# Nature Inspired Job Scheduling For E-Health Services In Mobile Cloud Computing

Rachhpal Singh, Rupinder Singh P.G. Department of Computer Science & Applications, Khalsa College, Amritsar (INDIA).

# ABSTRACT

Mobile Cloud Computing (MCC) is a computational frame applied in E-health services for solving computational demands. A novel mechanism based on popular nature-inspired Particle Swarm Optimization (PSO) technique used for job scheduling on computational mobile clouds. The particle's velocity and position in PSO is drawn-out from real job scheduling values applied in the health care system. The proposed mechanism is to dynamically create a nature-inspired optimal job scheduling in E-health services for job completed within a minimum span of time and also resources utilization in an effective manner using the mobile cloud computing environment. A comparison of Genetic Algorithm (GA) and Variable Neighbourhood Search (VNS) with the proposed PSO algorithm was done for evaluating the performance. Empirical outcomes illustrate the importance of the proposed mechanism and have an ability to get a feasible and faster schedule with significant convergence speed.

### Keywords:

Mobile Cloud Computing, Job Scheduling, Particle Swarm Optimization, Health Care System, Genetic Algorithm, Variable Neighbourhood Search, Nature Inspired Algorithms.

# **1. INTRODUCTION**

Mobile Cloud Computing is extensively known as an auspicious approach for the widespread health care solutions for the coming generations [1]. A number of applications use MCC environment to handle healthcare services [2] as shown in Figure 1.

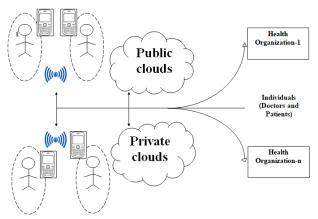


Figure 1.MCC in healthcare services

MCC engenders the data analysis outputs in the field of healthcare using MCC, subject to the urgency condition of the patient that helpful for medical database storage and for the information to physicians having easy access in future. This is possible by connecting the body of the patient with wireless network and collecting the data using vital signs and physiological signals with the help of private or public clouds through smart m achines or mobile phones.

MCC in the healthcare field is an electronically ultimate platform to collect, process, transmit, share and use patient records, medical images with doctor's database connectivity [2] [53]. Analysis of physiological data and telemonitoring the patient's records can be easily handled by using the computerized healthcare software using the internet known as E-health connected with MCC [3]. Further, the mobile cloud E-health system has been significantly influenced in multi-agent practitioners and consultants and also used the MCC based healthcare solutions [4]. In E-health system services provided by the mobile clouds classified into two ways. One is healthcare storage using mobile clouds and the second one is the simple use of mobile clouds for computing [5].

Researchers also discussed and established an intelligent job scheduling system for solving healthcare problems like patient data collection, data transmission, analysis of data and store huge amounts of data for future use with privacy and security in MCC environment [6]. Efficiency can be improved in the appointment system of patients and proper use of E-health based

job scheduling for timely access to the tasks. It optimizes the medical outcomes and patient satisfaction. Through MCC allocation of resources in E-health at multiple sites, health-based job scheduling becomes efficient for doctors and patients.

The aim of well-designed job scheduling and appointment process is to easy and timely access E-health services for doctors as well as for all the patients. It reduces waiting time, smooth workflow and matches the supply and demand of all the resources linked with health care. A well-designed scheduling appointments system solves the waiting times for patients, manage unscheduled jobs, minimizing the resources utilization and processes like double booking for faster work, pushing back dinner and shrinking lunchtime. Computational job sharing and scheduling is the objective of mobile clouds. In a mobile cloud environment, various resources and job scheduling naturally have dynamic working that varied as well as easily added and removed jobs/resources in MCC environment. Mobile cloud resources and management scheduling have the proper functionality for submission, scheduling, and monitoring of jobs. Mobile resources are distributed geographically under the supervision of different ownerships. Every owner has an exclusive technique of scheduling, managing jobs/resources. Also, every scheduler has own constraints, cost, and access policies in job scheduling and appointment system and proper utilization of resources. Job scheduling and appointments is an NP-complete problem in MCC environment [7]. This appealed to the consideration of investigators worldwide due to the complexity of the system and its importance in scheduling. There are a number of scheduling algorithms that classified into centralized and decentralized ways and to see the status dynamically or statically. Recently many nature-inspired meta-heuristics algorithms were introduced for the minimization of job execution and time completion optimally. Due to the inflexible problem's nature and importance of computing in mobile clouds, there is a requirement to reconnoiter other possibilities in generating the best heuristic to solve the problems. Mainly, complete exploration capability of both local/global optimum outputs, many new searching ways out using nature-inspired evolutionary meta-heuristics [8] [9] and soft computing mechanisms [10] were applied as a new emphasis of scheduling research.

Here, we introduced a novel mechanism PSO for E-health based appointments and job scheduling on mobile clouds. PSO applied to health-based job scheduling using mobile clouds represents the velocity and position of the particles (jobs)[11]. Here a mapping procedure was done in between the particles and job scheduling that dynamically produce an optimal schedule to finish the job scheduling having minimum execution time as well as minimum utilization of resources in an effective manner.

Mainly objective behind the success rate of swarm-based nature-inspired mechanisms is having the capability to solve the NP-hard problems or NP-complete problems. The benefit of swarm-based techniques trusts on the sharing of information between several agents that has co-evolution, self-organization and learning throughout to produce high efficient outputs [12]. Actually, every swarm individual acts and behaves in a combined manner for reproduction, foraging and jobs/resource allocation in an easy way. Also, some of the emerging computational techniques analyzed and programmed the solutions along with data mining and the internet of things that influenced the healthcare services, heart patients, diabetic patients and health industry astonishingly [13]. An ambient network paradigm is the Internet of Things that embedded with some of the popular software, sensing skills on computers have enormous world-wide ways out and make a change in the field of mining as well as computing [14]. Several researchers have used various data mining like iterative Dichotomiser 3, SVM, Nearest Neighbour, Randomly applied Forest approach and also some of the soft computing algorithms like GA, PSO, ACO, ABC to care and schedule health problems and services in human beings [15].

In the rest paper, related work studied in section 2. The health care based Job scheduling methodology explained in section 3. A dynamic mobile cloud-based health care job scheduling using PSO with performance evaluation is discussed in section 4. Experimental outputs of health services job scheduling using PSO in mobile cloud computing environment evaluated in the  $5^{th}$  section. Conclusion with future scope was done in section 6.

# **2. RELATED WORK**

Brandt et al. designed a user interface system for the integration and processing of the event having an effect on healthcare services delivered to patients [16]. Begur et al. designed an optimized DSS to solve a challenging scheduling problem like when, where and which nurse deals with which patient and also set the travel route that helps to physician for fulfillment of specified needs [17]. Further, Thompson et al. developed an efficient computer-based information program to manage health clinics by managing/scheduling work among employees in the clinic and determine the staff's and patients's needs with their job scheduling [18]. Fikar et al. reviewed a comprehensive overview related to scheduling and routing problems [19]. Othman et al. implemented an optimized management based decision support system to manage and help physicians to anticipate overcrowding for multi-healthcare job scheduling dynamic multi-agent systems [20]. Barg-Walkow et al. discussed a model to handle a complex healthcare environment making multiple job scheduling decisions in advance and during an emergency, time that help to the physicians [21].Abdelaziz et al. proposed a model for health care services using a cloud environment with PSO to optimize the virtual machines selections and improve the performance of health care services by minimizing the execution time of medical-related jobs or requests from the doctors/patients with proper utilization of cloud-based resources [22]. Abdelaziz et al. proposed a health care intelligent system using GA, PSO and parallel PSO in a cloud computing environment [23].

Islam et al. proposed a nature-inspired virtual machines migration idea for a heterogeneous mobile cloud computing system to handle smart healthcare processes in the smart cities [24]. Elhoseny et al. proposed a new optimized model for the selection of virtual machines using GA, parallel PSO and simple PSO in a cloud-IoT based environment to efficiently

manage big healthcare data and services [25]. Marynissen et al. presented a literature review on multi-appointment health care based job scheduling to satisfy the patients [26]. Peng et al. discussed the mechanisms, principles, and strategies related to real-time job scheduling for mobile machines for best scheduling in a dynamic environment [27]. Lo'ai et al. discussed a networked healthcare system in the mobile cloud computing environment to handle health-based big data [28]. Hanen et al. proposed a medical web service multi-agent system for handling the health care service in mobile cloud computing [29]. Liu et al. proposed a fine-grained health care control system using mobile cloud computing giving high-performance services [30]. Jemal et al. proposed a medical mobile cloud multi-agent healthcare services system for mobile web services in the healthcare domain to provide facilities and services for caregivers and patients to improve the healthcare system [31].

Sodhro et al. proposed a window-based optimized medical quality rate control mechanism for providing quality of services in the health care field using mobile edge computing [32]. Moreira et al. used a biologically inspired PSO for decreasing the computational cost of artificial neural network-based electronic health systems [33]. Samantaet al. proposed a novel authentication nature-inspired evolutionary simulation system to robust the biomedical contents to maintain patients' records electronically with multiple hospitals using GA [34]. Hussein et al. proposed a blockchain-based data-sharing system to tackle sensitive health care data using GA [35]. Zhang et al. reviewed a comprehensive investigation of PSO and compared it with other nature-inspired evolutionary techniques to achieve a multi-objective system in different areas for research work [36]. Ryalat et al. investigated PSO's various classifications to increase the execution speed and accuracy for the evaluation of medical image applications in storing and processing of patients' records in the health care system [37]. Liu et al. proposed a novel PSO to improve the accuracy of traditional clustering approaches for the maintenance of real-time patient attendance [38]. Butler-Henderson et al. studied the findings from an analysis of a subset of Australian Health Informatics Workforce Census 2018 data that was helpful for health informatics [39]. Kaur et al. presented a comprehensive review regarding human psychological disorders like depression, stress, anxiety, mood disorder etc. by mining various nature-inspired computing techniques [40]. Sharmaet al.explored and diagnosed the dataset of diseases using diverse data mining techniques on various lifestyle-based diseases [41]. Nilashiet al. studied the classification of diabetes disease by designing and developing a healthcare intelligence system with a machine learning approach [42]. Gautam et al. explored the performance and usage of ABC, ACO, FA, GSO and ALO algorithms in diagnosing various types and stages of diabetes and cancer [43]. Desmetet al. also discussed and reviewed existing approach related with health care emotions and moods [44]. Mostafaet al. applied a Naïve Bayes, Decision Tree and Neural Network classification approaches for Parkinson's disease evaluation [45].

# 3. JOB SCHEDULING METHODOLOGY

In the computational mobile cloud computing environment, a general framework was defined that focuses on mobile cloud resource broker, mobile cloud information server and domain mobile cloud resource manager [46]. Computational mobile clouds usually adopt the virtual and physical levels of information flow through the various mobile spots. Mapping in two or more than two layers and various resources was created in the mobile cloud computing environment [47]. Without any negotiation of the overheads, the proposed algorithm permits individual resources and job agents to interact semantically with neighboring jobs and resources. All the agents in this process have dynamic health resources and health-based job services and the main objective is to finish the jobs at the local level and then at the global level. Health services are used in job scheduling in such a way that it works like task scheduling in parallel/distributed computing. Chung and Chang [48] discussed a prototype to achieve a large scale system for dynamically accessing and management of health resources and jobs. A job scheduling health-based services are distributed in MCC environment and are as shown in Figure 2 as:

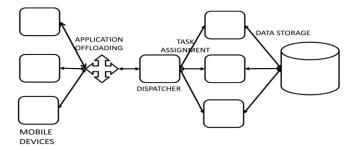


Figure 2.A job scheduling mobile cloud distribution system.

In mobile cloud computing, to get facts and figures regarding execution speed and complexity of the accessible mobile spots is a simple and easy process. In this operation, a problem occurs regarding job scheduling computations and the total time required for help to doctors and patients in the health care system. To intellectualize the job scheduling problem in the healthcare system as an algorithm, we dynamically estimated the length of the jobs from users and user applications having some specifications or past data. Job scheduling depends upon the type and capacity of mobile cloud spots and locations. A mobile cloud system is computational jobs/resources set having limited capacities. It may be connected with a workstation, hot spot mobile system, a supercomputing machine, a simple personal machine or clusters/grids so that any type of processing takes place easy.

Note that the computational capability of the mobile cloud system influenced by processors number, primary storage space, memory size, and some more stipulations.

The definition of a job is a single set process/data having multiple atomic tasks. Every task apportioned on a single machine having no preemption in the execution of job scheduling. It has scheduling requirements and input/ output data for job/task completion. The operations have some scheduling lengths of jobs expressed in the number of cycles. Service and resources utilized and stored related to healthcare services using MCC is as shown in Figure 3.

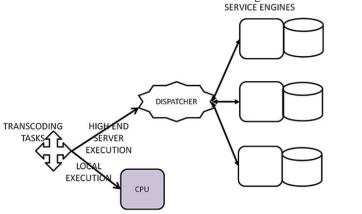


Figure 3.Transcoding of jobs (health services) in MCC.

Task mapping in a defined time interval of mobile cloud machines is a processing schedule where jobs can be easily operated. So the problem of scheduling can be solved easily with a set of tasks or jobs or operations with some specifications, optimal criteria and some constraints regarding the proposed mechanism. Let us take  $J_i$  (i=2,3.....n) independent jobs on MC<sub>i</sub> (i=1,2,.....m) heterogeneous mobile cloud spots. The objective of this operation is the proper utilization of mobile spots and to minimize the completion time effectively in health-based job scheduling. Every mobile cloud has a specified speed measured in CPUT. Similarly, the length of each job is measured by a number of cycles in the job scheduling process.

Every job  $J_i$  has job cycles as a scheduling element and the mobile cloud spots  $MC_i$  measure the calculating speed of every job in mobile cloud computing environment in cycles/second. So every  $J_i$  has scheduled on one of the mobile cloud nodes  $MC_i$  until either job completion or job termination. So all mobile cloud nodes at every stage have identical scheduling factors and so pre-emptions of job scheduling denied by the mobile spots to avoid any complexity and any difficulty in job scheduling operation. A particular schedule defined having some job execution specifications as well as completion time for all the operations or tasks for every job in a mobile cloud environment.

Objective can be formulated by defining  $C_{ij}$  (i=2,3,4.....m and j=2,3,4.....n) as the completion or finish time so that every mobile cloud node MC<sub>i</sub> completes the job scheduling.  $C_i$  denotes the time regarding mobile cloud computing on I mobile spots MC<sub>i</sub> that completes all the health-based jobs scheduled or services in the mobile cloud computing environment. Define  $C_{max}$  as the makespan or schedule length during job execution and scheduling. In job scheduling, the schedule is optimal if it optimizesmakespan and flow time during job scheduling and processing. Scheduling of shortest job in job scheduling on the fastest mobile cloud node is a conceptual rule to minimize the  $C_i$ . Similarly, scheduling of longest job in the job scheduling process on the fastest mobile cloud node is a simple rule for the minimization of  $C_{max}$ . Average job can be completed quickly by minimizing the  $C_i$  values, by minimizing the  $C_{max}$  factor at the cost of a number of jobs executed in a long time. So  $C_{max}$  minimization will give a best-optimized solution by maximization  $C_i$ .

## 4. DYNAMIC MOBILE CLOUD-BASED JOB SCHEDULING USING PSO

In a number of real-life based applications, it is vital to solve combinatorial optimization problems to handle job scheduling in mobile cloud computing environment dealing with healthcare services. Further, this field attracted the researchers using a nature-inspired heuristics approach and a system having a multi-agent concept for job scheduling optimization problems. The requirement of real-time results and incrimination of search space size will motivate research factors for job scheduling problems having nature-inspired optimized heuristic mechanisms. Here PSO in MCC environment solves the healthcarebased job scheduling services and optimizes it.

PSO is motivated by a pattern of an organism having social behavior that interact and live within big groups or swarms. It has swarm behaviors as in schools of fish, flocks of birds, swarms of bees, group of wolfs and also in humans having good social behavior. This concept emerged as the famous paradigm known as Swarm Intelligence (SI) [49]. This can be easily applied and implemented for solving a number of job scheduling optimization problems. Fast convergence is the main strength of this mechanism that is useful for the comparison of several globally optimized approaches favorably [50].

PSO has a swarm of particles that initialized having random candidate solutions as a population for solving the problem in a simple way. Particle movement is iterative in nature through a D-dimension or multiple dimension problem space for searching the new optimized solutions. Here f is the fitness value computed as a certain quality measure during different levels of job scheduling iterations. Every particle having a position value as a position-vector  $Ex_i$  (here i represented as index of the particle). Also, every particle has a velocity value as a velocity-vector  $Ev_i$ . It is very important to say, every particle has a good remembrance for storing the best position value in the iterative procedure for a vector value  $Ex_i$  in j<sup>th</sup> dimensional for  $Ex_{ij}$  iterative operation. The best-optimized value of position-vector in swarm is stored in a vector  $Ex_i$  in j<sup>th</sup> dimensional for  $Ex_{j}$ . During t iteration time, updation of velocity value from its previous velocity value to the new velocity value is shown in eq. (1). Also, the new position value is determined then by summarizing the previous position values and new velocity value as shown in eq. (2).

 $Ev_{ij}(n+1) = w^*Ev_{ij}(n) + o_1a_1(Ex_{ij}^{i}(n) - Ex_{ij}(n) + o_2a_2(Ex_{ij}^{i}(n) - Ex_{ij}(n))$ 

#### $Ex_{ii}(n+1) = Ex_{ii}(n) + Ev_{ii}(n+1)....(2)$

Here, the inertia factor is denoted by w and random numbers are denoted by  $o_1$  and  $o_2$ . This will maintain population diversity and are also distributed uniformly in the defined interval [0,1] having j<sup>th</sup> dimension value for i<sup>th</sup> particle value. Also  $a_1$  operates as a positive constant (known as the coefficient of self-recognition) and  $a_2$  operates as a positive constant (known as the coefficient of self-recognition) and  $a_2$  operates as a positive constant (known as the coefficient of the social component).

Now considering eq. (1), a particle will take decision for movement and direction having its own experience that is taken as storage purpose (as memory) for its best optimized past position value by experiencing effective particle in a swarm or group. Here, particle optimization mechanism, particle finds optimized outputs in defined problem having some array-based values (range). Note that in case, array values are not symmetrical, then can be interpreted to corresponding symmetrical array values. So as guidance for the particles, it is much effective in defined search space and also maximum moving value of distance in a single iteration process. It must be clamped in between maximum velocity and it is shown in eq. (3) and eq. (4).

 $Ev_{ij} = (+/-) (Ev_{ij})min(|Ev_{ij}|Ev_{max}).....(3)$ 

 $Ex_{ij} = (+/-)(Ex_{ij})min(|Ex_{ij}|Ex_{max}).....(4)$ 

The  $v_{max}$  has value p \* s having range p[0.1 -1.0]. Usually, it is selected as s, in other words, p = 1.0. A complete illustration of PSO algorithm is as below:

PSO Algorithm:
Step 1. First of all, take n as swarm particle size as an initial
value with some of the favorable parameters.
Step 2. Initialization of the velocities and the positions of all the
particles in a random order.
Step 3. Repeat
<i>Step 4. t++;</i>
Step 5. Compute fitness value or fitness function of every
particle;
Step 6. Compute $x_i^*$ as $x_i^* = \arg_{\min} value * f(x_i(t-1)) * f(x_i(t_1)) *$
$f(x_i(t_2) * \dots f(x_i(t_n);$
Step 7. for $i = 1$ to $n$
Step 8. Compute $x_i(t) = \arg_{min} value * f(x_i(t-1) * f(x_i(t)));$
Step 9. For $j = 1$ to Dimension
Step 10. Update $j^{th}$ dimension value of $Ex_i$ and $Ev_i$ according to
eqs.(1), (2), (3) and (4)
Step 11. Next j
Step 12. Next i
Step 13. Until terminating criteria met.
Step 14. Stop processing.

Here in eq. (1), w taken as inertia weight that has a vital role and is critically considered for PSO's convergence behavior. Employment of inertia weight controls the impact of past values of velocities on the present value. So, w is parameter normalizes a trade-off in the local search (nearby) and global search (wide-ranging) exploration powers of the particle swarms. A large value of inertia weight helps in global exploration for finding new areas, whereas a small value helps in local exploration change. An appropriate value of w inertia weight setup a balance in local and global exploration and subsequently outputs in a reduction of no. of iterations required to find the optimum output. Initially, take inertia weight value as constant. So, some experimental computations specify the setting of inertia as a large value for better optimization for the promotion of global exploration in the large search space.

These will reduction in some of the refined results [51]. Take initial value as 1.2 and w has a 0 value as a good choice. The  $a_1$  and  $a_2$  are two parameters that have not critical convergence of PSO as in eq. (1). Faster convergence can be done by proper fine-tuning and improve the local minima. Let us take  $a_1 = a_2 = 1.99$  as default values, but some of the experimental solutions specify  $a_1 = a_2 = 0.99$  and have better solutions. It is analyzed that to select  $a_1$  as a larger cognitive parameter than  $a_2$  as a social parameter gives a more optimized solution.

Some of the parameter settings for the genetic algorithms, variable neighborhood search algorithm, and particle swarm optimization are as in Table 1.

the internet of settings for the algorithms (GA, VIG, and IB							
Algo. Name	Parameter	Value of Parameter					
GA	Population size	30					
	Crossover Probability	0.5					
	Mutation Probability	0.01					
	Mutations Scale	0.1					
VNS	Sub-set of chromosome particles to	200					
	move through local search						
	Neighbourhood structure of VNS	200					
	Shaking of random variables	10					
	Local search applied	5					
	No. of iterations	50					
	Value of n	200					
PSO	Size of the swarm	30					
	a1 (self-recognition coefficient)	1.44					
	a <sub>2</sub> (social coefficient)	1.44					
	w (Inertia weight)	0.7 to 0.2					

#### Table 1: Parameter settings for the algorithms (GA, VNS, and PSO)

A Table 2 for showing the health-based services with an optimal schedule of  $j^{th}$  job (health service) on  $i^{th}$  mobile cloud grid MCG<sub>i</sub> node is as shown:

Mobile	Jobs	8										
Clouds	j <sub>1</sub>	j <sub>2</sub>	j <sub>3</sub>	j <sub>4</sub>	j <sub>5</sub>	j6	j <sub>7</sub>	j <sub>8</sub>	j9	J10	j <sub>11</sub>	j <sub>12</sub>
(MC)												
MC <sub>1</sub>	0	0	1	0	1	0	1	1	0	0	1	1
MC <sub>2</sub>	1	0	1	1	1	1	1	1	0	1	0	0
MC <sub>3</sub>	0	1	0	0	0	1	0	0	1	1	1	1
MC <sub>4</sub>	1	1	0	1	1	0	0	1	1	1	1	1

#### Table 2: An optimal schedule for (4,12).

A complete comparison of all the algorithms to measure the performance of every instance is shown in Table 3.

Table 3: Performance comparison b	between GA,	VNS and PSO
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Algorithm	Item name or event	Instance value						
considered	name	(4,12)	(4,120)	(10,70)	(12, 80)			
GA	Average makespan	46.123	85.743	42.927	32.099			
	Standard Deviation	(+/-)0.78	(+/-)0.69	(+/-)0.38	(+/-)0.59			
	Time	209.99	239.99	2199.11	2588.23			
VNS	Average makespan	44.561	88.778	51.555	40.189			
	Standard Deviation	(+/-)0.49	(+/-)5.99	(+/-)1.98	(+/-)7.56			
	Time	330.01	640.99	599.11	672.44			
PSO	Average makespan	45.123	82.987	40.124	35.99			
	Standard Deviation	(+/-)0.30	(+/-)0.52	(+/-)0.73	(+/-)0.64			
	Time	102.11	1400.33	1499.22	1513.99			

# 5. EXPERIMENTAL OUTPUTS OF HEALTH BASED JOB SCHEDULING USING PSO

We studied number of nature-inspired evolutionary meta-heuristics, ant colony optimization, artificial bee colony optimization algorithm, simulated annealing, variable neighborhood search algorithm, particle swarm optimization and genetic algorithm for scheduling the various health services related to job scheduling and resources utilization in grid environment, cloud computing environment and mobile cloud computing environment. From these all the techniques we have considered GA, VNS and PSO for simulation and experimental work. All incline to flourish in an environment that has a very big candidate solutions set. In the past, we worked on evolutionary algorithms to handle the job scheduling but as the

complexity as well as dimensions occurrence increased and so due to that execution time drastically increased also [52]. In the experiments, genetic algorithm and variable neighborhood search algorithm were compared with PSO to check the performance of job scheduling on different mobile spots so that optimized health services can be provided.

Every experiment was iterated 20 times randomly by considering different seeds (health services) operating with every algorithm. Every execution had a 60 \* p \* q fixed number of iterations. Here p denotes the number of mobile cloud nodes and similarly, q denotes the number of jobs in the schedule. Makespan values or schedule length of best-optimized solutions were stored in memory as the best-optimized value and further, by taking 20 different trials, the standard deviations and average values were computed. In a mobile cloud environment, our main focus is on the creation of fast schedules in minimum time. To improve the performance of health service based job scheduling, the job completion time was done on 20 iterations as one of the best-optimized criteria.

To illustrate the concept of experimental work job scheduling problem with small scale values having 4 mobile cloud nodes with 12 health-based job services were considered and is denoted as (4, 12). The health services job execution speeds measured are 5, 4, 1 CPUT. The health services length of 12 job execution on 4 mobile spots are 7, 14, 17, 22, 26, 29, 39, 44, 52, 58, 62, 66 cycles respectively. Table 2 shows optimized health-based job scheduling outputs on (4, 12) schedule (here ``1" denotes that job is scheduled on the respective mobile cloud grid node). Figure 4 illustrates a part of the whole process as four mobile cloud spots with 12 health-based jobs scheduling process.

Mobile	J1				J7			J10		
Cloud1										
Mobile	J2			J6				J12		
Cloud2										
Mobile	J3		J5				J11			
Cloud3										
Mobile	J4				J8				J9	
Cloud4										
	0	10		20		30	40		50	60

Figure 4.The job scheduling outputs for four mobile clouds with 12 jobs

The performance of GA, VNS and PSO algorithms is illustrated in Figure 5.

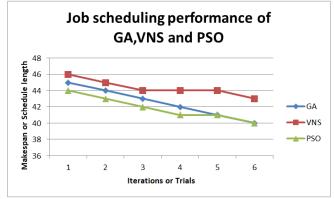


Figure 5. Performance for job scheduling (4, 12).

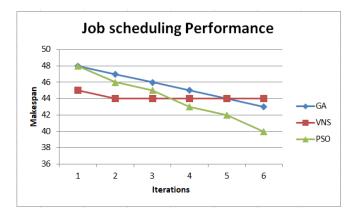
The empirical outputs (makespan or schedule length) for 20 GA executions were {45, 44, 43, 42, 45, 44, 43, 45, 42, 46, 43,44,46,41,45,44,43,47,42,43} having mean value as 43.85.

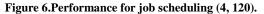
Also for 20 VNS executions, the solutions were {45.3, 44, 45, 44, 44, 45.6, 43, 45.3, 45, 44, 46, 47.1, 46.9, 44, 42.1, 44, 45, 46, 47, 44.2} having mean value as 44.5.

Similarly for 20 PSO executions, the results are {44, 45, 44, 46, 45, 44, 43, 44, 46, 44, 46, 46, 45, 44, 47, 44, 43, 45, 44, 48} having mean value as 41.3.

Note that the optimized output is 44, whereas GA has the best-optimized solution four times, VNS has the optimized solution six times and PSO has the best-optimized solutions eight times and PSO is good for job scheduling. Further, we took these three techniques for healthcare based scheduling by considering three jobs and mobile cloud nodes (MC,Job)

pairs as instance (4, 120), instance (10, 70) and instance (12, 80). Note that health service-based jobs in this process on various mobile cloud spots have been taken for once execution time as shown in Figure 6 and Figure 7.





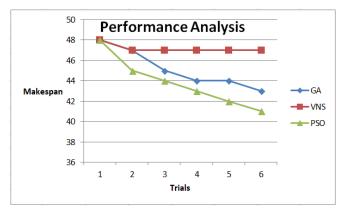


Figure 7.Performance for job scheduling (10, 70).

The performance of GA, VNS, and PSO for the schedule (12,80) is as shown in Figure 8. Table 3 illustrates the average makespan or schedule length values for the 20 experimental trials to show the execution time and standard deviations.

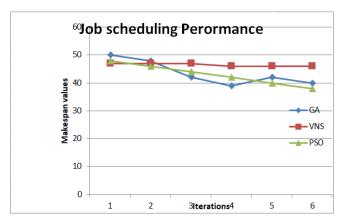


Figure8.Performance for job scheduling (12, 80).

Average schedule length makespan evaluation of VNS was optimized than GA in handling health-based services or jobs for the schedule (4, 12) but for bigger size problems it was reversed. Also from experimental schedules, PSO has better makespan as compared to GA as a primary algorithm and VNS as a secondary algorithm. Makespan outputs or schedule lengths of VNS appeared to more powerful and dependent on primary values (as initial) and provide initial results for evaluations. VNS for 20 iterations had big standard deviations. VNS gives some ``bad'' solutions in 20 iterations and so average values were the largest.

Generally larger the (MC,Job) pairs value that takes longer scheduling time. PSO has the least execution time to allocate all the health service-based jobs on the mobile cloud node, whereas GA was at the second position and VNS had more

execution time to finish the scheduling process. So PSO takes the shortest time as compared to the other two approaches in health care based job scheduling.

## 6. CONCLUSIONS AND FUTURE WORK

In this paper, we examined the problem regarding e-health services based on job scheduling in mobile cloud computing environment. For handling the problem of job scheduling, andanalysis was done by evaluating the number of nature-inspired evolutionary meta-heuristics techniques. A novel mechanism based on PSO to handle health care services job scheduling on the mobile cloud nodes. The particle's velocity and position were computed using PSO. This proposed mechanism generates dynamically an optimal schedule to finish the job executions in a minimum stipulated time period. We evaluated and compared the performance of PSO for mobile cloud-based job scheduling using VNS and GA approaches. Empirical investigations and evaluations showed that PSO has feasible schedules and fast convergence as compared to GA and VNS. This major focus of the research is to handle health care based job scheduling in MCC environment. In future research, the major work will be to measure the cost of the data transmission and also dynamic availability of resources on mobile clouds.

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