Multiprocessor task scheduling problem using hybrid discrete particle swarm optimization

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Abstract. Task Scheduling is a complex combinatorial optimization problem and known to be an NP hard. It is an important challenging issue in multiprocessor computing systems. Discrete Particle Swarm Optimization (DPSO) is a newly developed swarm intelligence technique for solving discrete optimization problems efficiently. In DPSO, each particle should limit its communication with the previous best solution and the best solutions of its neighbors. This learning restriction may reduce the diversity of the algorithm and also the possibility of occurring premature convergence problem. In order to address these issues, the proposed work presents a hybrid version of DPSO which is a combination of DPSO and Cyber Swarm Algorithm (CSA). The efficiency of the proposed algorithm is evaluated based on a set of benchmark instances and the performance criteria such as makespan, mean flow time and reliability cost.

Keywords. Cyber PSO; distributed systems; particle swarm optimization; swarm intelligence; task scheduling.

1. Introduction

Heterogeneous Multiprocessor System (HMS) is composed of computers with different speeds [1]. Task Scheduling (TS) is one of the key challenges in HMS. It can be classified into two categories based on the types of tasks [2]: tasks with no data dependencies (independent task) and tasks with precedence constraints (dependent task). In this paper, the scheduler schedules only the independent tasks in HMS. Independent tasks occur in many situations. For example, different users submit their jobs simultaneously to a super computer-center.

Heuristics are one of the suitable approaches to solve the TS problem in distributed systems. Some research works have been made in recent years using pure heuristics to discover near-optimal solutions [2, 3]. These heuristics are fast, simple and easy to implement. To improve the quality of solutions, meta-heuristics have been presented for TS problem. The most popular meta-heuristic algorithms in the literature are Genetic Algorithm (GA), Differential Evolution (DE), Simulated Annealing (SA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) [4].

PSO is a meta-heuristic algorithm proposed by Kennedy and Eberhart [1] in 1995, motivated by the flocking behavior of birds. This has been applied in wide area and different fields such as engineering, physics, mathematics

and chemistry. Task scheduling is the discrete optimization problems because it has discrete decision variables (e.g.: Task number or processor number). Discrete PSO (DPSO) was proposed to solve such kind of discrete problems efficiently [5, 6] because of discrete nature of the particles.

The performance of PSO greatly depends on its control parameters. Slightly different parameter settings may direct to different performance in the algorithm. Xin *et al* [7] presented Linearly Decreasing Inertia weight (LDI) for enhancing the efficiency and performance of PSO. Bansal *et al* [8] presented a comparative study on 15 strategies to set inertia weight in PSO. The four different modified PSO variants with respect to change of control parameters were addressed in TS problem [9]. Hamming inertia weight was proposed [10–12] to update the inertia weight in discrete domain. This weight was calculated based on hamming distance between the particles and the global best (leader particle) particle which ensures that the particles have not moved away from the leader particle. The proposed algorithm of this paper uses DPSO variant with hamming inertia weight to control the particles move only towards the leader particle of the swarm.

In PSO, a particle in the swarm should be interacted only with its previous best particle and the best particle of its neighbors. This is the main problem in PSO to restrict the learning capability of the particles. Peng *et al* [13] proposed Cyber Swarm Algorithm (CSA), which is an improved version of PSO. CSA allows particles to learn the knowledge from three leader particles such as previous best, the

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best particle of its neighbors and the historical best particles, which resulted in improved diversity. Peng *et al* [14] demonstrated the CSA for tackling the General Keyboard Arrangement Problem and also compared the efficiency of the CSA with standard PSO, Heuristic algorithm and Random algorithm. The cyber swarm is extended to solve multi-objective optimization problems namely Multi-Objective CSA (MOCSA). Peng and Ya-Tzu [15] illustrated the performance of MOCSA with NSGA-II and MOPSO.

The CSA algorithm [13–15] uses Global best (Gbest) model for the particle communication. In this model, all the particles will be attracted by the best particle found in the whole swarm. Therefore, the broadcasting of the best position and fitness information is very fast. This fast broadcasting may result in premature convergence (local optima) problem. The previous research work [16] presented Heap Intelligent DPSO (HIDPSO) approach which is based on Local best model (Lbest) for reducing the premature convergence problem in scheduling of meta-tasks in distributed systems. HIDPSO allows the particle to learn the knowledge only from two best positions such as Pbest and Lbest. This learning restriction may reduce the diversity of the algorithm. To address this issue, this paper presents the hybridization of HIDPSO with CSA namely Cyber HIDPSO (CHIDPSO) which will improve the diversity of the algorithm.

The remainder of the paper is organized as follows. Section 2 describes the problem formulation. The proposed algorithm is presented in section 3. Experimental results are reported in section 4. Section 5 presents the computational complexity of the algorithm. Finally, the conclusions are provided in section 6.

2. Problem formulation

2.1 Task model

A Heterogeneous Computing (HC) system consists of a number of heterogeneous Processor Elements (PEs) connected with a mesh topology. Let $T = \{T_1, T_2, \dots, T_n\}$ denote the n number of tasks that are independent of each other to be scheduled on m processors $P = \{P_1, P_2, \dots, P_m\}$. Because of the heterogeneous nature of the processors and disparate nature of the tasks, the expected execution times of a task executing on different processors are different.

Every task has an Expected Time to Compute (ETC) on a specific processor. The ETC values are assumed to be known in advance. An ETC matrix is $n \times m$ matrix in which m is the number of processors and n is the number of tasks. One row of the ETC matrix represents estimated execution time for a specified task on each PE. Similarly, one column of the ETC matrix consists of the estimated execution time of a specified PE for each task.

The TS problem is formulated based on the following assumptions:

- All tasks are available at zero time. Processors are always available.
- The execution time of each task on each processor is known and constant.
- Preemption is not allowed. Each processor can process only one task at a time.
- A task cannot be processed on more than one processor at a time.
- Each processor uses the First-Come, First-Served (FCFS) method for performing the received tasks.

2.2 Scheduler model

A static scheduler model in distributed systems is shown in figure 1. The scheduler manages two queues such as Task Queue (TQ) and Processor Queue (PQ). The scheduling algorithm in the central scheduler is started to work with TQ. TQ contains a set of tasks in a particle. The scheduler is responsible for distributing each task in the TQ to the individual PQ based on the workload of the each processor in the distributed systems. Once the scheduler completes to place all the tasks from the TQ to PQ, the processors will start executing the tasks in their own PQ.

3. The proposed CHIDPSO algorithm

The CHIDPSO incorporates the heuristic based swarm initialization, heap tree based particle communication and reference set in velocity update method for reducing premature convergence and improving the diversity of the algorithm. The complete flow of the proposed work is given in figure 2.

The following subsections describe in detail the steps involved in the CHIDPSO algorithm.

3.1 Swarm initialization

Swarm Initialization plays an important role in the performance of the CHIDPSO algorithms. IDPSO [17] algorithm was proposed in the previous work which improved the quality of the initial seed solution with the incorporation of heuristics such as Open Path greedy Opposite (OPO) and

Figure 1. Scheduling model for heterogeneous environment.

Figure 2. The flow diagram of CHIDPSO algorithm. *Where OPO – Open Path greedy Opposite; HGL – Heuristic based Greedy static Load balancing algorithm; Rset – Reference set; IM – Improvement Method (IM); SG – Subset Generation; SC – Solution Combination (SC).

Heuristic based Greedy Load balancing (HGL) in swarm initialization. Therefore, CHIDPSO uses OPO and HGL for swarm initialization to improve initial quality of the solutions.

3.2 Particle evaluation

In CHIDPSO, the particles are evaluated using the three performance metrics such as makespan, mean flow time and reliability cost.

3.2a Makespan: Makespan (MS) computes the throughput of the distributed systems, assuming C_{ij} ($i \in \{1, 2, \dots, n\}, j \in \{1, 2, \dots, m\}$) is the execution time for performing i^{th} task in j^{th} processor and W_j ($j \in \{1, 2, \dots, m\}$) is the previous workload of P_j . According to the above definition, makespan can be estimated using Eq. (1):

$$MS = \max \left\{ \sum_{ij} C_{ij} + W_j \right\} j \in \{1, 2, 3, \dots, m\} \quad (1)$$

3.2b Mean flow time: Flow time measures the Quality of Service of the distributed system. The value of Mean Flow Time (MFT) is used to evaluate the flow time. Assume k to be the total number of tasks assigned to processor P_i and F_{ji} the finishing time of task T_j on a processor P_i , ($i \in \{1, 2, \dots, m\}, j \in \{1, 2, \dots, n\}$), the calculation of mean flow time are given in Eqs. (2) and (3).

$$MFT = \frac{\sum_{i=1}^m M_Flow_i}{m} \quad (2)$$

$$M_Flow_i = \frac{\sum_{j=1}^k F_{ji}}{k_i} \quad (3)$$

3.2c Reliability cost: Reliability Cost (RC) [18] is the indicator of how reliable a given system is when a group of tasks are assigned to it. It is indirectly proportional to

reliability. RC is the summation of processor reliability and link reliability. Here, the tasks are independent of each other and there is no communication link between tasks. Therefore, link reliability is set to zero. In processor reliability, processor failures are assumed to be independent and it follows a Poisson process with a constant failure rate. The RC is defined in Eq. (4), where $X(T_i) = j$ indicates that task T_i is allocated to P_j and λ_j is the failure rate of processor P_j .

$$RC = \sum_{j=1}^m \sum_{X(T_i)=j} \lambda_j C_{ij}(T_i) \quad (4)$$

3.2d Fitness function: Fitness function is used to test the quality of the solution. Since it is a minimization problem, a better solution has the lower fitness value. The fitness function comprises tri-objectives such as MS, MFT and RC. This can be estimated using Eq. (5), where the weights W_1, W_2 and W_3 indicate the significance of the objectives in meta-task scheduling problem.

$$\text{Fitness} = W_1 \text{ Makespan} + W_2 \text{ Mean Flow Time} + W_3 \text{ Reliability Cost} \quad (5)$$

The CHIDPSO [16] experimented the fitness function with different weight values and concluded that 0.4, 0.4 and 0.2 for the weights W_1, W_2 and W_3 , respectively provided better results in the meta-task scheduling problem. Therefore, the CHIDPSO follows the same fitness function for evaluating the quality of the particles.

3.3 Update the particle's Personal best and local best position

The Pbest is the personal best position visited so far by a particle. The local best (Lbest) of the particle can be obtained through the Binary Heap Tree (BHT) based communication with its neighboring particles [16].

In CHIDPSO algorithm, the learning of the particles is not limited to communication with the Pbest and Lbest. And also, the learning involves particles from a dynamically maintained reference set. This learning knowledge of CHIDPSO improves the diversity of the swarm. The next subsection describes in detail about the reference set.

3.4 Reference set initialization and updation

The reference set consists of a mixture of historical best solutions and diverse solutions. This would improve the quality of the solutions and diversity of the algorithm, respectively. It is represented by $\text{refSet}[i], i = 1 \dots \text{REFSIZE}$, where REFSIZE is the size of the reference set. Generally, the REFSIZE is five times lesser than the swarm size [13].

3.4a Reference set initialization: Reference set initialization is the process of selecting the initial particles for reference

set. This is performed using the diversification generation method of Scatter Search (SS) [19]. Using this method, the proposed algorithm fills the reference set with S1 number of quality solution and S2 number of diverse solutions, which is explained as follows:

- Choose the best S1 number of particles from Pbest array with size N (This is known as the quality solution)
- Calculate S2 number of opposite particles of the selected S1 particles using OPO technique. (This is known as the diverse solution, therefore, $\text{REFSIZE} = \text{S1} + \text{S2}$).

The initialization is done only in the first iteration before updating the particle's velocity. The pseudo code for initializing the reference set is given in figure 3. This initialization process invokes the function *Function 1* for populating the solutions in the reference set. This function code is presented in figure 4.

Pseudo code 1: Reference set Initialization
Input: Pbest particles with size N; Output: refSet with size N/5
begin Arrange the Pbest particles in ascending order based on the Pbest fitness (PFit). // Invoke Function 1 to create an initial refSet with size N/5. Call Reference set solution selection (in Pbest, in N, in PFit, Out refSet). end

Figure 3. Initialization of reference set.

Function 1: Reference set solution selection
Input: ParticleSet, ParticleSet_Size, Fitness; Output: refSet with REFSIZE
Function Reference set solution selection(in ParticleSet, in ParticleSet_Size, in Fitness, out refSet) Set REFSIZE = N/5 //N is the Swarm size Set S1 = REFSIZE/2 //Store S1 number of high quality particles in refSet for each Particle _i in ParticleSet do // i varies from 1 to S1 refSet[i]=Particle _i // Store Particle _i and fitness to reference set RFit[i] = Fitness[i] end for Set S2 = REFSIZE – S1 //Store diverse particles in refSet for each Particle _i in refSet do // i varies from 1 to S1 calculate opposite particle oppParticle _i using OPO technique refSet[S2] = oppParticle _i Evaluate refSet[S2] using equation (5) and store the fitness in RFit[S2] S2 = S2 + 1 end for Particles in refSet are sorted in ascending order based on the RFit. End Function

Figure 4. Particles selection for the Reference set.

Figures 3 and 4 include the direction parameters in the pseudo code such as *in* and *out*, which indicate input to the function and output from the function, respectively. The reference set particles will get updated after the first iteration. The high quality and low quality particles will be selected from the reference set for updating the particles. Therefore, the particles in the reference set are arranged according to the quality of the particles such that the refSet [1] contains the high quality particle (least fitness) and refSet [REFSIZE] contains the less quality particle (highest fitness).

3.4b Reference set updation: Reference set is updated using Improvement Method (IM), Subset Generation (SG) and Solution Combination (SC) methods of Scatter Search (SS) algorithm.

The *Improvement Method* performs like a selection operation of Genetic Algorithm. The SG method generates subsets from the reference set. Since generating all the subsets from the reference set is a time consuming process, in order to reduce the time complexity of SG, IM is required to select the limited particles from the reference set for subset generation. Figure 5 depicts the procedure for the IM. Here, the IM selects two best particles and one worst particle from refSet to build selection set for SG.

The *Subset Generation method* generates subsets from the selected particles in reference set. It is categorized into three main types namely Sub type 1, Sub type 2 and Sub type 3. The experiments of the proposed algorithm with different subset types (1, 2, and 3) are conducted. The preliminary experiments shows that the subset of type 2 and 3 have a small probability of getting new better solutions, this may because our diversification generation module generates the diverse solutions using OPO heuristic. Therefore, only the subset of type 1 is adopted for this problem. Generally, the sub type 1 method is preferred to perform SG due to its simplicity and lesser time complexity when compared to other sub types [13]. Figure 6 shows the pseudo code for the subset generation method. This method invokes a function *Function 2*, which is given in figure 8. Function 2 generates the particles from the three subset combinations such as {(best1, best2)}, {(best1, worst)}, {(best2, worst)} based on the sub type 1 generation method of SG. An illustrative example of SG is given in figure 7.

From figure 7, it is evident that a single swap will provide two new particles and it requires 2 transfers (one in best 1 and another in best 2). If the particle size is n , then the SG method will perform n number of swaps and 2^n number of transfers. Finally, it will produce 2^n number of solutions. In order to reduce the number of swaps and

Pseudo code2:Improvement method	
Input: refSet with REFSIZE; Output: SelectionSet with size 3	
//Restrict the size of the SelectionSet so as to reduce the time complexity.	
begin	
//Store two best particles and one worst particle in Selectionset	
SelectionSet[1] = refSet[1]	//1 st best (best1)
SelectionSet[2] = refSet[2]	// 2 nd best (best2)
SelectionSet[3] = refSet[REFSIZE]	// worst
end	

Figure 5. Procedure for improvement method in SS.

Pseudo code3:Subset Generation Method	
Input: SelectionSet with size 3;	
Output: subSet1, subSet2 and subSet3 with each of size REFSIZE	
begin	
call Setgeneration (in SelectionSet[1], in SelectionSet[2], outsubSet1)	
call Setgeneration (in SelectionSet[1], in SelectionSet[3], out subSet2)	
call Setgeneration (in SelectionSet[2], in SelectionSet[3], outsubSet3)	
end	

Figure 6. Subset generation method.

Figure 7. Sample for the SG of {best1, best2}.

number of transfers, the SG method does not consider all the tasks for the swap. Instead of performing all the swap operations, it randomly selects the tasks for performing swap operation to generate the new solutions, as explained in figure 8.

Solution Combination method is the last phase of reference set updation. Figure 9 explains the procedure to perform the SG method. During this phase, all the generated subsets (subSet1, subSet2 and subSet3) in SG are combined

to make SolnCombine with REFSIZE * 4 number of particles. This is referred by the Eq. (6), where U performs to combine the particles from refSet, subSet1, subSet2 and subSet3 into single solution pool SolnCombine.

$$\text{SolnCombine} = \text{refSet} \cup \text{subSet1} \cup \text{subSet2} \cup \text{subSet3} \quad (6)$$

In CHIDPSO, each particle is having three leader particles such as Pbest, Lbest and systematically choose each member from the reference set as the third leader. Equation (7) is used to calculate the reference particle *RefParticle_i* of a Particle_i in the swarm with size N, where i varies from 1 to N. The three leader particles are updated before updating the velocity and position of the particle.

$$\text{RefParticle}_i = i \bmod \text{REFSIZE} \quad (7)$$

The following subsection describes the way to update the velocity and position of the particles in the swarm.

3.5 Updating the particle's velocity and position

The velocity of the particle is redefined to operate it in a discrete domain directly [12]. This velocity has four parts: old velocity, learning from Pbest, Lbest and Rset. This is calculated using Eq. (8). Here, the operators: U performs

Function 2: Setgeneration
Function Setgeneration(in set1, in set2, out Solutions)
Input: two solutions set1 and set2; Output: Solutions with size REFSIZE
Set x = 1 //limit the particle generation k to REFSIZE; //So that, the loop will terminate when k reaches to REFSIZE/2 (REF SIZE/2 * 2=REFSIZE) Do while(k ≤ REFSIZE/2) // swap tasks between set1 and set2 for each task _i in set1 and set2 d // i varies from 1 to n temp = set1[task _i]; temp1 = set2[task _i] set1[task _i] = temp1; set2[task _i] = temp for each task _j in set1 and set2 do // j varies from 1 to n if (i! = j) then if (temp1 = set1[task _j] then set1[task _j] = temp end if if (temp = set2[task _j] then set2[task _j] = temp1 end if end if //copy newly generated solutions to the solutions set Solutions[x] = set1; Solutions[x + 1] = set2; x = x + 2 //check j th and i+1 th value in set1 and set2 in order to avoid duplicate particle generation if ((set1[task _i] = set2[task _i + 1]) and (set1[task _i + 1] = set2[task _i])) then i = i + 1; k=k+1 //skip the comparison end if end for end for Loop

Figure 8. Set generations for the SG method.

Pseudo code 4:Solution Combination
Input: subSet1, subSet2 and subSet3 with each of size is REFSIZE
Output: refSet with REFSIZE
begin Set x = 1 Set SCSIZE = REFSIZE * 4 for each Particle _i in refSet, subSet1, subSet2, subSet3 do // parallel coping of i th solutions from refSet, subSet1, subSet2 and subSet3 to SolnCombine and hence, the index of SolnCombine is incremented by 4 SolnCombine[x] = refSet[i] SolnCombine[x + 1] = subSet1[i] SolnCombine[x + 2] = subSet2[i] SolnCombine[x + 3] = subSet3[i] x = x + 4 end for Evaluate particles in SolnCombine using equation (5) and store the fitness in SCFit Arrange the particles in SolnCombine in ascending order based on the SCFit fitness. // Invoke Function 1 to create the updated refSet with size N/5. Call Reference set solution selection (in SolnCombine, in SCSIZE, in SCFit, Out refSet). end

Figure 9. Procedure for the solution combination method.

merging operation and “Swap” represents the swapping sequence of the operands. The four coefficients: W , C_1R_1 , C_2R_2 and C_3R_3 represent the importance of old velocity, particle's Pbest, neighborhood best and reference set, respectively. In this paper, the learning factors C_1 , C_2 and C_3 are set to 1.

$$V_i^{(t+1)}(j) = A \cup B \cup C \cup D \quad (8)$$

Where

$$A = WV_i^t(j) \quad (9)$$

$$B = C_1R_1(Pbest_i^t(j) \text{Swap } present_i^t(j)) \quad (10)$$

$$C = C_2R_2(Lbest^t \text{Swap } present_i^t(j)) \quad (11)$$

$$D = C_3R_3(Rset^t \text{Swap } present_i^t(j)) \quad (12)$$

The CHIDPSO uses hamming distance based inertia. Moving the particles based on the hamming distance between the particles and their Local best that ensures that the particles have not moved away from the Lbest [12]. The Hamming inertia weight is calculated using Eq. (13), where W_0 is the random number between 0.5 and 1, H_i is the current hamming distance of ith particle from the Lbest and MDH is the maximum distance of a particle from the Lbest in that generation. The inertia weight (W) in Eq. (8) is calculated using Eq. (13).

$$W = W_0 \left(1 - \frac{H_i}{MDH} \right) \quad (13)$$

$$H_i = \text{Hamming distance}(Gbest^t, present_i^t) \quad (14)$$

$$MDH = \text{Max}(H_i) \quad (15)$$

R_1 , R_2 and R_3 in Eqs. (10), (11) and (12) are random numbers between 0 and 1. If three random numbers (R_1 , R_2 and R_3) are independent then the algorithm will face the following problems:

- Three random parameters are high: Pbest and social experiences (Lbest, Rset) are extremely used and the particle is moved too far away from the local optimum.
- Three random parameters are low: Pbest and social experiences (Lbest, Rset) are not used completely and the convergence speed is very low.

In order to address the above stated problems, CHIDPSO makes the dependency among the three random parameters to balance the personal and social experiences of the particle. In this method, one single random number R_1 is chosen then R_2 and R_3 are generated based on R_1 . Equations (16), (17) and (18) present the way to create a dependency among the three random numbers, where random(N) generates a random number between 0 and N, N is the swarm size.

$$R_1(t) = \text{random}(N)/N \quad (16)$$

$$R_2(t) = (1.0 - R_1(t))\text{random}(N)/N \quad (17)$$

$$R_3(t) = 1.0 - R_1(t) - R_2(t) \quad (18)$$

After updating the velocity, update the position of the particle using Eq. (19).

$$present_i^{(t+1)}(j) = present_i^t(j) \text{swap} V_i^{(t+1)}(j) \quad (19)$$

3.6 Stopping condition

The above iterative processes on a swarm will continue until a pre-defined maximum number of iterations have been reached or no change in the fitness value for consecutive iterations.

The average Relative Percentage Deviation (RPD) [5] is also calculated along with makespan, mean flow time and reliability cost for comparing the efficiency of the algorithms. It is calculated using Eq. (20), where P is the average result of the CHIDPSO algorithm and AC_i is the average result provided by other algorithms.

$$RPD = (AC_i - P)/P * 100 \quad (20)$$

4. Simulation results and analysis

The simulation results are attained using a set of benchmark ETC instances [20] for the distributed heterogeneous systems. The algorithms are coded in Java and executed in Net Beans IDE.

4.1 Benchmark instances description

The simulation is performed on the benchmark ETC instances [20] which are categorized in 12 types of ETC's based on three metrics: task heterogeneity, machine heterogeneity and consistency [5].

All instances consisting of 512 tasks and 16 processors are classified into 12 different types of ETC matrices according to the above 3 metrics.

The instances are labeled as a_b_c as follows:

- a shows the type of consistency; c – consistent, i – inconsistent, and s – semi-consistent.

- b indicates the heterogeneity of the tasks; hi – high and lo – low.
- c represents the heterogeneity of the machines; hi – high and lo – low.

4.2 Parameter set-up

The following parameters are initialized for simulating the algorithms.

- Population size: 50
- Number of iteration: 500
- The Failure rate for each processor is uniformly distributed [18] in the range from 0.95×10^{-6} /h to 1.05×10^{-6} /h.

The algorithms are stochastic based algorithms. Each independent run of the same algorithm on a particular problem instance may yield a different result. To make a better comparison of the algorithms, each experiment was repeated 10 times with different random seeds and average of the results are tabulated and presented.

4.3 Performance comparisons

Table 1 presents the comparison of objective values of the proposed CHIDPSO and the existing CSA algorithms.

From table 1, it can be observed that the heuristic based initialization and dynamic BHT based particle communication in CHIDPSO provided better results in most of the ETC instances when compared to the existing CSA algorithm. Compared to the existing CSA, the overall average performance improvement of CHIDPSO algorithm in terms of makespan is 75.65%, mean flow time is 85.36% and reliability cost is 32.11% across all ETC instances.

Table 1. Performance comparison of CHIDPSO with existing CSA.

ETC instances	Makespan			Mean flow time			Reliability cost		
	CHIDPSO	CSA	RPD	CHIDPSO	CSA	RPD	CHIDPSO	CSA	RPD
c_lo_lo	13123.42	31105.15	137.02	6140.413	7360.07	19.86	0.186019	0.139401	– 25.06
c_lo_hi	25201.01	31207.12	23.83	11638.44	35010.61	200.81	0.460741	0.440998	– 4.28
c_hi_lo	11096.34	35057.91	215.94	5962.06	7505.41	25.88	0.181204	0.225683	24.54
c_hi_hi	17103.05	20207.41	18.15	12002.87	24217.12	101.76	0.464482	0.489956	5.48
i_lo_lo	25101.27	32036.61	27.62	13162.99	22990.95	74.66	0.305049	0.440408	44.37
i_lo_hi	28056.91	32017.38	14.11	14008.09	23199.49	65.61	0.434033	0.490009	12.89
i_hi_lo	23072.86	34825.46	50.93	11322.52	21491.42	89.81	0.393784	0.429941	9.18
i_hi_hi	28045.24	35197.95	25.5	12072.92	21000.93	73.95	0.423777	0.475999	12.32
s_lo_lo	23106.64	44112.13	90.91	10000.69	20911.97	109.11	0.237494	0.469001	97.47
s_lo_hi	28002.32	36512.33	30.39	11163.52	22001.01	97.07	0.427074	0.490001	14.73
s_hi_lo	12015.36	41003.04	241.25	6016.54	7399.16	22.98	0.168483	0.420964	149.85
s_hi_hi	28053.28	37074.41	32.15	12732.82	30919.06	142.82	0.340823	0.489941	43.75
Average			75.65			85.36			32.11

The resource utilization [21] is the performance criterion for the scheduler to perform scheduling with balancing the load. The processor's utilization is defined as the percentage of time that processor P_j is busy during the scheduling time. The processor's utilization PU_j for the processor P_j is calculated using Eq. (21).

$$PU_j = \text{Aval}(P_j) / \text{Makespan} \quad \text{for } j = 1 \dots m \quad (21)$$

Where, $\text{Aval}(P_j)$ is the processor's availability time. The processor availability time is the time when the processor P_j completes the execution of all the assigned tasks.

The resource utilization RU is the average of processor's utilization, which is calculated using Eq. (22).

$$RU = \frac{\sum_{j=1}^m PU_j}{m} \quad (22)$$

Resource Utilization (RU) of CHIDPSO and CSA is calculated using Eq. (22) and the comparison of performance is presented in figure 10.

From figure 10, it can be inferred that the RU of CSA is varying from 0.5 to 0.9 and the proposed CHIDPSO is

Figure 10. CHIDPSO Vs CSA with respect to RU.

between 0.95 and 1.0 with respect to different ETC instances. The average percentage of RU of CSA is 79.39% and CHIDPSO is 97.43% across all ETC instances. Due to HGL load balancing heuristic in CHIDPSO, this algorithm utilized the resources efficiently than the existing CSA algorithm nearly more than 18%.

Table 2 presents the comparison of objective values of the proposed CHIDPSO and the previously proposed HIDPSO algorithms [16]. The multi-objective values makespan, mean flow time and reliability cost presented in table 2 show that the CHIDPSO gives better objective values than HIDPSO in most of the ETC instances due to the inclusion of the reference set.

From table 2, it can be observed that the reference set in CHIDPSO provided better results in most of the ETC instances when compared to the HIDPSO. Compared to HIDPSO, the overall average performance improvement of CHIDPSO algorithm in terms of makespan is 10.28%, mean flow time is 6.83% and reliability cost is 5.61% across all ETC instances.

The multi-objective optimization problems can be broadly solved using Aggregating approach and Pareto dominance approach. From literature, the NSGA-II and NSPSO are well-known Pareto dominance based algorithms for meta-task scheduling problem in distributed systems. The NSHIDPSO [22, 23] performed better in terms of makespan is 52.12%, mean flow time is 24.03% and reliability cost is 30.43% when compared to the existing NSPSO across all ETC instances. Compared to the existing NSGA-II, the NSHIDPSO provided better performance in terms of makespan is 54.22%, mean flow time is 61.39% and reliability cost is 31.89% across all ETC instances. Table 3 presents the performance comparison of CHIDPSO with NSHIDPSO.

The CHIDPSO uses aggregating approach for prioritizing the objectives based on their significance in the meta-task scheduling problem. This type of prioritization of

Table 2. Performance comparison of CHIDPSO with HIDPSO.

ETC Instances	Makespan			Mean Flow Time			Reliability Cost		
	HIDPSO	CHIDPSO	RPD	HIDPSO	CHIDPSO	RPD	HIDPSO	CHIDPSO	RPD
c_lo_lo	13178.05	13123.42	0.41	6449.38	6140.413	5.03	0.190886	0.186019	2.61
c_lo_hi	27724.31	25201.01	10.01	13028.21	11638.44	11.94	0.462184	0.460741	0.31
c_hi_lo	13059.35	11096.34	17.69	6205.41	5962.06	4.08	0.192498	0.181204	6.23
c_hi_hi	20220.51	17103.05	18.22	13075.56	12002.87	8.93	0.466072	0.464482	0.34
i_lo_lo	27581.99	25101.27	9.88	13127.56	13162.99	− 0.26	0.300782	0.305049	− 1.39
i_lo_hi	30292.47	28056.91	7.96	14039.73	14008.09	0.22	0.440281	0.434033	1.43
i_hi_lo	25617.19	23072.86	11.02	12531.76	11322.52	10.67	0.400137	0.393784	1.61
i_hi_hi	30074.69	28045.24	7.23	14235.47	12072.92	17.91	0.440129	0.423777	3.85
s_lo_lo	25275.83	23106.64	9.38	10008.87	10000.69	0.08	0.282976	0.237494	19.2
s_lo_hi	30963.36	28002.32	10.57	13023.25	11163.52	16.65	0.440449	0.427074	3.13
s_hi_lo	13289.39	12015.36	10.61	6285.19	6016.54	4.46	0.204667	0.168483	21.5
s_hi_hi	30964.36	28053.28	10.37	13016.89	12732.82	2.23	0.370017	0.340823	8.56
Average			10.28			6.83			5.61

Table 3. Performance comparison of CHIDPSO with NSHIDPSO.

ETC instances	Makespan			Mean flow time			Reliability cost		
	CHIDPSO	NSHIDPSO	EPD	CHIDPSO	NSHIDPSO	EPD	CHIDPSO	NSHIDPSO	EPD
c_lo_lo	13123.42	13575.71	3.44	6140.413	7057.59	14.93	0.186019	0.203629	9.46
c_lo_hi	25201.01	29532.34	17.18	11638.44	14899.98	28.02	0.460741	0.456905	− 0.83
c_hi_lo	11096.34	14038.69	26.51	5962.06	6113.44	2.53	0.181204	0.186552	2.95
c_hi_hi	17103.05	30154.79	76.31	12002.87	14212.73	18.41	0.464482	0.459649	− 1.04
i_lo_lo	25101.27	29387.81	17.07	13162.99	13567.78	3.07	0.305049	0.439342	44.02
i_lo_hi	28056.91	31201.97	11.21	14008.09	15526.79	10.84	0.434033	0.478627	10.27
i_hi_lo	25072.86	28983.85	25.61	11322.52	12598.62	11.27	0.393784	0.406979	3.35
i_hi_hi	28045.24	31893.02	13.72	12072.92	15134.51	25.35	0.423777	0.479243	13.08
s_lo_lo	23106.64	25233.79	9.21	10000.69	12013.17	20.12	0.237494	0.371189	56.29
s_lo_hi	28002.32	30964.19	10.57	11163.52	15201.51	36.17	0.427074	0.475745	11.39
s_hi_lo	12015.36	25278.29	110.3	6016.54	10801.23	79.52	0.168483	0.343588	103.9
s_hi_hi	28053.28	31780.99	13.28	12732.82	14364.17	12.81	0.340823	0.472012	38.49
Average			27.87			21.92			24.28

objectives is impossible in case of Pareto dominance approach. It is inferred from table 3, the reference set and aggregating approach in CHIDPSO provided better objective values than NSHIDPSO in most of the ETC instances. The average overall improvements of CHIDPSO compared with NSHIDPSO with respect to Makespan: 27.87%; Mean flow time: 21.92%; Reliability Cost: 24.28% across all ETC instances.

The numerical results of the algorithms are validated using hypothesis test. Here, the wilcoxon signed-rank test [16] has been used to statistically compare the performance of the proposed algorithms. This test is performed and the results are presented in table 4. In this test, it is essential that the following two parameters need to be set:

- *Null hypothesis (H_0)* is set to “No difference between two algorithms (CHIDPSO and HIDPSO)”

- *Alternate hypothesis (H_1)* is set to “CHIDPSO performs better than the HIDPSO”.

From table 4, the obtained wilcoxon test statistic W is 78, which is greater than the upper critical value obtained from the wilcoxon signed rank test table [16]. Hence, H_0 stands rejected and H_1 accepted. Thus, there is an evidence; at the 5% level of significance, that the proposed CHIDPSO performs better than HIDPSO.

The performance of CHIDPSO, HIDPSO and IDPSO are tested with large datasets. Table 5 presents the different ETC dimensions ($n \times m$ matrix; where n is the number of tasks; m is the number of processors) such as 1024×32 ; 4096×128 and 8192×256 .

The fitness values of the algorithms are calculated using Eq. (5), and the values with respect to different ETC dimensions 1024×32 and 4096×128 are given in table 6 and 8192×256 in table 7.

Table 4. Statistical comparison of fitness value of CHIDPSO with HIDPSO.

ETC Instance	HIDPSO (B)	CHIDPSO (A)	Diff. (B-A)	A. Diff.	O. Diff.	R.	S.R.
c_lo_lo	7971.01	7705.57	265.44	265.44	265.44	1	1
c_lo_hi	17877.11	14735.87	3141.24	3141.24	990.11	2	2
c_hi_lo	7905.94	6823.39	1082.54	1082.54	1082.54	3	3
c_hi_hi	13838.52	11642.46	2196.06	2196.06	1137.07	4	4
i_lo_lo	16295.88	15305.77	990.11	990.11	1290.95	5	5
i_lo_hi	18652.97	16826.09	1826.88	1826.88	1826.88	6	6
i_hi_lo	16059.66	13758.23	2301.43	2301.43	2046.06	7	7
i_hi_hi	18284.15	16047.35	2236.8	2236.8	2196.06	8	8
s_lo_lo	14533.93	13242.98	1290.95	1290.95	2236.8	9	9
s_lo_hi	18446.73	15666.42	2780.31	2780.31	2301.43	10	10
s_hi_lo	8349.87	7212.794	1137.07	1137.07	2780.31	11	11
s_hi_hi	18360.57	16314.51	2046.06	2046.06	3141.24	12	12
						W+	78
						W−	−
Wilcoxon test statistic	W						78

*Diff. – Difference; A. Diff. – Absolute Difference; O. Diff. – Ordered Difference; R. – Rank; S.R.–Signed Rank

Table 5. ETC dimension details.

ETC dimension	Number of tasks	Number of processors
1024×32	1024	32
4096×128	4096	128
8192×256	8192	256

From tables 6 to 7, it can be observed that the proposed CHIDPSO provides better results than the both HIDPSO and IDPSO algorithms in all the ETC instances. Therefore, the proposed CHIDPSO provides better performance in the large ETC instances also.

The performance improvements of the fitness values of the CHIDPSO in terms of RPD values are given below:

- 1024×32 : Improvements of CHIDPSO are 8.21% and 16.74% compared with HIDPSO and IDPSO, respectively.
- 4096×128 : Improvements of CHIDPSO are 6.07% and 12.60% compared with HIDPSO and IDPSO, respectively.
- 8192×256 : Improvements of CHIDPSO are 6.40% and 12.12% compared with HIDPSO and IDPSO, respectively.

All the simulation results with different ETC dimensions and the statistical test seem to indicate that the proposed CHIDPSO has shown a significant improvement when compared to CSA, IDPSO, HIDPSO, and NSHIDPSO algorithms for meta-task scheduling problem in distributed systems.

5. Computational complexity

This section presents the computation complexity [24] of the proposed CHIDPSO. The complexity analysis of the algorithm is explained in table 8.

Table 7. Fitness value comparison of the algorithms in terms of 8192×256 ETC instances.

ETC instance	CHIDPSO	HIDPSO	CHIDPSO	IDPSO
c_lo_lo	168.97	178.97	168.97	189.23
c_lo_hi	1700.92	1727.92	1700.92	1818.51
c_hi_lo	1671084.9	1771084.91	1671084.9	1878612.51
c_hi_hi	1.63E+07	1.73E+07	1.63E+07	1.88E+07
i_lo_lo	457.13	467.13	457.13	486.57
i_lo_hi	4394.04	4694.04	4394.04	4838.33
i_hi_lo	4362291.5	4662291.51	4362291.5	4804507.51
i_hi_hi	4.41E+07	4.71E+07	4.41E+07	4.91E+07
s_lo_lo	66.63	75.63	66.63	80.73
s_lo_hi	710.88	760.88	710.88	791.62
s_hi_lo	714728.21	774728.21	714728.21	828071.31
s_hi_hi	7165201.5	7565201.51	7165201.5	8071759.51

The looping variables involved in the algorithm are **N**: Swarm size; **n**: Size of the particle; **m**: Number of processors; **G**: Total number of iterations and the additional variable **k** is used to limit the creation of sub sets in SG method in reference set updation phase.

The six phases in CHIDPSO are Swarm initialization, Particle evaluation, Update Pbest, Find Lbest, Update reference set and Particle updation. These phases are executed in **G** number of times. The Reference set updation takes more time for execution when compared to other phases. Therefore, the worst case time complexity of CHIDPSO is $O(n^2)$. Table 9 presents the comparison of complexity of the proposed algorithm with other algorithms.

From table 9, it is inferred that the complexity of CHIDPSO is lesser when compared to the existing algorithms such as NSGA-II, NSPSO and NSHIDPSO. The CHIDPSO and the existing CSA have same time complexities. The complexity of CHIDPSO is slightly higher than IDPSO and HIDPSO. However, the simulation results and statistical test proved that the proposed CHIDPSO performs better than IDPSO and HIDPSO algorithms.

Table 6. Fitness value comparison of the algorithms in terms of different ETC instances.

1024 × 32					4096 × 128				
ETC Instance	CHIDPSO	HIDPSO	CHIDPSO	IDPSO	ETC Instance	CHIDPSO	HIDPSO	CHIDPSO	IDPSO
c_lo_lo	200.61	230.22	200.61	249.22	c_lo_lo	174.41	186.03	174.41	199.46
c_lo_hi	2006.41	2182.51	2006.41	2358.57	c_lo_hi	1801.54	1858.45	1801.54	1998.55
c_hi_lo	2000830	2260501	2000830	2591563.51	c_hi_lo	1800805	1874492.21	1800805	1993136.9
c_hi_hi	2.07E+07	2.30E+07	2.07E+07	2.50E+07	c_hi_hi	1.71E+07	1.89E+07	1.71E+07	1.99E+07
i_lo_lo	400.97	432.49	400.97	467.47	i_lo_lo	437.51	465.85	437.51	491.17
i_lo_hi	4001.79	4365.46	4001.79	4666.17	i_lo_hi	4200.75	4584.41	4200.75	4863.46
i_hi_lo	4001565	4362632	4001565	4679823.51	i_hi_lo	4359621	4653622.51	4359621	4831489.5
i_hi_hi	4.07E+07	4.44E+07	4.07E+07	4.73E+07	i_hi_hi	4.30E+07	4.67E+07	4.30E+07	4.87E+07
s_lo_lo	401.80	419.47	401.80	455.13	s_lo_lo	407.60	426.69	407.60	454.87
s_lo_hi	4000.13	4083.69	4000.13	4202.65	s_lo_hi	4092.41	4229.45	4092.41	4426.59
s_hi_lo	4001119	4208786	4001119	4477223.51	s_hi_lo	4064645	4245952	4064645	4572696
s_hi_hi	4.00E+07	4.17E+07	4.00E+07	4.49E+07	s_hi_hi	4.02E+07	4.22E+07	4.02E+07	4.58E+07

Table 8. Asymptotic time complexity of CHIDPSO algorithm.

Phase name	Asymptotic complexity
1) Swarm initialization	$O(N \ n \ m)$
i) Particle initialization: $O(n)$	
ii) Processor allocation: $O(N \ n \ m)$	
2) Particle Evaluation	$O(N)$
3) Update Pbest	$O(N)$
4) Find Lbest	$O(N \ n)$
5) Update reference set	$O(n^2)$
i) $O(n^2)$ – Subset Generation Method	
ii) $O(SCSize)$ – Solution Combination	
The maximum time complexity is $O(n^2)$	
6) Particle Updation	$O(N)$

Table 9. Complexity comparison of CHIDPSO algorithm with other algorithms.

Name of the algorithm	Asymptotic complexity
HIDPSO and IDPSO [16]	$O(N \ n \ m)$
NSGA-II, NSPSO and NSHIDPSO [22]	$O(M \ N^2)$
CSA and CHIDPSO	$O(n^2)$

6. Conclusion

Task Scheduling (TS) is a well-known discrete optimization problem, which is a main demanding issue in distributed systems. PSO is a well-known meta-heuristic algorithm for solving the scheduling problem. CSA is an improved version of PSO, which follows Gbest model for particles communication. The benefit of using the CSA is a reference set model. To reduce the premature convergence problem in CSA and utilize the advantages of CSA, the CHIDPSO was proposed and presented in this paper. This is a hybridization of HIDPSO and CSA. The efficiency of the algorithm is tested using the performance metrics such as makespan, mean flow time, reliability cost, fitness and resource utilization. The performance improvements of the proposed algorithm with other algorithms are compared based on the RPD metric. The incorporation of heuristic based initialization, BHT based particle communication and reference set in CHIDPSO resulted in reduced premature convergence problem and improved the diversity of the algorithm. The simulation results and hypothesis test confirmed that the CHIDPSO algorithm provided better performance than CSA, IDPSO, HIDPSO, and NSHIDPSO algorithms for meta-task scheduling problem in distributed systems. Future work of the research focuses on evaluating the efficiency of the CHIDPSO algorithm in dynamic and preemptive scheduling environment.

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