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An efficient meta-heuristic algorithm for grid computing

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Abstract A grid computing system consists of a group of programs and resources that are spread across machines in the grid. A grid system has a dynamic environment and decentralized distributed resources, so it is important to provide efficient scheduling for applications. Task scheduling is an NP-hard problem and deterministic algorithms are inadequate and heuristic algorithms such as particle swarm optimization (PSO) are needed to solve the problem. PSO is a simple parallel algorithm that can be applied in different ways to resolve optimization problems. PSO searches the problem space globally and needs to be combined with other methods to search locally as well. In this paper, we propose a hybrid-scheduling algorithm to solve the independent task-scheduling problem in grid computing. We have combined PSO with the gravitational emulation local search (GELS) algorithm to form a new method, PSO–GELS. Our experimental results demonstrate the effectiveness of PSO–GELS compared to other algorithms.

Keywords Grid computing · PSO algorithm · GELS · Scheduling · Independent tasks

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1 Introduction

Grid computing was introduced in the early 1990s by a supercomputing committee whose goal of using computing resources in a convenient form for calculations was complicated by the fact that the resources were distributed geographically. Grid computing enables controlling a wide range of heterogeneous, distributed resources to execute computations and data-intensive applications (Garg et al. 2010). The basic idea of grid computing is that participating machines share resources through a transparent and reliable software layer. The software layer is responsible for resource virtualization, resource discovery and search, and managing running applications. Two organizations that are working on developing large-scale data collections are the European data grid and Globus. Systems in a service grid provide services that cannot be provided with a single machine (Sullivan et al. 1997; Foster et al. 2002). The first phase of grid task scheduling is resource discovery, which generates a list of potential resources. The second phase includes gathering information about these resources and choosing the best set of resources matching the application's requirements. In the third phase, the task is executed, which involves file staging and cleanup (Yan-ping et al. 2008).

Grid resources are shared as distributed and heterogeneous resources that belong to organizations that have their own policies. Scheduling algorithms must therefore be consistent with changes in workloads and available resources to achieve acceptable performance and also to comply with time limits. The grid resource broker, which is responsible for scheduling applications for users, should be an efficient scheduling algorithm. Task scheduling is an NP-hard problem, and scheduling algorithms can be categorized into deterministic algorithms and approximate algorithms. Deterministic algorithms are able to find exactly the optimal result, but they cannot solve NP-hard optimization problems quickly, as their time to arrive at a solution increases exponentially. Approximate algorithms can find good (near optimal) solutions for optimization problems in a short time. Approximate algorithms can be categorized into heuristic and meta-heuristic algorithms. There are several measures for categorizing meta-heuristic algorithms, such as whether they are based on a single solution or on a population. Single-solution-based algorithms, such as simulated annealing (SA), tabu search (TS), and gravitational emulation local search (GELS), modify a single solution during the search process. In contrast, population-based algorithms, such as partial swarm optimization (PSO), genetic algorithms (GAs), and ant colony optimization, consider a population of solutions. In addition, some algorithms search the problem space globally, while others search it locally.

Most of these algorithms try to minimize makespan. Many meta-heuristic algorithms have been proposed for task scheduling in a grid environment, including GAs (Gao et al. 2005), SA (Orosz and Jacobson 2002), TS (Benedict and Vasudevan 2008), two-phase encoding particle swarm optimization (Shiau and Huang 2012; Shiau 2011), and PSO (Zhang et al. 2008). Hybrid meta-heuristic algorithms, in which one algorithm is used as the main algorithm and others are used to improve the solutions, are also being closely studied. These include the combinations GA–SA (Cruz-Chavez et al. 2010), GA–TS (Xhafa et al. 2009), GA–GELS (Pooranian et al. 2011, 2013b), PSO–SA (Chen et al. 2009), Queen Bee (Pooranian et al. 2012), HSPN (Shojafar et al. 2013, 2010), GLOA (Pooranian et al. 2013a), and PSO–TS (Padmavathi and

Mercy shalinie 2010). PSO has the better ability for global searching and has been successfully applied in many areas. It also has fewer parameters than either GAs or SA. Furthermore, PSO works well for most global optimization problems. But PSO's local search ability is weak, and there is a high probability of becoming trapped in a local optimum. In this paper, we combine PSO with GELS, a local search algorithm that improves PSO's performance in finding a solution. The proposed hybrid algorithm (PSO–GELS) decreases makespan and minimizes the number of tasks that miss their deadlines.

The rest of this paper is organized as follows. Section 2 summarizes previous related work in this field. Section 3 describes our computing system model. Sections 4 to 7 describe the intelligent PSO and GELS algorithms, and Sect. 8 describes our proposed algorithm in detail. Section 9 compares our proposed algorithm with several similar algorithms, and the final section presents our conclusion and future research directions.

2 Related work

A combined optimization algorithm using PSO and SA was proposed in Weijun et al. (2004) for the task scheduling problem. A particle consists of m segments and every segment has n different job numbers, representing the processing orders of n jobs on m machines. Thus, we have m machines and n jobs, which convert the continuous optimization problem to a discrete optimization problem. The real optimum values are rounded to the nearest integers. In this algorithm, the PSO results are given to the SA algorithm to avoid being trapped in a local minimum.

In Sivanandam and Visalakshi (2007), a combination of PSO and SA was proposed for scheduling independent tasks with a dynamically varying inertia to provide a balance between the global and local explorations. The algorithm requires less iteration than PSO on the average to find a sufficiently optimal solution. Hence, our proposed method also combines compatible AI algorithms to increase the speed of grid task scheduling.

The discrete PSO algorithm was proposed in Izakian et al. (2009) for task scheduling in grid systems. The scheduler aims to simultaneously minimize makespan and flow time. This algorithm uses a matrix in which each column represents a job's resource allocations and each row represents jobs allocated to a resource. This inspired us to illustrate our proposed method with a 2D matrix.

The method in Zhang et al. (2008) solves the task scheduling problem by using the PSO algorithm with the small position value (SPV) rule borrowed from random key representation. The SPV rule can convert continuous position values to discrete permutations in the PSO algorithm. Each particle represents a potential solution to the resource scheduling problem. Simulation results demonstrate that the PSO algorithm can perform better than GAs for large scale optimization problems. We will similarly demonstrate that our proposed hybrid method performs better than GAs.

In Mathiyalagan et al. (2010), a list scheduling algorithm is presented that uses PSO based on a TS, combining the advantages of both algorithms. It also uses a swap operation to create a new particle. Because we need fast convergence in a grid scheduling problem, and the inertia weight is the deciding factor for the convergence

speed of the PSO algorithm, the algorithm in Mathiyalagan et al. (2010) modifies the inertia equation. This increases the speed of convergence, boosts efficiency, and achieves better results. In this paper we also improved PSO by modifying the inertia parameter, and our algorithm achieves better performance than other methods and optimizes the results.

In Tao et al. (2011), the rotary chaotic PSO algorithm is presented for workflow scheduling in grid computing. A new method called the rotary discrete rule is proposed for changing a continuous space to a discrete space. The method avoids local optima in perturbations of the chaotic sequence, and it makes better modifications of particles than other methods such as Gauss or Cauchy. Our method also pays close attention to several quality of service (QOS) parameters such as availability, reliability, cost, and time concurrency. In our hybrid method, we use chaotic activity to schedule tasks.

In Liu et al. (2010), fuzzy matrices are used for the position and velocity matrix in PSO instead of real vectors. This method is shown to be better than SA and GAs in its speed of convergence and its ability to find optimal solutions. The paper dynamically generates an optimal schedule, completing the tasks within a minimal period of time as well as utilizing the resources efficiently. In our proposed method, we use an optimal scheduler with various parameters that will be discussed below.

In Yusof et al. (2010), the TS algorithm, which is a local search algorithm, is used for scheduling tasks in a grid system. The TS algorithm uses a perturbation scheme for pair changing.

In Joshua Samuel Raj and Vasudevan (2011), the SA algorithm is used to solve the workflow scheduling problem in a computational grid. Simulation results show that this algorithm is highly efficient in a grid environment.

In Barzegar et al. (2009), the GELS algorithm was used for resource reservation and scheduling. Here, if one resource is unable to execute a task within its designated deadline, the objective function switches resources and allocates the task to other resources for execution. Our proposed method uses the GELS algorithm in combination with PSO to improve some QOS parameters in grid scheduling.

3 Computing system model

Before presenting our proposed algorithm, we describe the computing system model on which the algorithm is based and assessed. Grid models are composed of a number of homogeneous machines that are used to run applications. Figure 1 shows an overview of the grid model. The scheduler system consists of a scheduler, an application model, and a set of computing machines. For the application model and homogeneous group of machines, an estimate of the expected time for each task to execute on each machine is known beforehand, and it is assumed that these values are available to the scheduler (Maheswaran 1999). The values have been stored in an $m \times n$ matrix ETC, where m is the number of machines and n is the number of tasks. Obviously, n/m will generally be greater than 1, with more tasks than machines, so that certain machines will need to be assigned multiple tasks. Each column j of the ETC matrix contains estimates of the expected running times of each task i on machine j. In addition, a $1 \times m$ matrix Ready stores the time that each machine requires to complete its current task. We consider

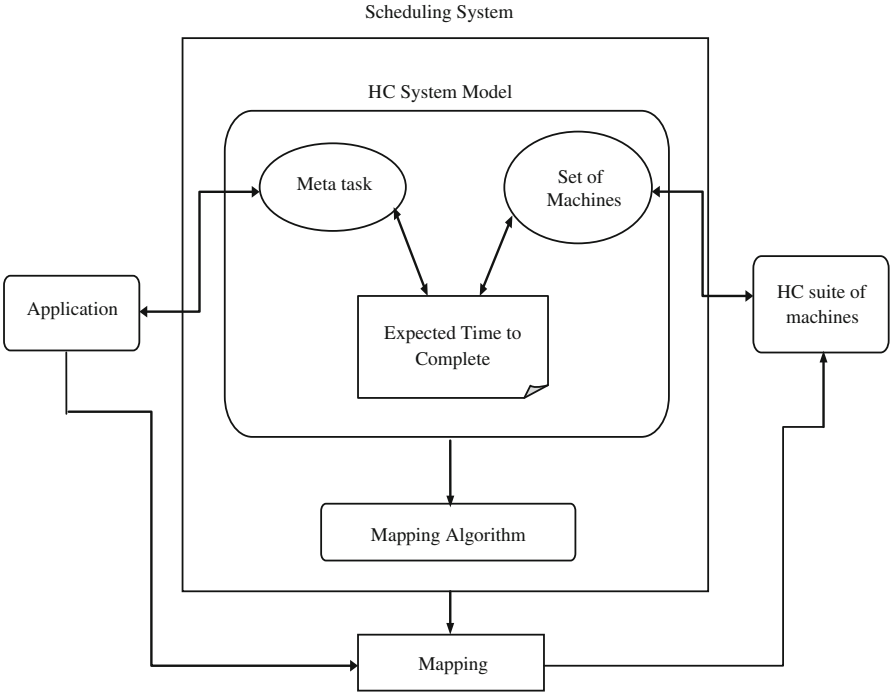


Fig. 1 Computing system model

how each task would be processed by each machine, since the goal is to minimize makespan. Makespan is defined to be the maximum of the possible completion times stored in a matrix Completion_Time, as in Eq. (1):

$$\begin{aligned} &\text{makespan} = \max(\text{Completion\_Time}[i, j]) \\ &\text{for } 1 \leq i \leq \text{n}, \quad 1 \leq j \leq \text{m} \end{aligned} \tag{1}$$

Completion_Time$[i, j]$ is the time for completing task i on resource j, calculated as follows:

$$\text{Completion\_Time}[i, j] = \text{Ready}[j] + \text{ETC}[i, j]. \tag{2}$$

The running time of each task for each resource must be calculated for the purpose of scheduling. If the processing speed of resource Rj is PS$_j$, then the processing time for task S$_i$ can be calculated by Eq. (3):

$$\text{T}_{ij} = \text{C}_i / \text{PS}_j \tag{3}$$

where T$_{ij}$ is the processing time of task S$_i$ by resource R$_j$ and C$_i$ is the computational complexity of the task S$_i$ (Abdollahi Azgomi and Eetezari-maleki 2010). The values obtained from Eq. (3) are stored in the ETC matrix.

The purpose of grid scheduling is that tasks should be allocated to resources in such a way that makespan and the numbers of tasks that miss their deadlines are minimized.

4 The PSO algorithm

The PSO algorithm, which was proposed in Eberhat and Kennedy (1995), is a stochastic optimization technique (Shi and Eberhat 1998) that operates on the principle of social behavior behind bird flocking and fish schooling (Shi and Eberhat 1999). For example, birds migrate to find food, and they begin by flying behind birds that have more experience and others then fly behind them; thus, birds use the experience of other birds in their orderly flying. Something that is interesting about the migration of birds is that if a bird feels it has more experience than the bird in front of it, they exchange positions so that the bird that has more experience moves to the forward position. In this way, the birds all use their experience to move to the correct place in their migration. The same situation occurs in schools of fish, and the idea used in the PSO optimization technique is taken from such behavior. It can be said that the swarm reaction has the ability to solve optimization problems.

In a PSO system, a swarm of individuals (called *particles*) fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position (pbest) it has visited, i.e., by its own experience and the experience of neighboring particles. When the neighborhood of a particle is the entire swarm, the best position in the neighborhood is referred to as the *global best position* of the particle, and the resulting algorithm is known as *gbest*. PSO has the following parameters:

V_{max}	maximum particle velocity;
ω	Inertia weight factor;
$Rand_1$ and $Rand_2$	random numbers with a uniform distribution on the interval [0, 1];
C_1 and C_2	positive constants, respectively called the *cognitive* and the *social* parameters.

When all particles have been initialized, an iterative optimization process begins in which the positions and velocities of all particles are revised through the recursive equations (4) and (5):

$$V_{i+1} = \omega V_i + C_1 rand_1 \left(pbest_i - X_i\right) + C_2 rand_2 \left(gbest_i - X_i\right) \tag{4}$$

$$X_{i+1} = X_i + V_{i+1} \tag{5}$$

where X_i and V_i are the position and velocity of the ith particle. Here, the particle flies through potential solutions toward $pbest_i$ and $gbest_i$ in a navigated way, while still exploring new areas by the stochastic mechanism to escape from local optima. The inertia weight can be dynamically varied by applying an annealing scheme for the ω-setting of the PSO, where ω decreases from $\omega = 0.9$ to $\omega = 0.1$[20] over the

entire run. In general the inertia weight ω is set according to Eq. (6):

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter \tag{6}$$

where $\omega_{\max}$ is the initial value of the weighting coefficient, $\omega_{\min}$ is the final value of the weighting coefficient, $iter_{\max}$ is the maximum number of iterations, and *iter* is the current iteration.

Performance is significantly improved by varying the inertia.

Pseudocode for the PSO algorithm (Cruz et al. 2003) is shown below in Algorithm 1. As can be seen, the initial positions and velocity of particles in the search area are determined randomly. Then the fitness function is calculated for all particles. Next, the fitness of all of the particles is compared, and if the fitness of any particle is less than the fitness of the related pbest particle that particles' coordinate is stored in pbest. Then gbest is set to the best pbest value. The new coordinates of the particles are obtained with (4) and (5). These steps are repeated for the maximum number of iterations.

5 The GELS algorithm: background

Voudouris and Tsang (1995) proposed the guided local search algorithm for searching a search space with an NP-hard solution. Webster (2004) proposed a powerful algorithm that he called the GELS algorithm. This algorithm mimicks gravitational attraction to search within a search space. Each response (problem solution) has different neighbors, which can be grouped based on problem-specific criteria. A dimension consists of the neighbors in a neighbor group. A primary velocity is defined for each dimension. A dimension that has greater primary velocity has a more apparent response (solution) for the problem. The GELS algorithm uses two methods to calculate gravitational force between the responses in a search space. The first method selects a response from the local neighbor space of the current response, and gravitational force is calculated for the two responses. The second method calculates gravitation force for all of the neighbor responses in a neighbor space of the current response rather than a single response. The GELS algorithm also uses two methods to implement movement in the search space. The first method allows movement from the current response toward the response to the current response in local neighbor spaces. The second method allows movement toward the responses outside of the current response's local neighbor spaces in addition to the neighboring responses. Each of these movement methods can be combined with each of the gravitational force methods; as a result, there are four models for the GELS algorithm.

Balachandar and Kannan (2007) used GELS to solve the traveling salesman problem and compared it with other algorithms such as hill climbing and SA. The results showed that when the size of a problem is small, all of the algorithms perform equally well, but when the size of a problem is large, GELS obtains better results than the other algorithms.

Algorithm 1 PSO Algorithm

```
INPUT: Matrix[Particles[No. resource]]
OUTPUT: gbest //Best Particle
BEGIN
 1.  For i=1 to M  //M=population size
 2.  {
 3.     Initialize P[i] randomly;
 4.      //P is the population of particles
 5.      Initialize v[i]=0;
         //(v=speed of each particle)
 6.      Evaluate P[i];
 7.      gbest=best particle found in P[i];
 8.  }//For
 9.  For i=1 to M
10.  {
11.      pbest[i]=P[i];
12.     //Initialize the "memory" of each particle
13.  }//For
14.  Repeat until (stopping criterion is satisfied)
15.     For i=1 to M
16.     {
17.         v[i]=wv[i]+C1Rand1(pbest[i]-
              P[i])+C2Rand2( gbest[i]-P[i]);
18.         //update speed of each particle
19.         //w=Inertia weight, C1 and C2 are
              positive constants
20.         //Rand1 and Rand2 are random
              numbers in the range [0,…,1]
21.         P[i]=P[i]+v[i];
22.         If a particle goes outside the
              predefined hypercube then it is
              reintegrated to its boundaries;
23.         Evaluate P[i];
24.         If new population is better
              then  pbest[i]=P[i];
25.         gbest=Best particle found in P[i];
26.     }//For
27.  Return gbest;
END
```

6 The GELS algorithm

The GELS algorithm begins with a primary response and a primary velocity vector consisting of the primary velocities. These velocities can be initialized by the user or randomly.

Using the primary velocity vector, a dimension that has the most primary velocity among the neighbors is selected for movement. The algorithm uses a pointer object that can move within the search space. This object always points to the

response with the greatest weight. For the first method, each iteration of the algorithm begins by selecting a dimension for obtaining a neighbor response to the current response, and a candidate response is selected from this dimension. The gravitational force of the current and candidate responses are calculated and then added to the primary velocity of the dimension that was used to obtain the candidate response; this is referred to as *updating* the primary velocity. In the next iteration, the primary velocity vector is checked and used to select the new movement direction for continuing the response search. For the second method, each iteration of the algorithm is similar to the iterations of the first method except that instead of considering gravitational force and updating the primary velocity vector for a single candidate response in the current dimension, the gravitational force of each candidate response in the current dimension is considered and the primary velocity for each candidate response in the current dimension is updated. This algorithm calculates the gravitational force f between two responses using Eq. (7):

$$\mathrm{f} = \frac{\mathrm{G(CU - CA)}}{\mathrm{R}^2} \tag{7}$$

where CA and CU are the candidate response and current response, respectively, G is a constant with the value 6.672, and R is the neighbor radius between the two responses in the search space. The value R can be constant or changed intelligently during any iteration. The algorithm terminates when one of the following occurs: either the primary velocity for all equal response dimensions (all elements of the primary velocity vector) is zero, or the maximum number of algorithm iterations has been reached (Webster 2004).

Another parameter used in this algorithm is the maximum primary velocity, which is the maximum value that elements of the primary velocity vector can have. The primary velocity parameter that selects the motion direction is used to obtain a neighbor, and this parameter can prevent increasing the motion of the primary velocity vector elements. Algorithm 2 presents the GELS pseudocode:

7 The PSO algorithm for solving the task scheduling problem

One of the key issues in successfully applying PSO to job scheduling concerns deciding how to encode a schedule as a search solution, i.e., finding a suitable mapping between problem solutions and PSO particles. In our proposed method, each particle represents a feasible solution for task assignment using a vector of n elements, where each element is a randomly produced integer value between 1 and m. Figure 2 illustrates the allocation of four tasks to four resources. For example, in Particle 1, tasks T_1 and T_3 are assigned to resource R_1 and tasks T_2 and T_4 are assigned to resource R_2 and R_3, respectively.

Algorithm 2 GELS Algorithm

```
INPUT: Velocity Vector[No. Resource]
OUTPUT: Best_Solution
BEGIN
  1.  V= Set initial Velocity Vector();
  2.  Best_Solution=Current_Solution;
  3.  Direction=Select Direction(V);
  4.  While (termination condition not met) do
  5.  {
  6.     Candidate_Solution=make
         neighbor(direction);
  7.     F=G*(Fitness(Candidate_Solution) –
         Fitness(Current_Solution))/R^2 ;
  8.     If Fitness(Candidate_Solution) >
         Fitness(Best_Solution))
  9.        Best_Solution= Candidate Solution;
  10.    Update Velocity Vector(V, F);
  11.    Direction=Select Direction(V);
  12. }//While
  13. Return (Best_Solution);
END
```

	T_1	T_2	T_3	T_4
Particle $_1$	R_1	R_2	R_1	R_3
Particle $_2$	R_1	R_3	R_4	R_2
Particle $_3$	R_3	R_4	R_1	R_2
....				

Fig. 2 Particle representation

7.1 Fitness evaluation

The initial population is generated randomly, with the velocity vector containing random values in the range $[-V_{max}, V_{max}]$ for each particle. Subsequently, a fitness value is used for evaluation. The aim of task scheduling is to minimize makespan, the time required for completing the execution of all tasks. We note that this time should always be equal to or less than the max deadline (MD) of all tasks. In our proposed method, an appropriate solution to the task scheduling problem is a move that minimizes not only makespan, but also the number of tasks that miss their deadline. We have also compared the performance and complexity of our proposed method for different values of n and m in the dynamic grid system to the performance of related methods, and our comparison shows that when the complexity changes, our method can adapt itself to the problem environment by changing its fitness function. Equation (8) is used to calculate the fitness function:

$$\text{fitness} = \frac{1}{\text{makespan}} + \frac{1}{\text{miss\_task} \times \text{MD}} \tag{8}$$

where miss_task is the number of tasks that miss their deadlines in the solution, and MD is the maximum deadline for all tasks.

7.2 Particle modification

Particles' velocities and positions are updated using Eqs. (4) and (5). After generating a new population, real values such as 2.25 may have been generated as particle positions. These values are invalid for indicating the number of resources. Therefore, the algorithm rounds the real values to the nearest integers. In this way, a continuous optimization problem is converted to a discrete optimization problem. Our hybrid algorithm uses Eq. (6) to calculate ω in each iteration of the algorithm. Selection of the correct inertia weights will greatly impact the algorithm's performance so that it avoids falling into a local minimum.

7.3 Force calculation

The gravitational force between the current and candidate particles is calculated using Eq. (9):

$$\text{force} = \text{G} \times \frac{\text{fitness (candidate\_particle)} - \text{fitness (current\_particle)}}{\text{R}^2} \tag{9}$$

8 The PSO–GELS algorithm

The PSO algorithm uses different search points, and these points are close to the optimum point with their pbest and gbest values. PSO can be used for continuous and discrete problems, and it is good for global searches in the problem space. But it is weak for local searches, with a significant probability of becoming trapped in a local optimum in the last iteration. PSO converges globally because it searches globally. It always tries to move to solutions that have better fitness functions in a purely stochastic search problem space. It does not pay close attention to local subspaces so it is unable to recognize and avoid local optima. As a result, PSO may become trapped in local optima and have a low convergence rate in the late iterative process. One option for addressing this problem is to use local search algorithms such as GELS or SA that can avoid local optima. SA is much slower than GELS when combined with PSO, so we have chosen to use GELS. Although GELS behaves like a greedy algorithm, it does not always move to better fitness functions. It tests available solutions to find the best solution and does not try to search the problem space purely stochastically.

Our proposed scheduling algorithm uses PSO as the main search algorithm, while GELS is used to improve the population. There are two reasons for using both algorithms. First, we need an algorithm that is based on a population that can search the entire grid space for this problem. Second, the grid environment is dynamic, so the scheduling algorithm must be fast enough to adapt with the natural grid environment and must be able to converge faster than other algorithms. Moreover, although PSO is weak for local searches, our combination of PSO with an algorithm that is strong in

Algorithm 3 PSO-GELS Algorithm

```
INPUT: Matrix[Particles[No. resource]]
OUTPUT: Best Solution[No. resource]
BEGIN
 1.  Create and initialize an m×n dimension
       swarm with P Particles;
 2.  Evaluate each particle's fitness;
 3.  Initialize Velocity_Vector;
 4.  Do while (the maximum number of
       generations is not reached)
 5.  {
 6.     Generate new swarm;
 7.     Evaluation swarm;
 8.     Find new gbest and pbest;
 9.     Update gbest of swarm and pbest of
          particle;
 10.  }// Do while
 11.  Current_Solution=gbest;
 12.  Best_Solution =Current_Solution;
 13.  Direction= Select Direction(V);
 14.  Repeat until stopping criterion is satisfied
 15.  {
 16.     Candidate_Solution= make
          neighbor(Direction);
 17.     Force calculation;
 18.     If( fitness(Candidate_Solution) >
          fitness(Current _Solution))
 19.     {
 20.        Best_Solution =
             Candidate_Solution;
 21.        Update Velocity_Vector(V,Force);
 22.        Direction= Select Direction(V);
 23.     } // If
 24.  } // Repeat
 25.  Return Best_Solution;
END
```

local searches addresses this weakness. Because GELS actions have a high computational cost for each particle in the PSO search and the grid scheduler should execute quickly, GELS is run on the global result of the last iteration of PSO. That is, an initial solution for GELS is provided by PSO during the hybrid search process. Algorithm 3 shows the pseudo code for the PSO–GELS algorithm.

9 Performance evaluation

This section discusses the performance of our proposed algorithms for scheduling independent tasks in a grid computing environment. These tasks relate to applications that have been submitted by users for execution. In their submissions, users can specify

Table 1 PSO algorithm parameters

Parameter	Value
V_{max}	Number of resources
C_1, C_2	1.49
Initial velocity	$[1, W_{max}]$
ω_{max}	0.9
ω_{min}	0.1

Table 2 GELS algorithm parameters

Parameter	Value
Initial velocity	$[1, W_{max}]$
W_{max}	Number of tasks
R	1

QOS parameters such as deadlines and optimum strategies for the system. Our simulation is implemented with Java software running under the Win XP operating system on a 2.66 GHZ CPU with 4 GB of RAM.

An application consists of several independent tasks. Each task has its own length, measured in terms of a million instructions. The task lengths are randomly defined values in the range (Min…Max), with a uniform task distribution. In the simulation, lengths are considered to be homogenous, and in the most homogenous state, the range of the distributed task lengths is (10,000…110,000). Resources in the grid have different processing speeds so that the various scheduling algorithms can be clearly compared. All of the resources have a single processor.

Scheduling algorithms that have optimal time as their goal can execute users' applications in the grid and deliver the results with the minimal possible time. Based on the resource owners and customers, some algorithms are more efficient than others for assigning the independent tasks to available grid resources in a way that minimizes the runtime consumed by tasks. Moreover, the numbers of tasks that miss their deadlines should be minimized. A proper algorithm can show acceptable results for users in various situations, such as short/long deadlines and homogenous tasks and users. We will discuss the different experimental situations for comparing PSO–GELS with other algorithms.

Before examining the results, we present the initial values of parameters used in the PSO and GELS algorithms. These are shown in Tables 1 and 2.

We compared our algorithm with other algorithms based on the situation depicted in Table 3. We considered the task lengths to be equal in all models. There is a uniform distribution of task lengths within the range indicated by the parameter. The iterations parameter indicates that each case has been executed five times, and the average of the calculated values is displayed. For example, Table 4 depicts the results obtained by the various algorithms. In this table, the values are calculated for 50 tasks with 10 resources and 100 iterations. The average column lists the average of five runs of the different algorithms; these results are the task scheduling problem solutions.

Table 3 Time optimization experiment results for various task lengths and execution rates

Parameter	Value
Algorithm type	Various
Task no.	Various
Deadline	Various
Task length	[100,000…110,000]
Experiment iterations	5

Table 4 Makespan average for five runs

Algorithm	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Average
PSO–GELS	82.66	82.1	90.71	86.66	83.8	85.186
PSO–SA	88.42	88.57	89.14	87	94.8	89.586
PSO	84.1	86	93	84.72	83.8	86.144
GA–GELA	82.8	93.9	84.3	104.0	85	90
GA–SA	104.33	103.875	90.375	87.66	91.57	95.562
GA	104.0	104.0	92.0	92.66	103.33	99.198
SA	177.33	134.	141.66	105.55	124.8	136.742

To show the significant performance of our PSO–GELS algorithm, we compared it with the SA, GA–SA, GA–GELS, GA, PSO–SA, and PSO algorithms under various conditions, including different numbers of tasks and resources with different numbers of iterations. The PSO–SA algorithm combines PSO and SA for solving the task scheduling problem, GA–SA combines GA and SA, and GA–GELS combines GA and GELS. The algorithms were tested for various cases and the makespan, execution time, and number of tasks that missed deadlines were calculated. Table 5 at the end of this article shows the makespan averages for the seven algorithms.

The results show that the makespan found by PSO–GELS is in most cases better than that found by the other algorithms. We expect a good scheduling algorithm to allocate resources to tasks with a minimal total runtime. Since PSO's convergence is faster than that of the GA, it is more suitable for grid scheduling. Moreover, PSO found better solutions than the GA. Because PSO cannot search locally, we combined it with the GELS method. The results show that PSO–GELS is better than PSO–SA; this is because GELS searches the problem space intelligently and does not work as the SA method does—searching quickly to find solutions with better goal function values—but does its job by examining present solutions; as a result, its algorithmic convergence is faster and it is able to find adequate solutions.

Figure 3a–d shows the makespan obtained by our proposed method compared with the other algorithms for 1,000 iterations on 10 and 20, resources for various numbers of input tasks. As can be seen in the figure, as the number of input tasks increases and the problem space grows, PSO–GELS performs better than the other algorithms. When the number of tasks increases to greater than 500, PSO–GELS produces a smaller makespan compared to the other algorithms. Additionally, when the number of available resources in the system changes, increasing from 10 to 20, PSO–GELS

Table 5 PSO–GELS makespan average compared with other algorithms

Iteration	(Task, resource)	SA	GA	GA–SA	GA–GELS	PSO	PSO–SA	PSO–GELS
100	(50, 10)	136.742	99.198	95.562	90	86.144	89.586	85.186
	(50, 20)	98.944	62.496	60.968	61.692	53.826	53.266	53.138
	(50, 30)	71.442	50.53	49.476	48.354	41.95	40.45	39.964
	(100, 10)	307.738	183.49	190.353	181.028	168.718	167.33	166.094
	(100, 20)	190.862	111.1742	111.646	109.548	102.542	100.714	99.897
	(100, 30)	138.632	99.25	89.822	88.91	75.904	**73.318**	75.238
	(300, 10)	973.728	638.082	597.8	581.842	521.568	511.532	494.466
	(300, 20)	585.848	352.698	337.648	350.686	297.389	288.962	286.066
	(300, 30)	384.928	262.166	256.664	259.664	**209.128**	216.402	209.592
	(500, 10)	1837.662	1105.56	1072.362	1087.216	918.336	**887.195**	911.099
	(500, 20)	833.996	602.174	571.796	587.042	493.954	504.33	484.848
	(500, 30)	721.596	449.73	446.646	442.182	**350.482**	352.978	352.704
	(1000, 10)	3443.596	2401.208	2319.28	2440.772	1989.53	2120.764	1937.73
	(1000, 20)	1653.262	1310.43	1255.288	1251.832	1096.666	1062.232	1017.326
	(1000, 30)	1410.196	892.414	917.496	903.632	750.75	**735.304**	757.326
	(3000, 10)	10066.928	8489.314	8078.916	8006.548	7365.264	**7282.062**	7303.596
	(3000, 20)	5565.994	4255.43	4292.203	4212.462	3604.518	3539.608	3528.852
	(3000, 30)	3710.328	2954.048	2836.95	2798.978	2525.713	2484.276	2472.258
	(5000, 10)	17820.598	14303.062	14597.194	14298.594	13353.398	13300.994	13077.332
	(5000, 20)	9091.598	7415.132	7432.38	7102.594	6404.416	6357.77	6302.026
	(5000, 30)	6077.596	5062.862	4996.796	4874.464	4392.909	4360.116	4313.384
300	(50, 10)	131.12	89.486	86.98	84.298	85.312	87.694	84.174
	(50, 20)	74.832	60.87	57.304	59.389	53.824	53.77	52.662
	(50, 30)	62.055	47.637	42.932	46.06	30.454	41.208	41.076
	(100, 10)	233.2	172.628	179.062	175.598	170.452	167.16	166.422
	(100, 20)	173.116	111.946	105.314	103.092	104.994	100.098	94.104
	(100, 30)	120.452	90.716	87.846	80.086	75.15	**70.572**	72.963
	(300, 10)	911.68	570.466	532.968	600.862	**518.268**	526.71	527.086
	(300, 20)	523.33	327.522	337.428	326.924	293.558	296.168	286.274
	(300, 30)	408.714	253.132	246.48	251.564	204.634	205.496	202.722
	(500, 10)	1492.616	1071.014	1037.942	1055.504	890.354	896.586	881.991
	(500, 20)	893.262	602.134	593.116	578.826	499.371	**493.9**	498.497
	(500, 30)	626.162	430.32	412.7152	408.282	**343.226**	339.331	343.413
	(1000, 10)	3416.932	2361.57	2408.914	2341.962	**1996.662**	1982.64	2048.876
	(1000, 20)	1785.73	1227.296	1244.67	1255.58	1094.373	1079.494	1057.576
	(1000, 30)	1193.396	886.596	867.146	870.664	732.248	722.843	698.876
	(3000, 10)	10555.664	8056.196	8051.328	8365.632	7292.462	7408.096	7199.13
	(3000, 20)	5108.662	4149.312	4358.014	4101.446	3630.56	**3527.966**	3533.242
	(3000, 30)	3617.996	2865.062	2958.53	2872.396	2472.288	**2404.406**	2439.382

Table 5 continued

Iteration	(Task, resource)	SA	GA	GA–SA	GA–GELS	PSO	PSO–SA	PSO–GELS
	(5000, 10)	16884.398	14513.396	14480.062	13735.464	**13113.462**	13261.394	13145.528
	(5000, 20)	9355.996	7311.996	7232.978	7368.728	6387.366	6495.002	6366.268
	(5000, 30)	6158.196	5025.482	4908.264	5075.128	4441.045	4473.182	4411.648
500	(50, 10)	(50, 10)	117.994	85.264	84.614	83.362	85.22	**83.774**
	(50, 20)	(50, 20)	69.88	55.876	51.366	51.941	54.116	53.011
	(50, 30)	(50, 30)	62.898	43.658	43.672	42.908	42.712	40.926
	(100, 10)	(100, 10)	261.364	175.084	171.817	168.714	176.688	170.432
	(100, 20)	(100, 20)	147.598	121.444	102.814	101.272	96.654	**95.227**
	(100, 30)	(100, 30)	104.8	82.8	78.18	80.522	**74.52**	74.857
	(300, 10)	(300, 10)	855.896	563.55	521.302	552.828	**506.026**	509.04
	(300, 20)	(300, 20)	494.314	339.752	337.19	301.632	**289.59**	296.211
	(300, 30)	(300, 30)	360.798	240.01	233.38	237.343	217.269	215.358
	(500, 10)	(500, 10)	1640.528	993.964	1000.569	954.652	**849.066**	894.495
	(500, 20)	(500, 20)	831.396	599.588	547.096	534.166	507.43	506.996
	(500, 30)	(500, 30)	631.046	418.472	401.71	398.078	355.896	357.54
	(1000, 10)	(1000, 10)	3260.796	2419.198	2161.618	2279.85	1985.768	1958.13
	(1000, 20)	(1000, 20)	1651.564	1263.748	1241.98	1211.298	1098.702	**1068.04**
	(1000, 30)	(1000, 30)	937.998	868.036	832.112	865.452	741.914	771.884
	(3000, 10)	(3000, 10)	10372.328	7724.066	7902.312	7670.23	7627.728	7268.512
	(3000, 20)	(3000, 20)	5426.33	4276.364	4271.764	4237.064	3780.672	3817
	(3000, 30)	(3000, 30)	3655.396	2813.612	2814.764	2297.882	2549.052	2533.717
	(5000, 10)	(5000, 10)	17514.126	14129.878	13994.396	14050.196	13533.398	13616.996
	(5000, 20)	(5000, 20)	9002.728	7088.228	7218.796	7036.364	6352.38	6537.594
	(5000, 30)	(5000, 30)	5042.46	4975.396	4896.182	4860.098	4314.304	4387.548
1000	(50, 10)	108.151	82.566	84.856	81.402	87.436	86.106	85.72
	(50, 20)	70.616	50.772	51.057	49.562	54.536	57.332	54.473
	(50, 30)	59.384	45.14	40.134	38.703	42.66	43.848	41.328
	(100, 10)	223.184	167.755	160.84	160.694	170.716	174.648	169.784
	(100, 20)	140.246	105.26	99.907	95.316	100.006	100.896	99.173
	(100, 30)	110.426	83.14	76.978	72.144	74.981	75.096	74.386
	(300, 10)	867.48	545.046	542.52	533.336	520.953	511.33	421.388
	(300, 20)	459.53	318.31	299.077	301.58	292.132	**288.673**	291.96
	(300, 30)	315.888	231.15	218.67	206.74	207.528	205.894	201.52
	(500, 10)	1495.312	933.798	935.794	932.23	856.9	888.534	851.614
	(500, 20)	1977.333	563.104	543.056	536.382	515.15	513.352	507.842
	(500, 30)	580.948	401.004	381.582	390.21	359.624	360.244	350.954
	(1000, 10)	3464.596	2035.652	2072.752	2169.282	1913.336	1986.5	1878.196
	(1000, 20)	1651.594	1211.262	1135.048	1168.844	**1053.176**	1071.952	1078.516

Table 5 continued

Iteration	(Task, resource)	SA	GA	GA–SA	GA–GELS	PSO	PSO–SA	PSO–GELS
	(1000, 30)	1116.864	856.032	847.732	833.698	750.054	732.017	724.133
	(3000, 10)	1007.093	7915.646	7768.732	7757.198	**7120.996**	7364.13	7345.594
	(3000, 20)	5425.13	4197.262	4023.55	3989.732	3694.2	3653.962	3563.424
	(3000, 30)	3760.06	2784.728	2782.68	2731.58	2482.12	2467.899	2448.768
	(5000, 10)	17649.86	13955.796	13298.514	13483.214	13444.662	13494.594	13347.796
	(5000, 20)	8881.194	7182.096	7065.698	7009.528	6525.274	6541.064	6344.172
	(5000, 30)	6019.264	4896.612	4813.212	4795.078	4348.716	4410.25	4264.454

Bold values indicate the points that the proposed method did not provide better results compared to other methods

adapts to the larger number of resources in the new scenario. It assigns tasks to the new resource queues, thus decreasing the makespan and the number of tasks that miss their deadline.

Figure 4 shows the average runtime for the various algorithms. Because PSO has fewer parameters than GA, it converges more quickly than the other algorithms. Therefore, since the grid environment is dynamic and its scheduling should be fast, PSO is better suited than GA. Since our proposed method uses a combination of PSO and GELS and each method has the same number of iterations, it seems natural that PSO–GELS should consume more runtime than PSO. By way of illustration, in PSO–GELS with 1,000 iterations, PSO and GELS each repeat with 1,000 iterations, but PSO without GELS repeats only 1,000 times. The results show that although PSO–GELS repeated more instructions than PSO, its execution time is close to PSO's. PSO–GEL's execution time is also better than the execution time of PSO–SA, even though both have the same number of repetitions. Although the time consumed by PSO–GELS is close to that consumed by PSO, its solution has a better makespan than PSO.

Figure 5 shows fail task rates in the case of 1,000 tasks and 10 resources for various numbers of iterations. PSO–GELS is the best, because its missed task deadline rate is lower than the others', and for 500 or more iterations it is zero. This means that all the allocated tasks have completed within their deadlines. For the other methods, convergence to zero is slow, and none of them actually reaches zero. For all algorithms, the missed task deadline rates are high for 100 iterations, but PSO–GELS's rate is lower for the initial iterations, and its rates drop rapidly as the number of iterations increases.

Figure 6 shows PSO–GELS's improvement in makespan compared with the other algorithms for the case (5000, 30). PSO–GELS clearly obtained the best makespan. For example, PSO–GELS' makespan for 5,000 tasks and 30 resources is approximately 29.2 % of SA's makespan, as recorded in Eq. (10):

$$\text{makespan (PSO}-\text{GELS)} = 0.292 \times \text{makespan (SA)} \tag{10}$$

Therefore, PSO–GELS should be used in place of SA for grid scheduling.

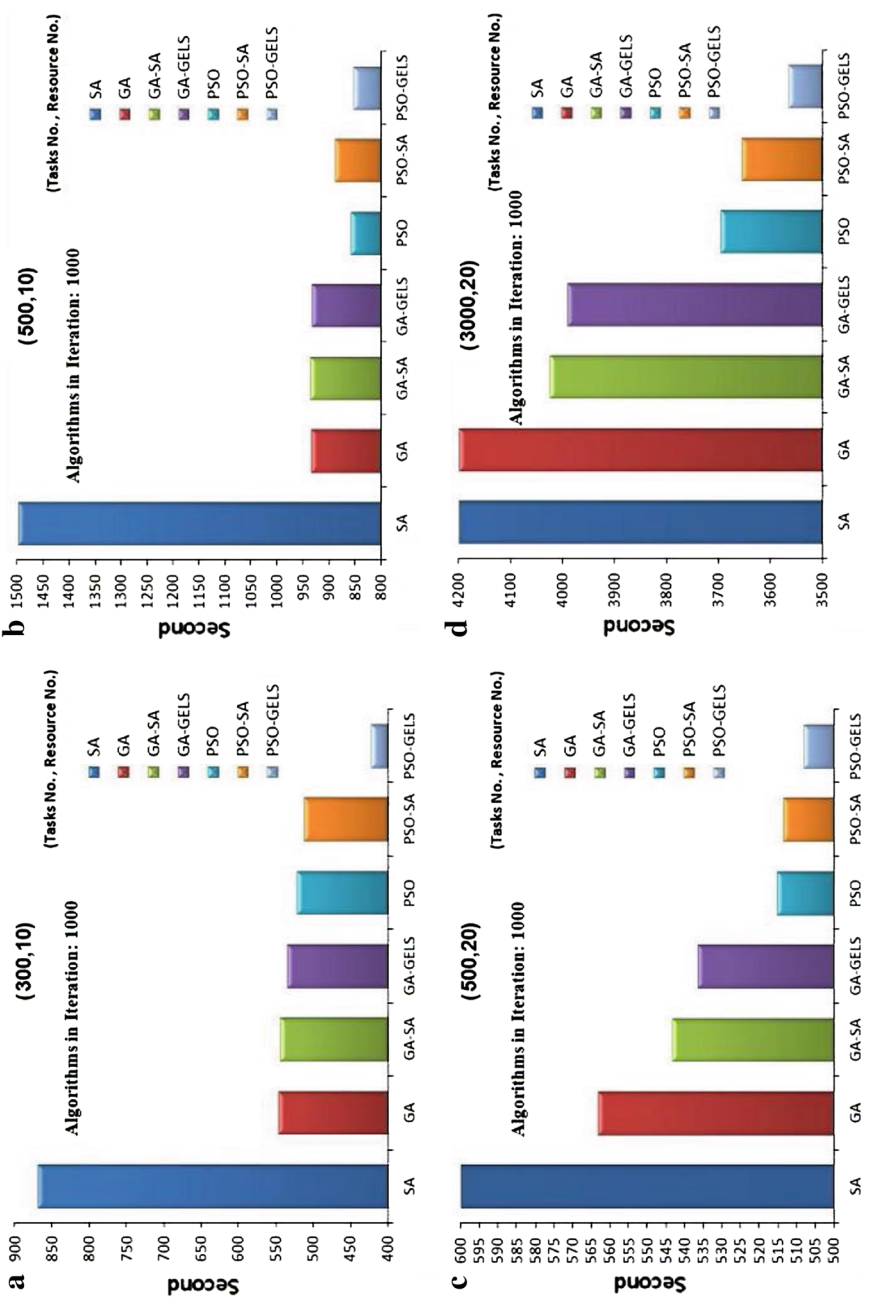
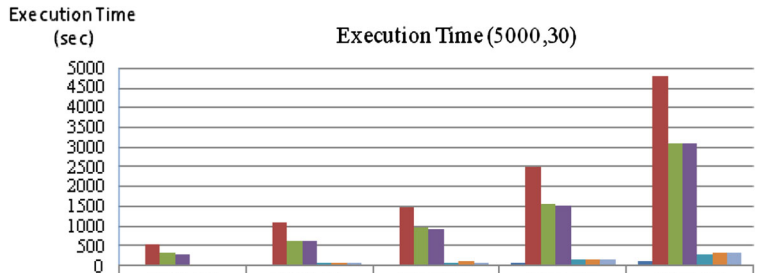


Fig. 3 Comparison of makespan for the different algorithms



	(5000,30) Iteration-100	(5000,30) Iteration-200	(5000,30) Iteration-300	(5000,30) Iteration-500	(5000,30) Iteration-1000
SA	33.4	44.4	51.2	72.4	121.6
GA	533	1082.6	1504	2504.6	4814.4
GA-SA	319.2	634.2	955	1559.4	3081.8
GA-GELS	314	618.2	927	1527.4	3106.2
PSO	38.2	70.4	100	161.8	311.4
PSO-SA	41.2	74.8	109.6	166	346.4
PSO-GELS	38.4	68.2	101.2	162.4	316.8

Fig. 4 Comparison of algorithms' average execution time for (5000, 30)

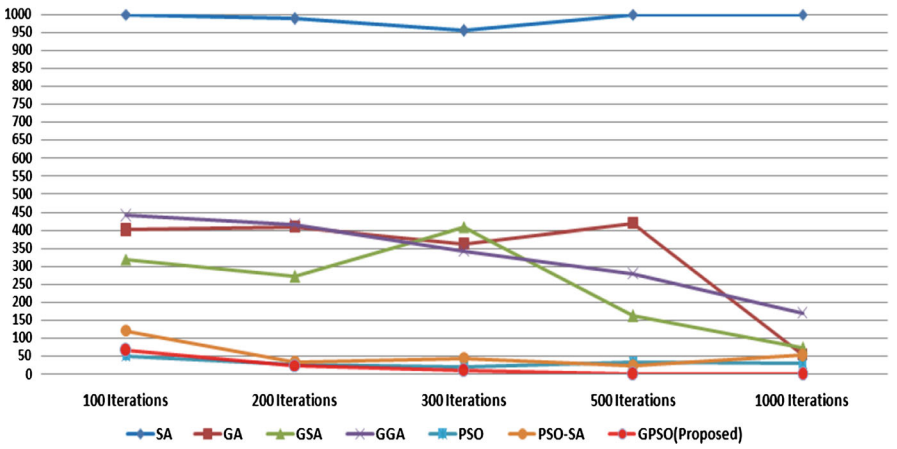


Fig. 5 Tasks that fail to meet deadlines rates for the case (1000, 10) for the various algorithms

10 Conclusion

Computational grids have different computational capabilities, including the use of idle resources as additional resources and parallel processing for increased performance. Resource management is an important part of grid computing and has an important role in controlling and monitoring the use of resources. The main function of a resource management system is scheduling tasks on resources. Since the resources are complex, distributed, heterogeneous, dynamic, and autonomous, resource allocation and task scheduling poses difficulties. Because scheduling tasks for a grid system is an NP-

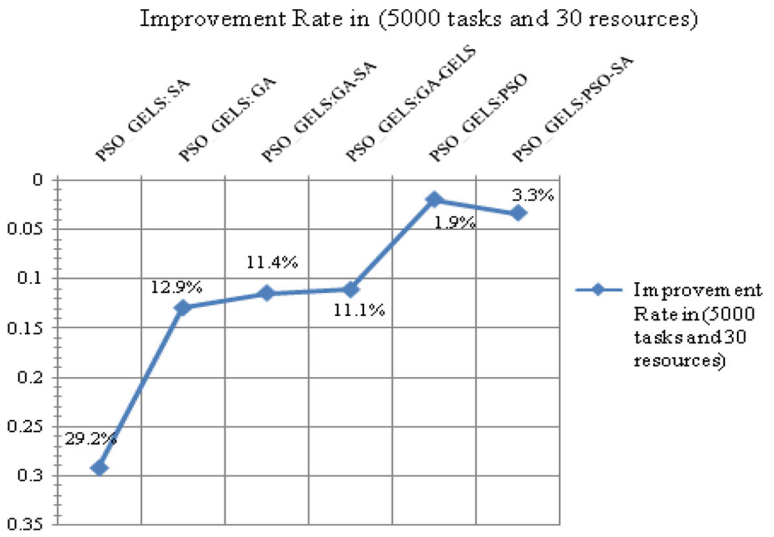


Fig. 6 PSO–GELS's makespan improvement over the other algorithms

hard problem, efficient algorithms for solving this problem will not be deterministic. Thus, much research has been devoted to heuristic algorithms. The present paper presents a novel task-scheduling technique for grid systems based on a hybrid PSO–GELS algorithm that minimizes makespan and the number of tasks that fail to meet their deadlines. Each particle in the PSO algorithm represents a feasible solution. The position vector for PSO is transformed from continuous values to discrete values by rounding the real values. The hybrid PSO algorithm performs better for local searches. Because GELS is used for the local search rather than other local search algorithms such as hill-climbing or SA, the hybrid algorithm finds better solutions than other algorithms. Overall, a comparison of the performance of PSO–GELS with existing methods through a simulation experiment shows that PSO–GELS perform better than the other algorithms.

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