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.

Implementation Methodology of Real-Valued Augmented Simulated Annealing Algorithm for Dependent Task Scheduling

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ABSTRACT:

As computing resources are distributed in multiple domains in the Internet, the computational and storage nodes and the underlying networks connecting them are heterogeneous. Thus the heterogeneity results in different capabilities for job processing and data access. To achieve the promising potentials of tremendous distributed resources, effective and efficient scheduling algorithms are fundamentally important. Real-valued Augmented Simulated Annealing (RASA) effectively exploits the essentials of Genetic Algorithm(GA) together with the basic concept of simulated annealing method guiding the search towards minimal energy states. This paper explains the methodology of application of RASA algorithm for the constrained task scheduling problems.

Keywords: *Real-valued Augmented Simulated Annealing, Constrained Task Scheduling, DAG, Makespan, Ranking*

INTRODUCTION:

A task scheduling is the mapping of tasks to a selected group of resources which may be distributed in multiple administrative domains. A scheduling problem is specified by a set of machines, a set of jobs/operations, optimality criteria, environmental specifications, and by other constraints[1]. Given an application modeled by the Directed Acyclic Graph (DAG), the scheduling problem deals with mapping each task of the application onto the available heterogeneous systems in order to minimize makespan [2]. DAG includes the characteristics of an application program such as the execution time of tasks, the data size to communicate between tasks and task dependencies. The task scheduling problem has been solved several years ago and is known to be NP-complete [3,4]. In general, task scheduling algorithm for heterogeneous systems is classified into two classes: static and dynamic [5]. In static scheduling algorithms, all information needed for scheduling must be known in advance [6]. Static task scheduling takes place during compile time before running the parallel application. In contrast, scheduling decisions in dynamic scheduling algorithms are made at run time.

PROBLEM DEFINITION:

The task scheduling problem is the process of assigning a set of *v* tasks in a DAG to a set of *q* computing nodes, which have diverse characteristics, without violating the precedence constraints. Before scheduling, the priority of execution of tasks is calculated based on the upward ranking methodology [4].The tasks are sorted in the decreasing order of the upward rank value. The highest priority task (with high rank value), has the highest scheduling

priority. If more than one task has equal upward rank value, the scheduling priority of the task is decided randomly.
In this paper, the schedule length of the given DAG application, namely makespan, is the largest finish time among all tasks, which is the actual finish time of the exit task, n_{exit} .The objective of the task scheduling problem is to minimise the makespan (fitness), without violating the precedence constraints of the tasks. The objective function is defined in Equation (1) [4].

$$fitness = Makespan = f(x) = \begin{cases} EFT(n_{exit}), & for\ single\ \ n_{exit} \\ max\{EFT(n_{exit})\}, & for\ multiple\ n_{exit} \end{cases} \quad (1)$$

where EFT is the Earliest Finish Time of the task n_i on the computing node p_j, defined in the Equation (2) [4].

$$EFT(n_i, p_j) = w_{i,j} + EST(n_i, p_j) \quad (2)$$

where $EST(n_i, p_j)$ is the Earliest Start Time of the task n_i on the computing node p_j, defined in the Equation (3) ([4].

$$EST(n_i, p_j) = \begin{cases} max\{avail\_time(p_j), ready\_time(n_i)\}, & if\ n_i \neq n_{entry} \\ 0, & if\ n_i = n_{entry} \end{cases} \quad (3)$$

where $avail\_time(p_j)$ is the earliest time at which the computing node p_j is ready for the task execution and $ready\_time(n_i)$ is the time when all data needed by n_i has arrived at the computing node p_j, defined in the Equation (4) [4].$ready\_time(n_i) = \max_{n_m \in pred(n_i)} (EFT(n_m) + c_{m,i})$ (4)

where $pred(n_i)$ is the set of predecessor tasks of the task n_i.

RASA ALGORITHM

The augmented simulated annealing method is the combination of two stochastic optimization techniques-genetic algorithm and simulated annealing. This method effectively exploits the essentials of genetic algorithm together with the basic concept of simulated annealing method, guiding the search towards minimal energy states. Real-valued augmented simulated annealing makes use of the replacement procedure which is controlled by Metropolis criterion. The algorithm 1 describes an implementation of the RASA[7].

Algorithm 1: Real-valued Augmented Simulated Annealing Algorithm

0) Initialize T_{max}, countermax, successmax
1)$T_t = T_{max}$, t =0
2) Generate P, evaluate P

```
while (not termination  condition)
      counter = success= 0
      while ( counter < countermax  ^  success < successmax)
          counter  = counter +1, t = t +1
          select mutation operator O
          select individuals I_t from P_t
          modify I_t  by O to generate I_t'
          p = exp((F(I_t) - F(I_t'))/T_t)
          if (u(0,1) ≤ p)
             insert I_t' into P_t
          end
          success = success+1
          evaluate P_t
      end
      decrease T_t
end
```

Where F (.) be the fitness of the individual.

4.1 List of mutation operators

The following set of real-valued operators, proposed in [23] is used for the implementation of RASA. In the sequel, we will denote L and U as vectors of lower/upper bounds on unknown variables, u (a, b) and u [a, b] as a real or integer random variable with the uniform distribution on a closed interval <a, b>.

4.1.1 Uniform mutation

Let k = [1, n]

$$ch_{ij}(t+1) = \begin{cases} u(L_j, U_j), & \text{if } j = k \\ ch_{ij}(t), & \text{otherwise} \end{cases}$$

4.1.2 Boundary mutation

Let k = u[1, n], p=u(0, 1) and set

$$ch_{ij}(t+1) = \begin{cases} L_j, & \text{if } j = k, p < 0.5 \\ U_j, & \text{if } j = k, p \geq 0.5 \\ ch_{ij}(t), & \text{otherwise} \end{cases}$$

4.1.3 Non-uniform mutation

Let k = [1, n], p = u(0, 1) and set

$$ch_{ij}(t+1) = \begin{cases} ch_{ij}(t) + \left(L_j - ch_{ij}(t)\right) f, & \text{if } j = k, p < 0.5 \\ ch_{ij}(t) + \left(U_j - ch_{ij}(t)\right) f, & \text{if } j = k, p \geq 0.5 \\ ch_{ij}(t), & \text{otherwise} \end{cases}$$

$$\text{where } f = u(0,1)\left(T_t / T_0\right)^b$$

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and b is the shape parameter.

4.1.4 Multi-non-uniform mutation

Apply non-uniform mutation to all variables of CHi.

4.1.5 Simple cross-over

Let k= [1, n] and set

$$ch_{il}(t+1) = \begin{cases} ch_{il}(t), & \text{if } l < k \\ ch_{jl}(t), & \text{otherwise} \end{cases}$$

$$ch_{jl}(t+1) = \begin{cases} ch_{jl}(t), & \text{if } l < k \\ ch_{il}(t), & \text{otherwise} \end{cases}$$

4.1.6 Simple arithmetic cross-over

Let k= u [1, n], p= u (0, 1) and set

$$ch_{il}(t+1) = \begin{cases} pch_{il}(t) + (1-p)ch_{jl}(t), & \text{if } l = k \\ ch_{il}(t), & \text{otherwise} \end{cases}$$

$$ch_{jl}(t+1) = \begin{cases} pch_{jl}(t) + (1-p)ch_{il}(t), & \text{if } l = k \\ ch_{jl}(t), & \text{otherwise} \end{cases}$$

4.1.7 Whole arithmetic cross-over

Simple arithmetic cross-over applied to all variables of CHi and CHj.

4.1.8 Heuristic cross-over

Let Scaling factor F = u (0, 1), j = [1, n] and k= [1, n] such that j ≠ k and set

$$CH_i(t+1) = CH_i(t) + F.\left(CH_j(t) - CH_k(t)\right)$$

IMPLEMENTATION OF RASA ALGORITHM FOR SCHEDULING DEPENDENT TASKS

The following subsections deal with the representation of solution, and the generation of initial solution.

4.1 Solution representation

The solution is represented as an array of length equal to the number of jobs [8]. The value corresponding to each position i in the array represent the node to which task i was allocated. The representation of the solution for the problem of scheduling 13 tasks to 3 computing nodes is illustrated in Figure 1. The first element of the array denotes the first task (n1) in a batch which is allocated to the computing node 2; the second element of the array denotes the second job (n2) which is assigned to the computing node 1, and so on.

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J	J	J	J	J	…	Ji	…
G	G	G	G	G	…	G	…

(a)

2	1	2	3	1	2	3	1	2	3	2	1	1

(b)

Grid Node	J2	J5	J8	J12	J13
Grid Node	J1	J3	J6	J9	J11
Grid Node	J4	J7	J10		

(c)

Fig. 1. (a) Solution Representation (b) Solution for the problem of 13 tasks and 3 computing nodes (c) Mapping of tasks with computing nodes for the solution given in (b)

4.2 Initial solution generation

Numerous methods have been proposed to generate the initial solution when applying meta heuristics to the scheduling problem in the heterogeneous environment [9, 10]. Random solution may also be generated to initiate the process.

4.3 Computational experiments

To illustrate, a small scale DAG scheduling problem involving 3 nodes and 10 tasks is considered (Fig 2) with the computation cost matrix given in Table 1.The upward rank and the order of the tasks for execution are given in Table 2 and 3 respectively. RASA algorithm was executed with the following parameters. Size of the population -15, T_frac -10^{-2}, T_frac_min - 10^{-4}, T_mult -0.9, Parameter q -0.09, Scaling factor -0.8, successmax(SM)-2,Number of iterations- 50. The makespan value obtained for the example problem is found to be 73.

Table 1 Computation cost matrix for random DAG

Task id	P1	P2	P3
1	14	16	9
2	13	19	18
3	11	13	19
4	13	8	17
5	12	13	10
6	13	16	9
7	7	15	11
8	5	11	14
9	18	12	20
10	21	7	16

Figure 2. An example DAG

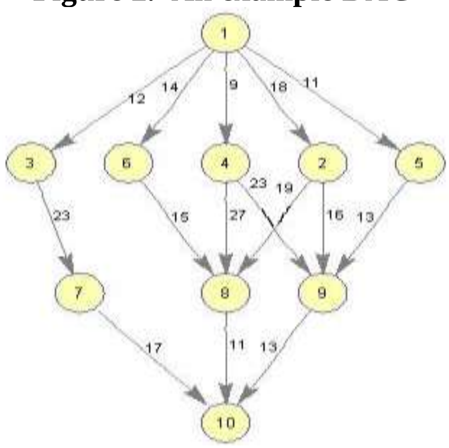

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Table 2 Upward rank of the tasks

Task id	Upward Rank
1	108.00000
2	77.00000
3	80.00000
4	80.00000
5	69.00000
6	63.33333
7	42.66667
8	35.66667
9	44.33333
10	14.66667

Table 3 Execution Order of tasks

Order of Task id
1
4
3
2
5
6
9
7
8
10

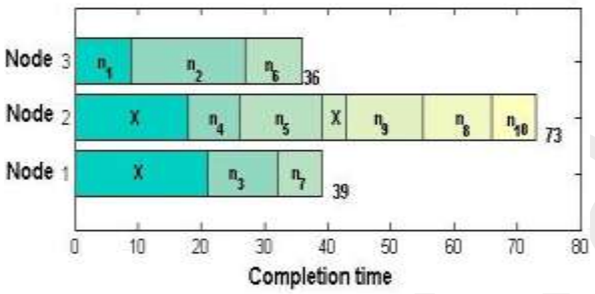

Figure 3. A schedule produced by the RASA algorithm for the example DAG

CONCLUSION

The methodology of implementation of RASA algorithm for the constrained dependent task scheduling problem had been discussed. The methodology adopted for this algorithm gives rise to the development of scheduling algorithms using other meta heuristic methods.

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