subclass identification module (SIM), and matchmaking module (MM) are the three modules comprising FBRS. A fuzzy logic system is used to determine the closeness of each course to a user query. The MM was carried out in fog (fog server), it acts as a channel for users to access the cloud and relays results from the fog nearest to the user.

Some researchers have used fuzzy methods to monitor electrical realms. Based on the aforementioned three-tier architecture, [181] a novel electrical load forecasting (ELF) technique was presented. The suggested technique is divided into two phases: (i) the load prediction phase (DP2) and (ii) the data preprocessing phase (DP2) (LP2). Using the information obtained from each fog that is connected to the entire cloud, both steps are carried out in a cloud data centre (CDC). The main addition of this study is the feature selection procedure, which selects the most useful features for the load prediction phase. Fuzzy-based feature selection (FBFS), a new feature-selection methodology, is described. It consists of two stages: the feature ranking stage (FRS) and feature selection stage (FS2). One study [182] suggested a model of FC that uses a fuzzy rule-based algorithm to automatically monitor and identify elements that affect the efficiency of solar panels. The fuzzy rule-based algorithm comprises research rules that indicate how efficiency, light intensity, output electrical power, temperature, and humidity are related to one another. The fuzzy logic paradigm was utilised in a study [185] to enhance decision-making performance. Instead of providing clear decision-making boundaries, it covers a broad variety of operational conditions. The proposed fuzzy inference system considers all the key input factors, including the real-time price per unit of electricity, outside temperature, time of day, interest of potential customers, and capacity of batteries to charge batteries. [191] suggested feature selection-based ranking (FSBR), a new hybrid feature selection technique, to improve smart grids. The filter and wrapper phases comprise the proposed technique. The entire set of data was subjected to various ranking processes in the filter phase, including relative weight ranking, effectiveness ranking, and information gain ranking. The output of these processes was then submitted to a fuzzy inference engine to produce the final rankings. During the wrapper phase, data are chosen based on the final rankings and given to three distinct classifiers (naive Bayes, support vector machine, and neural network) to choose the optimal set of features depending on the performance of the classifiers.

Although other studies used fuzzy methods to improve the driving monitoring system, [177] they presented and implemented a driving-support system that may either greatly benefit from significant advancements in VANETs or could work well as a stand-alone system. The proposed solution uses a non-intrusive integrated fuzzy-based system that can recognise dangerous conditions in real time and warn the driver of impending danger. An intelligent fuzzy-based driver monitoring system (FDMS) has been suggested [193] for safe driving. This demonstrated and contrasted the FDMS1 and FDMS2 fuzzy-based systems. To decide, FDMS1 takes into account the vehicle's environment temperature (VET), the amount of noise (NL), and the driver's heart rate (HR), whereas FDMS2, we add the respiratory rate (RR) as a new parameter to determine the driver's situational awareness (DSA).

In addition, some studies used fuzzy FC. Because there was only one paper in each specialty, they were not categorised. This section discusses these studies in detail. An SDN-based multi-access edge-computing framework for automotive networks was suggested in [190]. (SDMEV). Two primary algorithms are used in the suggested solution. To arrange vehicles based on their communication interfaces, a fuzzy-logic-based approach is first utilised to choose the head vehicle for each evolved node B (eNB) collocated with a road-side unit (RSU). To update the flow tables of the forwarding devices at the forwarding layers, an OpenFlow algorithm was implemented. [194] suggested the use of a multi-access, edge-based vehicular fog architecture. The combination of the FC and MEC with a vehicular cloud serves as its foundation. The purpose of this design is to bring the cloud close to users by utilising the underutilised infrastructure and vehicle resources. The authors suggested a fuzzy-logic-based technique to choose a collection of vehicles (fog nodes) to access either the MEC server or the cloud to maximise the usage of radio resources. For pond water quality monitoring, a study [176] developed an FC network model using a fuzzy rule-based algorithm. The metrics of temperature, pH, and dissolved oxygen (DO) were inputs from the pond water quality. Sensors on the fog network were used to obtain the values of these parameters in real-time. These data were subsequently transmitted and saved in a web server database. Fuzzy rule-based logic was used to handle data from a database that pertains to temperature, pH, and DO parameters. The inference engine uses these data as inputs. Using fuzzy temporal windows and fuzzy aggregation, a fuzzy cloud-fog technique was presented by [178]. The purpose of this study is to describe the linguistic uncertainty present in fog nodes, calculate and disseminate pertinent linguistic data (protoforms), and publish computed protoforms in the cloud to produce complex protoforms, thereby achieving a common objective. A study [184] described image pre-processing, a segmentation process using clustering methods via K-means and fuzzy C-means algorithms in a nebula network. The aim of this study is to pre-process image segmentation, for example, the image of a flock of chicks on the fog network based on clustering via the K-means and fuzzy C-means algorithms and test it to obtain the best segmentation results. Using the RMSE and PSNR parameters, the segmented image was evaluated and calculated. A study [186] proposed an automatic traffic light control system that can be implemented using RFID technology and artificial intelligence to determine the length of intersection traffic lights. The average vehicle speed value and the percentage of road occupancy are inputs into the fuzzy rule-based algorithm. The condition of traffic jams, percentage of traffic in each lane, average speed of cars in each lane, and actual duration of traffic lights are the outputs of the fuzzy rule-based algorithm. Fuzzy rule-based methods have been proposed [184] to employ a fuzzy rule-based fog network to regulate growth parameters in greenhouses. When executing data collection procedures, fuzzy rule-based methods are utilised to calculate the drip watering time and fog network as a platform to combat the latency issues. The design of an effective routing technique for vehicle-to-vehicle (V2V) communication in urban VANETs was proposed in [188]. As junctions, traffic lights, and traffic conditions have a significant impact on urban VANET routing performance, the authors presented an intersection distributed routing (IDR) technique. The quality of the road stretch is largely estimated using fuzzy logic. A model that combines fuzzy logic and deep neural networks were proposed in [189]. It uses Pythagorean fuzzy numbers (PFNs), which have a larger value space than standard fuzzy numbers and are therefore more interpretable. In addition, high-level transformations are obtained using neural representations. These two components are then merged to create an HPFDNN.

VI. ANALYSIS OF RESULTS

This section analyzes the results of the systematic review. In response to the RQs, we review the chosen articles in Section A before introducing a comparison of the articles in Section B.

A. OVERVIEW OF SELECTED STUDIES

As we can see in Figure 10, 70% of the papers were from ScienceDirect, 15% from Scopus, 11% from Web of Science, and 4% only from IEEE. There were 1990 articles in all databases. A total of 513 papers were discovered to be replicated across the databases after applying the first filter, which involved removing duplicates. In the second filter, unrelated papers were disregarded by scanning titles and abstracts.

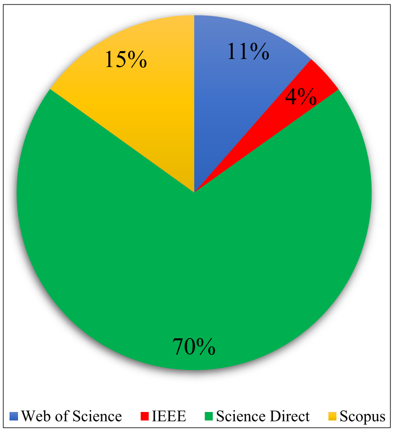

FIGURE 10. Articles percentage based on database.

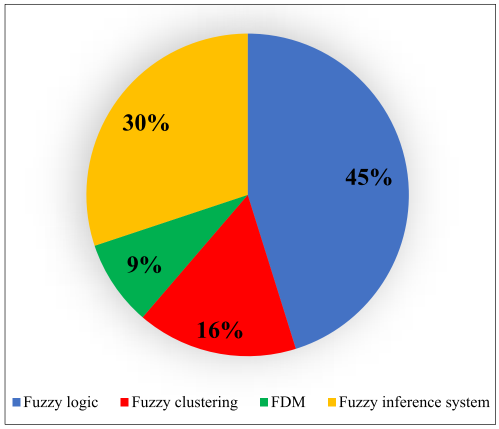

FIGURE 12. Fuzzy theory methods percentages.

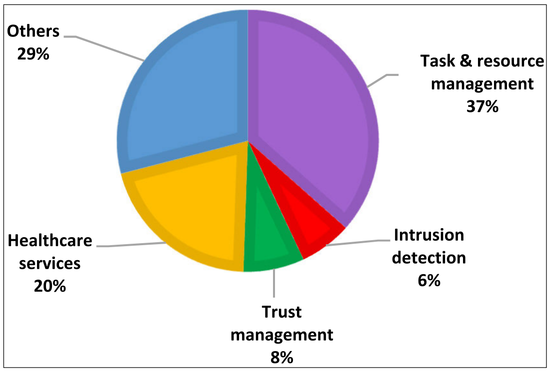

FIGURE 11. Fuzzy theory percentage in FC categories.

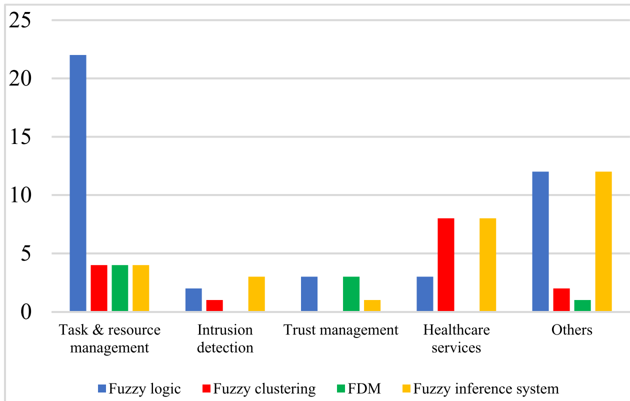

FIGURE 13. Percentages of fuzzy theory methods in FC.

Of the 1477 papers, 1378 papers were not related, whereas 94 papers used fuzzy FC.

B. RESEARCH OBJECTIVE AND TECHNIQUES

The review process of the selected articles on fuzzy theory in FC is covered in Section 5 within five main categories: task and resource management, intrusion detection, trust management, and healthcare services. The analytical and statistical reports of the research questions are presented based on the plan in Section 4.2, as follows:

- **RQ2:** Which kind of classification in research approaches can be applied to fuzzy theory in FC?

The use of fuzzy theory methods in FC fell into five categories, Figure 11 shows the statistical percentage of each category. Task and resource management studies accounted for the largest percentage of studies (37%), followed by 29% for others, 20% for healthcare services, 8% for trust management, and 6% for intrusion detection.

- Q3: What are the fuzzy methods used in FC?

Fuzzy methods are divided into four categories: fuzzy logic, fuzzy inference systems, fuzzy clustering, and FDM. Figure 12 presents the statistical percentages for each category. Fuzzy logic was the highest method used, 45%, whereas 30% for fuzzy inferences system, 16% for fuzzy clustering and 9% for FDM.

Figure 13 shows the percentage of fuzzy theory methods in each FC categories.

Fuzzy logic was utilised the most in task and resource management, accounting for 22 papers, whereas fuzzy inference systems, fuzzy clustering, and FDM each garnered four. The fuzzy inference was also the most popular method for intrusion detection, with three papers out of the six that used it, whereas fuzzy logic, fuzzy clustering, and FDM were not found in any of the articles. Fuzzy logic and FDM were both found in three trust management articles, whereas the fuzzy inference system was only used in one. No items in this category utilise fuzzy clustering.

In healthcare services, fuzzy clustering and fuzzy inference systems were the most used by eight articles, whereas fuzzy logic was found in 3 articles only. FDM was not used in any of the studies. In the "others" category, fuzzy logic and fuzzy inference systems were used the most by 12 articles, whereas fuzzy clustering and FDM were used by two and one articles,respectively.

- Q4: What popular evaluation tools are applied for fuzzy theory in FC?

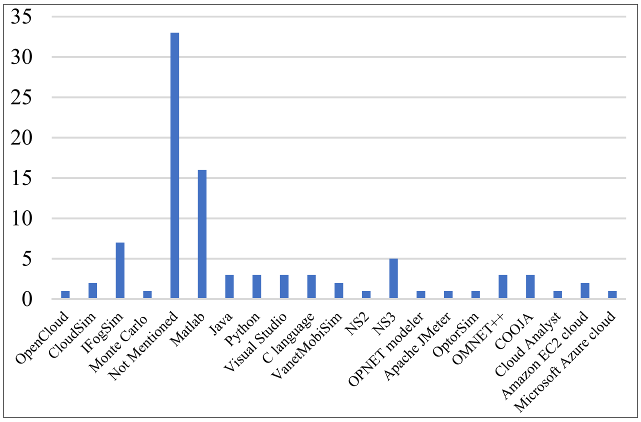

FIGURE 14. **Percentage of experiment tools.**

Figure 14 shows the percentage of evaluation tools used to evaluate the results of using fuzzy theory in the FC. The results show that MATLAB was used by 16 articles, iFogSim by seven articles, and NS3 by five articles, whereas Java, Python, Visual Studio, C language, OMNET++, and COOJA were used by three articles for each, CloudSim, VanetMobiSim, and Amazon EC2 cloud were used by two articles. One article each used OpenCloud, Monte Carlo simulation, NS2, OPNET modeller, Apache JMeter, OptorSim, Cloud Analyst, and Microsoft Azure cloud.

VII. LIMITATIONS AND OPEN ISSUES

Based on this review, many limitations and open issues were discovered in the articles. This section provides answers to RQ 5.

- **RQ 5:** What are the open issues and future trends of fuzzy theory in FC?

A. TASK AND RESOURCE MANAGEMENT

The fuzzy theory was used the most in task and resource management; however, the methods still need to be improved to obtain better results. However, there are still many limitations to task and resource management. This section presents the limitations and issues of our observations. The most important measurements were the response time, delay, cost, and energy consumption. These measurements were most commonly used in previous studies to evaluate fuzzy fog systems and models. Using fuzzy theory improved these measurements; however, the response time and delay still need to be improved by applying more fuzzy rules [88], [117]. Cost and energy usage continue to register high numbers for a variety of reasons. In addition, many studies were not considered when calculating them. [88], [90], [91], [100]. Scalability is a major issue in functional connectivity (FC). Scalability can be decreased by applying fuzzy theory; however, it still needs to be improved. Additionally, researchers used small datasets to assess their own work [92], [112].

B. INTRUSION DETECTION SYSTEM

In FC, the fuzzy theory is utilised to identify and forecast attacks; nevertheless, there are few studies that use fuzzy intrusion detection systems. The limitations and issues are discussed in this section. In general, the accuracy was still low, and the running time was excessive because of the large number of fuzzy rules employed in the publications that used fuzzy rules for attack detection. In terms of detection and prediction, the presented models or methods have historically significant false alarm rates [130], [132], [133], [134]. The proposed methods and models focus on specific types of attacks, for example, [130] to detect DDoS and collusion attacks only, while [131] focusing on phishing attacks. Additionally, some articles failed to mention or explain the datasets [127], whereas others [128] used limited datasets for testing and training. In this situation, expanding the datasets will help the system learn more, while also enhancing the IDS's ability to recognise and anticipate future attacks via FC. To shorten the detection and prediction times, the fuzzy rules must also be decreased. The detection still needs to be improved by using FDM to provide a recommendation to the system. After reviewing the papers, no study has used FDM, which can be a new direction for future studies.

C. TRUST MANAGEMENT

The fuzzy theory has been used in trust management in recent years. However, similar to intrusion detection, few articles have used fuzzy theory in trust management for FC. Therefore, there are some limitations to this study. One limitation is that trust is not dynamic [138], [140]. Trust in FC must be dynamic for two reasons. First, the network topology in the FC continuously changes. New objects join and leave the network. Second, objects in the network may alter their behaviour. Therefore, trust must be continuously computed. In addition, we found that no study has used fuzzy clustering in trust management for FC. This could be a new direction for future research.

D. HEALTHCARE SERVICES

The fuzzy theory has been used in healthcare services to improve patient monitoring and disease detection and prediction. Many researchers have tried to improve health services using fuzzy theory in FC; however, limitations exist and ought to be improved.

Researchers have mostly used fuzzy theory to improve disease detection; however, the accuracy still needs improvement [159], [160]. Some researchers have used fuzzy clustering for highly accurate detection. One study [167] used the FCM algorithm with high accuracy within a small dataset.

As mentioned in Section 7.1, many researchers have not calculated the cost and energy consumption [156]. Additionally, despite the fact that delay and response time are crucial parameters that have an impact on patient lives, they are not calculated [156], [163], [165].

Furthermore, after reviewing the papers, we observed that no study used FDM in healthcare services. Decision-making is very important, especially in healthcare services, because it must provide a decision after monitoring the patient's health or detecting the diseases. Additionally, to enhance patient health monitoring, it is necessary to determine the patient's criticality using fuzzy logic.

VIII. CONCLUSION

For various reasons, FC is regarded as a crucial research topic. Ongoing research projects are underway in this area. The fuzzy theory has been applied in many different directions of FC in this context. In this study, we conducted a systematic review of the use of fuzzy theory in FC. This study presents an SLR-based method by applying 1990 articles recently published between 2015 and 2022 by utilising an exploration query. 94 articles use fuzzy theory for FC in various ways. Five categories of fuzzy theory applications were identified. The top class of fog that uses fuzzy theory is task and resource management (37%), followed by healthcare services (20%), trust management (8%), intrusion detection (6%), and others (29%). By carefully reading and analysing various review articles, a large amount of crucial data was collected, such as problems, difficulties, and obstacles, as well as the inspiration, benefits, and recommendations found using fuzzy theory in FC. In this study, we discussed the problems, challenges, and issues, while also providing a variety of recommendations to identify actual and possible problems by applying fuzzy theory in an FC environment. Hence, research has motivated the proposal (or development) of fuzzy theory in FC. Additionally, we have included a thorough overview that illustrates the approaches to using fuzzy theory in FC. Moreover, we determined the weaknesses of the existing frameworks, systems, and methodologies to identify the scope that might be used in future research projects.

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