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An Efficient Cloud Computing Model for E-Health

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Abstract

Cloud computing has become an indispensable component of the E-health services sector. Based upon, the data of E-Health cloud is increasing day by day as a result of increasing patient data and medical team diagnoses. This leads to a huge amount of data being stored that is easy to lose during disaster occurred. In order to that, an optimization model named The Particle Swarm Multi-Objective Optimization (PSMOO) was proposed for serving and recovering data of the E-Health cloud during system failure. The Particle Swarm Optimization (PSO) algorithm was used for the E-Health data scheduling procedure. The proposed model has the ability to play an important role in achieving the reliability of the cloud computing E-Health environment by considering the available resources to prevent data loss. The model compared PSO and genetic algorithms to show that the proposed model is robust, integrated and reliable for the disaster recovery.

Keywords: Cloud Computing, E-Health, Disaster Recover, Particle Swarm Optimization Algorithm.

Introduction

Cloud-based E-Health data is increasing day by day as a result of increasing patient data and medical team diagnoses. This leads to a huge amount of data being stored in the cloud of E-health. Effective technology is much needed in case data is lost or destroyed when any type of disaster occurs. That in order to ensure the quality of the health services provided. Little previous research suggested some reliable and viable systems for disaster recovery (DR) plans in the e-health sector. Therefore, this paper presents a model for recovering the data of the E-Health cloud during system failure.

Cloud computing is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction (Mekawie and Yehia, 2021; Hon et al., 2022; Tsochev and Trifonov, 2021; Samundre and Rewatkar, 2022). Cloud computing is an easy way to increase IT service resources and equipment without the need for new infrastructure, operator training or the design of new software (Samundre and Rewatkar, 2022; Devadass et al., 2017). That reduces small business start-up expenses and the hurdles and difficulties small consortia face in their IT architecture (Samundre and Rewatkar, 2022). Cloud computing provides an infrastructure that allows medical centers to start with low initial capital costs. Beside that, it provides many services and applications in the E-health sector efficiently, quickly, in a secure manner, at a lower cost and in a pay-per-use manner (Devadass et al., 2017). World health organization is defined the E-Health as: "The cost-effective and secure use of information and communications technologies in support of health and health-related fields, including health-care services, health surveillance, health literature and health education, knowledge and research" (Hu and Bai, 2014). The goal of cloud-based E-Health is continuous improvement, participation and coordination in the sector of healthcare with the highest quality and at a lower cost (Kunwal et al., 2017). The spread of mobile health applications and the need to provide integrated health care systems are among the most important motives for adopting cloud computing in the E-Health sector (Al-Issa et al., 2019). Health care providers will easily access health data and thus provide better services, care, diagnosis and treatment to patients (Georgiou and Lambrinoudakis; 2020).

Data recovery in cloud-based E-Health faces very critical problems like the effective policies and plans taken for disaster recovery problems in the case of system failure (Manan and Ashraf, 2014). In order to provide an effective solutions, data is backed up to multiple locations in order to restore data back in the event of a disaster (AbuKhousa et al., 2012). Wherefore, the interruption in information infrastructure or E-Health services represents a major threat to the quality of health services (Kaushal and Khan, 2014). Thus, the adoption of cloud-based health organizations for disaster recovery plans helps to reduce the costs of building data centers and infrastructure (Georgiou and Lambrinoudakis, 2020).

The proposed model is designed based on the Particle Swarm Multi-Objective Optimization. It has the ability to resume its operations after a failure or interruption. The resources of Multi-cloud service providers can be used collaboratively by the DR service provider to reduce the risk of data loss and reduce backup costs, and gives more reliability and security to the service provided (Al-shammari and Alwan, 2018). The remainder of this research has been organized as the following: Section 2 presents the latest findings of previous researches and literature review within the reach of the topic. Section 3 presents the proposed model data recovery and its architecture. In addition to, the optimized data scheduling procedure model was explained. In section 4, the results are discussed and analyzed. Finally, section 5 presents the conclusion and the future work.

Related works

Oregon Health and Science University has performed a multifaceted business continuation and DR plan to treat risks that affect the data centers and the university electronic health record data retrieval (Gillin, 2018). The impact of the failure of electronic health record systems on health care institutions is discussed in (Shepard and MSN, 2017), which affects the effectiveness of providing health care to patients during a disaster. An international project is presented in (Norris et al., 2018) to develop disaster E-health management. The project helps to recover from disasters in the long term. The study (Andrade and Nogueira, 2018) indicated that adopting DR solutions during disasters significantly improves Internet of Things systems availability and business continuity. Authors in (Wang L and Alexander, 2014) explained how important cloud services are to DR for the E-health sector. Storing Electronic Medical Records on cloud-based computers is useful during a disaster. Healthcare providers can maintain communication with patients and continue to provide medical and healthcare services efficiently. The (DR-Cloud) system for multi-cloud based DR service is proposed that is suitable for several kinds of data DR scenarios and achieves optimization objectives effectively (Gu et al., 2014).

A multi-server system based on the Enriched Genetic Algorithm has been presented to recover the lost data by using four backup servers in the cloud. It offers reliability and availability for the client when the main cloud server loses its data and can offer data to clients (Challagidad et al., 2017). In the study (Perri et al., 2022), the authors introduced an IT infrastructure that ensures high reliability and resistance to failure by using a type of DR to run a web services cloud to ensure the continuity of cloud services.

Preliminaries and Methods:

Scheduling is an important issue in cloud computing and necessary to enhance performance [Arunarani et al., 2019; Kaur and Sharma, 2019). PSO algorithm was used in the scheduling data of the E-Health cloud because it has fewer parameters and easy to run. PSO has found a wide range of applications in functionality optimization, multi-objective optimization problems (Liu et al., 2016; Bharath et al., 2022). Also, the heuristic algorithm such as the genetic algorithm (GA) and the PSO can be used to solve the optimization problems (Arunarani et al., 2019; Kaur and Sharma et al., 2019). The PSO was introduced by Kennedy and Eberhurt in 1995. PSO is a population-based Swarm intelligence algorithm that deals with a set of random solutions called particles (p). The population is the number of particles in the search space. Particles are randomly initialized (Moh et al., 2022; Mercangöz, 2021).

Particles move to optimal positions based on objective functions (the fitness function F). The trajectory of each p is updated according to its individual trajectory history and the position of the squadron leader during the search. Each p in the search space has a position vector and a velocity vector. Each p considers a potential solution to the problem and searches the problem space for the optimal solution. The position of the p is affected by its best position so far in the problem space (pbest) and the position of the best particle in the problem space (gbest). The best particle is the best result (expressing the value of the fitness function) that has been achieved so far. The objective function (F) is determined by the best position for each p, along with the p with the best position in the current set (Liu et al., 2016; Bharath et al., 2022; Moh et al., 2022; Mercangöz, 2021; Quoc et al., 2022; Ali and Tawhid, 2017; Saber et al., 2021).

The positions of the particles and the velocity vectors are calculated in each iteration using equations 1 and 2 as shown:

$$v_i^{k+1} = \omega\, v_i^k + c_1\, rand_1 \times (pbest_i - x_i^k) + c_2\, rand_2 \times (gbest - x_i^k) \quad (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

The parameters of the equations 1 and 2 are illustrated in table 1. Table 2 illustrates the Pseudocode of the PSO in the proposed model.

Table 1: PSO Equations Parameters

Parameters	Description
v_i^k	velocity of particle i at iteration k
x_i^k	position vector of particle i at iteration k
ω	Inertia weight
c_1	Personal acceleration coefficient
c_2	Global acceleration coefficient
$rand_1$ and $rand_2$	random number between 0 and 1
$pbest_i$	best position vector of particle i
gbest	position vector of the best particle in the population

Table 2: PSO Pseudocode

```
Input: Requests = {R1, R2, R3,…….., RN}, Set PSO parameters
Output: The best particle (data) minimizes equation (3)
Start:
Step 1.Initialization:
        Initialize randomly particles velocities for k = 1, 2, ....., p
        Initialize randomly particles positions  for k = 1, 2, ....., p
        Set k=1
Step 2.Optimization:
        Evaluate the fitness function value Fi^k  for the particles (the cost function)
        If Fi^k ≤ F^k_best  then F^K_best = Fi^k,  pi^k = xi^k
        If Fi^k ≤ F^g_best  then F^g_best = Fi^k,  pi^g = xi^k : then Go to step 3
        Else
          Choose the particle with the best fitness value of all as gbest
          Update all velocities of particle vi^k for k = 1, .....,p according to equation  (1).
          WUpdate all positions of particle xi^k for k = 1, .....,p according to equation  (2).
          Set k = k + 1
          Go to Step 2
Step 3. End
```

The GA is also a heuristic adaptive search algorithm was used to schedule the data of the E-Health cloud, to verify the effectiveness and efficiency of the proposed model. The GA is a specific class of evolutionary algorithm (EA) inspired by ideas of evolutionary biology such as genetics. GA uses the operators Selection, Crossover and Mutation. The data here are considered solutions are known as chromosomes to be scheduled using the GA. Each chromosome contains a number of genes and an appropriate fitness value for it. A crossover takes place by selecting the best pair of chromosomes and selecting a random point in the chromosome to complete the process of crossover between them to get a better sequence. Then, the step of making a mutation for the offspring is started. The mutation causes the individuals' chromosomes to differ from those of their parents' individuals. After that, the formation of the new population for the next generation is produced (Hamad and Omara, 2016; Hamed and Alkinani, 2021). Table 3 illustrates the GA Pseudocode of the proposed model.

Once the best solutions are obtained, which are the chromosomes that achieve the appropriate fitness value, the required data is obtained and considered to be the best solution and the scheduling process is completed using the GA (Kaur and Sharma, 2019; Ali and Tawhid, 2017; Saber et al., 2021; Hamad and Omara, 2016; Hamed and Alkinani, 2021).

Table 3: GA Pseudocode

Input: Requests = {R_1, R_2, R_3,…….., R_N}
Start:
[Initial Population]: Create initial population (suitable solutions for the problem).
[Fitness]: Create the new population is the cost function and order by descending.
[Selection]: Two-parent chromosomes are selected according to the lowest fitness.
[Crossover]: Cross over the parents to form the offspring.
[Mutation]: Mutate a new offspring in a position of the chromosome.
[New population]: Generate the best new offspring in the population for the next generation, then run the algorithm.
[Loop]: Go to step 2, If the end condition is not satisfied: no chromosome satisfy the condition (the best bandwidth)
[End]: If the end condition is satisfied; the chromosome with the highest recovery bandwidth, stop, and return the best solution (the data required) in current population.
[Output]: Take the closest chromosome that fulfills the required condition in order.

The Proposed Model

The Particle Swarm Multi-Objective Optimization (PSMOO) consists of multi-cloud service providers. They are represented by CP1, CP2,...., CPm. The style of multi-cloud is appropriate for the data disaster recovery service of the data E-Health cloud. CP1 is responsible for the DR process for all the cloud providers in the multi-cloud and also includes itself. All the legitimate users of CP1 are the patients or admin for different roles like physicians, paramedical personnel, or any other medical team in the multi-cloud. They have identical authorities. Devices and portable systems means access systems to the E-Health cloud to obtain the available data, like: Home PC, Medical Tablet, Mobile Gateway, Healthcare Tablet- PC, and so on as shown in figure 1.

For authentication and access control policies; the patients have the authentication to access the cloud data, to register or log in to some of their data or submit their data to a doctor. Moreover, the doctor provides some professional advice to the patient. The medical team has the authorities it to access medical data according to the granted powers.

Security measures for the E-Health cloud have been performed as follows: the cloud service provider (the service administrator) has the permission to display the detailed registration information of the user and the medical team except for the password. This is a measure to protect the security of the E-Health cloud information. The cloud service provider also has the permission to delete a user or anyone in the medical team, once it is confirmed that it is a malicious or wrong user. The service administrator also has the permission to publish a notice and give some important feedback to the user for writing the information in the E-Health Cloud.

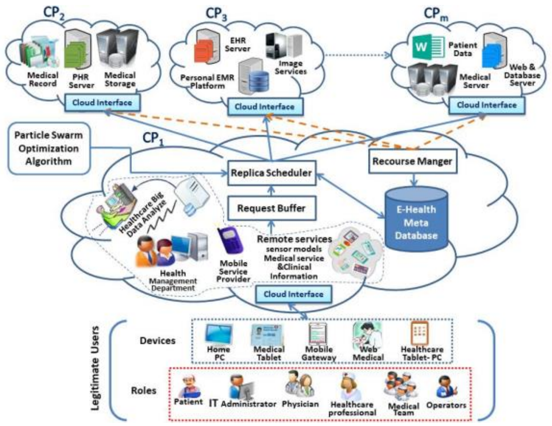

Figure 1: The Model Cloud E-Health Architecture.

When the data backup process is started, the CP_1 is responsible using DR to select the resources from CP_m this process is based on the optimizing scheduling strategy using the PSMOO model. The goal of the PSMOO is to reduce the cost of data backup to the lowest possible extent and reduce the time as much as possible. The data backup request R_N from the patient or legitimate user. The request is submitted to the CP_1 from the recovery proxy of the user via the cloud interface of the cloud provider CP_1. Data backup jobs are valid requests to be processed by CP_1, as shown in figures 1 and 2.

The PSO algorithm is used for E-Health cloud data scheduling because it is effective, reliable for data recovery, ease of use, efficiency and popularity in a wide range of use. In order to verify the desired result, the GA was used for scheduling the data of E-Health cloud to compare the results. Each CP has cloud interface storage to send or receive the data to and from the users. The proposed model serves patients and the medical team in the E-Health cloud who are authorized to access and review patients' data. The Metadata is the patient database in the cloud, which includes the data about the electronic medical record and the electronic health record, other healthcare data, and replicas' locations, see figures 1 and 2.

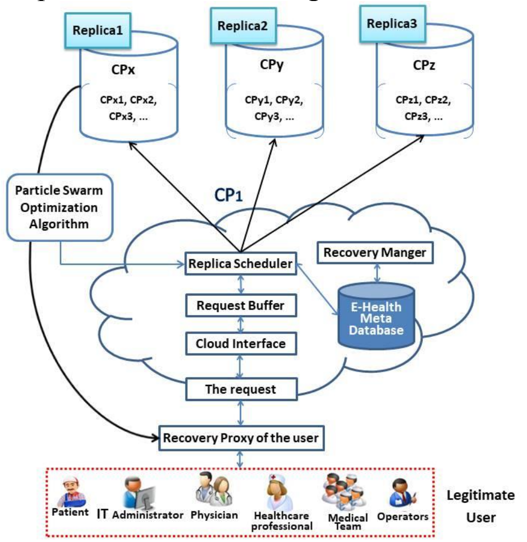

Figure 2: Three Locations of the Replica Data.

The Optimized Data Scheduling Procedure

The PSO was used in scheduling the data of the E-Health cloud, where it has been shown to be effective, reliable for data recovery and reduce the total cost. PSO was used for the data scheduling procedure because it has a faster convergence rate than GA. Also, it has fewer mathematical operators than in GA. This makes the DR process faster in the application.

From figure 2, the legitimate users send the requests to CP_1 which will have waited in the queue. Then, the scheduling will recomputed the requests that are currently presented and sorted them. Three Replicas of the E-Health cloud data are created in three different locations CPx, CPy, and CPz. The three locations will remain in CP_1 because it is responsible for the recovery process. Here, each location will be divided into three partitions as follows, as shown in figure 2:

CPx: CPx1, CPx2, CPx3, …; CPy: CPy1, CPy2, CPy3, …; and CPz: CPz1, CPz2, CPz3, …

where: CPx1 is the sub-location of the data recovery, CPx is the main or basic location of the data recovery. Many comparison are made for the data in the database, they are located in three locations and the data which fulfills the bandwidth condition of the required data. The data here are considered solutions and known as the particles to be scheduled using PSO.

Once the best solutions are obtained, the p value has the highest recovery bandwidth. Due to, the p that achieves the appropriate fitness value. i.e. the p value minimizes the cost of the DR process. The required data is obtained and considered to be the best solution and the scheduling process is completed by choosing the best solutions.

The Data Recovery Procedure

The data recovery procedure is used to achieve the lowest possible cost which is the bandwidth condition. The cost of the data recovery is the data storage cost and the network communication cost, they are calculated according to equation 3 (Suguna and Suhasini, 2015). So, this procedure should reduce the data recovery time and the data backup cost as much as possible. The use of PSO in the cloud E-health data scheduling process is more powerful, effective and integrated. The proposed model of DR is explained in detail in figure 3.

$$\text{Cost eq.} = \sum_{j=1}^{n} \sum_{i=1}^{m} (d_j * g_j * r_{ij} * sp_i * b_{ij} * tp_i) \quad (3)$$

Results and Discussion

In order to obtain the desired results, PSO algorithm was used with 1000 iterations for the execution according to Equation 3. Real numbers were used for encoding. Python 3.7.1 in windows 10 was used for the execution of the PSO algorithm and the GA. Table 5 shows the experimental setup of the PSO and GA.

Table 4: The Cost Equation Parameters

Parameters	Description	Bound Value
d_j	The store duration in hour at j th tasks data size	(1,30)
g_j	The size of the data in GB at j th tasks data size	(1,1000)
r_{ij}	The data replicas count, we have $\sum_{i=1}^{m} . \sum_{j=1}^{n} r_{ij} = 3$	(1,3)
sp_i	The service provider at i th service provider	(1,20)
b_{ij}	A Boolean variable, 1 if CPi contains n- tasks, otherwise 0	(0,1)
tp_i	The time processing for the task i-th	(0,60)

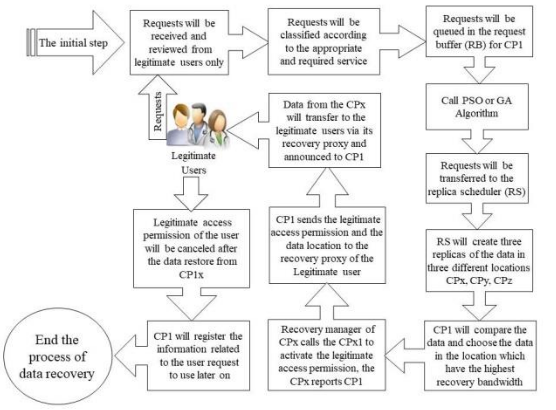

Figure 3: The Proposed model of Data Recovery.

Figure 4 shows the result of the PSO algorithm implementation in terms of fitness values for the iterations. In order to comparatively evaluate the proposed model, the GA was also used in scheduling the data of the E-Health cloud. It was correctly compared with the same conditions with 1000 generation like PSO with the same objective evaluation function in equation 3.

The diagram in Figure 4 shows the result of the GA implementation in terms of fitness values for the generation. The conditions are the same for both algorithms PSO and GA and the fitness function of equation 3 in both algorithms has been executed and evaluated with respect to both the reduction of the cost and time of the DR.

Table 5: PSO and GA parameters

Algorithm	Parameters	The value
The PSO Algorithm	Maximum number of iterations	Tmax=1000
	Population size (No. of solutions i.e. Particles)	p = 50
	Inertia weight (ω)	ω=0.72984
	Personal acceleration coefficient (c_1)	c_1=2.8
	Global acceleration coefficient (c_2)	c_2=2.05
	The parameters of the cost equation	n=6
	Number of execution iteration	30
The GA	Maximum number of iterations	ng = 1000
	Population size (No. of solutions i.e. chromosomes)	size=50
	Probability of crossover	pc=0.8
	Probability of mutation	pm=0.1
	Scale for mutations	pe=0.5
	The parameters of the cost equation	6
	Number of execution generation	30

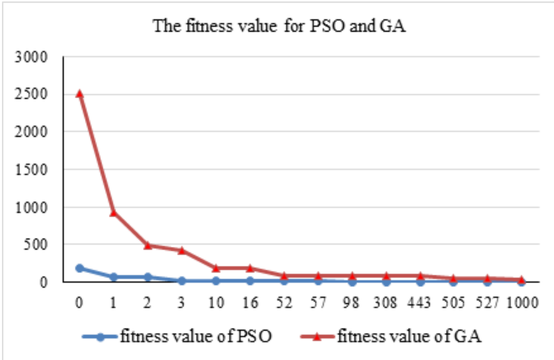

Figure 4: The PSO and GA convergence.

In order to analyze the performance of PSO and GA, they were executed with different numbers of tasks, as shown in table 6. It was observed that the total cost of the DR with PSO is fewer than GA for all tasks, see figure 5. Figure 6 shows that the proposed model was faster at all using the PSO instead of the GA to complete the data recovery.

Table 6: Number of tasks for PSO and GA

Number of tasks	Fitness Value of PSO	Fitness Value of GA
15	24	170.66
20	14	223.96
25	20	100.79
30	15	38.21
60	15	53.67
80	9	37.66
100	7	50.58

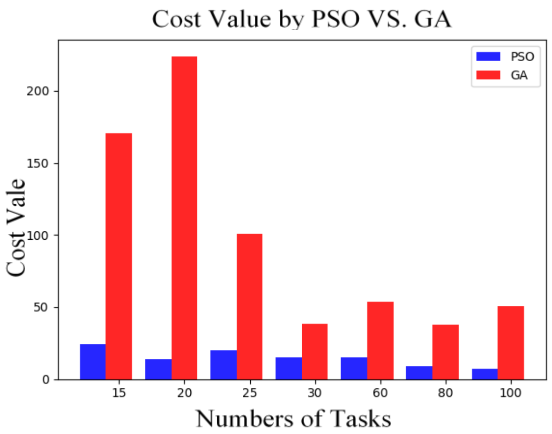

Figure 5: The comparison results of the total cost for the use of PSO and GA.

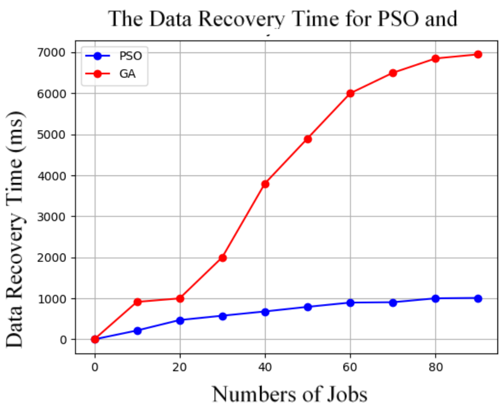

Figure 6: The comparison results of the data recovery time for PSO and GA.

It was found that PSO has a faster convergence rate comparing with GA, so it was be chosen to be applied in the proposed model. Besides, PSO contains fewer calculations and parameters than GA. Results have shown that the PSO algorithm is able to get a better schedule than GA based on a few time, see figure 6. In addition to, PSO reduces the overall cost of DR process and the required time for processing for the data recovery. Figure 7 illustrate the cost function values with 1000 iterations for the PSO and GA. It was seen that the PSO algorithm gets the optimal solution quickly comparing with GA.

Conclusion

The proposed model provides a solution for the disaster recovery problem in cloud-based E-Health system. The optimization algorithms PSO and GA are used in the model to perform lost data recovery processing. The results showed that the PSMOO model when using the PSO algorithm is more powerful integrated and reliable to address the DR problem. It was noticed that the proposed model using PSO algorithm is much faster to retrieve the data comparing with GA. The proposed model can play an important role in achieving the reliability of the cloud computing E-Health environment by considering the available resources to prevent data loss. In the future, the performance can be improved by applying the proposed model using the hybrid particle swarm optimization and the GA to perform the E-Health data cloud scheduling procedure.

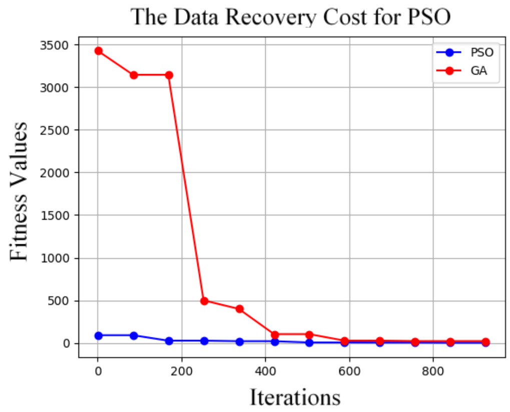

Figure 7: Comparison of fitness function with the use of PSO and GA.

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الملخص العربي

عنوان البحث: نموذج حوسبة سحابية فعال للصحة الإلكترونية

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أصبحت الحوسبة السحابية مكونًا لا غنى عنه في قطاع خدمات الصحة الإلكترونية. بناءً على ذلك، تتزايد بيانات سحابة الصحة الإلكترونية يومًا بعد يوم نتيجة لزيادة بيانات المرضى وتشخيصات الفريق الطبي. يؤدي هذا إلى تخزين كمية هائلة من البيانات التي يسهل فقدانها أثناء وقوع كارثة. من أجل ذلك، تم اقتراح نموذج التحسين المسمى The Particle Swarm Multi-Objective Optimization (PSMOO) لخدمة واستعادة بيانات سحابة الصحة الإلكترونية أثناء فشل النظام. تم استخدام خوارزمية تحسين (PSO) لإجراء جدولة بيانات الصحة الإلكترونية. النموذج المقترح لديه القدرة على لعب دور مهم في تحقيق موثوقية بيئة الصحة الإلكترونية للحوسبة السحابية من خلال النظر في الموارد المتاحة لمنع فقدان البيانات. تم مقارنة النموذج المقترح مع الخوارزمية الجينية لإظهار أن النموذج المقترح قوي ومتكامل وموثوق للتعافي من الكوارث.