Comprehensive study about different scheduling techniques for parallel applications in cloud computing

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Abstract— Parallel computing gives us an environment through which we can execute numerous assignments at the same time. It enables us to take care of enormous problem by separating it into multiple small problems. As energy utilization while satisfy deadline constraint by PCs has become a concern in recent years. This paper has exhibited a comprehensive review on the different swarm intelligence based energy efficient scheduling techniques. It has been observed that the scheduling in parallel condition is NP-hard in nature. The research on meta-heuristic based job scheduling methods have demonstrated that the utilization of Quick energy aware processor merging has low convergence rate overall world wide minimum even at high numbers of dimensions. Gravitational Search optimization algorithm has been generally acknowledged as a global optimization algorithm of current enthusiasm for disseminated advancement and control. Particle swarm optimization is constrained to beginning arrangement of particles, wrongly chosen particles tends to poor outcomes. Moreover, comparison among different job scheduling methods have displayed that no strategy is ideal for each case. At last, a few considerations about future challenges have been exhibited.

Keywords—Scheduling,Energy,DeadlineandPower

I. INTRODUCTION

Parallel computing provides us an environment through which we can execute many tasks simultaneously. It gives us opportunity to solve big problem by dividing that big problem into several smaller problems. As energy consumption while satisfying deadline constraint by computers has become a concern in recent years.



Figure1.Cloud computing environment for parallel applications

In computing, workflow is a general representation of different scientific applications in distributed system. Large

workflow is representing by DAG (Directed Acyclic Graph) where nodes indicates task and edges presents data flow.

As in this paper, Section I contains the introduction, Section II contain the related work, Section III contain the methodology which defines taxonomy of various scheduling techniques, Section IV describes results and discussion with the help of tables, Section V concludes research work with future directions

II. RELATED WORK

Guoqi Xie, et al. (2017) [1] proposed two algorithms EPM and QEPM for vitality diminishment continuously parallel application in a heterogeneous distributed computing framework than different techniques like DEWSTS calculation. EPM centre around to pick best processor to kill for limiting vitality consume while satisfy deadline constraint and QEPM focus to reduce computation complexity.

Aeshah Alsughayyir, et al. (2016) [2] provided energy minimization for computation in multi-clouds uses DVFS when HPC tasks were under deadline constraint. They used algorithm Energy Aware Scheduling Algorithm and compare it with Cloud Min-Min Scheduling algorithm. Comparison shows that EAGS algorithm consumes low energy by average of 63.9%.

Mateusz Zotkiewicz, et al. (2016) [3] presented a DAG for online energy aware and communication scheduling strategy in SaaS. It contains two phases, first phase set virtual

deadline of one task to central scheduler and these deadlines are determined by strategy that chooses that task which is less dependent on other. Second stage, jobs are allotted to servers according to load. It was basically implemented on Green Cloud Simulator.

Adam Gregory, et al. (2016) [4] provided resource manager for batch workload includes Map Reduce jobs. It empowers specialist organization to accomplish exchange off between vitality utilization, missed due date and executing time. The optimization problem in this paper is to manage the resources to solve he uses Constraint Programming.

Hao Li, et al. (2016) [5] used deadline requirement Vitality mindful calculation for planning the work process in heuristic approach for vitality utilization. For execution utilizes two sub calculations: undertaking mapping calculation for outline to their utility VMs and job merging algorithm for merging tasks in workflow which minimize time consume in data center .

Vahid Arabnejad, et al. (2015) [6] proposed PDC algorithm for E-science Scheduling for commercial clouds. PDC is used to minimize costs and deadline constraint. It had four phases : to separate greatest characteristic parallelism of work process; corresponding due date conveyance to parcel the client level characterize in first stage ; task determination as per need and occurrence choice from best as per execution. CloudSim simulation is used to implement PDC along with GAIN and IC-PCP.

Zhongjin Li, et al. (2015) [7] provided an algorithm for minimizing energy and cost .CEAS (cost and energy aware scheduling) uses CloudSim and four workflow applications. CEAS calculation utilizes five sub-calculations: VM choice calculation for mapping assignments to ideal VM for use cost; two undertakings are converged to limit cost and vitality utilization; VM reuse arrangement to use the VMs that are perfect; and undertaking slacking calculation to spare vitality by DVFS.

Kenli Li, et al. (2014) [8] proposed on scheduling BoT(Bags of Tasks) which was made up of independent stochastic tasks with execution time on heterogeneous platform with energy and deadline budget constraints on single processor. Here Clark's equation was used for find the variance of schedule length and expected value. ESTS calculation was utilized to for high planning execution BoT application with low time complexity.

Hamid Mohammadi Fard, et al. (2012) [10 proposed a general structure and heuristic calculation for multi-target static scheduling of work processes in heterogeneous registering situations. The calculation utilizes constraints indicated by the client for every target and approximates the ideal arrangement by applying a twofold system: augmenting the separation to the imperative vector for prevailing arrangements and limiting it generally. He presents four-objective makespan, economic cost, energy consumption, and reliability. The algorithm Played out a related bi-criteria scheduling heuristic and a bi-criteria genetic algorithm.

Qingjia Huang, et al.(2012) [11] provided an upgraded vitality proficient planning (EES) algorithm to diminish vitality utilization with SLA in Data centre running parallel applications towards the objective of guaranteeing the activity complete before the due date settled on before. Fundamental objective was to think about the slack space for the non-basic employments and endeavor to plan the tasks adjacent running on a uniform recurrence for worldwide optimality.

III. METHODOLOGY

Scheduling

Scheduling is the strategy by which work showed by a couple of means is allotted to scattered resources that aggregate the work. Scheduling makes it possible to have PC multitasking with a singular central getting ready unit (CPU). A scheduler may go for one of various targets, for example, increasing throughput (the total aggregate of work completed per time unit), restricting response (time from work getting the opportunity to be enabled until the point that the moment that the essential point it begins execution on resources), or constraining torpidity (the time between work getting the opportunity to be engaged and its subsequent fulfillment), boosting fairness (measure up to CPU time to every methodology, or all the more generally reasonable conditions as showed by the need and workload of every technique).



Figure2. Taxonomy of workflow scheduling

In Heterogeneous cloud computing system, DAG is used to represent real parallel applications like FFT, Diamond graph and Gaussian elimination. For suppliers, limiting the aggregate vitality utilization of an application is a standout amongst the most essential concerns. For client, the due date imperative of an application is a standout amongst the most vital nature of administration (QoS) necessity. To decrease vitality utilization in HCS, different methods including dynamic voltage-recurrence scaling (DVFS) and memory enhancement have been created. [1]Turning off processors is an accessible path in a few stages. DEWSTS calculation centre around both static and dynamic vitality utilization by turning off processor with modest number of tasks.EPM and QEPM calculations limit both static and dynamic vitality utilization by turn off best processor.

Energy consumption

Energy consumption is defined as the energy consumed by equipment when assignments are executed. DVFS algorithm calculation is for the most part used to lessen vitality .The power utilization for an application execution is made out of static and dynamic vitality utilization .Most work focuses on the dynamic energy consumption. Research into improving the energy consumption often focuses on the hardware, or programming techniques to improve energy efficiency. Realtime measurements are referred to as Dynamic Analysis, whereas Static Analysis means analyzing the code without necessarily having to run it.



[13]Types of Energy consumption

Dynamic Energy :

Dynamic energy consumption refers to measure the energy draw of its hardware when operations are performed. This method poses several problems: the equipment and time required to perform the measurement are expensive, it takes a significant amount of time to run a sufficient number of tests, and the tests themselves have to be accurate and cover at least regular usage, preferably more. Nevertheless, a proper analysis meeting these requirements can be used to identify bottlenecks in both the code and actual hardware, or satisfy specific energy or time constraints. This option is attractive for businesses, those working with potentially dangerous equipment, and other users in charge of maintaining hardware on a large scale; case studies have been performed on varied hardware such as networking devices, mobile consumer electronics and CPU hardware.

Static Energy:

The investment required to perform dynamic analysis, and its susceptibility for errors, opens up demand for a faster

Vol.6(3), Mar 2018, E-ISSN: 2347-2693

analysis lacking many of the requirements posed by actual power measurement. This form of analysis, which focuses on analyzing code or systems without running it or activating them, is referred to as static analysis. While it does not share the disadvantages of a dynamic analysis, it also does not provide the same advantages: without real measurement, the result of a static analysis will always be approximate. Accuracy instead depends on how accurate the models and rules for reasoning about the energy consumption are. The main draw of this form of analysis is the ease of application. Rather than having to acquire measuring equipment and perform all the required steps for a dynamic analysis, it may be executed on any system, independent of the actual hardware it is running on. However, one problem not present with dynamic analysis is the fact that, in general, it is very difficult, if not impossible without intervention, to completely predict a program's behavior. Concessions have to be made to accuracy in order to be able to perform the analysis as best as possible. Several projects present that focus on static analysis of code, some of which are described in greater detail below. In particular, this thesis focuses on extending an existing analysis, and applying these extensions.

Processor merging:

Processor merging is defined as completely satisfy the requirements of the jobs submitted by user. Two types of methodology exist in parallel environment that is either split job into sub jobs so called tasks and processor merging. Since sometimes, it is not possible to divide job into tasks in such a case ,if required number of resources by given resources is more than available number of resources then to implement given job processor merging will be used. Example we assume that job demand 66 processors, and let be assume server A has 32 resources, B has 16 resources and C has 32 resources, then job is not divisible. So job must be divisible.

IV. RESULTS AND DISCUSSION

Technique	Year	Objective	Energy	Deadline	Cost	Metrics
MOLS and	2012	Multi -	√	×	\checkmark	Makespan , reliability
Time Constraint		objective				
Partioning [10]		-				
Energy-aware		Bi-	√	✓	×	Energy used
stochastic tasks	2012	objective				
scheduling		-				
algorithm						
(ESTS)[18]						
Enhanced	2012	Bi-	√	\checkmark	×	Schedule length and energy
energy-efficient		objective				
scheduling (EES)						

Table 1 Summary of distinguished related work ordered utilizing scientific categorization

Vol.6(3), Mar 2018, E-ISSN: 2347-2693

Slack-time-	2013	Bi -	✓	\checkmark	×	Energy conservation
aware two-phase		objective				
scheduling		5				
framework ,ILP-						
based scheduler in						
offline[17]						
GMaP	2013	Bi-	✓	\checkmark	×	Energy cost and time
framework[9]		objective				85
		j				
Energy-aware	2014	Single	✓	×	×	Energy consumption
multi-job	2011	Single				Lineigj consumption
scheduling						
ontimization						
model bi-level						
genetic						
algorithm[12]						
Energy_aware	2014	Bi-	 ✓ 	\checkmark	×	Execution time and budget
stochastic	2014	objective		,		Execution time and budget
task scheduling		objective				
algorithm						
ESTS[8]						
Cat Sama	2014	D:				Cost and an arrest
Cat-Swarm-	2014	Bl-	v	×	v	Cost and energy
Optimization[14]	2015	objective				
Cost and	2015	Multi-	~	\checkmark	~	Makespan, cost
energy aware		objective				
scheduling						
(CEAS) [7]						
Proportional	2015	Bi-	×	\checkmark	~	Computation Cost and time
Deadline		objective				
Constrained						
(PDC) [6]						
TaPRA and	2016	Single	\checkmark	×	×	Completion time
TaPRA-fast		job				
that solve the SJS		scheduling				
problem.		and Online				
In online		scheduling.				
scheduling,						
OnTaPRA.[2						
0]						
Constraint		D.		1		
	2016	B1-	v	•	×	Energy consumption and time
Programming,	2016	B1- objective	v	•	×	Energy consumption and time complexity
Programming, IBM CPLEX CP	2016	bjective	v	·	×	Energy consumption and time complexity
Programming, IBM CPLEX CP Optimizer[4]	2016	B1- objective	v	·	×	Energy consumption and time complexity
Programming, IBM CPLEX CP Optimizer[4] Workflow	2016	B1- objective Single	✓ ✓	×	×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for	2016	B1- objective Single objective	✓ ✓	×	×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy	2016	Bi- objective Single objective	✓ ✓	×	× ×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization	2016	Bi- objective Single objective	✓ ✓	×	× ×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM)	2016	Bi- objective Single objective	✓ ✓	×	× ×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat	2016	Bi- objective Single objective	✓ ✓	×	×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm	2016	Bi- objective Single objective	× 	×	× ×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24]	2016	Bi- objective Single objective	▼ ✓	×	× ×	Energy consumption and time complexity Energy used
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware	2016	Bi- objective Single objective Bi-	× 	×	× ×	Energy consumption and time complexity Energy used Execution time and energy
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling	2016 2016 2016	Bi- objective Single objective Bi- objective	× • •	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm.	2016 2016 2016	Bi- objective Single objective Bi- objective	• • •	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS	2016 2016 2016	Bi- objective Single objective Bi- objective	× 	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two	2016 2016 2016	Bi- objective Single objective Bi- objective	× 	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms:	2016 2016 2016	Bi- objective Single objective Bi- objective	✓ ✓ ✓	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: iob mapping	2016 2016 2016	Bi- objective Single objective Bi- objective	· ·	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job	2016 2016 2016	Bi- objective objective Bi- objective	v • •	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5]	2016 2016 2016	Bi- objective objective Bi- objective	• •	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum	2016 2016 2016 2016	Bi- objective Bi- objective	× 	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies	2016 2016 2016 2016	Bi- objective Bi- objective Bi- objective	×	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume Execution time
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies Energy-efficient	2016 2016 2016 2016	Bi- objective Single objective Bi- objective Bi- objective	×	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies Energy-efficient DAG (MinD+ED)	2016 2016 2016 2016	Bi- objective Bi- objective Bi- objective	×	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies Energy-efficient DAG (MinD+ED) [3]	2016 2016 2016 2016	Bi- objective Single objective Bi- objective Bi- objective	✓ ✓ ✓	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume Execution time
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies Energy-efficient DAG (MinD+ED) [3] Energy-aware	2016 2016 2016 2016	Bi- objective Single objective Bi- objective Bi- objective	×	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume Execution time
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies Energy-efficient DAG (MinD+ED) [3] Energy-aware	2016 2016 2016 2016 2016	Bi- objective Single objective Bi- objective Bi- objective	× ×	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume Execution time Execution time
Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies Energy-efficient DAG (MinD+ED) [3] Energy-aware scheduling algorithm	2016 2016 2016 2016 2016	Bi- objective Single objective Bi- objective Bi- objective	✓ ✓ ✓ ✓	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume Execution time The number of rejected applications
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Programming, IBM CPLEX CP Optimizer[4] Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat Swarm Optimization[24] Energy aware scheduling (EAS)algorithm. The EAS comprises of two sub algorithms: job mapping algorithm and job blend algorithm[5] Minimum Dependencies Energy-efficient DAG (MinD+ED) [3] Energy-aware scheduling algorithm EAGS[2] Fixed Frequency Island- Aware L argeet	2016 2016 2016 2016 2016 2017	Bi- objective Single objective Bi- objective Bi- objective Bi- objective	✓ ✓ ✓ ✓ ✓	×	× × ×	Energy consumption and time complexity Energy used Execution time and energy consume Execution time The number of rejected applications Deadline and energy

Task First						
(FFI-LTF)						
heterogeneous						
Island-Aware						
Largest Task						
First (HI-						
LTF) Fixed						
Frequency Island-						
and Task-Aware						
Largest Task						
First (FIT-LTF)						
[16]						
EPM and	2017	Bi -	~	\checkmark	×	Computation time.
QEPM[1]		objective				-

Table 2 Summarization of tools and applications						
Technique	Software	Hardware	Application	Platform		
MOLS and Time Constraint Partioning [10]	GroudSim		WIEN2k and MeteoAG	Grid and Cloud		
Energy-aware stochastic tasks scheduling algorithm (ESTS)[18]	C++		BoT applications or parameter sweep applications,	Heterogeneous computing systems (HCS)		
Enhanced energy-efficient scheduling (EES)			Gaussian Elimination algorithm and Random DAG Generator	Cloud		
Slack-time-aware two- phase scheduling framework ,ILP-based scheduler in offline[17]	Online and offline	Four general purpose (GP) cores and four dedicated hardware accelerators (DHAs) and an L2 cache.		Multiprocessor systems-on- chips		
GMaP framework[9]	Monte Carlo			Cloud		
Energy-aware multi-job scheduling optimization model, bi- level genetic algorithm[12]	_	2.53 GHz Intel Xeon processor framework with 3.48 GB Smash running Windows XP.	MapReduce and Hadoop	Cloud		
WSEPT (weighted shortest expected processing time) and Energy-aware stochastic task scheduling algorithm ESTS[8]	C++		Bag-of-tasks (BoT)	HCS		
Cat-Swarm- Optimization[14]	Monte Carlo			Cloud		
Cost and energy aware scheduling (CEAS) [7]	Cloudsim		Monotage, CyberShake, LIGO	Cloud		
Proportional Deadline Constrained (PDC) [6]	CloudSim		EScience	Commercial clouds		
TaPRA and TaPRA-fast that solve the SJS problem. In online scheduling, OnTaPRA.[20]	Offline and online simulations		SJS-Relax-LP and online scheduling	Cloud		
Constraint Programming, IBM CPLEX CP Optimizer[4]	Java	3.2GHz Intel Center i7 CPU and 8GB of Slam window 7.2.6 GHz Intel CPU and 4 GB memory.	Map reduce	Cloud		
Workflow Partitioning for Energy Minimization (WPEM) algorithm and Cat	CloudSim			Cloud		

Table 2 Summarization of tools and applications

Swarm Optimization[24]				
Energy aware scheduling (EAS)algorithm. The EAS consists of two sub algorithms: task mapping algorithm and task merge algorithm[5]	CloudSim		Bio informatics and earth science,	Cloud
Minimum Dependencies Energy-efficient DAG (MinD+ED) [3]	GreenCloud		Online scheduling, SaaS applications	Cloud
Energy-aware scheduling algorithm EAGS[2]	SimJava		Iaas applications	Cloud
Fixed Frequency Island- Aware Largest Task First (FFI-LTF) heterogeneous Island-Aware Largest Task First (HI-LTF) Fixed Frequency Island- and Task- Aware Largest Task First (FIT- LTF)[16]	Gem5 and McPAT for the Alpha coresOdroid-XU3 platform for the A7 and A15 cores	Exynos 5 Octa (5422) processor with Cortex-A7 and Cortex-A15 islands, and also using gem5 and McPAT for out-of- order (OOO) Alpha 21264 and in-order simple Alpha 21264 islands	Blackscholes, bodytrack, ferret, swaptions, and x264, PARSEC	Cluster
EPM and QEPM[1]	Java	2.6 GHz Intel CPU and 4 GB memory	FFT, Diamond graph and Gaussian elimination	Cloud

V. CONCLUSION AND FUTURE SCOPE

This paper has exhibited a far reaching survey on the diverse swarm intelligent based energy effective scheduling strategies. It has been watched that the planning in parallel condition is NP-hard in nature. The examination on metaheuristic based employment planning strategies have demonstrated that the utilization of Quick energy aware processor merging has low convergence rate over worldwide minimum least even at high quantities of measurements. Gravitational search enhancement algorithm has been generally acknowledged as a worldwide advancement algorithm of current enthusiasm for dispersed optimization and control. Particle swarm advancement is constrained to beginning arrangement of particles, wrongly chose particles tends to poor outcomes. In addition, comparison among various job scheduling techniques have presented. The comparative analysis obviously demonstrates that the no procedure is ideal for each case.

In this manner, in near future we will propose a new hybrid Gravitational search algorithm and Quick energy aware processor merging algorithm for cloud computing environment. We mainly focus on the objectives like Speedup, Execution time, Power consumption and Energy cost.

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