A Survey on Soft Computing Techniques for Federated Learning- Applications, Challenges and Future Directions

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Federated Learning is a distributed, privacy-preserving machine learning model that is gaining more attention these days. Federated Learning has a vast number of applications in different fields. While being more popular, it also suffers some drawbacks like high communication costs, privacy concerns, and data management issues. In this survey, we define federated learning systems and analyse the system to ensure a smooth flow and to guide future research with the help of soft computing techniques. We undertake a complete review of aggregating federated learning systems with soft computing techniques. We also investigate the impacts of collaborating various nature-inspired techniques with federated learning to alleviate its flaws. Finally, this paper discusses the possible future developments of integrating federated learning and soft computing techniques.

CCS Concepts: • **Soft Computing Techniques**; • **Federated Learning**; • **Nature Inspired Algorithms**; • **Communication Cost**; • **General and reference → Surveys and overviews**;

Additional Key Words and Phrases: Particle swarm optimization, nature inspired algorithms, privacy, data management

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1 INTRODUCTION

Machine learning (ML) has been successful in recent years due to three primary characteristics that have contributed significantly to its extensive use and success [1]. The availability of big data, which is gathered across multiple areas such as image processing and mobile networking, is the first crucial aspect. The second aspect for ML for being successful is its recent advancements in processing power and innovative learning techniques. The third factor is the emergence of **Deep learning (DL)** models, which have been utilized to add intelligence to ML models and computational devices [2]. The use of DL models has shown a very high success rate. Traditional centralised ML needs local clients, such as smart phone users, to transfer their data directly to the central server for model training, which may result in significant private information leakage [3]. Though ML has been very successful in many fields it also has some drawbacks like:

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- Data Privacy is a major concern.
- Heterogeneous data cannot be handled efficiently.

These problems in traditional ML models led to the birth of a new and promising ML concept called **Federated Learning (FL)**. Google invented the FL concept in 2016 [4] with features like on-device training and privacy preservation. FL is a **Distributed Machine Learning (DML)** approach that allows several local devices to collaboratively train a common global model while the training data remained on edge devices [5]. This distributed strategy safeguards the privacy and confidentiality of user data. FL is potential enough to solve privacy concerns, reduce latency issues, increase the model robustness, and improve communication efficiency [6]. Many applications like healthcare [7], wireless communications, **Internet of Things (IoT)** applications [8], and vehicular networks [9] leverage the concept of FL.

The FL concept has its own set of advantages and disadvantages, which vary accordingly from one application to another application. Though FL reduces the amount of data sent to the cloud, it still needs a number of rounds of communication to transfer the trained model which leads to communication overhead. FL deals with heterogeneous devices, where the computational, calculations, and storage capabilities of each device differ and this is to be handled efficiently. Due to varying environments and configurations, the FL system generates data that is statistically diverse and has to handle it with proper techniques [10]. Although FL supports the concept of privacy, it is still necessary to take precautions to ensure that sensitive data is restricted to specific individuals or devices. Many studies are going on for mitigating the flaws in FL. The authors in [11] proposed a hybrid approach which uses both differential privacy and **Secure Multiparty Computation (SMC)** to reduce the interruption when more numbers of devices are added without compromising privacy. The study in [12] refers to a differential privacy preserving algorithm on the client side. This aims in hiding the data from the client, thereby preserving the privacy of client data. A HybridAlpha approach is implemented in paper [13], to preserve privacy in FL by employing an SMC protocol based on functional encryption. A brief survey about the communication efficient FL algorithms is presented in [14]. Also, this paper proposes some solutions to alleviate the communication and privacy problems. A communication-efficient FL framework that enables edge devices to efficiently train and transmit model parameters is discussed in [15]. An efficient-communication approach called FedCPF which contains three parts namely "Customized", "Partial", and "Flexible", is referred to in [16]. A **Communication-Mitigated Federated Learning (CMFL)** approach is proposed in [17]. The feedback related to the model update is given to the client. Every client checks if the feedback is relevant to the improvement of the model or not. CMFL avoids some unrelated updates to the server thereby reducing the communication overhead.

Despite the rapid development of FL and its introduction in various applications, the hurdles prevailing in FL implementation should also be mitigated. A thorough assessment that presents an overview of FL, **Soft Computing (SC)** techniques, and the application of soft computing techniques specially the bio-inspired algorithms to reduce the flaws of FL is lacking. Getting inspired from this fact, we will highlight on providing the fundamentals of FL, SC, and the application of SC techniques, especially the nature inspired algorithms in FL.

1.1 Comparisons and Contributions

When it comes to the survey papers on SC, a survey was presented in [18] which tells about various types of SC techniques like genetic algorithms, evolutionary computation, fuzzy techniques, and so on. The authors in [19] explain how SC techniques and empirical formulations can help in depth modeling such as around pipelines, bridges abutments, piles, and grade-control structures. The authors in [20] present a review on various SC techniques and also specify the flow charts related

Table 1. Summary of Review Papers on Soft Computing and Federated Learning

Reference	Summary of Work	Limitations
[18]	A survey which tells about various types of soft computing techniques like genetic algorithms, evolutionary computation, and fuzzy techniques	This study does not focus on the role of soft computing for FL services and applications
[20]	A study that describes the review of various soft computing techniques and also specifies the flow charts related to each and every SC technique	The application of soft computing techniques is not explained in this study
[21]	Soft computing techniques and various application areas where SC is implemented	The application of FL and soft computing techniques is not specified here
[22]–[26]	The application areas of Fuzzy logic and also the details of Fuzzy are explained here	Application of Fuzzy in FL areas is not explained here
[27]–[29]	The study gives a brief survey of the nature inspired algorithms	Application of nature inspired algorithms in FL is not elaborated in this study
[30]	This study gives a brief survey about FL and the applications of FL in various areas	This study should also refer to some soft computing techniques to rectify flaws in FL
[31]	This study gives a brief survey about the threats related to FL	This study does not refer to how soft computing will rectify the threats to FL
This Survey	The survey provides reviews about the various soft computing techniques that help in mitigating the problems in FL mainly focusing on nature inspired algorithms and FL	

to each and every SC technique. The survey in [21] focuses on the SC techniques and various application areas where SC is implemented. Surveys like [22], [23], [24], [25], and [26] highlight the details of fuzzy logic and also the application areas of fuzzy logic. The study in [27] gives a brief survey on several nature inspired algorithms. The authors in [28] and [29] go into great detail about bio-inspired algorithms.

With regards to FL, several surveys have been conducted over the last few years ([2], [30]). The study in [2] explains about different types of FL and also the applications of FL in various sectors. The authors of [30] investigate the primary challenges and survey of works in FL. A short survey on threats to FL is presented in [31]. Two types of threats on FL, namely poisoning attacks and inference attacks, are discussed in this paper.

A huge amount of research has been initiated to study the use of several SC techniques in mitigating some common problems related to FL. To mitigate the problem of communication cost, popular approaches are proposed like compression and sub-sampling of the client uploads [32], or quantization of the weights of the models are proposed. The authors in [33] suggested a method of temporally weighted aggregation and a synchronous model update strategy. A **Multi-Objective Evolutionary Algorithm (MOEA)** is implemented in [34] to improve the communication efficiency and performance of the model. Inspired by this, in this work we will be focusing on explaining the fundamentals of FL and SC, and reviewing state-of-the-art research works on an FL and SC combination. For clarity, the recent surveys are listed in Table 1.

Unlike previous works, our work provides a survey of the integration of FL and SC techniques, particularly bio-inspired algorithms. To the best of our knowledge, this work is the very first attempt on the integration of FL and SC techniques. The following is a summary of the major contributions made by our work.

- We present the fundamentals of distributed learning, Federated Learning, and an introduction to soft computing.

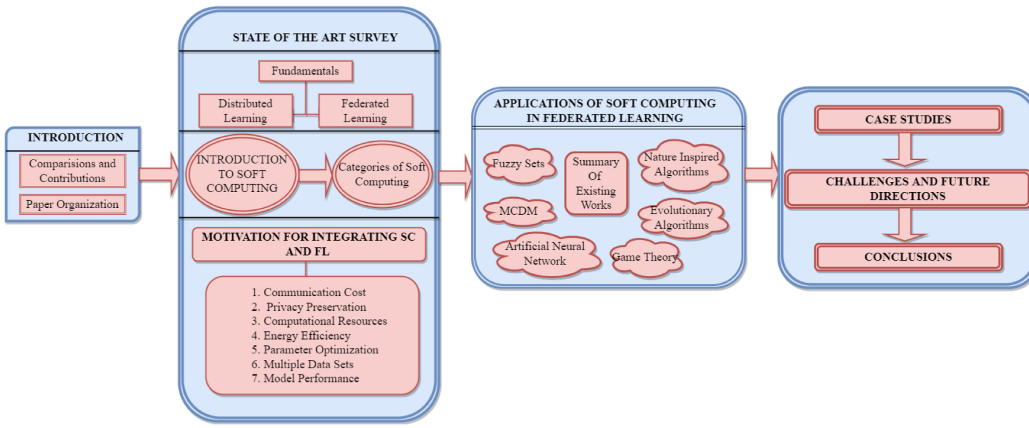

Fig. 1. Paper organization.

- We review the state-of-the arts on FL and SC, categories of soft computing, and motivation for integrating FL and soft computing.
- We also explain the applications of SC in FL and study the relevant case studies.
- The challenges associated with current studies on FL and soft computing are discussed in our survey, and further highlight open research issues that should be efficiently addressed.

1.2 Paper Organization

The remaining parts of this paper are organized as follows. Paper organization is explained in detail in Figure 1. In Section 2, we present the fundamentals of FL and **Distributed Learning (DL),** and provide an introduction to SC and also motivations of FL-SC integration. In Section 3, we review the applications of soft computing techniques in FL. Next, Section 4 presents the current case studies of the FL and SC combination. Challenges and future directions in the use of SC for FL are discussed in Section 5, and finally, we conclude the paper in Section 6. Figure 1 gives the complete picture of the organization of the paper.

2 STATE OF THE ART SURVEY

This section completely discusses about the fundamentals of DL, fundamentals of FL, and the Introduction to SC. Introduction to SC explains all about the different categories of SC.

Table 2 gives the list of abbreviations used throughout the paper.

2.1 Fundamentals of Distributed Learning

In recent years, rapid technological advancement has resulted in an incredible increase in data collection. ML techniques are increasingly being utilized to evaluate data sets and create decision-making systems where an algorithmic solution is not possible due to the problem's complexity [35]. Controlling self-driving cars, detecting speech, and forecasting customer behaviour are just a few examples [36]. The latency in training the models will sometimes lead to the utilization of distributed systems in order to increase the parallelization and performance as the data used for training sometimes may be in terabytes. Centralized ML cannot even be considered as a good option when the data is inherently scattered or too big to be handled by a single machine [37]. In order to address this problem, a **Distributed Machine Learning (DML)** has come into the limelight. In DML, the training is done across multiple nodes which have the subsets of the data [38].

In the case of the distributed model there are two ways of training approaches: parallelizing data or Model [39]. In the data-parallel approach, the data is split as many times as the worker

Table 2. List of Abbreviations

Abbreviation	**Description**
ML	Machine Learning
FL	Federated Learning
DL	Distributed Learning
DML	Distributed Machine Learning
AI	Artificial Intelligence
IoT	Internet of Things
SMC	Secure Multiparty Computation
CMFL	Communication-Mitigated Federated Learning
SC	Soft Computing
MOEA	Multi-objective Evolutionary Algorithm
IIoT	Industrial Internet of Things
ACO	Ant Colony Optimization
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
FA	FireFly Algorithm
CS	Cuckoo Search
ABC	Artificial Bee Colony
RFOA	Red Fox Optimization Algorithm
PBA	Polar Bear Algorithm
WOA	Whale Optimization Algorithm
ANN	Artificial Neural Network
FFNN	Feed Forward Neural Networks
FBNN	Feed Backward Neural Network
EC	Evolutionary Computation
EA	Evolutionary Algorithms
GP	Genetic Programming
GA	Genetic Algorithms
EP	Evolutionary Programming
ES	Evolutionary Strategies
MCDM	Multiple-Criteria Decision Making
MCDM	Multi-attribute Decision Making
MODM	Multi-Objective Decision Making
BIM	Building information modelling
AHP	Analytic Hierarchy Process
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
NAS	Neural Architecture Search
SDES	Sliding Differential Evolution Based Scheduling
UAV	Unmanned Aerial Vehicle

nodes, and all the worker nodes apply the same algorithm on the distinct data sets. In the parallel model approach, the similar data set copies are processed by the worker nodes in the different parts of the model [40]. DML can be used in various applications where massive amounts of data is generated like healthcare applications, sensors data, traffic sensor data, communications, and so on. DML also plays an important role in the field of big data analytics [41].

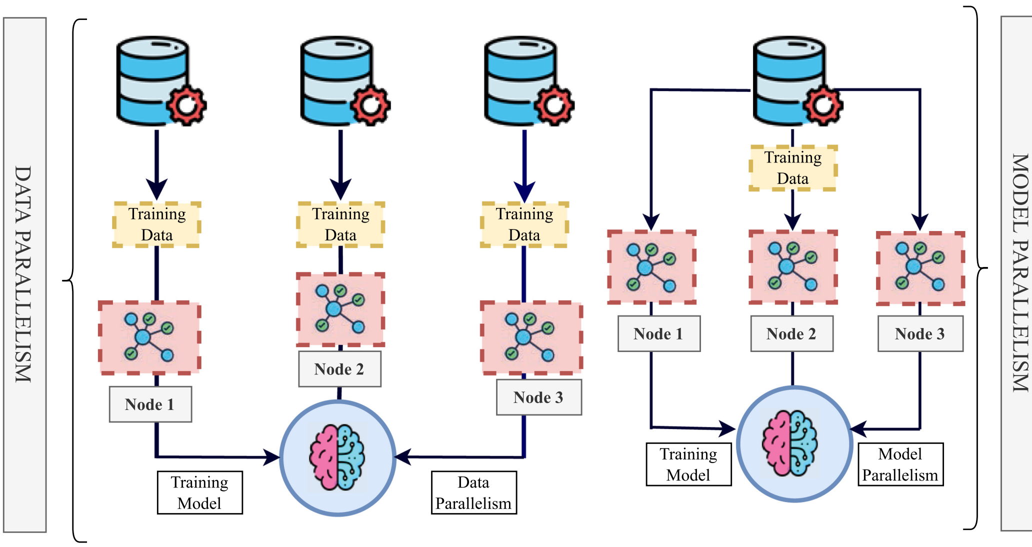

Fig. 2. Types of distributed learning: Model parallelism and data parallelism.

Figure 3 depicts the types of distributed Learning. DML is a growing ecosystem with a wide range of solutions with varying architectures, algorithms, performance, and efficiency [42]. To make DML feasible, some fundamental problems have to be solved. DML faces some limitations like fault tolerance, privacy, performance, portability, and a lack of fixed methods to evaluate the DML Algorithm. The following subsection discusses the concept of FL and how it differs from traditional ML and DML in terms of privacy and security [37].

2.2 Fundamentals of Federated Learning

FL is a DML approach where a number of users train a single model. FL is different and more for addressing the privacy problems [43]. Raw data is distributed to independent nodes containing local data in FL systems, and the models are trained on the local nodes with data stored in their respective nodes. Once the model has been trained individually, each of the new model weights is transmitted back to the central server and integrated to form a highly efficient model [44]. Using global data to train the model increases the model's efficiency by a significant amount. This also guarantees that the data in each node complies with data privacy policies and that any data leaks or breaches are prevented [3]. The advantages of FL over ML will be the privacy preservation, it reduces latency in communication and handles large amounts of data efficiently [44–47].

FL is considered to be the improved version of DML. However, few disparities between FL and DML make FL have more potential when compared to DML. FL can employ many security measures like block chain and differential privacy methods, and it enhances the security and privacy of data [48], but DML is not that efficient in using such measures. FL uses distributed nodes from multiple organizations located at different places, but DML does this with the nodes in a single cluster or a same organization [49]. The nodes incorporated in DML are typically data centers and they have good computational powers; whereas the nodes in the FL system can either be mobile devices which are battery dependant or devices which work in different environments which reduce their computational power. The authors in [50] explain about the fusion of FL and Industrial Internet of Things (IIoT). Figure 3 is the basic architecture of Federated Learning.

FL has some lingering issues in privacy of the data that is collected and distributed. Though only the models are sent to the central server and not the raw data, there is a chance of reverse

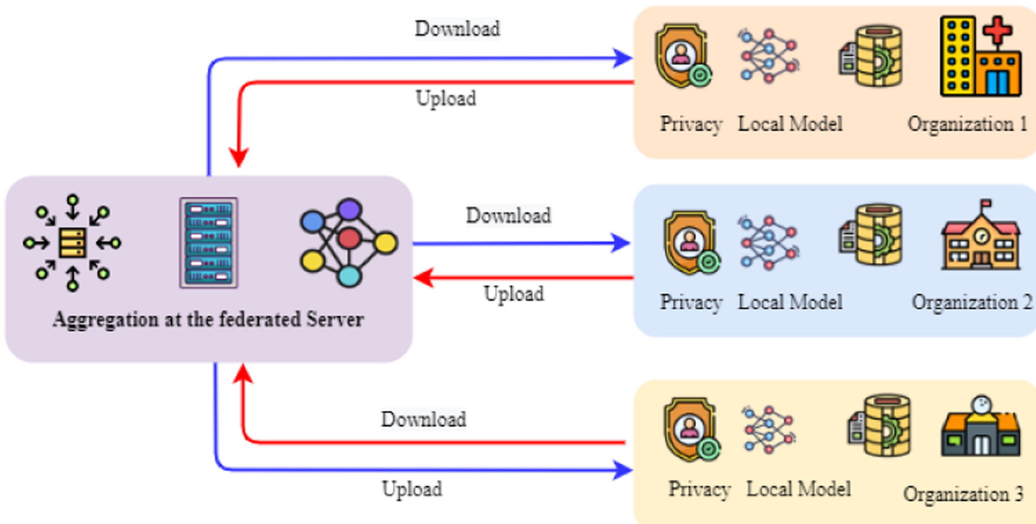

Fig. 3. Federated learning architecture.

engineering to identify the client data [51]. In federated learning, models from various devices are combined to create a better model. Device-specific factors may limit the generalisation of the models from some devices and may affect the accuracy of the next edition of the model. In federated learning, there is still some centralization where a central model leverages the output of other devices to create a new model. To create zero-trust federated learning models, researchers propose employing **block chain in federated learning (BlockFL)** and other technologies [52].

2.3 Introduction to Soft Computing

Soft computing is a collection of approaches aimed to simulate and enable solutions to real-world issues that are difficult to address mathematically [53]. Soft computing techniques are designed to tolerate imprecision, uncertainty, approximate reasoning, and partial truth [54]. It aspires to be as near to human decision-making as possible. The term Soft Computing was first given by Professor Lorfi Zadeh in 1981. He defined Soft Computing as a fusion of fields like Fuzzy logic, Neuro computing, evolutionary and genetic computing, and probabilistic computing [18]. It is different from Hard Computing which is a conventional computing model which completely relies on logical reasoning and numerical calculations. SC is an integrative field which creates a new phase of Artificial Intelligence which is named Computational Intelligence [55].

It tries to create a hybrid technology that incorporates the features of all the participating techniques. SC approaches have a wide range of applications and are an emerging subject that incorporates complementing components out of a range of techniques [21]. It wide spreads its applications in fields like medical imaging, computer vision, writing improvement, and air safety.

2.3.1 Categories of Soft Computing. Soft Computing is an approximation model that solves many real world problems. It is more prevalent in areas where the mathematical calculations cannot end up as a perfect solution for any problem [56]. Soft Computing mainly can be categorised as shown in Figure 4.

Fuzzy Logic. As the system's complexity grows, it becomes increasingly difficult and sometimes impossible to make exact statements about its behaviour, eventually reaching a threshold of complexity where the fuzzy logic method is the only approach to solve a problem [54]. Fuzzy theory

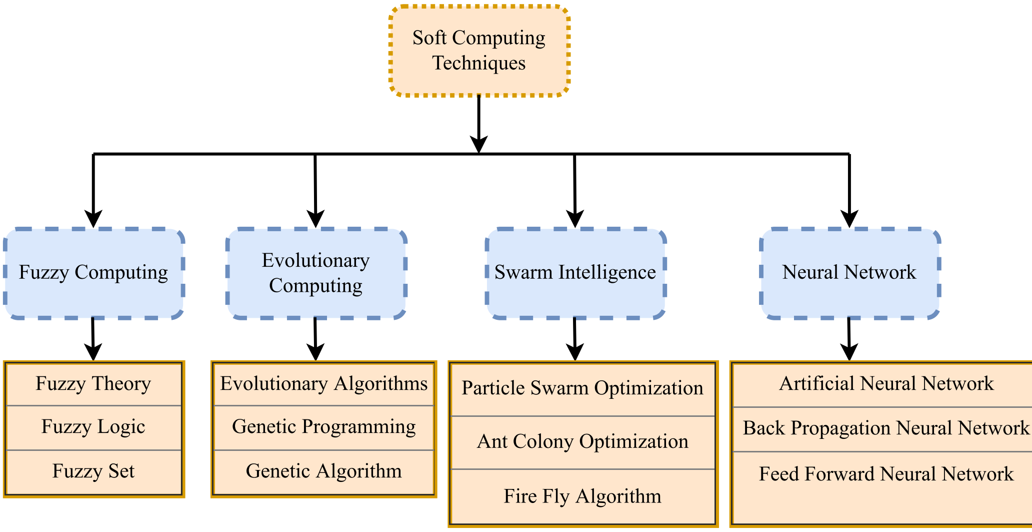

Fig. 4. Categories of soft computing.

gives the logic which is beyond the binary logic limitations. Fuzzy Logic was first coined by Lotfi A. Zadeh, professor for computer science at the University of California in Berkeley [57]. It enables a new approach in solving the control and classification problems [19]. Fuzzy Logic plays a key role in complex systems and proved to be efficient in steering and controlling complex applications. The drastic change in implementation of Fuzzy logic in applications ranging from daily use appliances to the high end systems has attracted many scientists and engineers towards it. It is used in controlling systems and design analysis as it lessens the time it takes for engineering development and sometimes to solve complex systems [20].

Fuzzy logic is a kind of multi valued logic that allows for the definition of intermediate values between conventional evaluations such as true/false, yes/no, high/low, and so on. Fuzzy sets implement the fuzzy logic. Fuzzy set theory describes a fuzzy set as a group of objects with a range of membership grades. Fuzzy Logic is briefed in Figure 5. A fuzzy logic system operates under the principle of assigning a certain output based on the likelihood of the condition of the input. In a subset of the reference set, the change from membership to non-membership is progressive rather than sudden. Several basic operations like intersect, negate, and unity can be performed on fuzzy sets [21]. Fuzzy logic is a good way to deal with incomplete data, imprecise knowledge, linguistic expression, and so on. Fuzzy logic has applications in many areas like automotive and Power Generation, consumer appliances, industrial process control, the medical field, and telecommunication network [22, 23]. Fuzzy Logic algorithms also suffer few limitations. Since the Fuzzy algorithms deal with inadequate and inaccurate data, the accuracy might not be up to a certain level sometimes and there is no single systematic approach to implement this logic, and these reasons pave a path for it not to be used widely.

Nature Inspired Algorithms:

Nature-inspired algorithms have recently seen widespread acceptance for a wide range of real-world optimization issues, including engineering trials, scientific research, and corporate decision-making [58]. These algorithms are based on the concept of randomization and are inspired by natural phenomena. Nature-inspired algorithms find optimal solutions for a broader range of problem domains in a reasonable amount of time when compared to standard optimization techniques [59]. Some of the popular nature-inspired algorithms are swarm intelligence, genetic

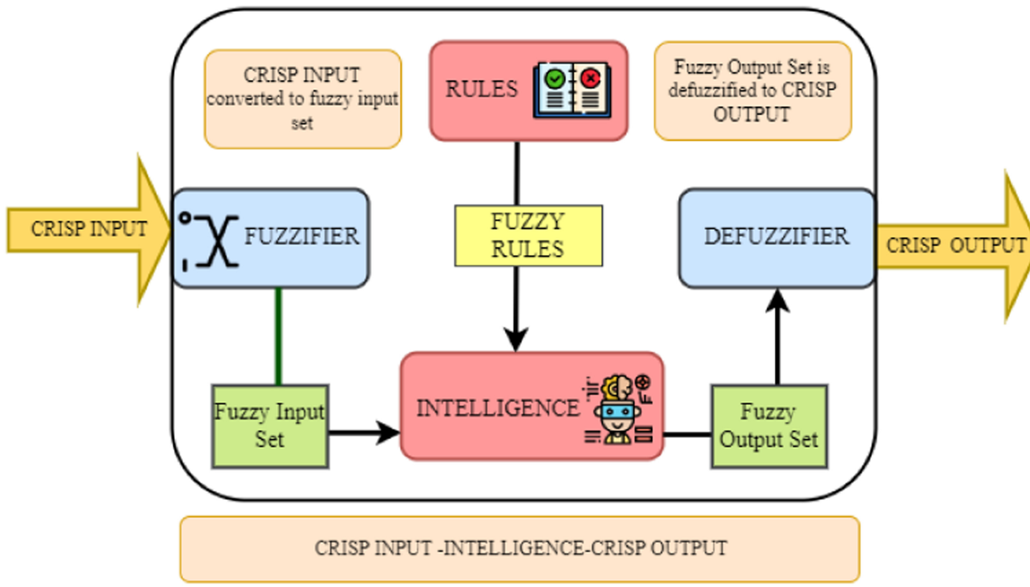

Fig. 5. Workings of fuzzy logic.

algorithm, evolutionary computation, bio-inspired algorithms, and other nature inspired algorithms. Let us study in detail about every algorithm which is inspired from nature. A good nature-inspired algorithm has features like a higher convergence rate, a shorter processing time, unbiased exploration and exploitation, and fewer algorithm-specific control parameters [27]. The fundamental parameters of any nature-inspired algorithm are exploration and exploitation. Any nature inspired algorithm needs two types of parameters namely common control parameters and algorithm specific control parameters which are also called regular parameters and dependant parameters, respectively [28]. Figure 6 elaborates the categories of Nature Inspired Algorithms.

Nature inspired algorithms can be grouped based on the sources from which they are inspired like swarm intelligence, natural evolution, biological based, science based, and others [26]. The popular nature-inspired algorithms are **Ant Colony Optimization (ACO)** [60], **Genetic Algorithms (GA)**, **Particle swarm Optimization (PSO)**, **FireFly Algorithm (FA)**, **Cuckoo Search (CS)**, **Artificial Bee Colony (ABC)** [61], **Red Fox Optimization Algorithm (RFOA)**, **Polar Bear Algorithm (PBA)**, **Whale Optimization Algorithm (WOA),** and so on. Genetic Algorithms are based on the basic principle of natural evolution. GA works on the concept of crossover, mutation and selection, and many advancements have been done in GA to improve its performance, effectiveness, and robustness [62]. PSO, FA, CS, and ABC are all swarm intelligence algorithms that are based on the behavior of creatures like bats, ants, bees, cuckoos, and fireflies. There are also other algorithms that are inspired by the behavioral patterns of biological systems and scientific concepts which are called biological based algorithms and science-based algorithms [63]. Table 3 is a comparative study of Soft Computing Algorithms. Many of the nature-inspired algorithms proposed so far have found to be quite efficient. Many algorithms produce satisfactory results, but none of them perform superbly in tackling all optimization issues. In other words, an algorithm may perform well for some tasks while it is under performing for others.

Artificial Neural Networks

A neural network is a set of algorithms that attempts to recognise underlying relationships in a set of data using a method that mimics how the human brain works [64]. Neural networks, in

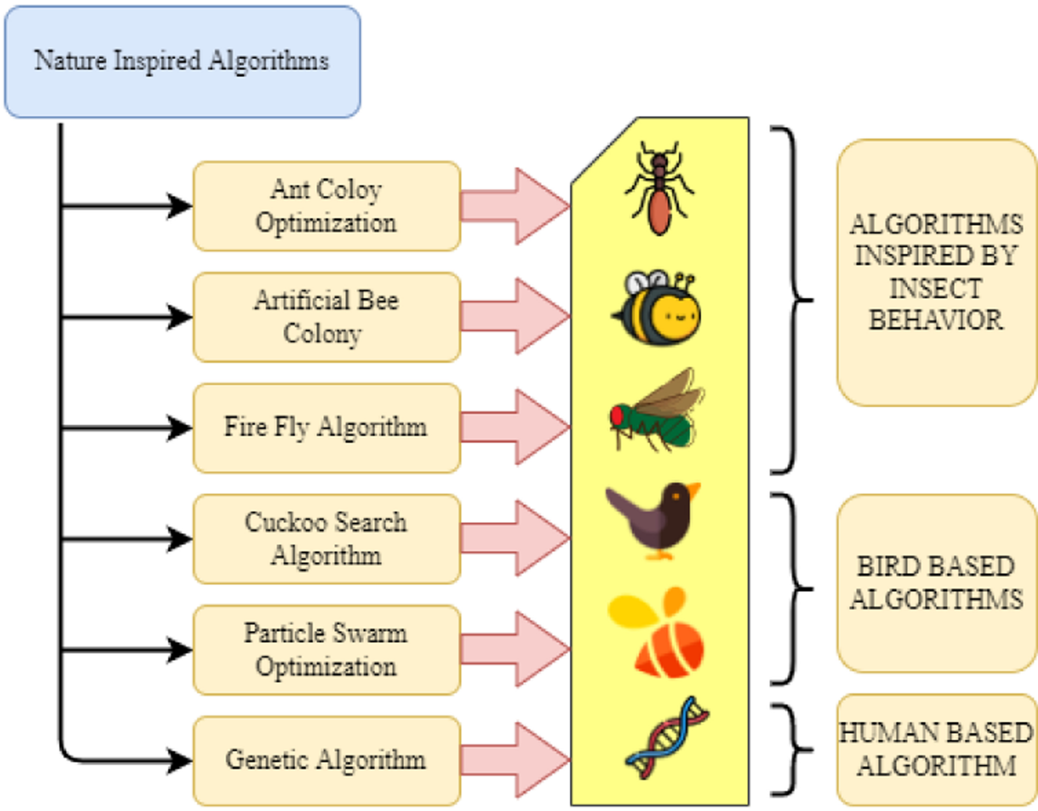

Fig. 6. Categories of nature inspired algorithms.

Table 3. Comparative Study of Soft Computing Algorithms

Algorithm	**Inspiring Creature**	**Inspiring Behaviour**	**Communication Action**
PSO	Birds and Fishes	Birds Flocking and Fish Schooling	Behaviour while Flying
ACO	Ants	Food Gathering Phenomenon	Pheromone Deposition
FA	FireFly	Attractive Phenomenon	Flash
ABC	Bees	Nectar Gathering Phenomenon	Waggle Dance
GA	Genetics	Genetic Phenomena	Genes making
RFOA	Red Fox	The hunting behaviour of Red Foxes	Behaviour
PBA	Polar Bear	The hunting behaviour of Polar Bears	Behaviour
WOA	Whales	The hunting behaviour of Whales	Behaviour

this context, refer to systems of neurons that can be organic or artificial in nature. Because neural networks can adapt to changing input, they can produce the best possible result without requiring the output criteria to be redesigned [65]. A neural network is similar to the neural network in the human brain. In a neural network, a "neuron" is a mathematical function that collects and categorizes data using a specific architecture. Curve fitting and regression analysis are two statistical methods that the network closely resembles [66]. **Artificial Neural Network (ANN)** has many applications in the real-world like in science, engineering, medicine, environment, mining, agriculture, climate, technology, business, arts, nanotechnology, and so on. The ANN can be classified as **Feed Forward Neural Networks (FFNN)** and **Feed Backward Neural Network (FBNN)** [67]. The FFNN is an ML classification algorithm which is similar to the human neuron processing units. FBNN uses the internal stage memory to process the sequence of data inputs [68]. The ANN is much different from traditional artificial intelligence and is considered to be a parallel distributed system which handles the intuition and unstructured information in a different manner and also covers the defects of AI. ANN can solve complicated problems which cannot be solved by modern computers [69]. ANN has many advantages like adaptive learning, self organization, parallel operation, and fault tolerance. ANN also has some disadvantages like the output is not clear and the time taken for processing changes according to the inputs is high and it is not suggest able to use when the input and output is known clearly [70].

Evolutionary Computation

Natural growth influences EC, which is a class of global optimization algorithms. The growth of a group of people who react to a problem is the starting point for this method. The initial population could be generated at random or by feeding it into an algorithm [71]. Individuals are assessed using a fitness function, with the output indicating how well they solve or come close to solving the problem. Individuals are then subjected to operators inspired by natural evolution, such as crossover, mutation, selection, and reproduction [72]. A new population is created based on the fitness values of newly evolved individuals. Some individuals are removed in order to maintain the population size as it is in nature. This process continues until the criterion for termination is met. The most common criterion for stopping the algorithm is when it reaches the specified number of generations. As the solution, the best individual with the best fitness value is chosen [73]. Computer scientists working in the field of evolutionary computation have done a lot of recent research on computational development. **Evolutionary Algorithms (EA)** are the algorithms that help in stochastic search. **Genetic Programming (GP)**, **Genetic Algorithms (GAs)**, **Evolutionary Programming (EP)**, **Evolutionary Strategies (ES)**, and others are the well known Evolutionary Algorithms. Different Categories of Evolutionary Computing are explained in Figure 7.

GP is a category of Evolutionary computation, a technique that draws inspiration from the biological process of Darwinian evolution. The main objective of evolutionary computation is to resolve complex computational problems by drawing inspiration from nature [74]. Genetic algorithms are a type of search method that uses genetic algorithms. The GA was the only EA that explicitly distinguished genotype from phenotype. Unlike genetic programming, evolutionary programming has a fixed model and the parameters are allowed to evolve. It was first used by Lawrence J. Fogel in the US in 1960 [75]. ES are a subclass of nature-inspired optimization methods that use mutation, recombination, and selection applied to a population of individuals containing candidate solutions to evolve better and better solutions iteratively. It has roots back to the mid 1960s.

Many kinds of research have been proposed on Evolutionary Computation. We will be discussing a few of them. The search-based data analytics problems were examined in [76], as well as the applications in bioinformatics. The potential applications of EC methods in solving data analysis problems were discussed and analyzed. Inference or prediction on a large or small number

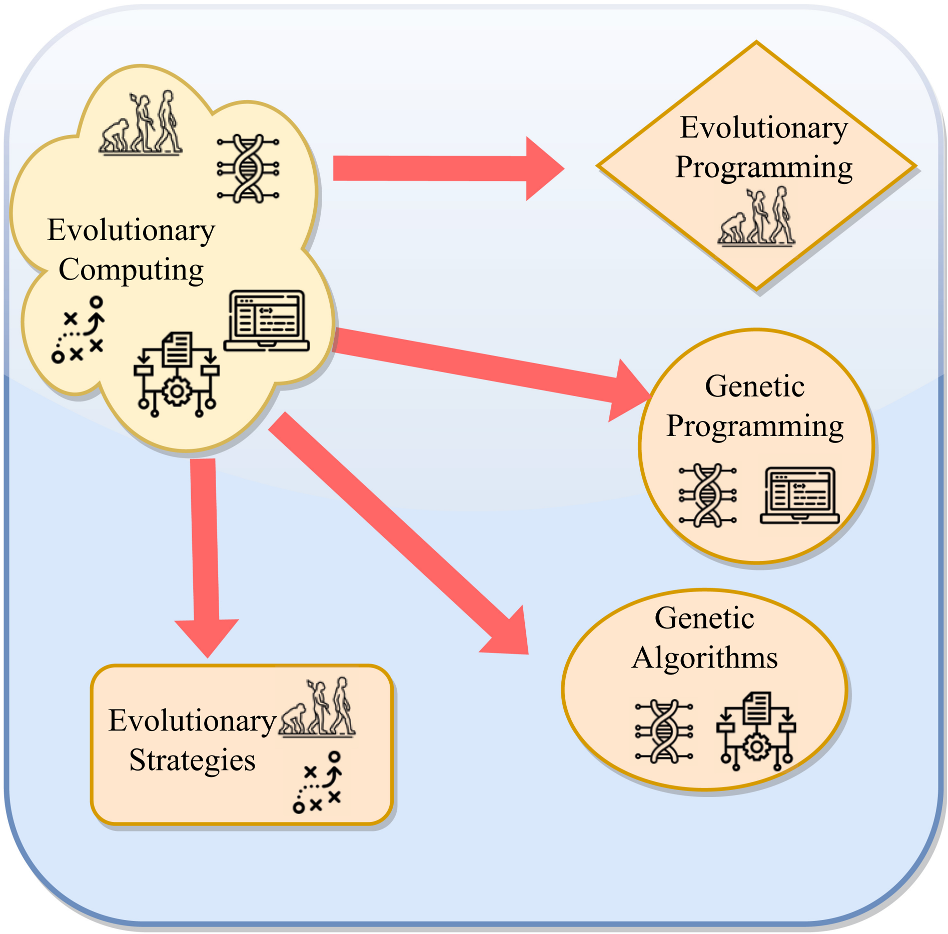

Fig. 7. Categories in evolutionary computing.

of data samples is a common problem in data analytics [77]. EC methods, which do not involve a complex mathematical model, are used to investigate collective behaviors in a population of solutions. The EC methods have proved significant success in solving problems that are complex, large-scale, computationally costly, dynamical, multi-objective, and so on. The paper [78] proposes a scheme for categorizing propagation problems into three categories: simulation, optimization, detection, and analysis. Propagation problems have been solved using evolutionary computation, a bio-inspired optimization method. The application of EC in a variety of social propagation problems is the focus of this paper. EC is a subcategory of soft computing and **artificial intelligence (AI)**. The following major challenges that ECs face are experiments aren't always repeatable, performance is poor, and real-time problems are not solvable.

Multi criteria Decision Making Algorithms

In today's world, so many decisions are made based on various criteria, so the decision can be made by assigning weights to various criteria, and all of the weights are obtained from expert groups. Making decisions is a complex and challenging task [79]. It is critical to identify the problem's structure and explicitly evaluate multiple criteria. The structure and solution of decision and planning problems involving multiple criteria is referred to as decision making. In many disciplines,

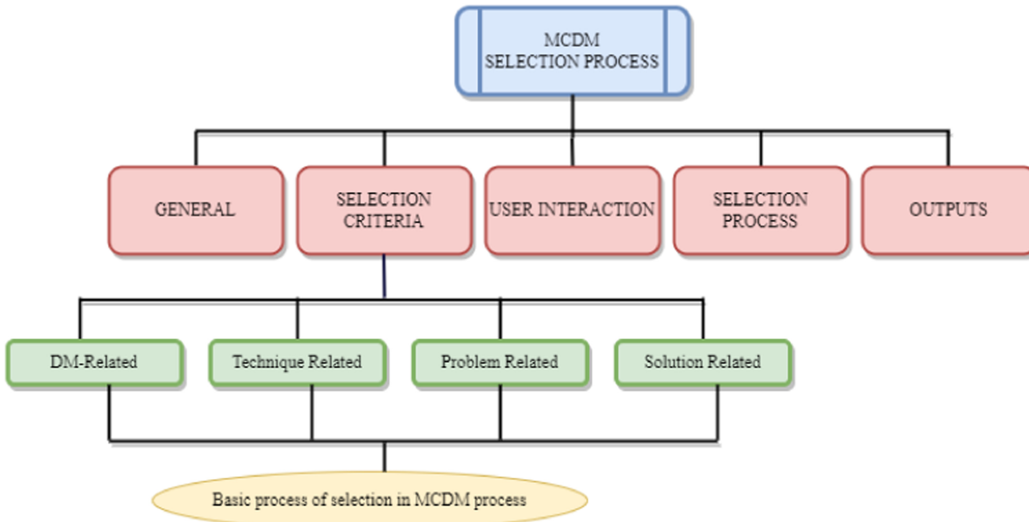

Fig. 8. Multi-criteria decision making.

Multiple-Criteria Decision Making (MCDM) has been one of the fastest growing problem areas. MCDM is the usual term for all methods that assist people in making decisions based on their preferences when there are multiple conflicting criteria [80]. Various methods of MCDM are explained in Figure 8. MCDM methods encompass a wide range of distinct approaches. MCDM methods are divided into two types: discrete MCDM, also known as discrete **Multi-attribute Decision Making (MADM)**, and continuous **Multi-Objective Decision Making (MODM)** [81]. Different types of data, multiple interests, and perspectives are described by MCDM, which is used for strategic evaluations and decision-making in complex problems with high uncertainty and conflicting objectives [82].

MCDM has a vast number of applications and many articles have explained its implementation in various scenarios. The MCDM and FL combination is regarded as an essential component for effective risk management in supply chain [83]. Utilizing the building information for supporting the decision-making is a key challenge in the engineering, construction and architecture industry. The connection between MCDM and **Building information modelling (BIM)** was discussed, and it can be used as a basis for evaluating how decision techniques are applied in practise [84]. This research identifies gaps in the current literature when it comes to combining MCDM and BIM. An extensive survey is done in [84] on the applications of fuzzy MCDM in civil engineering and discovers that risk assessment is the most concerned decision problem, cost is the most widely used evaluation criterion, fuzzy **Analytic hierarchy process (AHP)** is the most popular individual fuzzy MCDM model, and the combination of fuzzy AHP and fuzzy **Technique for order preference by similarity to ideal solution (TOPSIS)** is the most popular hybrid fuzzy MCDM model. The study in [85] aims to better understand the factors that influence freight transportation mode selection in Ghana through the decision-making process by identifying criteria that influence mode transportation decisions. To find the weights and suggest suitable alternatives for decision-makers in Ghana's Eastern transport regions, a combination of Fuzzy AHP and Topsis is used. MCDM bears many more applications individually and also in combination of other technologies like fuzzy, FL, and so on. Several methods in the MCDM technique face many problems when dealing with heterogeneous data.

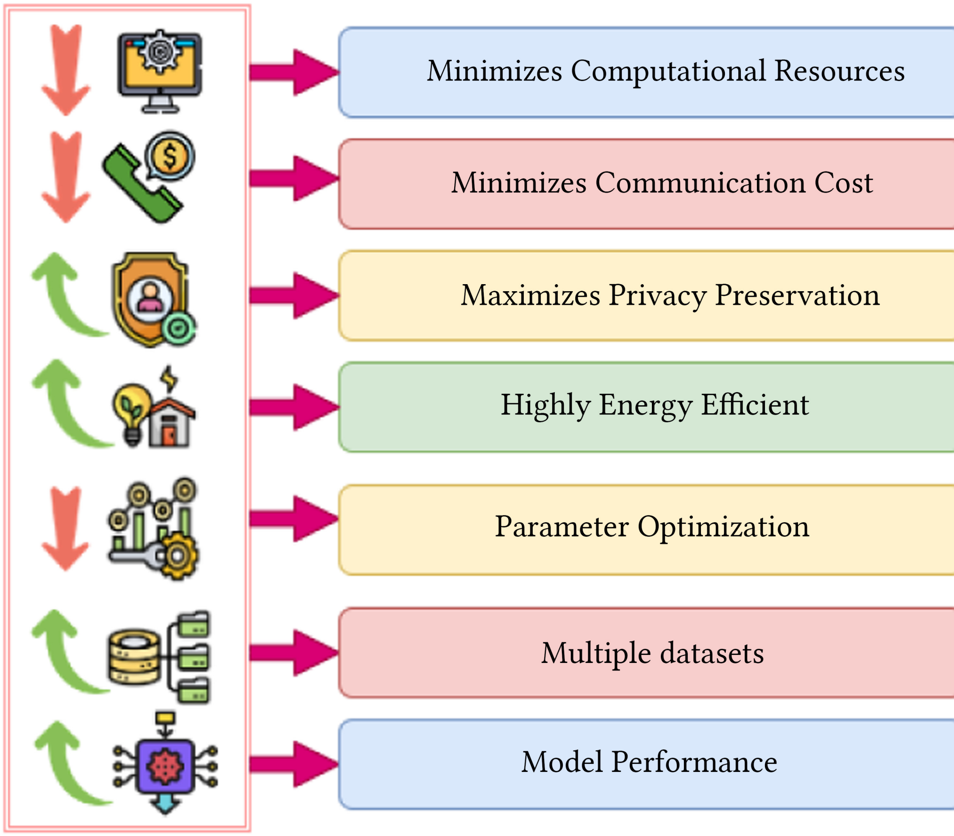

Fig. 9. Soft computing for FL.

2.4 Motivation for Integrating Federated Learning and Soft Computing

The motivation behind integrating Soft Computing and Federated Learning is specified in Figure 9.

- SC for Minimizing Communication Cost in FL:
  Federated learning is an up surging technique that prevents the leakage of personal data. Unlike centralized learning, which requires users to collect data and store it all on a cloud server, federated learning allows users to learn a global model while the data is distributed among their devices. However, when compared to the old centralized approach, the federated setup uses a significant amount of client communication resources, which is required for updating global models which leads to high communication cost. This seldom hinders this strategy from being widely adopted. To mitigate the communication cost problems, Hangyu Zhu et al. proposed a multi-evolutionary algorithm in [34] to enhance the structure of neural network models in FL. This method not only minimizes the communication costs but also improves the learning performance of FL.
- SC techniques for privacy preservation in FL:
  FL is a privacy-preserving DML framework that involves training statistical models across a group of mobile users while keeping data decentralized [86–88]. However, recent research has shown that when sharing model updates or gradients, users are still vulnerable to advanced inference attacks, which would hinder them from participating. The majority of

existing FL incentive mechanisms focus on workers' resource costs, while the cost of potential privacy leakage caused by inference attacks is rarely considered. Many Soft computing techniques have come into limelight which are used for enhancing privacy preservation in FL. The horizontal FL and ANN combination is one such technique which proves to be more effective in privacy preserving [89].

- SC for Minimizing computational resources in FL:
  FL is a distributed ML approach that enables privacy preservation but still faces two important technical challenges that limits its use. One is that, because a large number of model parameters must be transmitted between the server and the clients, federated learning places a high demand on communication. Another issue is that training large machine learning models in federated learning, such as deep neural networks, necessitates a significant amount of computational resources, which may be unattainable for edge devices such as mobile phones. The paper [90] proposes a real-time multi-objective evolutionary method for federated **neural architecture search (NAS)** that can effectively avoid extra communication costs and computational resources while optimizing the models' performance. This is accomplished through a two-sampling approach, in which a master model shared by all individuals in the same population is sampled, and the participating clients are sampled for training the global model.
- SC techniques for energy efficient FL:
  FL is considered to be promising ML technology that handles many challenges like privacy disclosure and high data transmission cost. FL poses many challenges in wireless communications like limited bandwidth, energy efficiency, and so on. Many kinds of research have been done for making FL an energy-efficient technique in wireless communication. The study in [91] specifies a perfect **sliding differential evolution based scheduling (SDES)** which produces a lower computational complexity compared with the existing methods. The proposed experiment is both an energy-saving and effective communication convergence. Table 4 explains the services provided by SC for Federated Learning.
- SC for Parameter Optimization in FL:
  FL faces various obstacles in terms of optimization, data privacy, and efficient communication as a result of the data privacy elements and developing a global model from distributed and diverse data sources. Existing FL research assumes fixed settings (architectures/structures, and other parameters) for ML models trained on local data sets at local hosts without investigating the optimal values for these parameters. The manual selection of these parameters by trial and error is time-consuming and necessitates a large experimental setup. The authors in [92] present a parameter setting method based on **Particle Swarm Optimization (PSO)** for the common parameters of local models trained by edge devices on local data in an FL context. This work, [93] offers a new hybrid technique called **genetic clustered FL (Genetic CFL)**, which clusters edge devices based on training hyper-parameters and genetically adjusts the parameters cluster-by-cluster. Then, by combining density-based clustering and genetic hyper parameter optimization, we present an approach that dramatically improves individual cluster accuracy.
- SC for supporting different data sets in FL:
  The older platforms like LEAF, pysyft, and FATE do not support the graph data sets, and the **Graph Neural Networks (GNN)** models. The unified system of FL and the GNN has fulfilled the concept of graph FL. The authors in the paper [94] have completely given full knowledge on how the unified system of FL and GNN will include the open data sets, baseline implementations, and programmable API's. FedGraphNN is also a benchmark which is easy to use for the researchers to solve the problems in the intersection of the FL and GNNs.

Table 4. Services Provided by Soft Computing for Federated Learning

Services	**Challenges faced by FL**	**Solutions provided by Soft Computing techniques**
Communication Cost	Communication cost is very high in FL	Multi-evolutionary algorithms enhance the structure of neural network models in FL thereby minimizing the communication costs.
Privacy	Privacy breaches happen sometimes in FL	The horizontal FL and ANN combination is one such technique which proves to be more effective in privacy preserving.
Computational Resources	Number of computational resources is more in FL	A real-time multi-objective evolutionary method for federated neural architecture search (NAS) can effectively avoid extra communication costs and computational resources while optimising the models' performance.
Energy Efficiency	Energy consumption is more due to the regular device updates in FL	A perfect sliding differential evolution based scheduling (SDES) produces a lower computational complexity compared with the existing methods. The proposed experiment is both an energy saving and effective communication convergence.
Parameter Optimization	The number of parameters applicable in FL model setup is large	A new hybrid technique called genetic clustered FL (Genetic CFL), clusters edge devices based on training hyper-parameters and genetically adjusts the parameters cluster-by-cluster.
Multiple data sets	The data sets handled can be different by FL	A unified technique called FedGraphNN is used to prove that FL can handle graph topology also.
Model Performance	Improper and inaccurate model	The combination of FL and some SC techniques, creates a high performing and accurate model.

- SC for improving the model performance in FL:
  The soft computing techniques will allow the improvement in the performance of the FL models either by the means of parameter optimization or by the means of reducing the number of rounds that are needed before aggregation. The work in the paper [93] explains that the performance of the models that are trained along with the genetic algorithm is more keen than that of the normal models. Also, the facts in this paper tell that the chance of vulnerability to poisonous attacks on FL models is also decreased by applying the soft computing techniques.

3 APPLICATIONS OF SOFT COMPUTING FOR FL

This section completely describes about the applications of Soft computing for Federated Learning. Each technique of SC can be applied to mitigate the flaws or to enhance the performance of FL.

3.1 Fuzzy Sets with FL

3.1.1 How Fuzzy Sets can Help FL. Fuzzy sets [95] can also help FL in handling the different data and to perform training and decisions in a proper way. Fuzzy also helps FL to improve the implementation speed of the FL model. Fuzzy sets helps in the privacy preserving FL approach.

3.1.2 Summarize Existing Works. It is difficult to arrive at a decision if no information is available. This uncertainty can be troublesome for a variety of artificial intelligence technologies. Dawid Pola proposed a framework based on federated learning and fuzzy consensus, which will do the classification while training of the data. This framework is proposed as a solution for medical purposes. The main advantage of this proposal is that it speeds up the training process in making a proper decision based on all data. This model can also be implemented on other data by remodeling the rules in the fuzzy system and additional classification techniques like artificial neural network can be implemented [96]. The author in [97] proposed a combination framework of both fuzzy and FL that is used to construct a solar power generation model where fuzzy helps in increasing the accuracy of the model.

Table 5. Briefs the Applications of Soft Computing and Federated Learning

Soft Computing Technique	How can SC help FL?	Summary of Existing works
Fuzzy Sets	Communication cost is very high in FL	Multi-evolutionary algorithms enhance the structure of neural network models in FL thereby minimizing the communication costs.
Nature Inspired Algorithms	Privacy breaches happen sometimes in FL	The horizontal FL and ANN combination is one such technique which proves to be more effective in privacy preserving.
Evolutionary Algorithms	Number of computational resources is more in FL	A real-time multi-objective evolutionary method for federated neural architecture search (NAS) can effectively avoid extra communication costs and computational resources while optimising the models' performance.
Artificial Neural Network	Energy consumption is more due to the regular device updates in FL	A perfect sliding differential evolution based scheduling (SDES) produces a lower computational complexity compared with the existing methods. The proposed experiment is both an energy saving and effective communication convergence.
MCDM	The number of parameters applicable in FL model setup is large	A new hybrid technique called genetic clustered FL (Genetic CFL), clusters edge devices based on training hyper-parameters and genetically adjusts the parameters cluster-by-cluster.
Game Theory	Selection of appropriate client	The combination of Game theory and FL will enable the selection of proper client before aggregation in FL.

3.2 Nature-inspired Algorithms with FL

3.2.1 How Nature Inspired Algorithms can Help FL. The nature inspired algorithms help in increasing the robustness of the FL system in unstable networks thereby increasing the network communication performance.

3.2.2 Summarize Existing Works. Low air quality is always hazardous to human health. **Air quality index (AQI)** prediction should be done accurately and on time as it has adverse effects on human health. Air quality data can be collected with high geographical and temporal resolutions using an **unmanned aerial vehicle (UAV)**. In the proposed work, a Distributed Federated Learning algorithm is used within a UAV swarm to collect air quality data using built-in sensors in the proposed work. Using swarm intelligence, a method for locating the area with the greatest AQI value is proposed. The data that is gathered is fed to a CNN-LSTM model to estimate the AQI. The proposed algorithm uses the PSO scheme where UAV swarm intelligence is helpful in identifying the harmful zones in a city and also enables privacy protection using the Federated Learning algorithm [98].

Federated Learning allows decentralization of the models and aggregates them at the server. FL suffers some drawbacks like limited communication bandwidth, and poor communication between the client and server. Large amounts of weights are received and transmitted in federated aggregation algorithms and also the accuracy level is reduced due to the unstable network systems. A **Federated particle swarm optimization** technique is implemented **(FedPSO)** which increases the communication performances by sending the score values instead of large weights. This work also reduces the size of data sent from clients to the servers. The server receives the trained model from the client with the best score [99].

Maximum research on FL focus on privacy and communication and limited attention is given on analyzing on the local training at the edge devices. Proper selection of the parameters plays a key role for building the local ML models. This work proposes a **Particle Swarm Optimization (PSO)**-based technique for optimizing the hyper parameter settings for local ML models in an FL context to achieve this goal. The parameters which are optimized in this proposal include the number of hidden layers, number of epochs, and the number of neurons. This study also focuses on two use cases, namely the smart city and **Industrial IoT (IIoT)** [92].

3.3 Evolutionary Algorithm with FL

3.3.1 How Evolutionary Algorithms can Help FL. FL is a distributed machine learning approach which solves many challenges of ML. Many challenges in FL can be solved by implementing the SC techniques and one such efficient and effective technique is through using EA. EA is a part of EC which tries to optimize many objectives of FL, like cost of communication, accuracy, complexity of model, and memory requirements [100]. Also, there are some implementations of FL and EA which enhance the communication efficiency and reduce the number of rounds of communication. There are many articles which explain how evolutionary algorithms can help in solving the problems of FL.

3.3.2 Summarize Existing Works. Federated Learning becomes more challenging to solve NAS problems. The evolutionary algorithms are used to solve many optimization problems and especially play an important role in Federated NAS. The EA solves the optimization problems in federated NAS. The paper [89] provides an extensive survey of the implementation of FL and NAS and the combination of FL and NAS. The two different approaches of federated NAS, namely the offline optimization and online optimization and disparities between single and multi-objective search, are also highlighted. Also, the survey discusses about a few more challenges of federated NAS. The paper [101] reveals the existing methods that are ineffective in optimization. This is the unique attempt of using per-node scaling in FL optimization. The study in [102] refers to an unique framework called **Coreset-Based Federated Learning (CBFL)**. CBFL involves a new distributed coreset construction and adaptive model evolution algorithms. The limited bandwidth reduces the communication efficiency in FL. The CBFL finds an optimized evolutionary model that makes the network adjust accordingly by removing the least significant connections thereby increasing the communication efficiency in FL. The authors in [103] propose a federated evolutionary optimization strategy called FL-AGCNS.

3.4 Artificial Neural Network for FL

3.4.1 How ANN can Help FL. Federated Learning is a recent trend that supports AI in moving the computation closer to the edge devices from the cloud server. The neural network majorly reduces the time taken for exchange of data between the edge devices and cloud node in Federated Learning [93]. Neural Network techniques assist in achieving goals like privacy protection and data compression.

3.4.2 Summarize Existing Works. The authors in [104] propose an application for federated learning quantization. The neural networks can be helpful in a time series prediction of data exchange in FL. The study also explains how neural networks can help in FL quantization by using two algorithms, namely FLQ and the DFLQ technique. The complete analysis of both the techniques is explained and how effectively the algorithms can help in the data exchange between the edge device and the cloud server. The study in [105] proposes an end-to-end **encrypted neural network (ENN)** to enhance the privacy of the FL model. This ENN has two sub networks to encrypting and decrypting the model updates thereby protecting the user privacy during the communication.

3.5 MCDM for FL

3.5.1 How MCDM can Help FL. Federated Learning is a distributed machine learning approach which has some lingering issues like privacy concerns, communication efficiency issues, communication cost concerns, and other issues. Many challenges in FL can be solved by implementing the soft computing techniques and one such efficient and effective technique is using multi-criteria decision making (MCDM). MCDM can help FL in handling sensitive information in a proper way and avoiding the adversarial attacks in adversarial training in FL.

3.5.2 Summarize Existing Works. For SC firms involved in the business of cold chain management, a novel **FL-enabled multi-criteria risk evaluation system (FMRES)** is proposed, which integrates horizontal FL and the **best–worst method (BWM)** to measure cold chain risks in an intelligent and adaptive manner. Without disclosing any sensitive information to a third party for model training and validation, an improved global **artificial neural network (ANN)** model can be obtained using horizontal FL in a privacy-preserving manner. Subsequently, the ANN model learns the required knowledge from the decision-makers so as to conduct the pairwise comparisons automatically for the deployment of BWM so as to prioritise and rank risk factors. Overall speaking, the study proposes an intelligent decision support system in designated SC firms that can identify, assess, and analyse the potential risk factors so as to get rid of the traditional expert-intensive risk assessment process [83]. MCDM techniques can help out in avoiding the bias in one dataset from another [106]. FL faces problems like data leakage based on the method used in aggregation phase. Adversarial training influences FL on how the aggregation takes place. Adversarial attack might also happen in the federated averaging because the collaboration techniques do not consider the node accountability. Taking in all these considerations, a unique model, MCDM, is proposed to avoid the bias in the multiple datasets that are trained on the same model. The authors in [107] discuss about how the electric grid working can be safeguarded from natural calamities and cyber attacks. The goal of this work is to create metrics for monitoring the resiliency of the cyber-power distribution system while protecting the privacy of consumers. The **IoT trustability score (ITS)** is calculated with the help of FL. The ITS and other factors that influence the electric grid working are integrated with the help of fuzzy multiple criteria decision making.

3.6 Game Theory for FL

3.6.1 How Game Theory can Help FL. Game theory can help in creating an accurate and appropriate aggregating model by selecting the appropriate clients [108, 109]. Even before the model aggregation is done in the federated learning process, the clients can be selected based on their performance to participate in the aggregation of the FL model. Based on some games like Hedonic games, Stackleberg game, coalition game theory and others, the clients are selected based on their eagerness to participate in the aggregation. Game theory works based on the incentive mechanism and provides few incentives to the clients based on their interest to participate in providing the data for training purposes.

3.6.2 Summarize Existing Works. The work in [110] proposed that the incentive mechanism used to select the client can help in improving the energy efficiency and training performance of FL. Two game theories namely the Stackelberg and the coalition game theory are used to make the FL model energy efficient and fair, respectively. Authors in [111] proposed a propFair method that introduced a proportional fairness method to achieve equity and equality between the clients. Based on the same concept, the work in [112] reference proposed a framework called VerFedSV that calculates the Shapley values to select fair clients and which is originated from cooperative game theory. A framework called pFedSV is proposed in paper [113] to address the critical challenges in FL like identifying the optimal client for collaboration. A Nash equilibrium game A Game-theoretic Approach for Robust Federated Learning is played between the server and the client to enable the server to capture only good and valid updates from the client [114].

Table 6. An Accurate FL Model is Created based on Fuzzy Clustered Federated Learning Algorithm

Application	Description	Benefits
Medical field	FL and Fuzzy consensus	FL and Fuzzy consensus can make the disease classification task much faster and easier when compared to the regular task.
Smart City Services	Particle Swarm Optimization and FL	Traffic prediction models are used as a surrogate for smart city services.
IIoT Services	Particle Swarm Optimization and FL	Predictive maintenance models are used as a proxy for industrial IoT services.
Air Quality Prediction	Particle swarm Optimization and FL	The suggested approach fine-grained monitors and forecasts the AQI, with privacy protection provided by FL.
Cold chain management	Multi criteria Decision Making and FL	In a cold chain network, a trustworthy federation of MCDM and FL is created to identify and assess cold SC hazards in a methodical manner.
Solar Power Generation Model	Fuzzy and FL	Based on Fuzzy Clustered Federated Learning Algorithm best and accurate FL model is created.

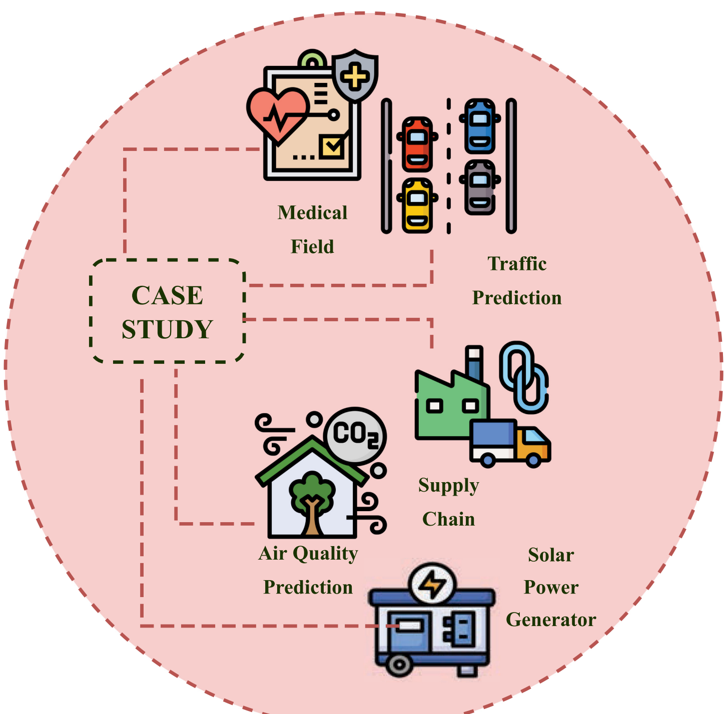

Fig. 10. Case studies.

3.7 Case Studies

Table 6 elaborates the case studies where the combination of Soft Computing and Federated Learning is used. Figure 10 shows different case studies of Soft Computing and Federated Learning.

Use Case 1:
Medical Field: The study in [96] proposes a medical solution that can be regarded as a medical expert system. Each medical system has a database here which have all the records and exam

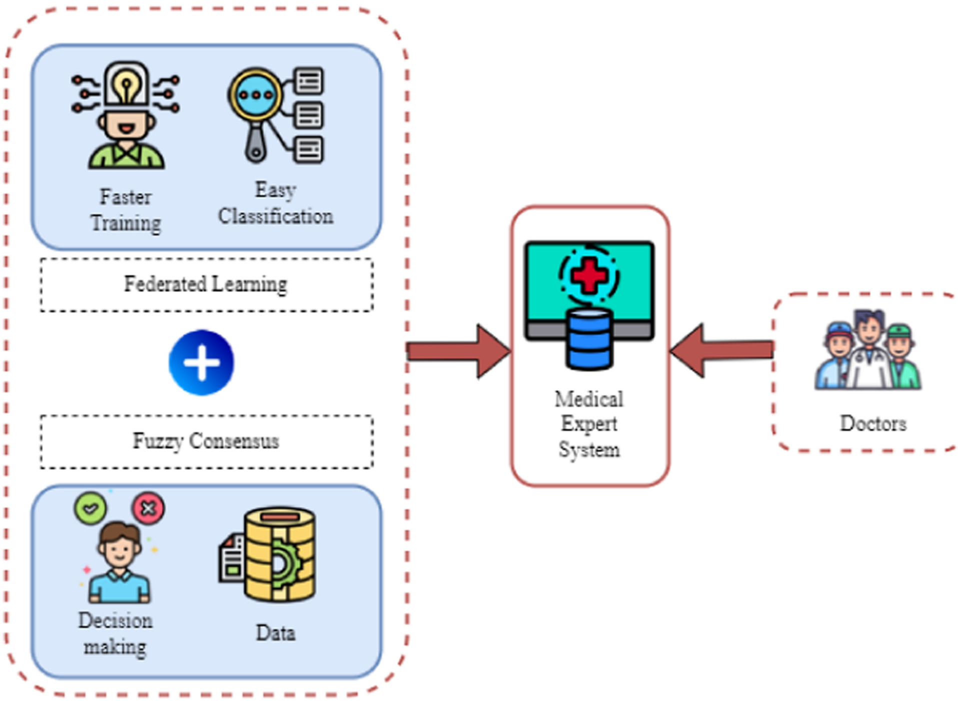

Fig. 11. Medical field.

results. The doctor from each hospital can update the database and classify the disease based on the collected data from patient. FL and Fuzzy consensus can make the classification task much faster and easier when compared to the regular task. Figure 11 is the case study of SC and FL in medical field.

Use Case 2:
Traffic Prediction: PSO is proposed by the authors of [26] to optimize the hyper parameter settings for deep **Long Short-Term Memory (LSTM)** models trained at the edge in a FL environment. Two use-cases are used to evaluate the suggested approach. Traffic prediction models are used as a surrogate for smart city services in the first case study. Figure 12 is the case study of SC and FL in Traffic Prediction. Predictive maintenance models are used as a proxy for IIoT services in the second case study.

Use Case 3:
Air Quality Prediction: The PSO technique is used in this article [7] to develop an algorithm that uses UAV swarm intelligence to locate the most dangerous zone in the city. The use of UAV swarms to sense aerial air quality is proposed. The suggested approach fine-grainedly monitors and forecasts the AQI, with privacy protection provided by FL.

Use Case 4:
Cold Chain Management: The combination of MCDM and Federated learning enables the risk identification in cold chain management. It was discovered in this study [83] that including the FL mechanism into the MCDM process is efficient in obtaining pairwise comparison knowledge from experts. In a cold chain network, a trustworthy federation is created to identify and assess cold SC hazards in a methodical manner.

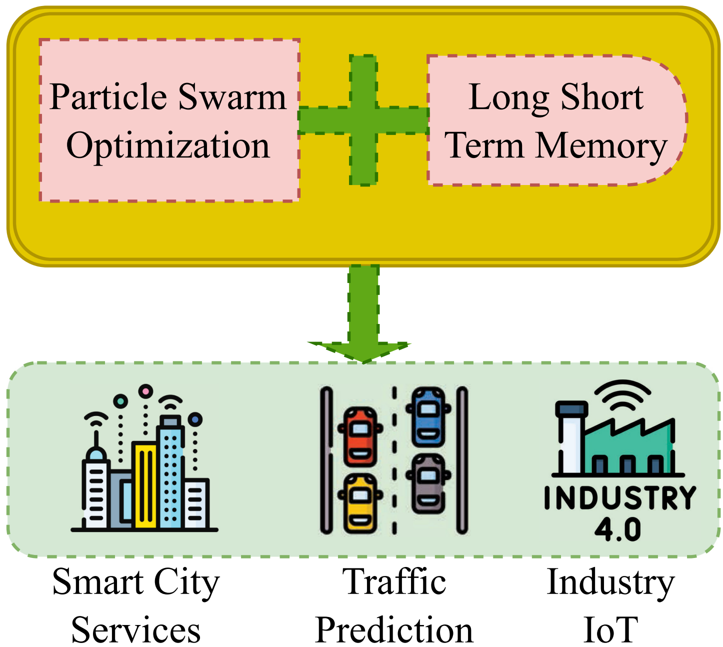

Fig. 12. Traffic prediction.

Use Case 5:
Solar Power Generation Model: FL proved to be a promising technique in constructing the solar power generation forecasting model. In order to construct an accurate FL model, fuzzy technique can be used where each local generator is included in one or more cluster. Many Soft computing techniques have come into limelight which are used for enhancing privacy preservation in FL [97].

4 CHALLENGES AND FUTURE RESEARCH DIRECTIONS

In this section, challenges faced by implementing several soft computing techniques and Federated Learning together are addressed that will present a path for future research. Table 7 details the challenges and Future Directives. **Need of proper handling of real time data sets:**

When handling the real time Big Data, generation of labels for large amounts of data is not feasible. Real time data is always unpredictable in terms of size and velocity and this has to be handled in a proper way.

Solution: This can be handled with the use of supervised learning. Supervised learning enables the mapping of input and output pairs with the help of input and output pairs.

Improper client selection:

The combination of FL and SC has proved to be a complimenting technique in making the FL model robust. But sometimes the model has improper and inefficient clients which may lead to a poor FL model and also leads to malicious attacks.

Solution: A proper SC algorithm should be implemented in order to select an enthusiastic and appropriate client. The algorithms should also help in detecting the backdoor attacks where a malicious client can be replaced with an other outperforming client.

Table 7. Challenges and Future Directions

Challenge	Description	Solution
Real time Data	Cannot Handle the heterogeneous data	Several FL algorithms along with soft computing techniques can be implemented to work with the real time data to fetch the accurate results.
Communication Failures	Client dropouts can lead to communication Failure	We prefer to use a variety of network protocols, such as the gossip protocol, to improve network communication efficiency in the situation of frequent client drops and restricted network bandwidth.
Improper Data Acquisition	Data Acquisition	The data acquisition can be done using an efficient communication algorithm between multiple clients.
Limited support for handling the graph data sets	Different Data sets	The algorithms should be chosen in such a way that they accelerate the speed of training in large graphs. The accuracy gap should also be mitigated with the help of proper algorithms.
Improper client selection	Client Selection	The combination of FL and SC has proved to be a complimenting technique in making the FL model robust. But sometimes the model has improper and inefficient clients which may lead to a poor FL model and also lead to malicious attacks.

Limited support for handling the graph data sets:
Though the FL and SC duo handle the graph data sets efficiently, there are a few complications related to the privacy of the data in this combination. Also handling the graph topology and network topology in FL is not as easy as handling the unique data sets in FL.
Solution: The algorithms should be chosen in such a way that they accelerate the speed of training in large graphs. The accuracy gap should also be mitigated with the help of proper algorithms.
Communication Failures:
Communication failures and client dropouts are the major problems faced in the federated optimization using soft computing techniques [81]. Client dropouts will lead to the lesser participation of clients which in turn leads to the formation of an improper model. The global model formed due to the drop of clients is poor and inefficient.
Solution: We propose to use a variety of network protocols, such as the gossip protocol, to improve network communication efficiency in the situation of frequent client drops and restricted network bandwidth.
Improper Data Acquisition:
The data placed at different places and statistically heterogeneous devices cannot be acquired easily and in a proper manner. Difficulty in collecting well distributed data may lead to an improper global model [81]. Data collection from different sites is also very expensive.

Solution: Efficient algorithms can help in data gathering from different and multiple locations. The algorithms should help in reducing the cost of data gathering and also protect the privacy of data that is gathered [115]. Heterogeneous data can be handled in such a way that the generic parameters of each client are modeled at the server. The privacy of the sensitive information is guaranteed in this case [73].

5 CONCLUSION

In this article, the combination of several soft computing techniques and FL is explained. The fundamentals of Distributed Learning, Federated Learning, and different categories of SC techniques are elaborated. The motivation for integrating SC techniques and FL is thoroughly examined, including how SC aids in lowering communication costs, preserving privacy, reducing computational resources, making FL models more energy efficient, and parameter optimization. Besides, the applications of SC in FL are also explained in this survey paper. We have also proposed several case studies that are prevalent till now, related to SC and FL. Finally, key research challenges and future directions have been highlighted and discussed.

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