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Survey of Various Meta-Heuristic Algorithms for Parallel Job Scheduling

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Abstract: This paper presents an overview of various nature-inspired optimization algorithms for scheduling problems. Nature is a vast source of inspiration to solve complex problems (NP-hard) in computer science as it shows extremely diverse, dynamic, robust, complex and fascinating techniques. It helps to find the optimal solution in order to solve the problem keeping perfect balance among its components. Nature inspired algorithms are meta-heuristics which are motivated by the nature in order to solve various optimization problems. For the past decades, great research efforts has been concentrated on these techniques. The surprising results increase the scope and practicality of these meta-heuristic techniques exploring new areas of application and more opportunities in computing.

Keywords: Parallel computing, multi-objective optimization, scheduling, co-allocation, multi-clusters, meta-heuristics

1. INTRODUCTION

1.1PARALLEL COMPUTING

Parallel computing is referred to as the simultaneous use of multiple computing resources in order to solve a computational problem. To be run using multiple processors, a problem is divided into different parts which then can be solved concurrently.

Each part is further broken down into a set of instructions. Instructions from each part then execute concurrently on different processors.

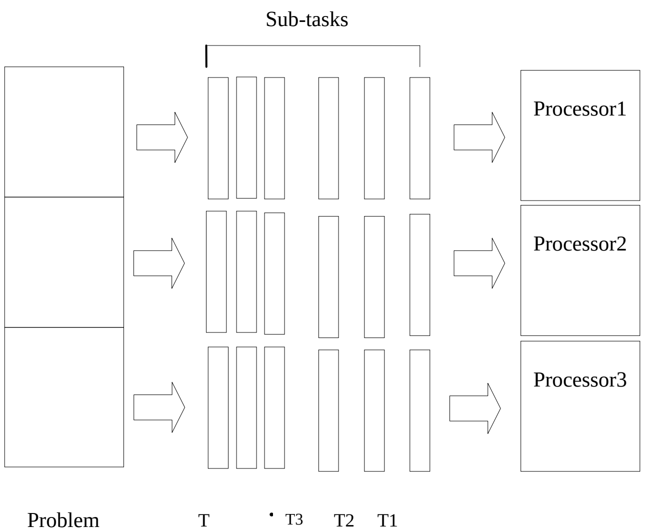

Fig. 1: Allocation of parallel tasks to processors

1.2 SCHEDULING

Scheduling means to determine the order of job execution i.e. which job will execute on which machine within the specified time period.

While scheduling jobs, the scheduler performs the following steps:

1. Information gathering of tasks.
2. Selecting resources
3. Planning
4. Allocating resources according to planning
5. Monitoring

1.3 CO-ALLOCATION

The scheduler distributes jobs across various clusters to allocate those jobs that cannot be assigned to a single cluster. This allocation strategy is referred to as co-allocation. It can maximize the job throughput by reducing the waiting times. So, jobs that would otherwise wait in the queue for local resources can start its execution earlier. This helps to improve system utilization and reduce average queue waiting time. However, mapping of tasks across the cluster boundaries may result in poor overall performance when the co-allocated jobs contend for inter-cluster network bandwidth. Moreover, the heterogeneity of processing and communication resources increases the complexity of the scheduling problem [14].

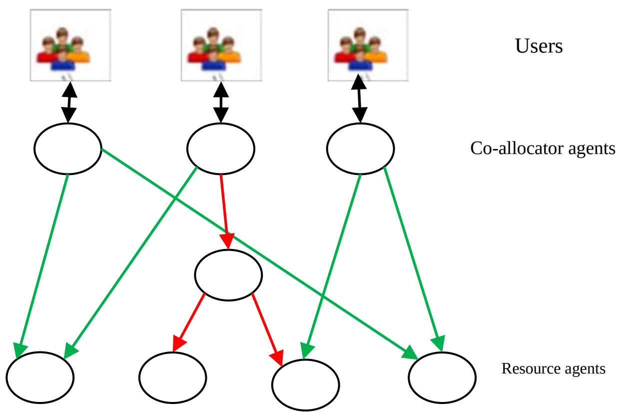

Fig. 2: Co-allocation of tasks

2. META-HEURISTICS

Optimization is a general mathematical problem in all engineering disciplines. It literally means finding the best possible solution.

2.1 FLOWER POLLINATION ALGORITHM

This technique was developed by Xin-She Yang in 2012. It is inspired by the flower pollination process of flowering plants. The FPA method has been extended for multi-objective optimization. The following rules are used:

(1) Biotic cross-pollination can be referred as a process of global pollination, and pollen carrying pollinators move in a way that obeys Levy flights.
(2) Abiotic pollination and self-pollination are used for local pollination.
(3)Pollinators like insects may develop flower constancy and it is equivalent to a reproduction probability which is proportional to the similarity of two flowers that are involved.
(4) The interaction or switching of local pollination and global pollination is controlled
by a switching probability that is biased towards local pollination.

2.2 INTELLIGENT WATER DROPS ALGORITHM (IWD)

IWD is a population based technique which was proposed by Hamed Shah-hosseini in 2007. It is inspired by the processes in natural river systems comprising the actions and reactions which occurs between water drops in the river and the changes which occur in the environment that river is flowing [11]. On the basis of observation of the behavior of water drops, an artificial water drop is developed which possesses some of the remarkable properties of the natural water drop. The Intelligent Water Drops has two important features:
1. The amount of the soil it carries, i.e. Soil (IWD).
2. The velocity with which it is moving now i.e. Velocity (IWD).

2.3 PADDY FIELD ALGORITHM (IWD)

This algorithm was Proposed by Premaratne in 2009 and it operates on the reproductive principle dependant on the proximity to the global solution and population density similar to plant populations. This algorithm does not involve combined behavior nor crossover between individuals though it uses pollination along with dispersal. PFA constitutes five basic steps.

1. Sowing:
2. Selection:
3. Seeding:
4. Pollination:
5. Dispersion:

2.4 GROUP SEARCH OPTIMIZATION ALGORITHM (GSO)

The group search optimizer (GSO), was investigated at the University of Liverpool .It is also a population based optimization technique and adopts the producer–scrounger (PS) model to design optimum searching methods that are inspired by animal foraging behavior. Like PSO, the population of the GSO is called a group and every individual of this population is called a member. In the search space, each member knows its own position, its head angle and a head direction.

2.5 ARTIFICIAL IMMUNE SYSTEM ALGORITHM (AIS)

AIS algorithm was proposed by Dasgupta in 1999 .Artificial Immune algorithm is based on clonal selection principle and it is also a population based technique .AIS is motivated by the human immune system which is a largely evolved, parallel and distributed adaptive system which exhibits these strengths: immune recognition, reinforcement learning, feature extraction, immune memory, diversity and robustness. The artificial immune system (AIS) combines these strengths and is gaining huge attention because of its powerful adaptive learning and memory capabilities. The main search power in AIS relies on the mutation operator and thus it is the efficiency deciding factor of this method. The steps in AIS are as follows:
1. Initialization
2. Cloning,
3. Hyper mutation

2.6 GENETIC ALGORITHM (GA)

A Genetic Algorithm (GA) is a class of evolutionary algorithms which involves search and optimization. Genetic algorithms were first used by J.H. Holland. It mimics the process of natural evolution so as to create artificial processes for a "clever" algorithm in order to find the solution of complex problems like job scheduling in computational grid.

3. COMPARISON OF VARIOUS META-HEURISTIC ALGORITHMS

ALGORITHM	OPERATORS	APPLICATIONS	CONTROL PARAMETERS
Paddy Field Algorithm (PFA)	• Dispersal • pollination	• Continuous function optimization. • Neural Network Parameters Optimization	• Population size • Initial value of the maximum number of seeds.
Flower pollination algorithm (FPA)	• Pollinators	• Job scheduling, • Continuous function optimization	• Switch probability • Reproduction probability
Group Search Optimization Algorithm (GSO)	• Scrounging • Ranging • producing	• Benchmark functions • Mechanical design optimization problems.	• Population size • percentage rangers • Number of rangers • Head angle
Artificial Immune System	• immune operators	• computer security	• Population size

Algorithm (AIS)	• cloning • hyper mutation	• anomaly detection • clustering /classification	• Number of antibodies to be selected • multiplier factor β
Genetic Algorithm (GA)	• Crossover • Mutation • Selection • Inversion	• optimization problems • rule extraction	• Population size • Max generation number • cross over probability • mutation probability

4. RELATED WORK

Eloi Gabaldon et al.[1] suggested that after the free sources happen to be configured, completely new possibilities occur intended for cutting down power utilization by giving ideal matching of parallel programs to free computing nodes. Eloi Gabaldon et al. [2] proposed a genetic algorithm for organizing job-packages connected with parallel jobs for source federated environments. With regards to proposition seemed to be to determine the task schedule and also offer allocation to enhance the application operation and also process throughput. Rahmani. A. M et al. [3] presented the Genetic Algorithm in order to solve the scheduling problem of dependent jobs in which the population quantity and the number of generations are dependent upon the number of tasks. In this the number of iterations are stable for any task and it offers the advantage if the number of tasks are less, so long computational time was not used and if the number of tasks are large the probability of finding the appropriate solutions is provided by the further repetition of algorithm. Also, SA was used to decrease the time of calculations. Alejandro Acosta et al. [4] attended to the challenge regarding adjusting existing codes and also libraries in heterogeneous environment. The authors planned dynamic load controlling libraries which allow parallel code to generally be adapted to heterogeneous environments for lots of problems. The cost introduced by this technique was minimum as well as over head to the coder was negligible. Blanco et al. [5] proposed diverse techniques for determining the best scheduling of sets of job packages, and proposed a new job execution order to minimize their overall execution time, based on a Mixed Integer programming model. Due to the intractable nature of the problems, it is desirable to explore other avenues for developing good heuristic methods for the problem. Mitsuo Gen [6] suggested that scheduling as an important tool for the manufacturing system, where it may have a major impact on the productivity of the production process. In order to get an optimal solution to scheduling problems it gives rise to complex combinatorial optimization problems. But, most of them fall into the class of NP-hard combinatorial problems.Xin-She Yanga [7] proposed the multi objective design optimization problems require multi objective optimization methods to solve, and it is often very difficult to obtain high-quality Pareto fronts correctly. The authors extended the flower pollination algorithm (FPA) in order to solve multi objective optimization problems. Shmueli et al. [8] proposed a backfilling technique in which later jobs are packaged to occupy the holes and increase utilization without delaying the earlier jobs. Tsafrir et al. [9] proposed a method of selecting the most suitable jobs to be moved forward on the basis of system-generated response time predictions. These techniques are based on the job arrival order, only moving jobs forward that meet specified deadline requirements .Jones et al. [10] proposed bandwidth-centric job communication model which captures the interaction as well as impact of simultaneously co-allocating jobs across multiple clusters and dynamic model was compared with previous research which utilizes a fixed execution time penalty for co-allocated jobs.Hosseini,et al.[11] proposed a new problem solving method called "intelligent water drops" or IWD method which is based on the processes that occurs in the natural river systems and the actions and reactions which take place between water drops in the river and the changes that happen in the environment that river is flowing. Muthuvelu, et al. [12] deployed lightweight tasks individually on grid resources that lead to a situation where communication overhead dominated the overall application processing time. The communication overhead was reduced by grouping the lightweight tasks at the meta-scheduler before the deployment. Kołodziej et al. [13] addressed the independent batch scheduling in computational grid as a bi-objective global minimization problem with makespan as well as energy consumption as the main criteria. The authors applied the *dynamic voltage and frequency scaling* model for the management of the cumulative power energy utilized by the grid resources. They developed three genetic algorithms as energy-aware grid schedulers, which were empirically evaluated in three grid size scenarios in static and dynamic modes. The simulation results confirmed the effectiveness of the proposed genetic algorithm-based schedulers in the reduction of the energy consumed by the whole system and in dynamic load balancing of the resources in grid clusters, which was sufficient to maintain the desired quality level(s).

Blanco et al. [14] presented a new scheduling method that allocateed multiple jobs from the system queue simultaneously on a heterogeneous multicluster, by applying co-allocation when it is necessary. Theis method was composed by a job selection function and a linear programming model to find the best allocation for multiple jobs. The proposed scheduling strategy has shown to reduce the execution times of the parallel jobs and the overall response times. Christobel et al. [15] proposed a novel discrete particle swarm optimization (DPSO) algorithm based on the particle's best position (pbDPSO) and global best position (gbDPSO) was adopted to find the global optimal solution for higher dimensions. This novel DPSO yielded better schedule with minimum computation time compared to Earliest Deadline First (EDF) and First Come First Serve (FCFS) algorithms which comparably reduces energy. Other scheduling parameters, such as job completion ratio and lateness, were also calculated and compared with EDF and FCFS.

5. COMPARISON TABLE

Name of Author	Title of paper	Technique	Parameters					
			Makespan	Flowtime	Energy consumption	Overhead	Utilisation	Performance
Bucur (2016)	Scheduling policies for processor coallocation in multi cluster systems.	A Genetic algorithm based on weighted blacklist	Yes	No	Yes	No	No	No
Shmuel (2015)	Backfilling with lookahead to optimize the packing of parallel jobs.	Backfilling algorithm	No	No	No	No	No	Yes
Carreter	Genetic algorithm based schedulers for grid computing systems.	MIP-based scheduling	Yes	No	No	No	No	No
Cocana (2015)	Energy-efficient allocation of computing node slots in HPC clusters modeling	Dynamic load balancing	No	No	Yes	Yes	No	No
Sid Ahmed Makhlouf (2011)	Resources Co-allocation Strategies in Grid Computing	Co-allocation strategy	No	No	No	No	Yes	No
Gerald Sebi (2012)	Scheduling of parallel jobs in a heterogeneous multi-site environment	Greedy scheduling strategy	Yes	Yes	No	No	No	No

CONCLUSION

Most of the research work done for job scheduling is for sequential jobs. For scheduling parallel jobs Genetic algorithm has been applied but this algorithm suffers from local optima problem. Also, its convergence speed is slow. So, in future hybridization of genetic algorithm with some other meta-heuristic can be done to optimize the make span and flow time of parallel jobs.

REFERENCES

[1] Gabaldon, Eloi, et al. "Blacklist muti-objective genetic algorithm for energy saving in heterogeneous environments." The Journal of Supercomputing (2016): 1-16.

[2] Gabaldon, Eloi, et al. "Particle Swarm Optimization Scheduling for Energy Saving in Cluster Computing Heterogeneous Environments." Future Internet of Things and Cloud Workshops (FiCloudW), IEEE International Conference on. IEEE, 2016.

[3] Rahmani, Amir Masoud, and Mojtaba Rezvani. "A novel genetic algorithm for static task scheduling in distributed systems." *International Journal of Computer Theory and Engineering* 1.1 (2009):

[4] Acosta, Alejandro, et al. "Dynamic load balancing on heterogeneous multicore/multiGPU systems." High Performance Computing and Simulation (HPCS), 2010 International Conference on. IEEE, 2010.

[5] Blanco, Héctor, et al. "MIP model scheduling for multi-clusters." European Conference on Parallel Processing. Springer Berlin Heidelberg, 2012.

[6] Gen, Mitsuo, and Lin Lin. "Multiobjective evolutionary algorithm for manufacturing scheduling problems: state-of-the-art survey." *Journal of Intelligent Manufacturing* 25.5 (2014): 849-866.

[7] Yang, Xin-She, Mehmet Karamanoglu, and Xingshi He. "Flower pollination algorithm: a novel approach for multiobjective optimization." *Engineering Optimization* 46.9 (2014): 1222-1237.

[8] Shmueli, Edi, and Dror G. Feitelson. "Backfilling with lookahead to optimize the packing of parallel jobs." *Journal of Parallel and Distributed Computing* 65.9 (2005): 1090-1107.

[9] Tsafrir, Dan, Yoav Etsion, and Dror G. Feitelson. "Backfilling using system-generated predictions rather than user runtime estimates." *IEEE Transactions on Parallel and Distributed Systems* 18.6 (2007).

[10] Jones, William M., et al. "Characterization of bandwidth-aware meta-schedulers for co-allocating jobs across multiple clusters." *The Journal of Supercomputing* 34.2 (2005): 135-163.

[11] Hosseini, Hamed Shah. "Problem solving by intelligent water drops." *Evolutionary Computation, 2007. CEC 2007. IEEE Congress on*. IEEE, 2007.

[12] Muthuvelu, Nithiapidary, et al. "Task granularity policies for deploying bag-of-task applications on global grids." *Future Generation Computer Systems* 29.1 (2013): 170-181.

[13] Kołodziej, Joanna, et al. "Energy efficient genetic-based schedulers in computational grids." *Concurrency and Computation: Practice and Experience* 27.4 (2015): 809-829.

[14] Blanco, Héctor, et al. "Multiple job co-allocation strategy for heterogeneous multi-cluster systems based on linear programming." *The Journal of Supercomputing* 58.3 (2011): 394-402.

[15] Christobel, M., S. Tamil Selvi, and Shajulin Benedict. "Efficient scheduling of scientific workflows with energy reduction using novel discrete particle swarm optimization grids." *The Scientific World Journal* 2015 (2015).