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Resource Provisioning for Cyber–Physical–Social System in Cloud-Fog-Edge Computing Using Optimal Flower Pollination Algorithm

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ABSTRACT The rise of cyber-physical-social systems (CPSS) as a novel paradigm has revolutionized the relationship among humans, computers and physical environment. The key technologies to design CPSS directly related to multi-disciplinary technologies including cyber-physical systems (CPS) and cyber-social systems (CSS). Unfortunately, the design of CPSS is not an easier process because of the network heterogeneity, complex hardware and software entities. At the same time, fog computing is emerged as an expansion of cloud computing which efficiently addresses the abovementioned issue. Resource provisioning is a main technology involved in fog computing. This paper devises a novel fuzzy clustering with flower pollination algorithm called FCM-FPA as a resource provisioning model for fog computing. At the earlier stage, the resource attributes are standardized and normalized. Next, the fuzzy clustering with FPA is developed for partitioning the resources and the scalability of resource searching has been minimized. At last, the presented resource provisioning algorithm based on optimized fuzzy clustering has been devised. The performance of the proposed FCM-FPA model has been tested using a set of two benchmark Iris and Wine dataset. The experimental outcome ensured that the FCM-FPA model has shown proficient results over the compared methods by offering maximum user satisfaction and effective resource provisioning.

INDEX TERMS CPSS, big data, resource provisioning, clustering, flower pollination algorithm.

I. INTRODUCTION

The evolving computing model of CPSS develops on basis of CPS as well as CSS. Different types of sensors and actuators are applied to monitor the nature of external environment as shown in Fig. 1 and the simulation outcome are transferred to a cyber world, where it has been examined to acquire the state of the external world and produce the electronic representations of applied external entities [1]. The digital representation has been applied to retrieve a knowledge regarding the condition of a physical world and optimizing by actions generated from actuators. Hence, the associated study is concerned with the combination of external processes as well as processing to integrate the physical and cyber world as named as CPS [1]. The Internet of Things (IoT) model tends to interlink the computers to objects with self-configuration abilities which act a major part in converging physical as well as cyber worlds by assuring the energy efficiency to transfer data. The combination of CPS with IoT leads to a relativity among physical world tracking, screened with

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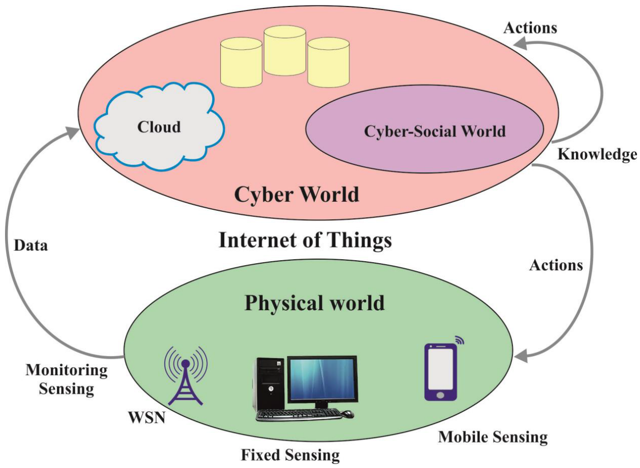

FIGURE 1. Basic architecture of CPSS.

linked smart objects, through the computation process of a cyber world. It enables the modeling as well as reasoning of physical platform that has been integrated with effective communication and data processing that results in productive activation. The types of devices are capable of monitoring the outer platform, as shown in Fig. 1, where the attached sensor network deployments like Wireless Sensor Networks (WSN) to monitor the external world [2], smart home appliances and sensor installations for air quality tracking [3]. The maximum deployment cost of attached sensors and lack of spatial coverage results in mobile sensing units, mostly with city authorities, which has sensors, and public transportation system.

The developing application of sensor induced smart phones as well as effective communications among the users in which personal tools are the significant devices to sense and point regarding an inconvenient atmosphere. Massive numbers of smart phone users could form a versatile sensing devise, by giving a local data such as noise levels [4], traffic conditions and so on. These sensed data could be collected and realized by processes of cyber world. Improving numbers of individuals share the data to nearby real-time, city-related events or earthquakes which can be done through the online social media which refers that, it can be treated as corroborative information source [5]. Hence, the related model is named as CSS. It applies a data on social nature as well as association to offer related data services, for instance, to identify the neighborhoods as well as communities from a city or from urban regions. This method which assumes the human and social dynamics as a core portion of CPS is named as CPSS [6].

CPSS undergo characterization with the application of deep interplay from sensors, actuators and smart things which are applied in the external environment; "richer technology-mediated social interactions" [7] as well as latest reasoning has been used to collective intelligence. Modern cities are CPSS, which has the possibility to deploy inexpensive sensing devices, sensors, administration primitives on the city-centric data as well as citizens sharing and interchanging city relevant messages on social media. The massive number of data can be attained by sensing external phenomena with shared sensor and supplied with city inhabitants using sensor embedded smart phones which is capable of providing closer real-time settings.

Extraction of knowledge from the data can be processed by applying big data analytics that helps in developing a structure of urban area, where it activates the smart applications as well as services, also to assist making decision for city authorities and inhabitants [8]. Executions of CPSS developments are evolving the routine smart urban systems, which differs from a command and control, modern applications, smart vehicle, smart social producing systems, etc. These domains were based on productive observation of urban physical structure and harsh platform to be combined with a data collected by a smart cyber processes for delivering the enhanced services to users, deploying an applicable waste management models and suggested methods which depends upon citizen priorities, approximate, road and pollution status. Therefore, the final outcome of urban big data system meets the ability of developing maximum sustainable as well as eco-friendly environment [9].

Resource provisioning is a main technology involved in fog computing. This paper devises a novel fuzzy clustering with flower pollination algorithm called FCM-FPA as a resource provisioning technique for fog computation. At the earlier stage, the resource attributes are standardized and normalized. Next, the fuzzy clustering with FPA is developed for partitioning the resources and the scalability of resource searching has been minimized. At last, the new resource provisioning model that depends upon optimized fuzzy clustering has been devised. The performance of the proposed FCM-FPA model has been tested using a set of two benchmark Iris and Wine dataset. The experimental results illustrate that the developed technique is capable of improving user satisfaction and efficiency of resource provisioning.

II. RELATED WORKS

CPS growth tracks the foundation of development to mechatronic system that integrates the strategies of mechanical, and electrical engineering regarding the industrial processing. With respect to abstraction, the development processes support the conversion of the developed patterns as physical systems [10].

In embed methods, the main aim is to process the system induced inside an external system, for example, thermostat.

CPS techniques were developed to be successors of embedded systems [11], combine the communication model, collectively with control mechanism. CPS is associated with sensing and management of external criteria by networks of interlinked devices to attain the predefined goals. The application which has been initiated from an engineering factor acts with a management as well as tracking of outer environments by a tightly fixed shared system of sensors as well as actuators [12]. These systems are triggered to the direction of disseminating the data predicted with mobile CPS with smaller latency to offer realistic services [13]. Instances of CPS execution such as adaptive air ventilation modules [14] as well as MediaCup [15] that predicts the temperature of contents alerts the users with respect to abstraction as well as correlation among the physical and cyber portion. The model of IoT is connected with CPS in several literature works on distinctions among 2 models.

Few researches work [16] illustrates that, CPS aims on connecting a physical and cyber worlds, IoT mostly deals with an exclusive recognition of heterogeneous tools as well as smart objects and also link to Internet. Reference [17] states that, if there are identity among CPS and IoT, where device relation to attain the predetermined goals, IoT is comprised with a horizontal view of hardware units which communicates with one another, while CPS assumes the vertical method encompassing networked hardware, processing the controlling mechanisms. An alternate study [18], the variations of system structures of CPS as well as IoT signifies an interchanging ability. The improved abstraction level in IoT is related to many unknown factors with respect to contribution to system task.

In [19], a Fuzzy Clustering Algorithm with Particle Swarm Optimization (FCAP) is proposed for Resource Scheduling Algorithms in Fog Computing environment. Initially, the standardization and normalization of the resource attributes takes place. Next, the fuzzy clustering with the particle swarm optimization (PSO) for resource provisioning and the scaling of the resource searching is minimized. At last, a new resource scheduling algorithm is derived using optimized fuzzy clustering. The simulation results indicated that the FCAP algorithm has attained maximum user satisfaction and better scheduling results.

III. PROPOSED METHOD

A. PROBLEM FORMULATION

In fog computation resource provisioning operation, if users provide the tasks, then it has been divided as massive operation to numerous subtasks. Later, the subtasks would be given to a task scheduler at fog platform in which a task provisioning principle as well as QoS suggest to make decisions in a task scheduler. It is capable of gathering provisioning data from customers, resource tracking as well as cloud gateways, and declares every task to corresponding fog resource. Hence, it is proposed with a resource provisioning technique for discovering an optimized matching of tasks as well as resources. The main objective of resource monitor is to verify the fog resource pools, such as memory resources, processing resources, as well as bandwidth resources. If requisition of tasks for terminal users which are capable of processing additional computation of fog computing, such tasks might be provided with cloud servers to future computation. As a result, based on the definite provisioning pattern, resources as well as user requests attains the relative match, and last provisioning outcome would be submitted to the users.

Initially, let n tasks and m resources be a task set $T = \{t_1, t_2, t_3, \cdots, t_n\}$, and the fog resources set is $R = \{r_1, r_2, r_3, \cdots, r_m\}$, and rational resource provisioning has been accomplished based on a definite provisioning principle. When compared with other models, the task and resource techniques were expressed as given in the following: The tasks set which are provided by users are constrained with n fog tasks. The p-th task can be presented with T_p, and features are defined as 1D vector $T_p = \left\{t_{id}, t_{len}, t_{comp}, t_{netw}, t_{stor}, t_{dat}\right\}$; where t_{id} represents a task value; t_{len} denotes a task length; t_{comp}, t_{netw}, and t_{stor}, are task's computational power, bandwidth limit, as well as memory requirements of a resource, correspondingly; and t_{dat} implies that data should be computed by a task. In fog computation, external resources could be allocated using virtualized resources. By considering that m resources are present is a collection of fog resources, the qth resource is implied with R_q, and features are defined as 1D vector $R_q = \left\{r_{id}, r_{comp}, r_{netw}, r_{stor}\right\}$. In this approach, r_{id} denotes a resource value; and r_{comp}, r_{netw}, and r_{stor} are processing energy, bandwidth utilization, and memory potential of a resource, correspondingly [19]. In order to report the connections of entities in a method, it is provided with a resource provisioning network structure in fog computation.

For provisioning process, the following rules have been applied. The constraints of processing nodes in a resource pool: the processing resources as well as memory space are applied by the tasks should be inside a scope of fog computing nodes. Every computing node is capable of handling a single task simultaneously; but, every computational node could be implemented at a same time. User task execution limitation: every task has to be allocated to particular fog computing nodes and implemented through 1 fog computing node. Here, QoS has been assumed as validation index that is applied for determining the efficiency of resource provisioning. It can be significant procedure to measure the service satisfaction. Each user is comprised with diverse resource requirements. For better facility users, the QoS has to be enhanced.

B. FUZZY C-MEANS ALGORITHM

FCM is generally applied to group instances where the application of the FCM is based on the guarantee of opening bunch focus or participation incentive to the features of reviews. It offers a mechanism of assembling of information concentrates that populate some multidimensional space to a specific number of different clusters. The basic favored standpoint of fuzzy c – denotes that the clustering offers permission to the continuous enrollment of information concentrates on clusters determined as degrees. It is figured out that the cluster focuses on the utilization of Gaussian weights, exploits expansive introductory approaches, and comprises procedures for taking out, bunching. The basic target of iterative bunching and fuzzy c-Means determination is to restrict the weight inside clustering entirety of squared blunder target capacity and is represented as follows.

$$O_e = \sum_{i=1}^{d}\sum_{j=1}^{c} m_{ij}^{e}||f_i - c_j||^2 \tag{1}$$

where O_e represnets the Objective function and Fuzziness Index, d, m, c as Membership of i^{th} data to j^{th} cluster center, feature vector and j^{th} cluster center. The FCM allows every element vector holds a position with every bunch with a truth esteem (in the vicinity of 0 and 1.

C. FLOWER POLLINATION ALGORITHM (FPA)

The biotic pollination, cross-pollination, abiotic pollination and self-pollination modules were described in a field optimization as well as induced in a flower pollination technique [20]. The pollination task encloses a sequence of tedious operations in plant generation principles. A flower and the corresponding pollen gametes tend to provide a reliable solution for the optimization issue. The advantages of FPA are listed here. FPA provides a simpler flower analogy with lightweight computation based on only one control parameter (i.e., switch condition, p) unlike GA, HS, and PSO. It also offers a balanced intensification and diversification of solutions through the adoption of lévy flight (i.e., random walks that are interspersed by long jumps) and switch condition, which can be employed to change among global search and intensive local search.

Flower constancy has been decided as accurate solution which may be a perceptible one. In case of global pollination, the pollinator transmits pollen from longer distances to high fitting. In other cases, local pollination is carried our inside a small region of an exclusive flower has been carried out in a shading water. Global pollination takes place with a possibility which is named as switch probability. When the phase has been eliminated, local pollination can be replaced. In FPA method, there are 4 rules as given in the following:

- Live pollination as well as cross-pollination is termed as global pollination and the carriers of pollen pollinators apply the levy fight.
- Abiotic as well as self-pollination are referred as local pollination.
- Pollinators are insects, which is capable of developing flower constancy. It is defined as the production probability to 2 applied flowers.
- The communication of global as well as local pollination could be managed with switch possibility.

Hence, the 1st and 3rd rules are represented as:

$$x_q^{t+1} = x_p^t + \gamma \times L(\lambda) \times \left(g_* - x_p^t\right) \tag{2}$$

where x_p^t = pollen vector at iteration t; g_* is a current best solution from other current producing results; γ = a is the scale factor for controlling step size; and L denotes strength of pollination that has been related to a step size of levy distribution. Levy flight is defined as a set of random computation which has the length of every jump that applies levy

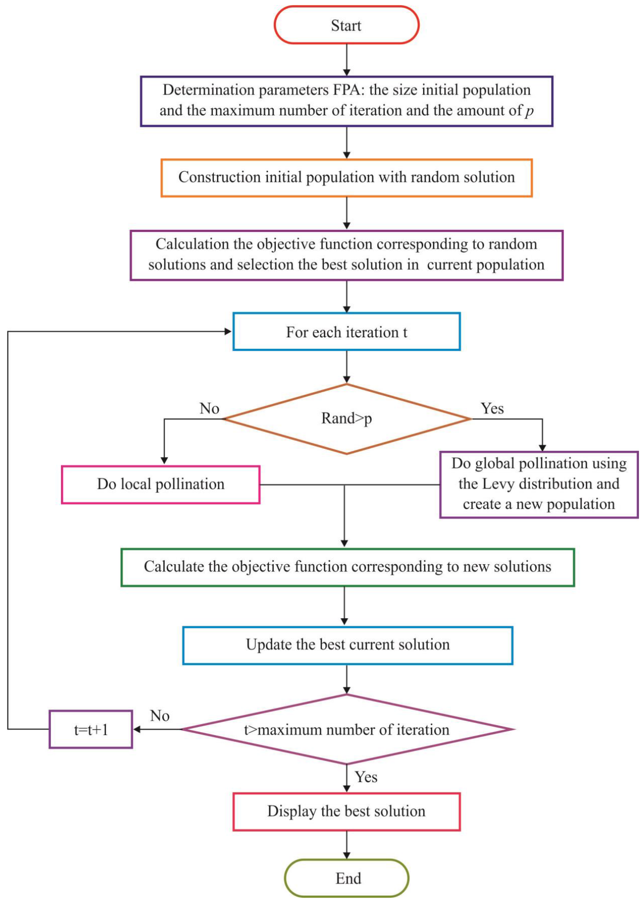

FIGURE 2. Flowchart of the FPA.

probability distribution function with infinite variance. Then, L is a levy distribution as provided with:

$$L \sim \frac{\lambda \times \Gamma(\lambda) \times \sin\frac{\pi\lambda}{2}}{\pi} \times \frac{1}{S^1 + \lambda} S \gg S_0 0, \tag{3}$$

where $\Gamma(\lambda)$ = standard gamma function.

In case of local pollination, the 2nd and 3rdrules are expressed as:

$$x_p^{t+1} = x_p^t + \varepsilon\left(x_q^t - x_k^t\right) \tag{4}$$

where x_q^t and x_k^t = 2 pollens from diverse flowers from a similar plant. In arithmetic format, when x_q^t and x_k^t comes from the similar species are chosen from homogeneous population, which is referred as a local random walk and ε is comprised with a uniform distribution in [0, 1]. Fig. 2 depicts the flowchart of the FPA [21].

D. HYBRIDIZATION OF FUZZY C-MEANS WITH FLOWER POLLINATION ALGORITHM (FCM-FPA) FOR RESOURCE ALLOCATION

According to the conventional Fuzzy C-Means (FCM) clustering model and Flower Pollination Algorithm (FPA), it is presented with FCM-FPA method to reach resource provisioning in fog computing. The key objective is to apply

FPA model in FCM technique. The FCM clustering model from [22] is used to computes the degree of every sample point comes under the cluster with the application of membership function (MF). Assume the cluster sample set as $X = \{x_1, x_2, x_3 \ldots, x_n\} \subset R^d$, where x_p implies a d dimension vector. There is basic requirement to classifier the sample set as c classes. Fix the cluster center as $V = \{v_1, v_2, v_3 \ldots, v_c\}$, and describe the degree where sample points come under the j-th class as μ_{ij}. Also, the fuzzy matrix of sample space X is $U = (\mu_{ij})$. The FCM method is signified as subsequent objective function for extremum problem:

$$Q = \min \sum_{p=1}^{n} \sum_{q=1}^{c} \mu_{ij} \left\| x_p - v_q \right\|^2 \tag{5}$$

such that, $\sum_{q=1}^{c} \mu_{pq} = 1, \mu_{pq} \in [0, 1], q = 1, 2, \cdots, n$, $q = 1, 2, \ldots, c$. In Eq. (6), μ_{pq} implies the degree of belongingness to q-th d ata point of p-th cluster, v_q represents q-th cluster, $\|x_q - v_q\|$ denotes a Euclidean distance from sample points x_p to a cluster center v_q, and m signifies a fuzzy index. Additionally, U and V is represented as:

$$v_q = \frac{\sum_{p=1}^{n} \mu_{pq}^{m} x_p}{\sum_{p=1}^{n} \mu_{pq}^{m}} \tag{6}$$

$$\mu_{pq} = \frac{1}{\sum_{k=1}^{c} \left(\frac{||x_p - v_q||}{||x_p - v_k||} \right)^{\frac{2}{m-1}}} \tag{7}$$

This mechanism is named as local optimization technique that approaches for optimal solution by applying hill climbing. The key objective is to improve the affinity among objects divided as similar cluster as well as to reduce the similarity from diverse clusters. The fuzzy method is an enhancement of normal C-Means technique. The ordinary C-Means technique is in separating data, whereas FCM is said to be more suitable fuzzy division. The FCM method computes the degree where every sample point comes under a definite cluster with an application of MF. Also, there is lack of threshold values in this model. The major aim of soft partitioning has been applied as membership matrix, and final outcome of result becomes more complex. Hence, the model lies within a local minimum value as well as sensitive to primary value. The FPA technique is named as heuristic method comprised with the merits of fast convergence as well as global optimization, thus it is integrated with FCM method to resolve the merits and demerits of FCM technique as named as FCM-FPA model.

In FCM-FPA technique, the key objective of FCM approach is to compute the cluster centre, and $x_p = (v_{p1}, v_{p2}, \cdots, v_{pq}, \cdots, v_{pc})$ shows a cluster centre set with a single pollen in FPA, where v_{pq} depicts q-th cluster center in p-th clustering technique. When a population size is N, then it has N clustering techniques.

The fitness level of every pollen denotes the superiority of clustering effect which can be chosen with clustering centre. In order to estimate every pollen, this approach utilizes the above FF value:

$$f(x_p) = Q \tag{8}$$

The smaller Q is, the smaller the single pollen fitness where clustering effect would be far better.

Based on the FF score, the local positions as well as global position were estimated, and velocity and location of all pollens should be upgraded. By applying the above phases, the FCM-FPA model could attain a global approximate result. The FCM has been implemented to reach a global optimal solution repeatedly. Here, it has been applied with FCM-FPA method for completing the fog resources clustering.

In case of fog computation, the resource attributes as 3 classes: computation, storage, and bandwidth. Diverse operations are comprised with various resources. Only few types of computational tasks and computation resources are highly effective whereas some bandwidth tasks, bandwidth resources are considered to be essential. Hence, to face the needs of different users, the resources are clustered into groups. Because of the dynamicity as well as heterogeneity of fog resources, it can be very hard to define the unique resources. Here, it is applied with FCM-FPA model to cluster the resources on the basis of multidimensional attributes. The collection of fog resources $R = \{r_1, r_2, r_3, \cdots, r_m\}$ shows that m fog resource nodes as well as every fog resource node consists n features. In Eq. (6), r_{pq} is q-th feature attribute of resource r_p.

In advance to fuzzy clustering, it is essential to normalize the data for diverse process indicators. The step for clustering fog resources has been provided in the following. In a fog computing platform, because of the existence of diverse fog resources, actual data can be processed in a straight forward manner, as the impact of clustering outcome which are meant to be irregular. Hence, to resolve the immediate effects which are caused due to the case of translation, SD conversion has to be applied to standardization the resource matrix data.

$$r'_{pq} = \frac{r_{pq} - \overline{r_{pq}}}{S_q} \tag{9}$$

$$\bar{r} = \frac{1}{m} \sum_{q=1}^{n} r_{pq} \tag{10}$$

$$S_q = \sqrt{\frac{1}{m} \sum_{p=1}^{n} \left(r_{pq} - \bar{r}\right)^2} \tag{11}$$

where maximum value of resources in q-th dimension feature is $\bar{r}$, $\overline{r_{pq}}$ indicates the maximum value of the q-th feature attribute of resource r_p and SD of every resource in q-th dimension feature is S_q. The computed data satisfies a standard normal distribution that refers mean as zero and SD as one. A reputed resource data is not capable of satisfying the planning of fuzzy matrix. Hence, translation-range has been applied for converting data in matrix to be attained from the interval of [0, 1].

$$r''_{pq} = \frac{r'_{pq} - \min\left\{r'_{pq}\right\}}{\max\left\{r_{pq}\right\} - \min\left\{r'_{pq}\right\}} \tag{12}$$

where, $\min\left\{r'_{pq}\right\}$ shows a lower value in $\left\{r'_{1q}, r'_{2q}, \ldots, r'_{mq}\right\}$, and $\max\left\{r'_{pq}\right\}$ depicts a higher value in $\left\{r'_{1q}, r'_{2q}, \ldots, r'_{mq}\right\}$.

The projected fuzzy clustering model that depends upon FPA has been applied for clustering the computed resource matrix data. The process involved in the FPA is given below. In the first step, initialization of pollen population takes place where each pollen comprises arbitrarily generated cluster centers that portions the resources as 3 classes, and collective numbers of cluster centers are mentioned to be 3. In the second step, the membership matrix μ_{pq} is determined and estimated the cluster center c_q based on Eq. (13). Hence, FF valued has been applied for calculating the fitness measure as well as compute the single extreme score and global extreme score. If higher values of iterations are satisfied, then it has been terminated to reach the desired cluster center.

$$c_q = \frac{\sum_{p=1}^{n} \mu_{pq}^{m} x_p}{\sum_{p=1}^{n} \mu_{pq}^{m} x_p} \tag{13}$$

Next, in the third step, the local and global pollution of pollens are constantly upgraded using Eqs. (1) and (3). When there are a higher number of iterations, then it is terminated to get a collection of cluster centers. In the fourth step, the attained simulation outcome is considered as initial value of FCM model and implemented to reach the global optimal solution repeatedly. Finally, in the fifth step, once the clustering functions are completed, the fog resources have been portioned as 3 units namely, computing, storage, and bandwidth resources. Once the fog resources were divided, then the resource scale of a provisioning process has been limited. User needs should be classified as diverse classes. The proper resource category has been found where user requirements were mapped with the resources from a class. In order to complete the resource provisioning, it is applied with simple weight matching.

IV. RESULT ANALYSIS

In order to the efficiency of this model, it has been employed with MATLAB. The resource nodes as well as user requests has been declared in a random manner. The resource nodes were classified as 3 features such as computing power, bandwidth ability, as well as storage potential. The FCM-FPA model has been applied for clustering the fog resources. This implementation can be applied with a produced resource dataset as well as Iris dataset of a UCI ML database. Additionally, it is examined and compared with 2 models interms of convergence of objective function.

Figs. 3 and 4 show the difference of objective functions in conventional FCM, FCAP techniques [19] as well as FCM-FPA models by means of iterations for 2 data sets. As mentioned in the 2 figures, it has been pointed that, FCM-FPA method is comprised with faster convergence speed when compared with existing FCM approach.

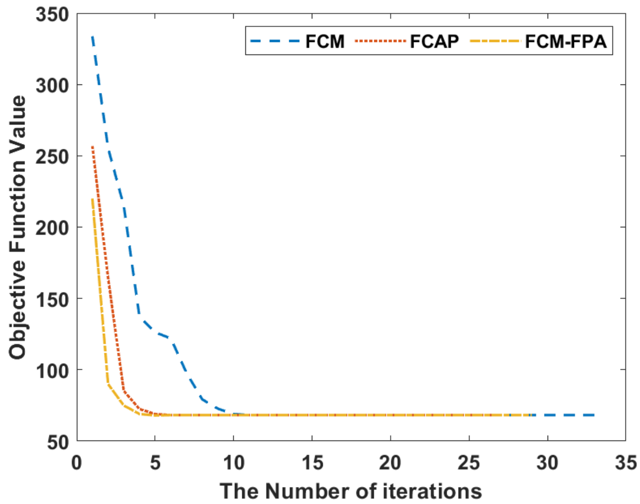

FIGURE 3. Objective function value curve for the Iris data set.

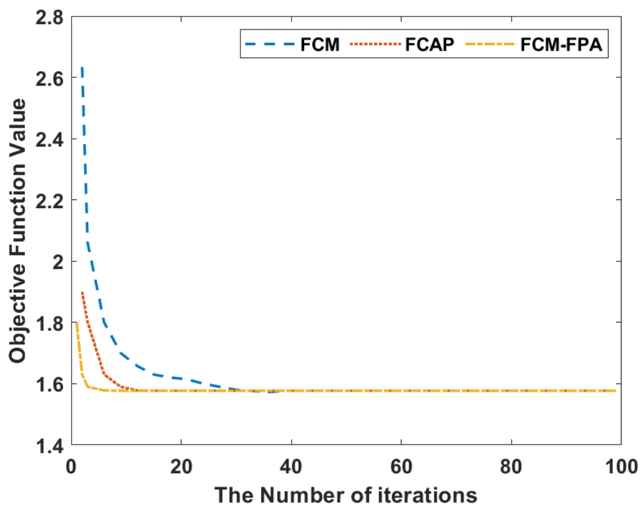

FIGURE 4. Objective function value curve for the Wine dataset.

The major cause for this task is FPA method which is capable of finding cluster centre rapidly and to process the global search for resolving a problem in fuzzy clustering which lies in local minimum value. Once the clustering resources are divided, the values of matching resources in users' requirements are limited as resource provisioning might be carried out in an effective manner.

To validate the accuracy of clustering model, it has been employed with Iris and Wine datasets to examine the function of this method. These 2 approaches have been implemented 20 times per iteration, and the maximum analyses of indicators were assumed. The simulation outcomes are depicted in Table 1 and Figs. 5 and 6.

While assessing the results of the FCM-FPA method interms of correct and error clustering samples on Iris dataset, it is shown that the FCM-FPA method shows enhanced results over the existing models. It is noted that the FCM method correctly clusters a set of 134 samples and a set of 16 samples

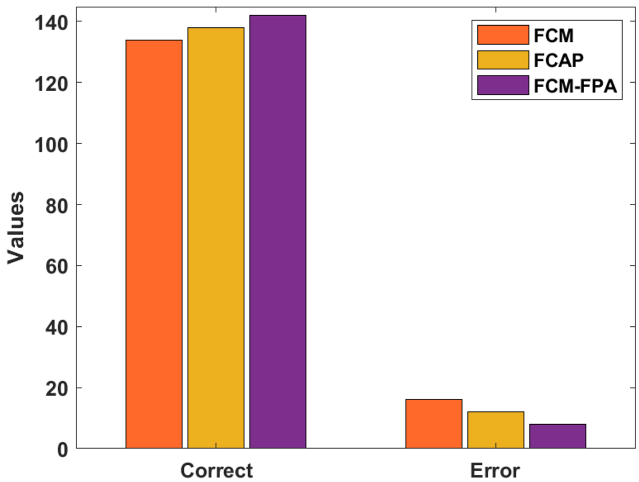

FIGURE 5. Correct and Error analysis of Iris dataset.

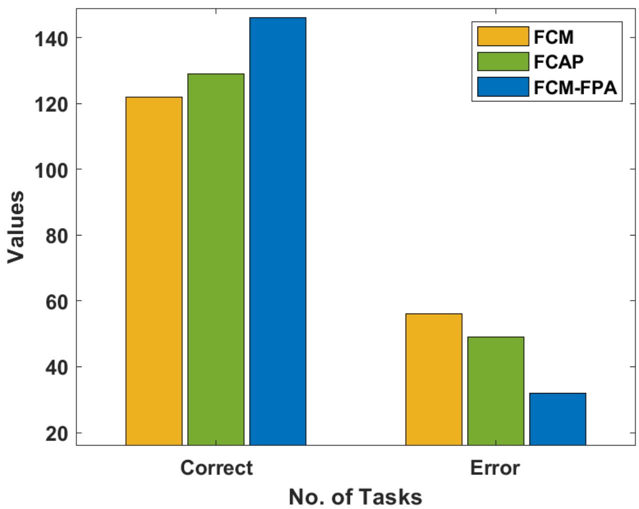

FIGURE 6. Correct and Error analysis of Wine dataset.

undergo error clustering. At the same time, the FCAP model shows slightly better performance, which correctly clusters a set of 138 samples and a set of 12 samples undergo error clustering. Along with that, it is exhibited that the FCM-FPA model has shown optimal results by correctly clusters a maximum of 142 samples and a set of 86 samples undergo error clustering.

During the application of results attained from FCM-FPA algorithm with respect to correct as well as error clustering instances on Wine dataset, it is illustrated that FCM-FPA model exhibits the improved outcome when compared with previous techniques. It is evident that the FCM approach exactly clusters a collection of 122 samples and a group of 56 samples are error clustering. Simultaneously, the FCAP method depicts a moderate function, that accurately clusters a set of 129 samples as well as a collection of 49 samples undergo error clustering. In line with this, it is executed that the FCM-FPA scheme has illustrated best results by optimally clusters a higher number of 146 samples and a set of 32 samples undergo error clustering.

TABLE 1. Comparison of the clustering accuracy for exiting with proposed method.

Method	Dataset	Correctly Clustered Samples	Error Clustered Samples	Correct Value
FCM	Iris	134	16	89.33
	Wine	122	56	68.50
FCAP	Iris	138	12	92.00
	Wine	129	49	72.50
FCM-FPA	Iris	142	8	94.66
	Wine	146	32	82.02

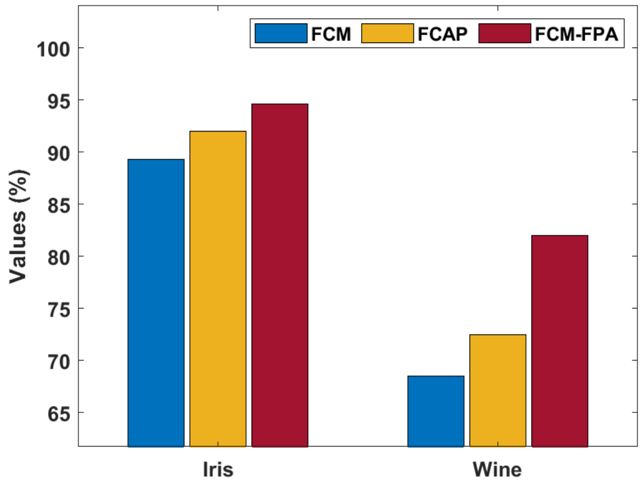

FIGURE 7. Correct rate analysis.

Fig. 7 and Table 1 shows the correct rate analysis of the proposed and existing models under two datasets. On the applied Iris dataset, the proposed FCM-FPA method shows optimal results with a maximum correct rate of 94.66% whereas the FCM and FPAP models results in lower correct rates of 89.33% and 92% respectively. On the applied Wine dataset, the proposed FCM-FPA method offers better performance by attaining a maximum correct rate of 82.02% whereas the FCM and FPAP models results in lower correct rates of 68.50% and 72.50% respectively. These values ensured that the FCM-FPA model offers effective performance by attaining maximum correct rate over the compared methods.

As shown from Table 1, the FCM-FPA model is comprised with maximum clustering accuracy value when compared with existing FCM method. The FCM clustering technique simply lies into local minimum, and clustering effect is comparatively better. The FCM-FPA approach is capable of attaining global optimal solution which becomes relatively good. Once the fog resource is clustered, the operations could be mapped with diverse resources, and, to a limited level, the effectiveness of resource maintenance is enhanced.

In this experiment, the user needs are portioned as computing, bandwidth, and storage based on diverse requirements. Various kinds of user requirements would be chosen to map the diverse classes of resources, and last matching outcome would be returned again to users. Consequently, the user satisfaction examining is shown in Table 2 and Fig. 8.

TABLE 2. Comparison of user satisfaction.

No. of Tasks	FCM-FAP	RSAF	MIN-MIN
30	2.8	2.5	1.8
60	3.6	3.2	2.0
90	3.7	3.5	2.3
120	4.1	3.7	2.4
150	4.5	4.0	2.6
180	4.8	4.4	2.8
210	5.0	4.3	2.7

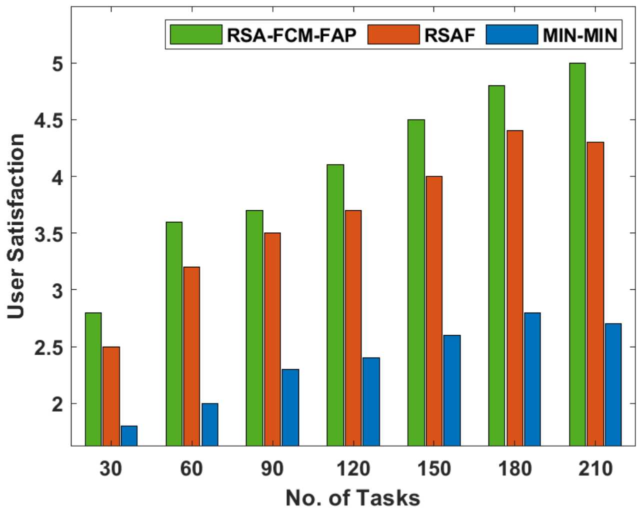

FIGURE 8. User satisfaction analysis under varying number of tasks.

Under 30 tasks, the proposed FCM-MAP model has shown maximum user satisfaction of 2.8 whereas the RSAF and MIN-MIN models have resulted to a lower user satisfaction of 2.5 and 1.8 respectively. Under the application of 60 tasks, the deployed FCM-MAP method has implemented higher user satisfaction of 3.6 while the RSAF and MIN-MIN techniques have concluded in less user satisfaction of 3.2 and 2.0 correspondingly. By using 90 tasks, the presented FCM-MAP approaches has exhibited best user satisfaction of 3.7 while the RSAF and MIN-MIN frameworks have provided with minimum user satisfaction of 3.5 and 2.3 respectively. Under 120 tasks, the projected FCM-MAP system has given optimal user satisfaction of 4.1and the RSAF and MIN-MIN schemes have shown a lesser user satisfaction of 3.7 and 2.4 respectively.

With respect to 150 tasks, the newly developed FCM-MAP model has illustrated higher satisfaction of 4.5 while the RSAF and MIN-MIN techniques have shown a less user satisfaction of 4.0 and 2.6 correspondingly. Under the application of 180 tasks, the applied FCM-MAP model has shown maximum user satisfaction of 4.8 while the RSAF and MIN-MIN approaches have concluded in a minimum user satisfaction of 4.4 and 2.8 correspondingly. Under 210 tasks, the presented FCM-MAP model has depicted higher user satisfaction of 5.0 while the RSAF and MIN-MIN approaches have concluded in a lesser user satisfaction of 4.3 and 2.7 respectively. The proposed method finds applicable in real time scenarios like healthcare sector. The proposed method can be applied for resource provisioning of the IoT devices attached to the patient body, which needs to transmit the sensed data to the cloud. In such a situation, the proposed FCM-FPR model can be applied to allocate the resources.

V. CONCLUSION

This paper has devised an effective resource provisioning method for fog computing in CPSS called FCM-FPR model. The proposed model involves a set of three stages. In the beginning, the resource attributes are standardized and normalized. Next, the fuzzy clustering with FPA is developed to partition the resources and the scalability of resource searching has been minimized. Then, devised resource provisioning model relied on optimal fuzzy clustering has been devised. The performance of the proposed FCM-FPA model has been tested using a set of two benchmark Iris and Wine dataset. The experimental outcome illustrates that the deployed technique has the ability to boost the user convenience and the efficiency of resource provisioning.

CONFLICT OF INTEREST

Every author refers that, it is not have any conflict of interest about publication of this article.

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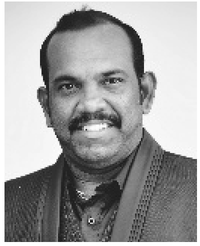

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