INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

Energy Efficient Scheduling of Real Time Tasks on Large Systems and Cloud

by

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A thesis submitted in partial fulfillment for the degree of Doctor of Philosophy

in the
Department of Computer Science and Engineering

Under the supervision of
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December 2018

Declaration of Authorship

I, Manojit Ghose, do hereby confirm that:

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This is to certify that the thesis entitled **"Energy Efficient Scheduling of Real Time Tasks on Large Systems and Cloud"** being submitted by **Mr. Manojit Ghose** to the department of *Computer science and Engineering, Indian Institute of Technology Guwahati*, is a record of bonafide research work under my supervision and is worthy of consideration for the award of the degree of Doctor of Philosophy of the institute.

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Dedicated to

Late Prafulla Bala Ghose (my grandmother)

Acknowledgements

I feel extremely humble and blessed when I look back and feel the amount of kindness, encouragement, help, and support that everyone has offered during the journey of my Ph. D. Our success is not only determined by our own effort and dedication, but it is actually a collective outcome of the efforts, sacrifices, contributions, help, and support of others. I take this platform to thank each one of them who has directly or indirectly helped me to reach this stage.

I start by expressing my deep and sincere gratitude to my thesis supervisor Dr. Aryabartta Sahu for his valuable guidance, constant support, persistent encouragement. I wouldn't have been completed this work without his expertise, valuable inputs, and suggestions. His friendly nature always helped in healthy debates and discussions. I specially thank him for his tireless efforts and countless numbers of revisions of the thesis and publications. He is indeed a helpful person and a great human being. I couldn't have attended the conferences abroad without his generous help and support. I am indeed ever grateful to him.

Next, I would like to thank my thesis co-supervisor Dr. Sushanta Karmakar for his invaluable guidance and the advice throughout my Ph. D. tenure. I would like to express my gratitude and gratefulness to all the members of my Doctoral Committee, Prof. Diganta Goswami, Dr. Santosh Biswas, and Dr. Partha Sarathi Mandal for their constructive criticism and corrective feedback. Their valuable suggestions and inputs helped me a lot to improve the quality of my work.

Further, I would like to sincerely thank Prof. S. V. Rao, the Head of the Department of Computer Science and Engineering and other faculty members for their constant supports and helps, and encouragements. I specially thank Prof. Hemangee K. Kapoor, Prof. Pradip K. Das for their generosity. Furthermore, I express my thanks and regards to all the technical and administrative staff members of the department for their help whenever I asked for. I would also like to take the opportunity to thank my Government for providing such a high-class facility which stands far beyond the life of an average Indian citizen.

I am ever grateful to Prof. Sukumar Nandi and Prof. Ratnajit Bhattacharjee for their encouragement, help, and support whenever I needed. They remain a source of inspiration for me. I would also to express my sincere thanks and gratitude to Mrs. Nandini Bhattacharya for her constant love and care. Also, I would like to express my appreciation and thanks to some of my teachers whose words of encouragement still motivate me to work. They are Prof. Manoj Das, Mr. Sushanta Saha, Mr. Subhendu Saha, Dr. Rupam Baruah, and others.

I had a wonderful time at IIT Guwahati, met many beautiful minds, spent quality time, and finally made good friends. All of them have directly or indirectly helped me to achieve my dream. To name a few of them, they are Nilakshi, Parikshit, Chinmaya, Shirsendu, Binita, Debanjan, Roshan, Shounak, Satish, Pradip, Shibaji, Sathisa, Himangshu, Rakesh, Hema, Sourav, Ferdausa, Needhi, Mayank, Pranab, Barasa, Vasudevan, Sanjit, Sanjay, Diptesh, Rahul, Sayan, Rajashree, Udeshna, Rana, Biplab, Arunabha, and others. I also worked with a couple of masters students during my Ph. D. They are Pratyush, Sawinder, Anoop, Sandeep, and Hardik. It was indeed a wonderful experience to work and share ideas with them. I also thank all my well-wishers, friends inside and outside the IIT Guwahati. I sincerely thank my colleagues at DUIET for extending their help and support during the last phase of my Ph. D.

During the course of my study, I had the opportunity to know some amazing human beings: Dr. Devanand Pathak, Mr. Vishnu Prakash, Mr. Avinash Tiku, Mr. Ram Bahadur Gurung, Dr. Azd Zayoud, and others. It was indeed a matter of joy and fun to learn various skills from them.

Finally, I express my thanks and regards toward all the family members for their constant support. It was a tough time for them to accept my decision of joining the Ph. D. leaving my job. But finally, they are happy and I could bring a smile to their faces. I also express my thanks to the anonymous reviewers of my papers and thesis for their constructive comments and feedbacks.

Abstract

Large systems and cloud computing paradigm have emerged as a promising computing platform of recent time. These systems attracted users from various domains, and their applications are getting deployed for several benefits, such as reliability, scalability, elasticity, pay-as-you-go pricing model, etc. These applications are often of real-time nature and require a significant amount of computing resources. With the usages of the computing resources, the energy consumption also increases, and the high energy consumption of the large systems has become a serious concern. A reduction in the energy consumption for the large systems yields not only monetary benefits to the service providers, but also yields performance and environmental benefits as a whole. Hence, designing energy-efficient scheduling strategies for the real-time applications on the large systems becomes essential.

Considering power consumption construct at a finer granularity with only DVFS technique may not be sufficient for the large systems. The first work of the thesis devises a coarse-grained thread-based power consumption model which exploits the power consumption pattern of the recent multi-threaded processors. Based on this power consumption model, an energy-efficient scheduling policy, called Smart scheduling policy, is proposed for efficiently executing a set of online aperiodic real-time tasks on a large multi-threaded multiprocessor system. This policy shows an average energy consumption reduction of around 47% for the synthetic data set and approximately 30% for the real-world trace data set as compared to the baseline policies. Thereafter, three improvements of the basic Smart scheduling policy are proposed to handle different types of workloads efficiently.

The second work of the thesis considers a utilization-based power consumption model for a virtualized cloud system where the utilization of a host can be divided in three ranges (*low*: utilization is below 40%, *medium*: utilization is from 40% to 70%, and *high*: utilization is above 70%) based on the power consumption of the host. Then two energy-efficient scheduling policies, namely, *UPS* and *UPS-ES* are designed addressing this range based utilization of the hosts. These scheduling policies are designed based on the urgent points of the real-time tasks for a heterogeneous computing environment. Experiments are conducted on CloudSim toolkit with a wide variety of synthetic data set and real-world trace data including the Google cloud tracelog and Metacentrum trace data. Results show an average energy improvement of almost 24% for the synthetic data set and almost 11% for the real-world trace as compared to the state-of-art scheduling policy.

As the cloud providers often offer VMs with discrete compute capacities and sizes, which leads to discrete host utilization, the third work of the thesis considers scheduling a set of real-time tasks on a virtualized cloud system which offers VMs with discrete compute capacities. This work calculates a utilization value for the hosts, called *critical utilization* where the energy consumption is minimum and the host utilization is maintained at this value. The problem is divided into four sub-problems based on the characteristics of the tasks and solutions are proposed for each sub-problem. For the sub-problem with arbitrary execution time and arbitrary deadline, different clustering techniques are used to divide the entire task set into clusters of tasks. Results show that the clustering technique can be decided based on the value of the critical utilization.

The fourth work of the thesis considers scheduling of online scientific workflows on the virtualized cloud system where a scientific workflow is taken as a chain of multi-VM tasks. As the tasks may require multiple VMs for their execution, two different VM allocation methodologies are tried: *non-splittable* (all the VMs executing a task must be allocated on the same host) and *splittable* (VMs executing a task may be allocated to different hosts). In addition, this work discusses several options and restrictions considering migration and slack distribution. A series of scheduling approaches are proposed considering these options and restrictions. Experiments are conducted on the CloudSim toolkit and the comparison is done with a state-of-art scheduling policy. Results show that the proposed scheduling policy under non-splittable VM allocation category consumes a similar amount of energy as the baseline policy but with a much lesser number of migrations. For the splittable VM allocation category, the proposed policies achieve energy reduction of almost 60% as compared to the state-of-art policy.

Contents

List of Figures

List of Tables

Abbreviations

HT	Hardware Thread
DVFS	Dynamic Voltage and Frequency Scaling
LMTMPS	Large Multi-Threaded Multiprocessor Systems
FWC	Front Work Consolidation
RWC	Rear Work Consolidation
UBWC	Utilization Based Work Consolidation
ED	Early Dispatch
HIU	Handling Immediate Urgency
BPC	Base Power Consumption
TPC	Total Power Consumption
TEC	Total Energy Consumption
UBA	Utilization Based Allocation
IPC	Instantaneous Power Consumption
UPS	Urgent Point aware Scheduling
UPS-ES	Urgent Point aware Scheduling - Early Scheduling
FUP	Future Urgent Point
CUP	Critical Urgent Point
GWQ	Global Waiting Queue
EARH	Energy Aware Rolling Horizon
SCUP	Scheduling at Critical Urgent Point
STC	Scheduling at Task Completion
SWC	Scheduling With Consolidation
NSVM	Non-Splittable VM allocation
SVM	Splittable VM allocation
SFT	Slack To First task
SFW	Slack Forward
SDF	Slack Forwarding and Distribution

Notations

P_{Base}	Base power consumption of a processor
δ	Power consumption of a thread in a processor
a_i	Arrival time of a task
e_i	Execution time of a task
d_i	Deadline of a task
s_i	Start time of a task
f_i	Finish time of a task
v_{jk}	j^{th} VM on k^{th} host
$CP(v_{jk})$	Compute capacity of VM v_{jk}
e_{ijk}	Execution time of task t_i when executed by VM v_{jk}
$rt(v_{jk})$	Ready time of VM v_{jk}
$st(v_{jk})$	Start time of VM v_{jk}
$slk(t_i)$	Slack time of task t_i
u_c	Critical utilization of a host
$t_{i,p}$	i^{th} task of a workflow WF_p
a_p	Arrival time of a workflow
d_p	Deadline of a workflow
$n_{i,p}$	VM requirement of the task $t_{i,p}$
$l_{i,p}$	Length of the task $t_{i,p}$
e_{ipjk}	Execution time of the task $t_{i,p}$ when executed by the VM v_{jk}

Chapter 1

Introduction

1.1 Multiprocessor Scheduling

In general, multiprocessor scheduling is defined as executing a set of tasks $T = \{t_1, t_2, t_3, \cdots, t_n\}$ on a set of processors $P = \{P_1, P_2, \cdots, P_m\}$ to meet some predefined objective functions [5, 6, 7]. A scheduling problem is represented by a triple $\alpha|\beta|\gamma$ where α indicates processor environment, β indicates task environment and γ indicates objective function.

Processor environment (α): The processor environment is characterized by a string $\alpha = \alpha_1\alpha_2$ where α_1 indicates machine type and α_2 is an integer which indicates number of machines. α_1 can have values P, Q, R, etc. P indicates identical parallel machine, that is, the processing time of a task is same for all the machines. Q indicates uniform parallel machine, that is, the processing time of a task depends on the speed of the machine. R indicates unrelated parallel machine, that is, the processing time of the tasks are not related at all.

Task environment (β): The task environment in a multiprocessor scheduling specifies the properties of the task set. This is represented using a string $\beta = \beta_1\beta_2\beta_3\beta_4\beta_5\beta_6$. These parameters are described below.

- β_1 indicates whether preemption is allowed or not. A value *pmtn* means preemption is allowed and an empty field indicates preemption is not allowed.
- β_2 indicates the precedence constraints among the tasks in the task set. An empty value indicates that the tasks are independent.

- β_3 indicates the release time or the arrival time of the tasks.
- β_4 indicates some additional specifications like the processing time of the tasks.
- β_5 specifies the deadline of the tasks if any. A task with a specified deadline is called a real-time task.
- β_6 indicates whether the task set is to be processed in a batch processing mode.

Objective function (γ): The objective function of a scheduling problem is also termed as the optimality criteria for the problem. The objective functions can be the bottleneck objectives or the sum objectives. One of the most common optimality criteria in multiprocessor scheduling is the total schedule length. This is also called as *makespan* time in literature. Makespan time indicates the completion time of the task which finishes at last. This is expressed as $C_{max} = \max\{C_i\}$, where C_i is the completion time of task t_i and i varies from 1 to n (n is total number of tasks). Other common objective functions of multiprocessor scheduling problem are total flow time $\sum_{i=1}^{n} C_i$, total weighted flow time $\sum_{i=1}^{n} w_i C_i$, etc. In case of real-time tasks, the optimality criteria are normally expressed using the deadline of the tasks. One common objective function in this case is $L_{max} = \max\{C_i - d_i\}$, where d_i is the deadline of a task t_i, and L_i is termed as lateness. Other objective functions can be the number of tasks missing their deadline constraints, number of tasks failing service level agreements, etc. Moreover, the objective function of a scheduling problem can also be expressed as a combination of two or more different functions.

Example of some scheduling problems:

- $P|pmtn|C_{max}$ denotes the scheduling problem with M identical machines where a set of tasks is to be executed to minimize the total schedule length, and the preemption of the tasks is allowed. This can be solved in $O(n)$ time where the tasks are assigned to the processors in any order with a uniform share of processing time. A task is split into parts in case it requires more time than the share [8].
- $P||C_{max}$ denotes the scheduling problem with M identical machines where a set of tasks is to be executed to minimize the total schedule length, and

the preemption of the tasks is not allowed. When preemption is not allowed, the problem becomes difficult and this problem is proved to be NP-hard [8]. For the two processor case (represented as $P2||C_{max}$), the problem gets mapped to the subset sum problem where n numbers (i.e. tasks) needs to be partitioned into two subsets with almost equal sum and the problem is a known to be a NP-complete problem [9].

- $R|pmtn; r_i|L_{max}$ denotes the problem of scheduling a set of tasks on a multiprocessor system of unrelated machines to minimize the maximum lateness. The tasks can have arbitrary arrival time. This problem can be solved polynomially by formulating linear programs considering the tasks in non-decreasing order of their deadlines [8].

1.2 Classification of Multiprocessor Scheduling Algorithms

Scheduling algorithms can be classified based on various parameters [6]. Here we mention a few classifications which are based on some important parameters.
Preemption: If the execution of a task is interrupted at any time to assign the processor to some other task, it is called preemptive scheduling. When the task execution cannot be interrupted at all, it is called non-preemptive scheduling. However, if the tasks can be preempted at certain points only, the scheduling is termed as co-operative scheduling.
Priority: If the priority of a task changes in the course of execution, it is termed as dynamic priority scheduling. If the priority of the tasks does not change during execution, it is termed as static priority scheduling. Priority of a task may be assigned based on parameters, such as deadline, laxity, execution time, etc.
Migration: When a task can migrate from one processor to any other processor, it is termed as global scheduling. When a task cannot migrate from one processor to another, it is termed as partitioned scheduling. But when a task can migrate from one processor to a set of processors, it is termed as semi-partitioned scheduling.
Online or offline: An online task is the one whose information becomes available only after its arrival. Scheduling algorithm decides dynamically whenever the tasks arrive at the system. These scheduling algorithms are termed as online scheduling. On the other hand, offline scheduling deals with the tasks whose information is available beforehand.

1.3 Real Time Scheduling

Real-time systems are the ones which must confront to both the functional correctness as well as temporal correctness [6, 10]. The systems must show logically correct behavior on correct time. A task in a real-time system possesses a temporal parameter, which is called the deadline of the task. These deadlines can be categorized into two types: hard and soft. A task with a hard deadline must finish its execution before the deadline. However, in the case of a soft deadline, the task execution may exceed its deadline. In that case, some penalty is imposed [11]. On the basis of the arrival time, the task set in a real-time system can be mainly categorized as *periodic*, and *aperiodic*. A periodic task is one which is activated at a regular time interval or period. That is the arrival time of the tasks are known beforehand. An aperiodic task is one which is activated or released irregularly. Thus the arrival time of the tasks become known after they actually arrive at the system.

1.3.1 Scheduling of periodic real-time task scheduling

There is a wide variety of scheduling algorithms available for the periodic real-time tasks [6, 7]. Here, we briefly discuss some of the popular scheduling techniques in the context of real-time task scheduling.

Rate monotonic: Rate monotonic (RM) is a fixed priority preemptive scheduling technique for periodic tasks. This scheduling technique assigns priority to the tasks based on their periods. A task with a shorter period (i.e., higher request rate) gets higher priority. Priority is assigned before the execution and it is not changed during the course of execution. RM is an optimal scheduling algorithm in case of uniprocessor system in the sense that if some fixed priority scheduling technique can schedule a task set, then the task set can also be scheduled by RM [12]. Joseph and Pandya [13] showed that a real-time system under RM scheduling technique is schedulable if and only for all t_i, $(r_i) \leq p_i$, where r_i is the the release time and (p_i) is the period of task t_i.

Deadline monotonic: An immediate extension of RM scheduling technique is deadline monotonic (DM) which was proposed by Leung and Whitehead [14]. This is a fixed priority, preemptive scheduling technique for periodic tasks. Priority of the tasks is assigned based on their relative deadline values. The task with the shortest relative deadline is executed first. The DM scheduling algorithm is also an optimal scheduling algorithm in case of uniprocessor system in the sense that if some fixed priority scheduling technique can schedule a task set, then the task set can also be scheduled by DM [12].

Earliest deadline first: Earliest deadline first (EDF) is implicitly a preemptive scheduling technique where priority is assigned based on the deadline of a task. A task with earlier deadline indicates higher priority and it preempts the execution of a task with a later deadline. EDF is found to be an optimal scheduling technique for uniprocessor systems in the sense that if any task set is schedulable by an algorithm, then EDF can also schedule the task set.

1.3.2 Scheduling of aperiodic real-time task scheduling

In this section, we present some of the popular scheduling algorithms for the aperiodic tasks.

Jackson's algorithm: This is another popular algorithm for scheduling a set of aperiodic tasks. This algorithm considers scheduling a set of synchronous tasks on a single processor to minimize the maximum lateness. This algorithm is a non-preemptive version of EDF and commonly termed as the earliest due date (EDD) first scheduling. EDD algorithm guarantees that if any feasible schedule exists for a task set, then the algorithm finds it. The algorithm runs by sorting the tasks based on their due date. Thus for a task set with n tasks, the algorithm takes $O(nlogn)$ time.

Earliest deadline first: As the EDF scheduling policy does not assume anything about the periodicity of the tasks while scheduling, it works for both periodic and aperiodic tasks in the same way (EDF is already defined for periodic tasks in the previous section). This is also known as Horn's algorithm [15]. The complexity of this algorithm depends on the implementation of the ready queue. If the ready queue is implemented as a list, then the complexity becomes $O(n^2)$. If the ready queue is implemented as a heap, then the complexity becomes $O(nlogn)$.

Least laxity first: This is an immediate derivation of EDF scheduling technique where the priority of a task changes during the course of execution. Priority of task t_i at time instant t is calculated as $d_i - t$; which is the laxity value at that time instant. This is a dynamic priority-based preemptive scheduling technique. The complexity of this algorithm is $O(n_1 + n_2^2)$, where n_1 is the total number of requests in a hyper-period of periodic tasks in the system if any, and n_2 is the total number of aperiodic tasks in the system [16].

Bratley's algorithm: This algorithm tries to find a feasible schedule for a set of non-preemptive independent tasks for a single processor system. The algorithm does an exhaustive search in order to get a solution. While doing so, the algorithm constructs a partial schedule by adding a new task in each step. A path is discarded whenever the algorithm encounters a task which misses its deadline. This algorithm is a tree-based search algorithm and for each task, the algorithm might need to explore all the partial paths originating at that node. Thus the time complexity of this algorithm becomes $O(n \cdot n!)$.

1.4 Aperiodic Real-Time Task Scheduling on Multiprocessor Environment

The above-mentioned algorithms were initially designed for a single processor system. But as we move into the multiprocessor systems, a new dimension is added to the scheduling problems, that is, the number of processors is increased from 1 to m. Choosing a processor from a pull of free processors is termed as allocation problem and is popularly known as mapping [17]. The allocation problem is often viewed as a bin packing problem and several popular bin-packing heuristics, such as First Fit, Next Fit, Best Fit, Worst Fit, etc. are clubbed with the uniprocessor scheduling algorithms. In addition, the multiprocessor scheduling algorithms make use of another factor for designing efficient scheduling policies. This is called **migration** of tasks from one processor to another. In case of migration, the execution of one task on a processor is preempted and the task is assigned to another processor. Thus the task needs to shift (i.e. migrate) from one processor to another.

Majority of the scheduling problems for the aperiodic task set on multiprocessor environment are non-polynomial except for task sets with restricted execution time and the deadline [5]. Thus various heuristics are proposed to solve these problems. When these algorithms are clubbed with the bin packing algorithms [18] to fit into the multiprocessor environment, they are named as Earliest Deadline First - First Fit (EDFFF), Earliest Deadline First - Best Fit (EDFBF), Earliest Due Date First - Best Fit (EDDBF), etc. [19, 20, 21, 22].

1.5 Large Systems and Cloud

Large systems refer to the computing platform where a number of computing nodes (or systems) are connected via a high-speed network to form a single computing hub. These computing hubs are also known as data centers. The basic objective of these systems is to meet the computation requirement of the recent high-end scientific applications of various domains. These systems include Cluster, Grid, and Cloud. In Cluster computing, the physical distance between the participating nodes is not much, and they are often connected using LAN (local area network). The computing nodes in a cluster are typically of homogeneous nature. In the case of Grid computing, the computing nodes are geographically distributed and belong to multiple administrative domains. The grid is a decentralized distributed computing paradigm where the users rent the computing facility on an hourly basis. On the other hand, Cloud comes under a centralized model where a single service provider usually owns the resources.

1.5.1 Cloud computing and virtualization

Cloud computing is an emerging resource sharing computing platform which offers a large amount of space and computing capability to its users via the Internet. The users are charged as "pay-as-go" model based on their resource usages. There exist various definitions of the cloud computing paradigm. One of the commonly accepted definitions proposed by the National Institute of Standards and Technology (NIST) is

"cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" [23].

Figure 1.1 shows the three-layered architecture of a typical cloud computing paradigm. The system consists of an application layer, a virtualization layer, and a hardware layer. The user requests arrive in the form of applications or tasks. These tasks are accumulated in a single place for its processing based on the underlying scheduling policy. The next layer is the virtualization layer. This layer plays the most vital role and makes the cloud computing paradigm the popular, efficient and attractive. This layer accepts the requests from the application layer. The user tasks may require any specific application software or operating system (OS), etc. for

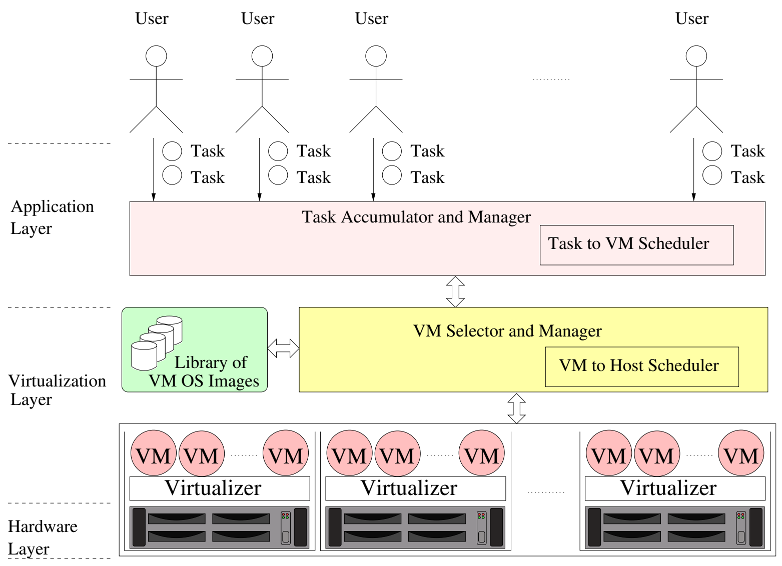


FIGURE 1.1: Cloud computing architecture

their execution. The job of the VM scheduler and manager is to facilitate an appropriate virtual machine (VM) which meets the requirement of the task. If required, a VM with the requirement is created with the help of the VM OS library. The bottom-most layer is the hardware layer which consists of the physical hosts where the VMs are placed with the help of the virtualizer. The main benefit of this architecture is that it can cater the user requests with any specific OS and platform requirements irrespective of the host OS and underlying hardware. In addition, various OSes can run together in the form of VMs sharing the resources of the same hardware. This reduces the hardware requirement and thereby the cost.

1.6 Real-Time Scheduling for Large Systems and Cloud

Large computing systems such as the cloud provide some important features to its users, such as dynamic pricing model, reliability, scalability, elasticity, dynamic and seamless addition and removal of resources, etc. These features have attracted applications from several domains for their deployment [24, 25, 11]. These applications are often of real-time nature. Thus the real-time scheduling for large systems becomes crucial.

The traditional real-time scheduling algorithms try to improve utilization bound, reduce approximation ratio and resource augmentation, and to improve some empirical factors like the total schedule length, total laxity, number of deadline misses, etc. On the other hand, the deployed applications typically consist of hundreds of compute-intensive, data-intensive and communication intensive tasks. Thus a significant amount of computing resource is required to execute these applications. Hence, the traditional scheduling algorithms are not adequate. For efficient execution of these applications on the large systems, they should be scheduled in an energy-efficient way. The energy-efficient execution of these real-time applications (or tasks) benefits both the users and the service providers. In the next section, we discuss the energy consumption scenario for the large systems.

1.6.1 Workflow Scheduling for Large Systems and Cloud

Several scientific applications of different domains such as astronomy, astrophysics, bioinformatics, high energy physics, etc. are modeled as scientific workflows or tasks graphs [26, 25]. These workflows typically consist of hundreds of compute-intensive, data-intensive and communication intensive tasks. Thus a significant amount of resource is required to execute them. Another characteristic of scientific workflow is the variation in their resource requirement.

The traditional computing platforms, such as grid and clusters are not adequate to handle such high resource intensive applications and the variation in their resource requirement. On the other hand, the emerging cloud computing platform is found to be a better choice [27, 28]. As the scientific workflows require a large number of computing resources for execution, it is imperative to schedule them on the cloud not only in a performance-efficient way but also in an energy-efficient way.

1.7 Energy Consumption in Large Systems

1.7.1 Power consumption models

Modern day's computer systems are built using the complementary metal-oxide semiconductors (CMOS) technology. There are mainly two components in the power consumption of a CMOS circuit: *static* and *dynamic*. The static component is dependent on the system parameters, such as number and type of transistors, process technology, etc. On the other hand, the dynamic power consumption is basically driven by the circuit activities and traditionally it was believed to be the major contributor [29]. A wide volume of research on scheduling is done which considers only the dynamic power consumption [30, 31, 32, 33, 34].

Mathematically, we write

$$P_{total} = P_{base} + P_{dyn} \tag{1.1}$$

where, P_{base} is the static power consumption, and P_{dyn} is the dynamic power consumption.

The dynamic power consumption is expressed as a function of voltage (V) and operating frequency (f). Mathematically, it can be written as follows.

$$P_{dyn} = \frac{1}{2}CV^2f \tag{1.2}$$

Again, there are various power consuming components present in a large system (such as cloud). The total energy (or power) consumption of such a system comprises of their individual power consumptions. These components include CPU, memory, disk, storage, and network. Various studies [35, 36, 37] have been done to express the total power consumption as a combination of these components. For instance, Ge *et al.* [35] have used energy consumption of CPU, memory, disk, and NIC (network interface card) to model the energy consumption of the system. Song *et al.* [36] expands this model where they expressed the energy consumption as a product of the power consumption of the components with the operation time of the corresponding component.

Though there are many power consuming components in a typical server, the CPU is the major contributor [38, 39] and a wide range of scheduling algorithms are proposed considering the energy consumption of the processor only [30, 40, 41, 42]. As reported in [1], the CPU consumes almost 60% of the total power consumption for a Xeon based server and Figure 1.2 shows the component-wise power consumption for that server. We see that the processor consumes 60% of the total power, and memory is the second highest contributor with 19%. We also present the power breakdown of a server placed at the Google data center using Figure 1.3. Though memory consumes a significant chunk of power, CPU remains to be the major contributor.

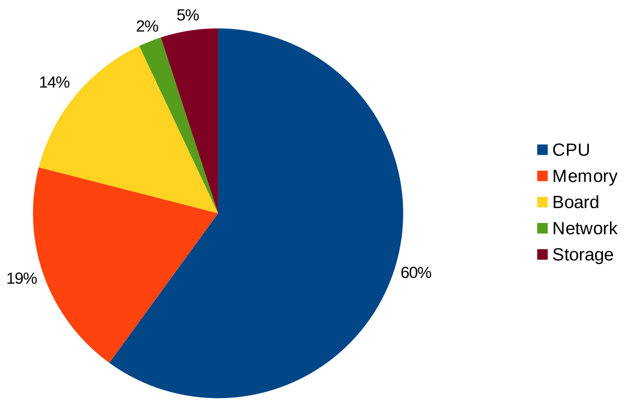


FIGURE 1.2: Component wise power consumption values for a Xeon based server [1]

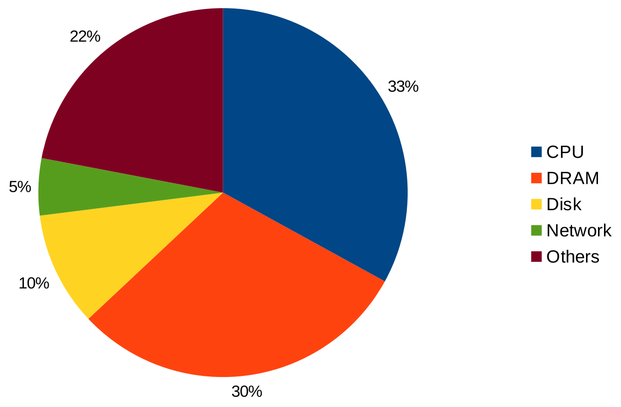


FIGURE 1.3: An approximate power breakdown of a server in Google data center [1]

Now the power consumption of a processor is expressed as a function of its utilization, processor frequency, etc. Fan *et al.* [37] made a significant contribution by proposing a power model where the CPU power consumption is expressed as a linear function of its utilization. This can be written using the Equation 1.3.

$$P(u) = P_{Base} + (P_{busy} - P_{Base}) \times u \tag{1.3}$$

where, $P(u)$ is the estimated power consumption at utilization u, P_{Base} is the power consumption when it does not execute any workload (utilization is zero). This is the static component of the power consumption and for the large systems, it is often considered as 60% to 70% of the total power consumption [43, 44, 45]. P_{busy} is the power consumed when the server is fully utilized. A significant amount of research on energy-aware scheduling policies considered this power consumption model in their work [45, 46, 47].

In case of a virtualized environment, the total power consumption can also be expressed as the summation of the individual power consumptions of the VMs and the base power consumption [48], and this can be written as

$$P_{total} = P_{base} + \sum_{i=1}^{\nu} P_{vm}(i) \tag{1.4}$$

where, P_{base} indicates the static component, $P_{vm}(i)$ indicates the power consumption of the i^{th} VM, and ν indicates the total number of VMs placed on the server.

Scheduling policies which target the dynamic power consumption of the hosts (or processors) primarily uses the DVFS (dynamic voltage and frequency scaling) technique by reducing the frequency and voltage to reduce the power consumption. In DVFS technique, the operating voltage and frequency of the processors are adjusted dynamically to adjust the speed of the processor. This in tern, effects the power consumption of the processor [33, 49, 50, 51, 52]. On the other hand, scheduling policies for the large systems, in general, try to reduce the static power consumption by reducing the number of active components of the system [53, 54, 55, 56].

In addition to the computation energy consumption discussed above, a significant chunk of the total energy consumption of a data center is contributed by the cooling devices, AC/DC transformation devices, etc. We consider the total computation energy as the total energy of the system and use this throughout the thesis.

1.7.2 Impact of high power consumption

High energy consumption in the servers and data centers has many demerits, and this can be categorized in three directions: (i) economic, (ii) performance, (iii) environmental. The energy consumption of a data center is almost equal to that of 25,000 households and it is around 2.2% of total electrical usages [48]. In addition, the energy consumption cost of a data center is increasing significantly. This yields a high operating electricity cost. Furthermore, high energy consumption imposes a higher cooling cost. Data center owners need to spend a significant portion of their budget for powering and cooling their servers. For instance, it is reported that Amazon spends almost 50% of their management budget for powering and cooling the data centers [57]. In [58], Koomey presented that the total power drawn by the servers is increasing every year and if the rate continues, then the server's energy consumption will exceed its hardware cost [59].

The second factor is the performance. High energy consumption increases the system temperature and it is reported in [60] that with an increase in every 10°C in temperature, the failure rate of an electronic device doubles. The last factor is the adverse impact on the environment due to the emission of CO_2. In addition to the monetary and performance issues, high energy consumption increases the CO_2 emissions and contributes to the global warming [61]. In the year 2007, it is reported that the ICT (Information and Communication Technology) industry contributed about 2% of the global CO_2 emissions [62] and it is expected to increase by 180% till 2020.

1.8 Motivation of the Thesis

Nowadays, the number of processors and number of threads per processor have increased to a significant number in compute systems. Thus the processing capability of these systems is sufficient enough to handle most of the recent applications. But the primary concern for these computing systems is the growing energy consumption. High energy consumption in the large systems has various demerits. Thus a reduction in the energy consumption not only reduces the operating electricity cost for the service providers, but it also reduces the other maintenance costs and CO_2 emission. In spite of resulting high energy consumption, large systems (e.g., cloud) are gaining popularity for various attractive features. Numerous real-time tasks (i.e., applications) are also being executed in these systems. To support the high demand of these applications at times, the systems are over-provisioned with resources (deploy more than the actual requirement). It is observed that one of the major reason for high energy consumption is the poor utilization of the computing hosts. Thus in order to reduce the energy consumption, the system utilization need to be improved. Moreover, scheduling can potentially improve the overall utilization and performance of the system. As a result, the energy consumption has become one of the major optimality criteria for scheduling and the energy-efficient scheduling for large systems has gained the attention of the research community in the recent time.

As the processor is the major source of power consumption, the energy-efficient scheduling approaches mainly consider the power consumption of the processors.

The scheduling policies try to reduce the power (or energy) consumption of the processor in different ways. Out of these, a majority of the research exploits the DVFS technique, and they focus only on the dynamic energy consumption of the processor. It is still a challenge to design an energy-efficient scheduling technique for the real-time tasks considering both static and dynamic energy consumption of the processors and satisfying other criteria, such as meeting the deadline constraints of the tasks.

Another promising way to increase the utilization of the system resources is by virtualization [63, 48]. Here, a set of virtual machines (VMs) is created on the top of physical hardware. User tasks are assigned to the VMs and the VMs are placed on the physical machines (also called as hosts). Cloud is the most popular virtualized system of the recent time and it is considered to be the future for energy-efficient computing paradigm. Energy-efficient scheduling for the cloud system adjusts the compute capacity of a VM as per the requirement and assigns the user tasks on them. A majority of these scheduling policies assumes a continuous domain for the compute capacity of the VMs. But in practice, the service providers often offer VMs with discrete compute capacity. Our third work considers a virtualized cloud system which deals with the VMs with discrete compute capacities.

With the increase in the popularity of the cloud computing paradigm, several applications from different domains are getting deployed. These applications are often of real-time in nature and they have huge resource requirements. Thus their efficient execution is very much crucial. These applications are modeled as scientific applications and various scheduling algorithms are developed for efficiently executing the scientific applications in the cloud environment. But the majority of the work mainly focuses on (i) reducing the overall execution time, (ii) meeting the deadline constraint, (iii) ensuring the quality of services, etc. It is still a challenging and promising research area to schedule these scientific applications (which are represented as scientific workflows) on the cloud in an energy-efficient way while satisfying other essential criteria such as the deadline. Moreover, the amount of research on real-time scheduling tasks with multiple VM requirement is thin. Hence our fourth work is about scheduling a set of online scientific workflows on the cloud environment.

1.9 Contributions of the Thesis

The thesis proposes a number of energy-efficient scheduling policies for efficiently executing real-time tasks on the large multi-threaded systems and the cloud. While doing so, the thesis considers different machine and task environments. The contributions can be summarized as follows.

1.9.1 Scheduling online real-time tasks on LMTMPS

In our first contribution, we consider scheduling a set of online independent aperiodic real-time tasks on a large compute systems where the processors are equipped with the multi-threaded feature. We name such systems as large multi-threaded multiprocessor systems (LMTMPS). Based on the power consumption pattern of some of the recent multi-threaded processors, we devise a simple power model where the total power consumption of a processor depends on the number of active threads of that processor. Then we propose an energy-efficient real-time scheduling policy, named *smart scheduling policy* which is designed based on the urgent point of the tasks. This policy works on two fundamentals, (i) all the switched-on processors are always tried to use fully, and (ii) new processors are not switched-on as long as possible. The proposed policy shows an average energy reduction of around 47% for the synthetic dataset and around 30% for the real trace dataset. Furthermore, we have proposed three variations of the basic smart policy to improve the energy consumption further and to handle special kinds of workloads. These are (a) *smart - early dispatch* scheduling policy, (b) *smart - reserve* scheduling policy and (c) *smart - handling immediate urgency* scheduling policy.

1.9.2 Scheduling online real-time tasks on virtualized cloud system

The second contribution of the thesis deals with scheduling the same task set for a virtualized cloud computing environment. Here the hosts are heterogeneous, and each host can accommodate a number of virtual machines (VM). VMs are also heterogeneous with respect to their compute capacities and energy consumptions. Under this setup, we consider a region based non-linear power consumption model for the hosts which is derived from the power consumption pattern of a typical server. Accordingly, we set two thresholds for the utilization of the hosts and depending on the urgency of the tasks, the scheduler dynamically uses the threshold value. In this work, we first introduce the concept of urgent point for a real-time task in case of a heterogeneous cloud environment and then propose two energy-efficient scheduling policies, (i) urgent point aware scheduling (*UPS*), and (ii) urgent point aware scheduling - early scheduling (*UPS-ES*), for efficiently executing a set of online real-time tasks. As compared to a state-of-art policy energy-efficient policy, the proposed policies achieve an average energy reduction of around 24% for the synthetic data and approximately 11% for the real-trace data.

1.9.3 Scheduling real-time tasks on VMs with discrete utilization

The third contribution of the thesis considers a cloud system where the VMs are of discrete compute capacity. The discrete compute capacity contributes a discrete utilization to the hosts. We introduce the concept of critical utilization where the energy consumption of the host is minimum. The scheduler tries to maintain the utilization of all the running hosts close to the critical utilization. In order to propose solutions to this problem, we first divide the task set into four different cases. Case 1 handles tasks with the same length and same deadline. Case 2 deals with tasks of two different lengths but the same deadline. In case 3, we consider tasks with arbitrary lengths but the same deadline. Finally, the task set with arbitrary length and the arbitrary deadline is considered under case 4. The solution method starts by proposing a solution of case 1, then the solution of case 1 is used to solve case 2 and so on. For case 4, we apply four different techniques to cluster the tasks and to bring it under case 3. The experimental results show that depending on the value of the system parameter, we can decide the task clustering technique.

1.9.4 Scheduling scientific workflows on virtualized cloud system

All the above problems consider real-time tasks which are independent but in this contribution, we consider a set of online dependent real-time tasks for efficiently executing in the cloud environment. The dependent task set is represented by scientific workflows. Each workflow contains a chain of multi-VM tasks and it arrives at the cloud system with a predefined deadline. We use three different approaches by efficiently utilizing the slack time of each workflow to decide the best scheduling time for a task of a workflow. We have exploited two different possibilities for allocating the VMs of a task, (i) non-splittable, (ii) splittable. We propose a series of energy-efficient scheduling policies considering different allocation policies, different migration strategies, and different slack distribution techniques. Along with the energy consumption of the system, we analyze the migration count and split count for each policy. As far as energy consumption is concerned, proposed policies under the non-splittable VM allocation category performs at par with the state-of-art policy. But they perform much better than the state-of-art policy terms of the number of migrations. But proposed policies under splittable VM allocation category performs significantly better than the state-of-art policy both in terms of energy consumption and migration count.

1.10 Summary

Nowadays, the number of processors and the number of threads per processor have increased to a significant number in compute systems. Thus the processing capability of these systems is sufficient enough to handle most of the recent applications. As the processing capability increases, the power (or energy) consumption also increases by a significant margin. The high power consumption for the large systems has many demerits and thus reducing power consumption will benefit both the users and the service providers in several ways. Though there are many power consuming components present in a computing system, the processor alone consumes a significant portion of that. Thus the research community mainly focuses on the power consumption of the processors while designing energy-efficient scheduling techniques.

There are three components of any scheduling problem: machine environment, task environment, and optimality criteria. Different work on scheduling considers different values for these components and present solutions accordingly. In our work, for the machine environment, we consider both virtualized and non-virtualized system with a large number of processors. For the task environment, we consider both independent and dependent real-time task set. We set the optimality criteria as the minimization of energy consumption without missing the deadline constraints of the tasks. Hence the focus of this thesis work is to design scheduling approaches for executing real-time applications (expressed as real-time tasks) on large systems to minimize the energy consumption of the system while meeting the deadline constraints of the tasks. The first work considers a non-virtualized large multi-threaded multiprocessor system (LMTMPS) and the other three works consider a virtualized cloud system. The power (or energy) consumption of the system is taken as a function of the utilization of the hosts, or the number of active threads in a processor, or the summation of the power consumption of the running VMs of a host.

1.11 Organization of the Thesis

The rest of the thesis is organized as follows:

- Chapter 2 presents brief literature summarizing the seminal works in the area of the energy-efficient scheduling of large systems.
- Chapter 3 presents the first contribution, where the scheduling of aperiodic online real-time tasks is considered for LMTMPS.
- Chapter 4 describes our second contribution, which deals with the scheduling of aperiodic online real-time tasks for the heterogeneous virtualized cloud system.
- Chapter 5 considers scheduling for a virtualized cloud system where the utilization values of the VMs are discrete. We put forward a mathematical analysis regarding the energy consumption and the utilization of the hosts.
- Chapter 6 presents a series of scheduling heuristics for a set of multi-VM dependent tasks, represented by scientific workflows.
- Chapter 7 finally concludes the thesis with some possible future research directions.

Chapter 2

Energy Efficient Scheduling in Large Systems: Background

The scheduling algorithms whose optimality criteria is the reduction of the power consumption or the energy consumption is commonly known as energy-efficient (or energy-aware) scheduling. In this Chapter, we present a brief overview of literature in the context of the energy-efficient scheduling techniques, specially for the large systems. The work can be broadly studied in two approaches: (i) fine-grained, (ii) coarse-grained. Fine-grained approach basically deals with the dynamic power consumption of the hosts. Scheduling approaches under this category extensively use the DVFS technique in various ways. On the other hand, scheduling approaches under coarse-grained category primarily deal with the static power consumption of the hosts whose aim is to minimize the number of active hosts.

2.1 Fine Grained Approaches

A reduction in the operating frequency of the processor ideally results in a cubic reduction in the dynamic power consumption of the processor. But with a reduction in the operating frequency, the execution time of the task running on that processor increases. Thus the primary idea of the DVFS technique in the context of real-time task execution is to adjust the operating frequency such that the power consumption can be reduced without missing the deadline of the task. Here we present a few seminal works for non-virtualized and virtualized systems which uses the fine-grained approach to reduce the energy consumption.

2.1.1 Non-virtualized system

Weiser *et al.* [31] was the pioneer to start the research in this direction by associating power consumption with scheduling and used DVFS technique to study the power consumption of some scheduling techniques. They took advantage of CPU idle time and reduced the operating frequency of CPU so that the tasks were finished without violating any deadline. Aydin *et al.* [32, 64] ported this idea for real-time systems where they initially designed a static algorithm for computing the optimal frequency for a periodic task set assuming their worst-case behavior. After that, they devised an online speed adjustment algorithm for dynamically claiming the energy not used by the tasks finishing earlier than the worst case time and achieved up to 50% power saving as compared to the worst-case scenario. Zhu *et al.* [33] has extended the technique proposed by Aydin *et al.* [32] for the multiprocessor environment. In their policy, they mention about teo different approaches for utilizing the slack created by a task to reduce the energy consumption. In first approach, slack created by a task in one processor was utilized by another task in the same processor, and in the second approach, the slack was shared among the tasks in different processors.

Isci *et al.* [65] has proposed a global power management policy for chip multiprocessors where every processor can operate in three different modes: turbo (no reduction), eff1 (5% voltage and frequency reduction), eff2 (15% voltage and frequency reduction). They studied the relationship between the operating modes of the processors and the corresponding performances. Lee and Zomaya [66, 67] have proposed makespan-conservative energy reduction along with simple energy conscious scheduling to find a trade-off between the makespan time and energy consumption, where they reduced both makespan time and energy consumption of precedence constraint graph on heterogeneous multiprocessor systems supporting DVFS technique. Recently, Li and Wu [49, 68, 69] have considered the execution of various task models by further exploiting the DVFS technique for both homogeneous and heterogeneous processor environments.

The above studies mainly consider the small systems. DVFS technique is equally used for the high-performance computing (HPC) systems and clusters. For instance, Hotta *et al.* [70] used the DVFS technique to design a scheme for the high-performance computing (HPC) clusters where the program execution is split into multiple regions, and the optimal frequency is chosen for the individual region. Ge *et al.* [50] has designed an application-level power management framework and proposed scheduling strategies for scientific applications in case of distributed

DVFS enabled clusters. Kim *et al.* [71] considered scheduling of bag-of-tasks applications, and presented scheduling approaches considering space shared and time shared resource sharing strategies. The applications were scheduled in an energy-efficient manner and the quality of service (QoS) is measured as meeting the deadline constraints of the applications. In [51], Chetsa *et al.* presented a partial phase recognition based dynamic power management architecture for the HPC systems. They have designed two setups. In first setups, they consider optimization of the processor power consumption only and in the second setup, processor, disk, and network power consumptions are considered. Chen *et al.* [72] considered energy-efficient matrix multiplication in a DVFS enabled cluster where they divide the matrices and the computation is distributed among different cores. In case of computation phase, the CPU frequency is set to the highest level and in case of idle and communication phase, the frequency is set to the lowest level.

2.1.2 Virtualized system

In the context of a virtualized system, the user tasks are assigned to the VMs and the VMs execute on the CPU cores. The speed (or the compute capacity) of a VM is determined by the operating frequency of the underlying processor. The speed is typically expressed in terms of million instructions per second (MIPS). Whenever the speed (i.e. the compute capacity) of a VM increases, the power consumption increases but the execution time of the task assigned to that VM decreases. The DVFS based energy-efficient scheduling algorithms in the virtualized environment adjust the speed of the VMs as per the requirement. In this section, we present a few important works in this direction.

In [73], Calheiros and Buyya considered scheduling of urgent bag-of-tasks using DVFS where they assume that one CPU core is exclusively available to one VM. Changing the frequency of the core directly reflects the speed of the VM running on it. The algorithm specified four different operating conditions and they are ranked accordingly. The conditions are: (i) task is executed by a running VM without increasing its frequency, (ii) task is executed by a running VM but an increase in frequency is needed, (iii) task is executed by an idle VM placed on an active host, (iv) task is executed by an idle VM and the host is brought to an active state from a sleep or low power consuming state. The algorithm categorizes the first condition as the best and the last condition as the worst.

In [74], Elnozahy *et al.* have proposed five different energy-efficient scheduling policies which considered both DVFS and node on-off technique to reduce the power consumption of the server clusters. The first policy is termed as independent voltage scaling (IVS) which employs different voltage levels to the individual server. The second policy is termed as the coordinated voltage scaling (CVS) where the scaling is applied to different processors in a coordinated way. The third one is termed as VOVO (Vary On and Vary Off) where the entire server is turned on or off. The last two policies are the combination of IVS and CVS with VOVO (VOVO-IVS and VOVO-CVS).

Recently, Zhu *et al.* [30] has considered scheduling of aperiodic real-time tasks on the cloud. They proposed an energy-efficient scheduling algorithm, named *EARH* which is based on a rolling horizon optimization technique. The primary idea here is to consider the previously scheduled (but not started execution) tasks from local queues of the VMs while scheduling new tasks. But in their approach, they have considered only the dynamic energy consumption of the hosts; and the target utilization of hosts is 100%.

Wu *et al.* [52] considered scheduling of real-time tasks in the cloud environment where each task is specified with a minimum and a maximum frequency. Similarly, each server is specified with a minimum and a maximum working frequency. To execute a task on a specified server, it must satisfy both the minimum and maximum frequency conditions. The policy uses the DFVS technique to set the working frequency of a task on an appropriate server.

2.2 Coarse Grained Approaches

The primary idea of the coarse-grained scheduling policies is to reduce the number of active hosts in the large system or data center. Whenever a host becomes active, it consumes a significant amount of power even if it does not execute any task. This is the base power consumption of the host. A reduction in the number of active hosts reduces the overall power consumption of the system. The dynamic power management (DPM) technique uses this coarse-grained approach to reduce the power consumption of the system. DPM uses different power consumption states for the components and dynamically switches between the states as per the requirement [75]. In the following subsections, we present a few seminal works for non-virtualized and virtualized systems which uses the coarse-grained approach to reduce the energy consumption.

2.2.1 Non-virtualized system

Chase *et al.* [53] proposed a coarse-grained power management techniques for Internet server clusters where an energy conscious switch is placed on top of the servers that maintain a list of active servers. Depending on the traffic behavior and a predetermined threshold value of utilization of the servers, the switch dynamically adjusts the list by keeping them either in active mode or low power mode. In [76], Chase *et al.* have extended this idea to develop an economic model based architecture, called *Muse* to find the trade-off between the service quality and the cost in terms of energy. The policy avoids static over-provisioning of resources by dynamically allocating sufficient resources to meet certain quality requirements. Choi *et al.* [77] studied the characteristics of the applications running in data centers in order to impose appropriate bounds on power consumption. They presented consolidation techniques which are based on two kinds of power budgets: average and sustained. Costa *et al.* [78] designed a three-level energy aware framework, named GREEN-NET which was based on the distributed automatic energy sensors. They developed an adapted resource and job management system (OAR) unit to facilitate automatic shut-down of the nodes in under-utilized periods.

In [54], Pinheiro *et al.* have proposed strategies for inspecting the system status periodically and then to dynamically add or remove computing nodes to the cluster based on the requirements. After addition or removal of the nodes, a load re-distribution policy runs to decide the placement and migrations of the load from one node to another to ensure system performance. The authors have also imposed several restrictions to limit the number of migrations. Zikos *et al.* [55] proposed three scheduling policies for a set of heterogeneous servers with different power consumption and performance. One policy reduces energy consumption with average response time. Another policy is customized for performance but consumes high energy consumption. The last one performs best for medium load scenario. The author considered compute-intensive tasks where the service time is not known. Research is also done considering the energy consumption cost of the data centers. For instance, Jonardi *et al.* [79] proposed two heuristics for geographically distributed data centers where they studied the co-location (CL) interference effect of workloads. They claimed that the heuristic *FDLD-CL* (Force Directed Load Distribution) performs better when the workload profile does not change rapidly and *GALD-CL* (Genetic Algorithm Load Distribution) performs better otherwise.

As the cooling energy is a significant chunk of the total energy in data centers, a good number of works [80, 81, 82, 83, 84] is done to reduce the thermal energy consumption. For instance, Oxley *et al.* [81] considered a noble framework for heterogeneous computing systems where they used offline analysis to find optimal mapping of workload to the cores. In [84], Oxley *et al.* considered scheduling tasks on a heterogeneous compute systems with given thermal and deadline constraints. They studied the effect of the co-location on the execution time of the tasks and proposed greedy heuristics for the same.

2.2.2 Virtualized system

All the above studies presented some exciting results, but none of them considered the virtualization technique in the system. Virtualization technology is known to be a promising technique to improve the resource usages in the cloud. In a virtualized system, tasks are assigned to the VMs and the VMs are placed on the hosts. Energy efficient scheduling in virtualized environment mainly deals with two parameters to reduce the energy consumption [85, 86, 56]. The first parameter is the *consolidation* of the VMs into a fewer number of hosts and the second parameter is the efficient placement of VMs on the hosts of the cloud resource. Here we present a few seminal works in the context of the energy-efficient scheduling in a virtualized environment.

Consolidation operation mainly targets to reduce the number of active hosts in the system. To reduce the number of active hosts, the hosts should be utilized to their maximum capacity [30, 44, 45]. For instance, Lee and Zomaya in [45], developed two energy-efficient scheduling policies: *ECTC* and *maxUtil*; both the policies try to utilize the switched-on processors fully (i.e. 100%). MaxUtil takes the task placement decision based on the host utilization while ECTC takes the decision based on the energy consumption of the task only. On the other hand, a wide range of research [46, 86, 87, 88] is done where the host is not utilized fully, rather they are used to a threshold value. The idea behind using threshold-based utilization approaches is that the system performance degrades when the host utilization crosses a limit. In addition to reduce the energy consumption, these policies also aim to meet the performance or the service level agreement (SLA) of the user tasks.

Verma et al. [89] has done a nice study regarding the power consumption pattern of various HPC applications and the typical workload behavior of a virtualized server and in [90] they developed a framework called pMapper where the applications are placed onto different servers for execution based on the utilization values of the server. Srikantaiah et al. [56] studied the relationship between the energy consumption and the performance of the system which was determined by the CPU (or processor) utilization and disk utilization. The problem was viewed as a bin packing problem where applications are mapped into servers optimally.

Lee *et al.* [45] proposed two energy-efficient scheduling algorithms for a virtualized cluster where they expressed the power consumption of a processor as a linear function of utilization and the servers are utilized to their full capacities. Beloglazov *et al.* [46] proposed a series of heuristics to dynamically allocate VMs and manage resources at runtime depending on the overall utilization of the system. In [91], authors presented two ant colony optimization based approaches for VM placement and VM consolidation. They studied the trade-off between the energy consumption and the SLA requirements.

Chen *et al.* [44] considered the execution of independent real-time tasks on a virtualized cloud environment where the task execution time of the tasks comes with some uncertainties. They reduce the overall energy consumption of the system while meeting the task's guarantee ratio. Hosseinimotlagh *et al.* [92] proposed a two-tier task scheduling approach for the cloud environment where the benefits of both the users and the service providers are taken into consideration. The global scheduler efficiently maps the tasks to the VMs while the local scheduler tries to utilize the hosts with an optimum CPU utilization. The task scheduler initially assigns the minimum average computing power to each and the remaining computing power is distributed among the tasks in a proportionate way. In [93], *Shi et al.* presented a series of approaches for scheduling embarrassingly parallel tasks in the cloud where they initially provide an analytical solution to the resource allocation problem. Then they formulate a single job scheduling problem as a linear program where they aim to schedule only one job which contained multiple tasks within it. Furthermore, they design an online scheduler for periodically scheduling the tasks by applying shortest job first policy.

Majority of the VM consolidation problem considers only the CPU utilization while allocating the VMs on the hosts. But a few research has been conducted where the other parameters such as memory, disk, etc. are also considered in addition to the CPU. For instance, Mastroianni *et al.* [85] considered memory in addition to the CPU utilization. They claim that the deterministic approach of VM consolidation is not suitable for large data centers and they proposed a probabilistic approach to tackle the problem. The effectiveness of their approach is measured using five different parameters: resource utilization, number of active servers, power consumption, migration frequency, and SLA violation. SLA violation is expressed as an overload of the CPU utilization. They have validated their claim by conducting experiments for both CPU intensive and memory intensive applications. In [94], authors have used a bi-directional bin packing approach to placing the VMs on the hosts. They have used linear regression and K-nearest neighbor regression prediction models to estimate the future resource utilization.

Research has also been done to predict the future resource requirement. For instance, in [86], authors use an exponentially weighted moving average (EWMA) load prediction method to estimate the future resource requirement. They introduce the concept of skewness among the hosts to maintain a uniform resource utilization of the hosts. They reduce the energy consumption of the system by reducing the number of active hosts and maintain the performance by avoiding host over-utilization. Authors used four different threshold values to balance between the energy consumption and the system performance. CPU intensive, memory intensive, and network intensive workloads are clubbed to together as a mix to improve the resource utilization. In [88], authors have presented a profiling-based framework for server consolidation where they studied the co-location effect of different types of workloads. They further design a way to transform the current VM allocation scenario into a target VM allocation scenario with the minimum migration count.

2.3 Energy Efficient Workflow Scheduling

2.3.1 Workflow scheduling on large systems

Workflow scheduling on large systems such as grid and cloud system has been extensively studied from a few years. As the problem is known to be an NP-hard [95], numerous heuristic and meta-heuristic approaches [96, 97, 27, 98, 26, 95, 99] are proposed which mainly aim to reduce makespan time, the overall cost of execution, energy consumption, etc. Studies have also been done which considered deadline centric and budget constrained execution of scientific workflows in the cloud. For instance, Abrishami *et al.* [96] has initially proposed a partial critical path (PCP) algorithm to minimize the execution cost of workflows in grid and then they extended the idea for cloud environment and proposed two algorithms, namely, IaaS Cloud partial critical paths (*IC-PCP*) and IaaS Cloud partial critical paths with deadline distribution (*IC-PCPD2*).

Topcuoglu *et al.* [97] has proposed two popular scheduling algorithms, heterogeneous earliest finish time (*HEFT*) and critical path on a processor (*CPOP*) for a set of bounded heterogeneous processors. These algorithms are based on list scheduling where the tasks are ordered based on their upward rank value in case of *HEFT* and summation of upward and downward rank in case of *CPOP*. Lin and Lu [100] has extended *HEFT* and proposed an algorithm called, scalable heterogeneous earliest finish time *SHEFT* for a dynamically changing cloud environment. Calheiros and Buyya [27] has addressed the challenges of performance variations of resources in public clouds while meeting deadline constraints of scientific workflows. They have proposed an algorithm called, enhanced IC-PCP with replication (*EIPR*) which facilitates the replication of tasks and reduces total execution time.

In meta-heuristic approach, for instance, Rahman *et al.* [26] initially proposed a critical path based adaptive scheduling techniques, namely, *DCP-G* (dynamic critical path for the grid) for the grid and cloud computing environment. Then they proposed a genetic algorithm based adaptive hybrid heuristic algorithm for the hybrid cloud system. In [95], Rodriguez and Buyya proposed a particle swarm optimization based scheduling technique to minimize the workflow execution cost where they additionally considered the performance variation and VM boot time in the cloud on top of typical cloud properties. Zhou *et al.* [98] proposed an ant colony optimization based algorithm to find the best computing resource for a task by dividing the ants into two sets: forward-ants and back-ants.

2.3.2 Energy-efficient scheduling of workflows

Now we present a few seminal works where minimization of energy consumption is considered as the main or one of the co-objectives. For instance, Pietri *et al.* [101] proposed two energy-efficient algorithms for executing a set of workflows on a virtualized cloud environment where they aimed at reducing energy consumption while maintaining the cost budget and deadline constraint.

Durillo *et al.* [102] has developed a multi-objective energy-efficient list-based workflow scheduling algorithm, called *MOHEFT* (Multi-Objective HEFT) where they present a trade-off between the energy consumption and the makespan time. They performed extensive experiments with different workflow characteristics. The proposed algorithm achieved shorter or same makespan time as compared to HEFT algorithm but with lesser energy consumption. Cao *et al.* [103] proposed energy-efficient scheduling technique for executing a set of scientific workflows in a collection of data centers. Depending on the amount of energy consumption, they considered four different modes for servers: active, idle, sleep and transition in their work. Authors used the DVFS technique and tasks were run at optimal frequencies to reduce the energy consumption. In [28], Bousselmi *et al.* initially partitioned the workflow to reduce network energy consumption by reducing the amount of data communication among them. Then in the next step, they used the cat swarm optimization based heuristic to schedule each partition on a set of VMs in an energy-efficient manner. Chen *et al.* [104] designed an online scheduling algorithm, called, energy-efficient online scheduling, *EONS* to schedule tasks from different workflows. System resources are dynamically adjusted to maintain the weighted square frequencies of the hosts.

Recently, Li *et al.* [61] addressed both energy consumption and the execution cost while guaranteeing the deadline constraints of the tasks. The authors considered an hourly based pricing model for the VMs and a task is mapped to an optimal VM. They developed strategies to merge sequence tasks and parallel tasks for meeting performance constraints by reducing execution cost and energy consumption. They have also used the DVFS technique to use the slack time efficiently. Xu et al. [41] considered the execution of online scientific workflows to minimize the energy consumption of cloud resources. The authors transformed the workflow into a set of sequential tasks. They applied a static time partitioning to calculate the arrival time of the individual task of the workflow. The authors considered homogeneous VMs with heterogeneous hosts. At the time of scheduling, the scheduler considers all the running tasks as new tasks with possibly lesser length and schedules them along with the current tasks. We consider a similar setup in our last contribution where we deal with scheduling real-time dependent tasks.

Table 2.1 lists some seminal work in the area of energy-efficient scheduling policies for the cloud environment. The table also contains the key considerations of each of the work and some lacunae in their work.

Research work	**Key considerations**	**Major lacunae**
Hotta et al. [70]	DFVS; Split program execution	Manual program instrumentation
Calheiros and Buyya [73]	DVFS; Four different operating conditions	Only one VM per core
Zhu *et al.* [30]	Rolling horizon optimization	Considers only dynamic energy; host utilization 100%
Wu *et al.* [52]	Minimum and maximum frequency for tasks and servers	No proper construct for energy consumption; Number of VMs in a host determines the SLA
Lee and Zomaya in [45]	Maximizes resource utilization to save energy	No task order; Schedules immediately as a task arrives
Xiao *et al.* [86]	Threshold on utilization; load prediction	No justification on Threshold values; Difficult if application dependent
Farahnakian *et al.* [94]	Bi-directional bin packing using CPU and memory	Migration cost is calculated based on VM memory only; No clear mapping for tasks to VM
Ye *et al.* [88]	Co-location effect of different types of workloads; Migration count	Studied only four types of applications; Performance depends on target conslidation scenario
Mastroianni *et al.* [85]	VM consolidation considering CPU and RAM	Only VM to host allocation; No task characteristics
Cao *et al.* [103]	DVFS with four different modes for servers	Do not consider the deadline constraints of the tasks or workflow
Pietri *et al.* [101]	Two approaches for scientific workflow: budget-constrained and deadline-constrained	Homogeneous hosts; Migration is not considered
Bousselmi *et al.* [28]	Network energy consumption	No deadline is considered; Not suitable for online data
Xu *et al.* [41]	Homogeneous VMs on heterogeneous hosts	Static partitioning of tasks; Migration not considered

Table 2.1: Some major works in the area of energy-efficient scheduling in cloud computing environment

Chapter 3

Scheduling Online Real-Time Tasks on LMTMPS

This chapter first presents an energy-efficient scheduling policy for executing a set of online independent real-time tasks on a large computing system where the processors are empowered with the multi-threaded facility. We term this kind of computing systems as Large Multi-threaded Multiprocessor Systems (LMTMPS). Further, the chapter presents three variations of the basic scheduling policy to efficiently handle some special cases. The proposed scheduling policies consider a thread-based power consumption model which is devised based on the power consumption pattern of some of the recent commercial processors.

3.1 Introduction

Nowadays, various scientific and real-time applications of different domains such as avionics, bioinformatics, signal processing, image processing, etc. are being deployed in the large systems, for their efficient execution [24, 27]. These applications typically consist of hundreds of compute-intensive, data-intensive and communication intensive tasks. Thus a significant amount of resource is required to execute these applications. On the other hand, the compute systems of today's world is equipped with a large number of processors and these processors are empowered with the multi-threaded feature. Thus the processing capability of these systems is sufficient enough to handle these high-end applications. But with an increase in the processing capability, the energy consumption of these large systems is also increasing. This growing energy consumption has sought the attention

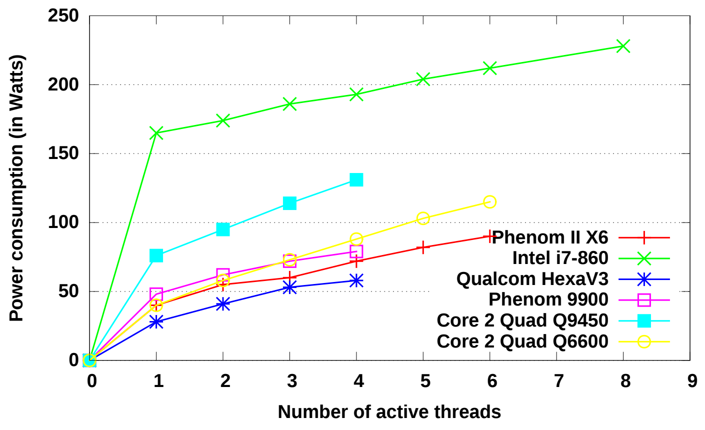


FIGURE 3.1: Power consumption plot of a few recent commercial processors with number of active threads [2, 3]

	Power Consumption (in Watts)						
#Active-threads→ Processor ↓	1	2	3	4	5	6	8
Phenom-II-X6	40	58	73	88	103	115	-
Intel i7-860	165	174	186	193	204	212	228
Qualcom Hexa V3	40	55	60	72	82	90	-
AMD-Phenom-9900	76	95	114	131	-	-	-
Core-2-Quad Q9450	28	41	53	58	-	-	-
Core-2-Quad Q6600	48	62	72	79	-	-	-

TABLE 3.1: Power consumption behaviour of commercial processors [2, 3]

of the research community of to a great extent. As a result, a good number of scheduling algorithms for reducing the energy consumption of such large systems are proposed [53, 76, 50, 70, 71, 55]. Majority of these research consider power consumption at a finer granularity and use the DFVS technique to reduce the energy consumption. For instance, Hotta *et al.* [70] split the program execution into multiple regions and each region is executed using an optimal frequency for that region. Ge *et al.* [50] considered a distributed DVFS environment to reduce the energy consumption of the cluster. But none of these energy-efficient scheduling approaches for the large systems sufficiently consider scheduling of the real-time tasks in their work. In this chapter, we consider scheduling of online real-time tasks for a large multi-threaded multiprocessor system and consider the power construct at a coarser granularity.

Figure 3.1 shows a plot of the power consumption of a few recent multiprocessors (multi-threaded processors) versus the number of running hardware threads (HTs) in them. We see that the power consumption values follow an interesting pattern. Whenever a processor gets switched on and executes a task using one HT (processor with one active thread), it consumes a significant amount of power. After that addition of subsequent active thread, the additional power consumption of processor due to the additional thread is small. So power consumption of already switched on processor due to the addition of an active thread is incremental. For example, Qualcom Hexa V3 consumes 40 watts with 1 active thread (power consumption values are also listed in Table 3.1). When it runs its 2^{nd} thread, it consumes 55 watts. The difference 15 watts ($= 55 - 40$) is the power consumption for the 2^{nd} thread. Similarly, on activation of subsequent threads, the processor consumes additional 5 watts ($= 60 - 55$), 12 watts ($= 72 - 60$), 10 watts ($= 82 - 72$) and 8 watts ($= 90 - 82$) respectively. A similar power consumption pattern is observed in case of Intel Xeon Gold processors [105]. For instance, for a given workload, Xeon Gold 6138 processor with 20 cores consumes 60 watt when it starts execution with 1 core. Then the power consumption increases linearly with active core count until it reaches 107 watt for 10 cores. Further, the power consumption increases and reaches 127 for active core count of 20. Following this interesting power consumption characteristics of a few commercial multiprocessors (multi-threaded processors), we devise a simple but elegant power consumption model both for the single processor and for the whole compute system. The existing scheduling algorithms for the real-time tasks do not consider this interesting power consumption behavior of the processors.

The contributions of this chapter can be summarized as follows.

- We derive a simple but elegant power consumption model for the processors following the power consumption characteristics of some of the recent multiprocessors (multi-threaded processors) and used this model to measure the processor power consumption while scheduling a set of online real-time tasks.
- We propose four energy-efficient real-time scheduling policies, named (a) *smart scheduling policy*, (b) *smart - early dispatch scheduling policy*, (c) *smart - reserve scheduling policy* and (d) *smart - handling immediate urgency scheduling policy* to reduce the total energy consumption of the system without missing deadline of any task.
- As the execution time and deadline of tasks play a significant role in scheduling, we consider six different execution time schemes and five different deadline schemes for the tasks in our work.

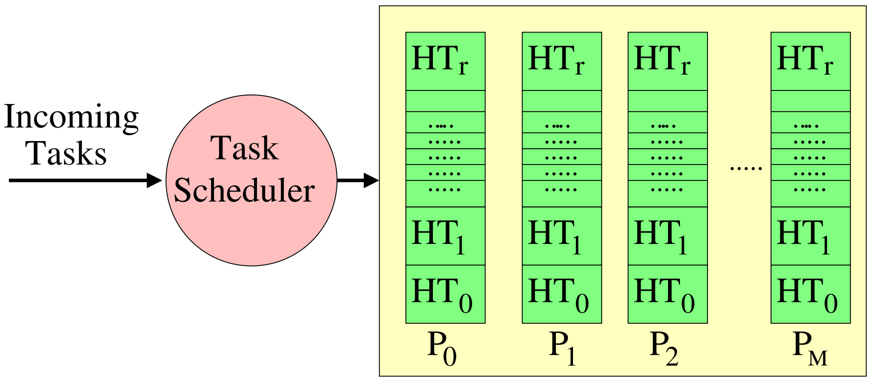


FIGURE 3.2: Online scheduling of real-time tasks on LMTMPS

- We examine the instantaneous power consumption for different scheduling policies and then compare the overall energy consumption of our proposed policies with five different baseline scheduling policies for both real-world trace data and synthetic data covering a wide range of variations.

3.2 System Model

Our considered system can be represented by Figure 3.2. The system mainly has two parts: the task scheduler and the processing block. Task scheduler accepts a set of aperiodic real-time tasks which are to be scheduled on the chunk of processors in an energy-efficient manner. The processing block consists of M homogeneous processors (P_0, P_1, ..., P_M) where M is sufficiently large. All the processors are multi-threaded processors, and each processor can support r hardware threads (HTs). Considering such large number of processors is justified because the modern day's systems (e.g., cloud system) can provide virtually infinite computing resources to their users [106, 107]. In this work, we assume power consumption model at higher granularity level and ignore the DVFS capability of the processors even if the DVFS facility is available to all the processors because the DVFS approach alone may not be suitable to handle the energy-efficiency of the large systems. We use HT and virtual processor interchangeably throughout this chapter.

We assume that all the tasks are uni-processor tasks that is, they require only one HT for their execution. We also assume that one virtual processor (HT) of a processor executes only one task at a time and utilizes 100% of the compute power of that virtual processor throughout the task execution. Once all the HTs of a processor is filled with tasks, a new processor is switched on if required. If an HT of any processor becomes free in between, a new task is allocated to that HT or an existing task may be migrated to this processor based on the situation.

As already mentioned in Section 3.1 of the chapter, we have analyzed the power consumption pattern of a few commercial multi-threaded processors and found that the total power consumption (TPC) of the processors increases with the increase in the number of active threads. Furthermore, all the processors consume a large amount of power whenever they start operation. This large amount of power consumption is referred as *base power consumption* (BPC) of the processor in our model. Then with an increase in one active HT, the power consumption also increases by some margin. This is termed *per thread power consumption* and the value of the same is much smaller as compared to BPC. Thus the processor power consumption of such large multi-threaded multiprocessor systems (LMTMPS) can be expressed using Equations 3.1 and 3.2.

Power consumption of a single multi-threaded processor can be expressed as:

$$P_s = P_{Base} + i.\delta \tag{3.1}$$

where P_s is power consumption of the processor, P_{Base} is base (or idle) power consumption of that processor, i is number of HTs which are in running state (active) and δ = per thread power consumption. In general value of δ is much smaller as compared to P_{Base}. Typically P_{Base} is 5 to 10 times greater than δ [2, 3].

And, the power consumption for the complete system can be modeled as:

$$P_{LMTMPS} = L.(P_{Base} + r.\delta) + (P_{Base} + i.\delta) \tag{3.2}$$

where P_{LMTMPS} is the total power consumption of the system, L is the number of fully utilized active processors, and r is the number of HTs in a processor.

A fully utilized processor consumes $(P_{Base} + r\delta)$ amount of power as all the r HTs remains active there. Thus $L.(P_{Base} + r\delta)$ is the power consumption of all the fully utilized active processors and $P_{Base} + i\delta$ represents the power consumption of one

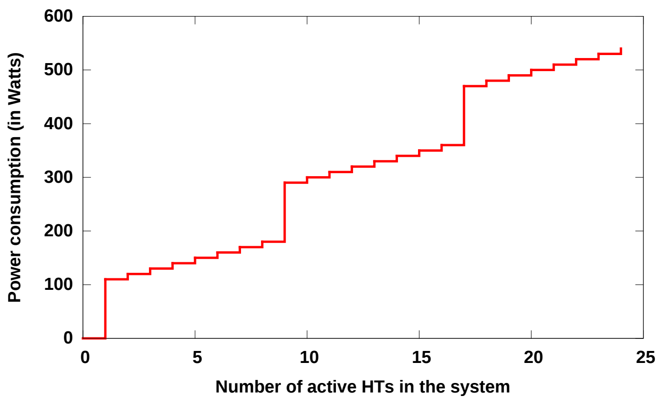


FIGURE 3.3: Power consumption of LMTMPS (when values of $P_{Base} = 100, \delta = 10$ and $r = 8$)

partially filled processor where i number of HTs are active in that. In case there is no processor is partially filled in the system, the value of $P_{Base} + i\delta$ is 0. Here, we assume that the scheduler has a task consolidation agent which regularly migrates tasks from an active host to another so as to consolidate tasks into a fewer number of processors (hosts); and this is done such that at the end of the consolidation process, at most one processor remains partially filled. All other remaining active processors become fully utilized. Processors without an active HTs are switched off. In this process, neighboring processors are chosen so as to reduce the power wastage due to distribution.

3.3 Power Consumption Model

Figure 3.3 shows an example cased for the power consumption behavior of our considered system. In this example case, the processor BPC is taken as 100 Watts. That is whenever a processor is started, it consumes 100 Watts of power. On activation of each thread, additional 10 Watts of power is consumed by the system; which is the thread power consumption δ. We have considered every processor can accommodate a maximum of 8 HTs. We observe from the graph that power consumption value increases significantly with a sharp jump when active thread number (also called virtual processor) reaches 1, 9 and 17. When the system runs 8 threads, the power consumption of the processor becomes 180 ($=100 + 8 \times 10$) Watts. When the active thread count reaches 9, the power consumption value increases by 110 Watts and the total system power consumption becomes 290 ($= 180 + 110$) Watts.

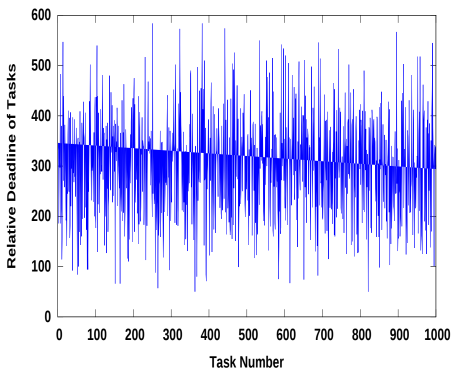
Thus in our considered system, the total processor power consumption value is not proportional to the number of active HTs (or utilization) of the processor. But most of the earlier research considers them to be proportional specially, in case of scheduling real-time tasks. A similar type of power consumption model was used by Gao et al. [108] where they considered the power consumption of a virtualized data center as a function of the server utilization. Lee et al. [45] also used another similar energy model where the energy consumption of a processor was expressed as a function of its utilization. But in our case, we consider the power consumption of a processor with respect to its number of active HTs. In addition, we consider the BPC of processors, which is the static component of the processor power consumption.

3.4 Task Model: Synthetic Data Sets and Real-World Traces

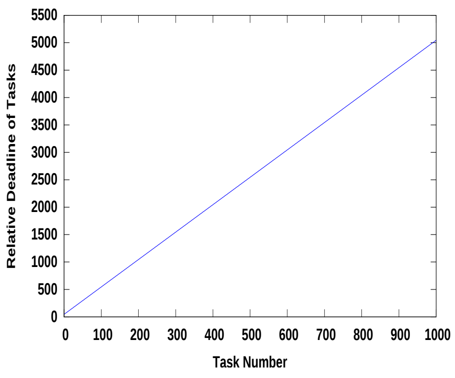
In this work, we consider scheduling of a set of online aperiodic independent real-time tasks, $T = \{t_1, t_2, t_3 \ldots\}$ onto a large multi-threaded multiprocessor system. Each task t_i is represented by three-tuple $t_i(a_i,\ e_i,\ d_i)$ where a_i is the arrival time, e_i is the execution time (or computation time) and d_i is the deadline of the task. For all t_i, $d_i \geq (a_i + e_i)$. All the tasks are assumed to be sequential and uni-processor that is, a task is executed by only one HT (virtual processor) and utilize 100% of the compute power of the virtual processors throughout their execution. We consider scheduling of both synthetic real-time tasks and real-world trace data which are described in the following subsections.

3.4.1 Synthetic tasks

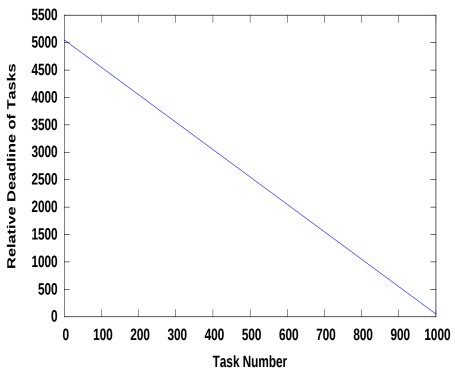
As already explained in the previous subsection, we consider three parameters of a task: arrival time, execution time, and deadline. In the synthetic data set, we assume that aperiodic independent real-time tasks are entering to the system following Gaussian distribution. That is, the inter-arrival pattern of the tasks follow the Gaussian distribution. For the execution time and deadline, we consider various schemes. We describe these in the following subsections.



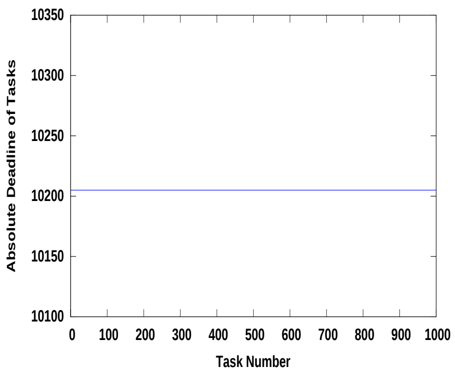
(a) Gaussianly distributed ($\mu = 10$ and $\sigma = 5$)



(b) Increasing ($k = 3$)



(c) Decreasing ($k = 3$)



(d) Common

FIGURE 3.4: Different deadline schemes with $\mu = 10$ and $\sigma = 5$

3.4.1.1 Execution time variation

As the execution (or computation) time of tasks is a key factor in scheduling and it has a significant impact on the performance of the system [109, 110], we have considered a wide variety of task execution time with different distributions in order to establish the effectiveness of our work. Here we have considered four different distributions: **Random, Gaussian, Poisson** and **Gamma**. In random distribution, the execution time e_i of a task t_i is randomly distributed between 1 to R_{max}, where R_{max} is a user-defined value. In addition, we consider two simple distributions where execution time of tasks is expresses as a function of task sequence number or time: $INC(i)$ and $DEC(i)$. In $INC(i)$, execution time of tasks increases with task number. $INC(i)$ is taken as $k.i$, $i \in \{1, 2, \ldots, N\}$. Similarly, in $DEC(i)$, execution time of tasks decreases with task number. $DEC(i)$ is taken as $k.(N + 1 - i)$, $i \in \{1, 2, \ldots, N\}$.

3.4.1.2 Deadline variation

Performance of various real-time applications also depends on their deadline values. Thus in addition to the variations of execution time, we have considered five different variations in the deadline of tasks. The slack of a task mainly determines the variation in deadline scheme. For a task t_i (a_i, e_i, d_i), the value of $d_i - (a_i + e_i)$ is called slack time (SLK) of the task. This slack time can be a function of time, a function of task sequence number, a function of some external parameters or a constant. Different deadline schemes considered based on the variation of the slack time of tasks are stated below.

1. **Deadline Scheme** 1 **(Deadlines are assigned based on the randomly distributed slack)**
   In this scheme, the slack time for the tasks is randomly distributed. Deadline of a task t_i arriving at time a_i is $d_i = a_i + e_i + z$; where z is slack time and the value of z is random number varies in the range 0 to Z_{max}. Tasks under this deadline scheme have similar relative deadlines. Relative deadline of a task is the absolute deadline of the task minus its arrival time.

2. **Deadline Scheme** 2 **(Deadlines are assigned based on the Gaussian distribution of slack)**
   Under this scheme, the slack time of tasks varies as per Gaussian distribution. The deadline of a task is expressed as: $d_i = a_i + e_i + g(\mu, \sigma)$; where the function $g(\mu, \sigma)$ is follows discretized Gaussian distribution with parameter μ and σ as mean and variance respectively. Figure 3.4(a) shows an example plot of relatives deadline of tasks verses task number with $\mu = 10$ and $\sigma = 5$.

3. **Deadline Scheme** 3 **(Deadlines are assigned based on increasing slack)**
   This scheme says that the relative deadline of tasks is tight initially and with an increase in time (or task sequence number of tasks), the deadline becomes relaxed. The tight deadline means that the slack time of a task is comparatively less and relaxed deadline means that the slack time of a task is comparatively more. In this Scheme 3, deadline of the task d_i is represented as $d_i = a_i + e_i + INC(i)$; where i is sequence of task and the value of function $INC(i)$ is increase as i increase, $i \in \{1, 2, \ldots, N\}$, and N is number of tasks. Figure 3.4(b) represents an example plot of the relative deadline of tasks versus task number. We have taken $INC(i) = k \cdot i$ with $k = 3$ for the example.

4. **Deadline Scheme** 4 **(Deadlines are assigned based on decreasing slack)**
   This is the opposite to last scheme. Here the relative deadline of tasks are relaxed initially and with increase in time (or task sequence number of tasks), the deadline becomes tight. Mathematically, it can be represented as $d_i = a_i + e_i + DEC(i)$; where i is sequence of task t_i, the value of function $DEC(i)$ decreases as i increase, $i \in \{1, 2, \ldots, N\}$, and N is number of tasks. Figure 3.4(c) demonstrates this scheme. We have taken $DEC(i) = k \cdot (N - i)$ with $k = 3$ for the example.

5. **Deadline Scheme** 5 **(Common deadline for all the tasks)**
   This a special kind of scheme which is popular as common due date problems in literature [8]. Here the absolute deadlines of all the tasks are the same. Mathematically, this can be expressed as $d_i = D$; where D is the common deadline for all the tasks and $D \geq max\{a_i + e_i\}$. Figure 3.4(d) represents an example plot of the absolute deadline of tasks versus task number to represent this scheme where the deadlines for all the tasks are taken as 10205 time unit.

3.4.2 Real-world traces

In addition to synthetic real-time tasks with many variations (as described in the previous subsection), we have also considered four different real workload traces: MetaCentrum-1, CERIT-SC, Zewura and MetaCentrum-2 in our work [111]. These traces contain the job attributes of a few clusters which were generated from PBSpro and TORQUE traces at various times. CERIT-SC workload trace consists of $17,900$ jobs collected during the first 3 months of the year 2013. MetaCentrum-1 workload trace has job descriptions of $495,299$ jobs which are collected during the months of January to June of the year 2013. Zewura workload trace contains $17,256$ jobs of 80 CPU clusters which are collected during the first five months of the year 2012. MetaCentrum-2 workload trace consists of $103,656$ jobs descriptions of 14 clusters containing 806 CPUs which are collected during the first five months of the year 2009. The logs also contain several other useful information such as node descriptions, queue descriptions, machine descriptions, etc.

3.5 Objective in the Chapter

In this chapter, we wish to design energy-efficient scheduling policies for online aperiodic independent tasks onto large multiprocessor systems (with multi-threaded processors) such that all the tasks meet their deadline constraints. Here we assume the system with a sufficiently large number of processors i.e. that the computing capability of the system is very high. In general, the large systems consume a considerable amount of power. There is a static component in the power consumption of the large system, and the total power consumption (TPC) of such systems depends hugely on the number of active processors. Furthermore, in a multi-threaded processor, the power consumption is depended on the number of the active threads of the processor and static power consumption (i.e., BPC). Thus the power consumption in such multi-threaded multiprocessor systems under the considered model is non-proportional to resource utilization of the system (resource utilization of the system can also be expressed as the total number of active threads). In this work, we have used this power consumption behavior to minimize the total energy consumption (TEC) of the system.

3.6 Standard Task Scheduling Policies

In this section, we present three standard task scheduling policies, namely, utilization based scheduling policy, front work consolidation and rear work consolidation. We also state the standard earliest deadline first policy and describe the state of art task scheduling policy, namely, utilization based work consolidation policy in details.

3.6.1 Utilization based allocation policy (UBA)

In this policy, the utilization value of a task is used as a determining parameter for its allocation. Utilization of a task is the required amount of processor's share to execute the task such that the task is finished exactly at its deadline (in a uni-processor environment). Utilization u_i of task t_i can be defined as.

$$u_i = \frac{e_i}{d_i - a_i} \tag{3.3}$$

where, e_i is the execution time, d_i is deadline and a_i is the arrival time of the task t_i.

As the tasks enter the system, they are assigned the required (u_i) portions of the processor's share for their executions. For a task in LMTMPS, it requires the u_i amount of processor's share throughout its execution time from a_i to $d - 1$. This policy assumes that an infinite number of migrations and preemptions are allowed for the tasks. Virtually, a task t_i start execution in the system from its arrival time a_i to its deadline d_i but with the least processor share u_i. The start time (s_i) and finish time (f_i) of a task t_i is given by Equation 3.4.

$$s_i = a_i; \qquad f_i = d_i \tag{3.4}$$

At any instant of time t, the total number of virtual processors required to execute all the tasks and to meet their deadlines can be defined as the summation of utilization values of all the tasks present in the system. It can be written as

$$PN_t = \left\lceil \sum_{i=0}^{N_{active\_tasks}} u_i \right\rceil \tag{3.5}$$

where, PN_t is number of virtual processors required and N_{active_tasks} is total number of tasks currently running in the system (or the number of tasks for which $a_i \leq t \leq d_i$).

This policy provides the minimum processor share (i.e. utilization) required for a task for all the time instants from the arrival time till the deadline of that task. Thus the execution of a task t_i spreads for the whole duration with minimum processor requirement u_i at every time instant between a_i and d_i. It aims to reduce the instantaneous power consumption of the processor by allocating the minimum amount of processor share. This policy is mainly of theoretical interest as the premise in this scheduling policy is that the value of PN_t gets calculated continuously and the way PN_t is calculated, the system requires virtually huge number of migrations to perform scheduling in an actual scenario.

Theorem 3.1. *Total energy consumption of the system with UBA is minimum if the followings hold*

- *Processor (system) instantaneous power consumption PC_t is proportional to instantaneous processor (system) utilization, and that is $PC_t \propto PN_t$.*

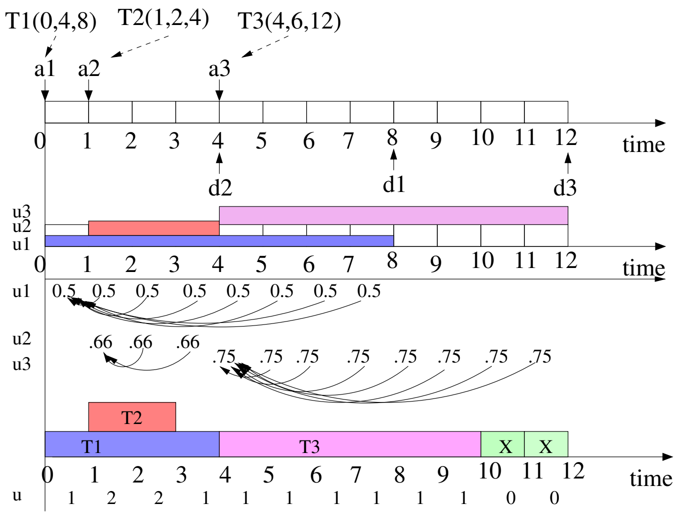


FIGURE 3.5: Illustration of front work consolidation of real-time tasks

- *All the processors are single threaded and all tasks are sequential.*
- *Unrestricted number of migrations and preemptions are allowed for all the tasks without any cost.*
- *Number of processors in the system is sufficiently large (we can assume it to be ∞)*

Proof. Total energy consumption of the system can be represented as

$$E = \int_{t=0}^{\infty} PC_t.dt = K.\sum_{t=0}^{\infty} PN_t \tag{3.6}$$

where K is proportionality constant.

The total amount of utilizations (from all the tasks) at the time instant t is PN_t and thus $\sum_{t=0}^{\infty} PN_t$ is the total amount of utilizations in the system for the entire duration of the tasks execution. This total amount of utilizations does not depend on the tasks execution order. Thus any scheduler yields minimum this amount of utilizations. Hence, the energy consumption happens to be minimum. □

3.6.2 Front work consolidation (FWC)

In this policy, the execution of tasks is brought towards the front of the time axis. As soon as a task arrives, it is allocated to an HT of a processor so that the execution of the task starts immediately. Here, start time (s_i) and finish time (f_i) of a task t_i is given by Equation 3.7. Since the execution of a task begins as soon as it reaches the system, the policy can also be called as as-soon-as-possible (ASAP) policy. This kind of immediate allocation is feasible because we considered the system with sufficiently large number compute resource (processors). This scheduling policy turns out to be *non-preemptive* and *non-migrative* (do not require migration of tasks).

$$s_i = a_i; \qquad f_i = a_i + e_i \tag{3.7}$$

To describe the front work consolidation (FWC) policy, let us consider an example with three tasks $t_1(a_1 = 0, c_1 = 4, d_1 = 8)$, $t_2(1, 2, 4)$ and $t_3(4, 6, 12)$ as shown in Figure 3.5. We can calculate utilization of task t_1 (u_1=0.5) between time 0 and 8, utilization of task t_2 (u_2 =0.667) between time 1 and 4, and utilization of task t_3 (u_3=0.75) between time 4 and 12. If we schedule these tasks based on utilization then at least one task will be in execution between time 0 to 12 and it is shown in the middle part of Figure 3.5. In front consolidation, we try to consolidate (i.e. summing up) all the utilization values towards the beginning of time axis and thus for all the tasks, utilization values get consolidated towards the arrival time of tasks. As we assume that the tasks are sequential and they can be executed on one processor at a time, consolidated utilization of one task t_i in any time slot cannot exceed $u_i \cdot \frac{d_i - a_i}{e_i}$. Consolidated utilization indicates the total amount of work to be done for a task with a particular utilization value. If the consolidated utilization exceeds this limit then it needs to be put into next time slot and the process is continued until there is no work left. In the above case, for task t_1, the total consolidated utilization becomes $u_1 \cdot (d_i - a_i)$=0.5 $\cdot$ 8=4, so it needs to be spread into four slots with consolidated utilizations $u_1 \cdot \frac{d_1 - a_1}{e_i}$=0.5 $\cdot$ (8 − 0)/4=1 in all the time slots from 1 to 4. Executing the example tasks set using this FWC policy, there will be no work in time slot 11 and 12. If there is no work, there is no power consumption (static power). This reduces the overall energy of the system.

Lemma 3.2. *If all the conditions of Theorem 3.1 hold then the total energy consumption of the system with front consolidation scheduling is minimum*

Proof. In front consolidation scheduling policy, the policy consolidates the task execution or utilization to the front and it does not increase the total system utilization. As the amount of work needed to execute in both cases is the same and instantaneous power consumption of the system is proportional to utilization, this policy also consumes minimum energy. □

If the instantaneous power consumption of the system is not-proportional to instantaneous system utilization then the above lemma is not true and in case of the multi-threaded processor, they are not proportional. Thus the Lemma 3.2 does not hold for the multi-threaded multiprocessor system.

3.6.3 Rear work consolidation (RWC)

This task scheduling policy is similar to the previous but here the tasks are consolidated towards their deadlines. All the tasks get accumulated and added to the waiting queue as soon as they arrive. A task lies in the waiting queue as long as its deadline constraint allow it to wait. Then the execution begins at their respective *urgent points* only. Urgent point is the time at which if the task starts its execution and runs without any interruption, it will be completed exactly at its deadline. This policy can be called as *Delayed Scheduling Policy.* since the execution of a task is delayed until the system time reaches its urgent points. This is also known as as-late- as-possible (ALAP) [112, 113]. Since the considered system is assumed to have sufficiently large number compute capacity, tasks can be scheduled under this policy without missing their deadlines. Start time (s_i) and finish time (f_i) of a task t_i is given by Equation 3.8.

$$s_i = d_i - e_i; \qquad f_i = d_i \tag{3.8}$$

Lemma 3.3. *If all the conditions of Theorem 3.1 hold then the overall system energy consumption with rear work consolidation scheduling is minimum.*

Proof. In rear consolidation scheduling, the policy consolidates the task execution or utilization to the rear end of the task deadline and it does not increase the total system utilization. As the amount of work needed to execute in both UBA and RWC are same and instantaneous power consumption of the system is proportional to utilization, this also consumes minimum energy. □

3.6.4 Utilization based work consolidation (UBWC)

Here the scheduler intends to keep the active processor count minimum. The execution time of the tasks are divided into unit length and they are distributed across the time axis such that no task miss their deadlines and the total number of active processors remain minimum [114, 56, 115, 116]. Processor count increases when the total utilization exceeds a whole number. For a processor with r HT, we can safely assume that when a unit execution time of a task get scheduled at any time slot, the utilization of that slot increases by $\frac{1}{r}$. For a processor with single HT, UBWC policy will consume an equal amount of energy as previously discussed policies: UBA, FWC, and RWC. But multi-threaded processor systems, the policy reduces the energy consumption significantly. This is because the task execution is serial and in every time instant the policy aims to keep the processor count minimum and minimum processor count implies the minimum amount of static energy consumption which is a significant portion.

Every incoming task to the system has arrival time a_i, deadline d_i and execution time e_i. When a task t_i arrives at system at a_i, there may be some tasks already present in the system and their remaining part of execution must have been scheduled between a_i and $\max\{d_j\}$, where d_j is the deadline of the task t_j currently present in the system except t_i. For systems with enough number of multi-threaded processors having r threads per processor, the UBWC scheduler inserts $e_i \cdot \frac{1}{r}$ units of computation between a_i and d_i with preference to early slots, so that it minimizes the number of running processors in every time slot between a_i and d_j. This minimization criteria for UBWC can be written as

$$\min \left\{ \sum_{t=a_i}^{d_j} \left\lceil \frac{number\ of\ task\ scheduled\ at\ time\ t}{r} \right\rceil \right\} \tag{3.9}$$

where r is the number of HTs per processor. In general, if we switch-on a new processor it consumes a significantly high amount of energy as compared to executing on an HT (virtual processor) of an already switched-on processor. This scheduling policy requires preemption and migration of the tasks; but the number of preemptions and number of migrations for a task t_i is bounded by $e_i - 1$ if we assume the time axis is discretized in the unit time slot.

Lemma 3.4. *For systems with an infinite single-threaded processor ($r = 1$), if all the conditions of Theorem 3.1 hold then the total energy consumption of the system with utilization based consolidation scheduling is minimum.*

Proof. The amount of work in UBWC remains same as that of UBA. When the instantaneous power consumption of the system is proportional to the processor utilization, it consumes the same amount of energy as UBA and thus the energy consumption is minimum. □

3.6.5 Earliest deadline first scheduling policy (EDF)

Earliest deadline first (EDF) is a well-known scheduling policy where tasks are considered depending on their deadlines. The task with the earliest (i.e., closest) deadline value is selected for execution first [117]. The scheduling policy considers all the waiting tasks and the one with minimum deadline value is taken for execution. EDF policy requires a fixed number of processors for its execution. In our work, we consider the non-preemptive version of EDF with a minimum processor count so that no task misses its deadline. The start time of task t_i and finish time of the same task follow the inequalities 3.10 and 3.11.

$$a_i <= s_i <= (d_i - e_i) \tag{3.10}$$

$$(a_i + e_i) <= f_i <= d_i \tag{3.11}$$

3.7 Proposed Task Scheduling Policies

Here we present four energy-efficient task scheduling policies to run a set of online aperiodic independent real-time tasks on the large multi-threaded multiprocessor system. The system follows the power consumption model which was described in Section 3.2. The power model assumes non-proportionality between the instantaneous power consumption and instantaneous system utilization. Execution of the tasks in all the policies is almost continuous (ignoring time for migration), that is $e_i = (f_i - s_i)$, where e_i, s_i, and f_i are the execution time, start time and finish time of a task t_i respectively. Based on our experimental evidence, task execution with our designed scheduling policies consume less amount of overall energy on LMTMPS as compared to UBWC and other policies (experimental validation is given in Section 3.8), even if all the tasks execute continuously. These task scheduling policies are described in the following subsections.

3.7.1 Smart scheduling policy (Smart)

We have designed a task scheduling policy for online real-time tasks called *smart scheduling policy* for the large multi-threaded multiprocessor system. This scheduling policy focuses an important parameter that is *time*. Typically scheduling policies focus on selecting a task from a set of tasks (*which* factor) for execution to a machine from a set of machines (*where* factor) whenever the machine is available for execution. But our proposed scheduling policy also considers the instant of time when a task to be dispatched (*when* factor) for execution even if machines are available for execution. Depending on the system state, the policy handles this *when* factor in a smart way such that the overall energy consumption is minimized. The policy is based on two main ideas: (i) to keep the number of active hosts as low as possible, (ii) to maximize the utilization of all the active hosts.

The proposed smart scheduling policy can be explained using the Algorithm 1. This is an online scheduling policy and the policy runs in case of the occurrence of an event. The events can be (i) the arrival of a task, (ii) the completion of a task, (iii) occurrence of the urgent point of any task. The policy first runs through the waiting queue and finds if there are any urgent tasks (line number 5 in the pseudo code). An urgent task is a task whose execution must start immediately to avoid deadline miss. Whenever the execution time (e_i) of a task t_i is equal to the difference between the deadline (d_i) and current time, it becomes urgent (line number 3 of Procedure find_UrgentTask()). The policy then schedules all the urgent tasks either to the free threads of the running processor (if available) or to threads of the newly switched-on processor. After scheduling the urgent tasks of the system, the policy considers if there are any free HTs available in the active processor list. These processors are termed as partially filled processors. If available, then the policy selects waiting tasks from the queue and schedules on them. For simplicity, in this scheduling technique, tasks were selected in first come first serve (FCFS) basis. This policy was then improved and tasks were selected based on their deadline values which is described in Subsection 3.7.4.

The smart scheduling policy can be described using Figure 3.6. The Figure shows the power consumption versus the number of active threads (active threads is also called active virtual processor) similar to Figure 3.3. As already explained in Section 3.3, the system power consumption value makes a sharp jump whenever the number of active HTs reaches a certain value. This observation motivated us to introduce two points: (i) **wait** and (ii) **go**. The focus of the scheduling policy to hold the system in *wait* state. But the deadline for the tasks might not permit

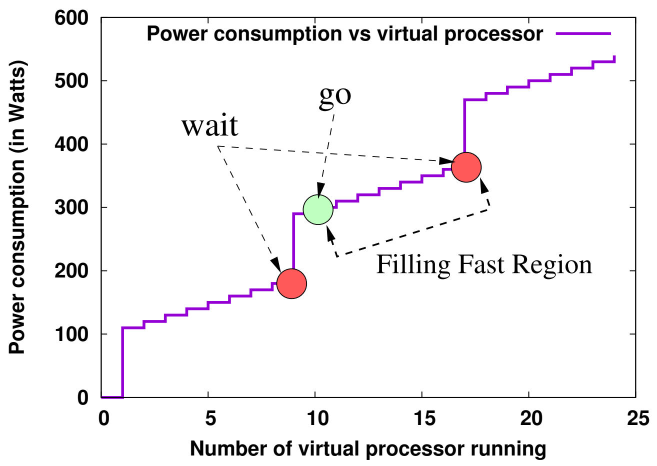


FIGURE 3.6: With extra annotated information to Figure 3.3 to explain the smart scheduling policy ($C = 100, \delta = 10$ and $r = 8$)

Algorithm 1 **Smart scheduling policy**

```
1: $t \leftarrow currentTime$;
2: while an event occurs do
3:     if a task arrives, add the new task to $WaitingQueue$.
4:     while $t_i = find\_UrgentTask()$ is not NULL do
5:         if free HT exists in any one of the active processor then
6:             allocate $t_i$ to a free HT
7:         else
8:             Switch on a new processor and initiate a HT on it.
9:             Allocate $t_i$ to the HT.
10:        $s_i \leftarrow t;\ f_j \leftarrow t + e_i$
11:        Remove $t_i$ from the $WaitingQueue$
12:    while there is free HTs in any processor do
13:        Choose a task $t_j$ from $WaitingQueue$ based on the some policy
14:        Assign the $t_j$ to a free HT of that processor.
15:        $s_j \leftarrow t;\ f_j \leftarrow t + e_j$;
16:        Remove $t_j$ from the $WaitingQueue$
```

```
1: procedure FIND_URGENTTASK()
2:     for each task $t_i$ in Waiting Queue do
3:         if $d_i = e_i + currentTime$ then
4:             return $t_i$
5:     end for
6:     return NULL
7: end procedure
```

the system to wait at this point for a long time. Once the system is required to move to *go* point, the scheduling policy enters into a hurry mode. Here the policy looks for the tasks in the waiting queue. If tasks are available, they are scheduled.

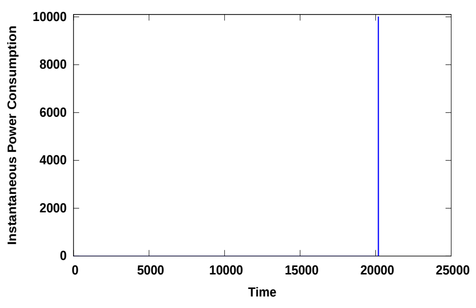
This task dispatch process is continued until the system reaches the next *wait* point. This is indicated by *Filling Fast* region in the Figure. The significance of the *wait* point is that all the active processors are utilized fully. Smart is an online scheduling policy and it takes scheduling decision dynamically at runtime. Even if the actual execution time of a task is not known beforehand and the actual execution time of a task is mostly lesser than the specified worst-case execution time (e_i), the smart policy can handle this dynamic situation because the mapping of tasks to the HTs of a processor is done irrespective to the execution time of the tasks.

3.7.2 Smart scheduling policy with early dispatch (Smart-ED)

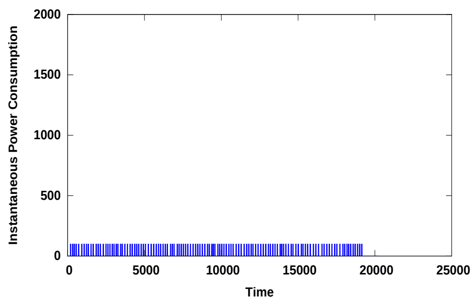
In smart scheduling policy, initially, all the arrived tasks wait in the waiting queue until the time instant when further waiting will result in a deadline miss. At this time instant, at least one task becomes urgent. We name this time instant as *urgent point*. If the urgent points for many tasks ($>> r$) get accumulated to one time instant, then we need to switch on many processors and it will create a high jump in the instantaneous power consumption value. To handle such situation we have modified our proposed smart scheduling policy and the modified policy includes early dispatch along with the smart scheduling.

In smart scheduling with early dispatch policy, at any time instant, a new processor is switched on if the number of waiting tasks $\geq r$. After switching on the processor, r number of tasks from the waiting queue is selected and are allocated to all the threads of the newly switched-on processor. The selection can be done using any policy. We have used EDF in our case. Using EDF, the schedule provides the further advantage of delaying the occurrence of the next urgent point. It might also avoid the occurrence of the urgent point itself. Here the tasks are dispatched earlier than the urgent point.

Figure 3.8 shows an example of task scheduling system, where 10 tasks (with $e_i = 4$) arrived at the system on or before time 3 and the earliest deadline of the tasks is at time 9. So the scheduler switches on a new processor (assuming each processor has $r = 8$ HTs) and schedules execution of 8 tasks (based on EDF) on to the system at time 3. Based on EDF, the selected and scheduled tasks at time 3 are t_4, t_1, t_2, t_3, t_5, t_{10}, t_6, and t_9 of HTs $hwt0$ to $hwt7$ of processor $P0$. In this



(a) **Smart Policy**



(b) Smart-ED Policy

FIGURE 3.7: Instantaneous power consumption for common deadline scheme with $\mu = 20$, $\sigma = 10$

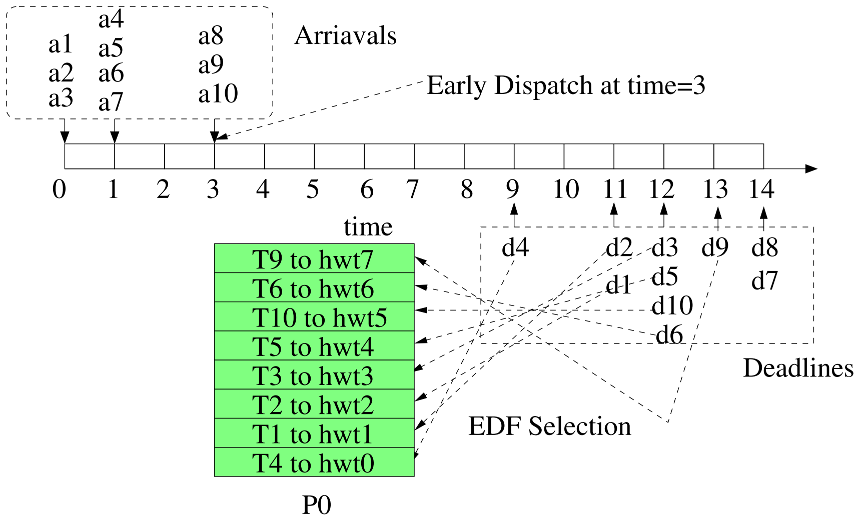


FIGURE 3.8: Smart scheduling policy with early dispatch (Smart-ED)

policy, at all the time instants, the scheduler selects the earliest deadline task and schedules onto an already switched-on processor if any HT is free.

This policy also reduces the power consumption by fully utilizing the switched on processors. This policy efficiently handles the common deadline scheme where the sharp jump in the instantaneous power value near the urgent point is avoided. Instead, the policy tries to distribute the power consumption value across the timeline equally. Figure 3.7 shows the instantaneous power consumption for both smart and smart-ED policy for the common deadline scheme. This figure clearly depicts the difference between these two policies. Smart policy shows a huge jump in the power consumption value from 0 to 12570 units at time 20155. On the other hand, Smart-ED policy equally distributes the power consumption value across the time slots. This policy is preferred over the smart policy when the system is not capable of handling such high value of power consumption or a huge jump in the value. Another benefit of this policy is that it reduces the waiting time for the tasks.

3.7.3 Smart scheduling policy with reserve slots (Smart-R)

This is a variation of the smart scheduling policy where a fraction of the processor capacity is reserved for future urgent use. In the filling fast region (as described in Figure 3.6), all the free HTs of the processor is not filled; rather a few threads (called *Reserve Factor*) are kept free such that they can execute suddenly arriving urgent tasks (for these tasks slack time $(d_i - (e_i + a_i))$ is almost zero). This reduces the number of processors to be switched on (by compulsion) for servicing the suddenly arriving urgent tasks. This, in turn, reduces the power consumption. This policy will be highly beneficial for the applications where some critical tasks (having a tight deadline) arrive in between regular tasks.

3.7.4 Smart scheduling policy with handling immediate urgency (Smart-HIU)

In the baseline smart scheduling policy, when there is free HTs (represented by fast filling region in Figure 3.6), the policy selects some tasks from the waiting queue using FCFS in order to utilize the free HTs. But it might so happen that FCFS method selects tasks whose deadlines are relatively far. The near deadline tasks will eventually become urgent in near future. This urgency may force the system to start a new processor. Again it is already discussed earlier that switching on a processor by compulsion generally increases energy consumption and it is always beneficial to avoid the compulsion scenario.

So in this modified smart scheduling policy (Smart- handling immediate urgency scheduling policy), we select and execute the tasks whose deadlines are near. That is tasks with the earliest deadline (immediate urgent) from the waiting queue is selected to utilize the free HTs. This, in turn, results in forming a long time gap between the current time and time of occurrence of the next urgent point. This longtime gap allows the scheduler to avoid switching on a new processor and this eventually reduces the instantaneous power consumption of the system.

3.8 Experiment and Results

3.8.1 Experimental setup

A simulation environment is created to simulate large multi-threaded multiprocessor system for carrying out the experiments where maximum processor number, the maximum number of threads for each processor, the base power consumption of the processor, thread power consumption, etc. can be varied. The simulation environment has an embedded task generator, which is capable of generating tasks with different deadline schemes, different execution time schemes as discussed in Section 3.4.1. Also, the simulation environment can take real-world trace datasets as input. The created simulation environment produces a large variety of statistics which includes the instantaneous power consumption of the system for all the time slots (or instants) and the overall system power consumption. These output parameters are captured for all the scheduling policies for different input parameters. To the best our knowledge, the existing energy-efficient scheduling techniques of real-time tasks in case of large compute systems are not directly comparable to our work and thus we performed all the comparisons with the standard task scheduling policies which were discussed in Section 3.6.

3.8.2 Parameter setup

3.8.2.1 Machine parameters

Research says that idle (or static) power consumption of a processor (or host) is around 60% to 70% of the total power consumption (TPC) [45, 43]. In this work, we have taken TPC of all the processors as 100 Watt and thus base power consumption (BPC) becomes 70 Watt for each processor (i.e. 70% of 100). Each processor can run at most $r = 8$ HTs and thread power consumption is taken as $\delta = 3.75$ Watt ($= (100 - 70)/8$).

3.8.2.2 Task parameters

The task sets consists of both synthetic data and real-world trace which are described in Section 3.4. The inter-arrival time between consecutive tasks in the synthetic data follows a discrete Gaussian distribution. We used four pairs of (μ,

Computation scheme	**Parameter values**
Random	$R_{max} = 100$
Gaussian	$\mu = 100, \sigma = 20$
Poisson	$\mu = 100$
Gamma	$\alpha = 50, \beta = 10$
Increasing	$k = 2$
Decreasing	$k = 2$

Table 3.2: Different experimental parameter values for execution time schemes

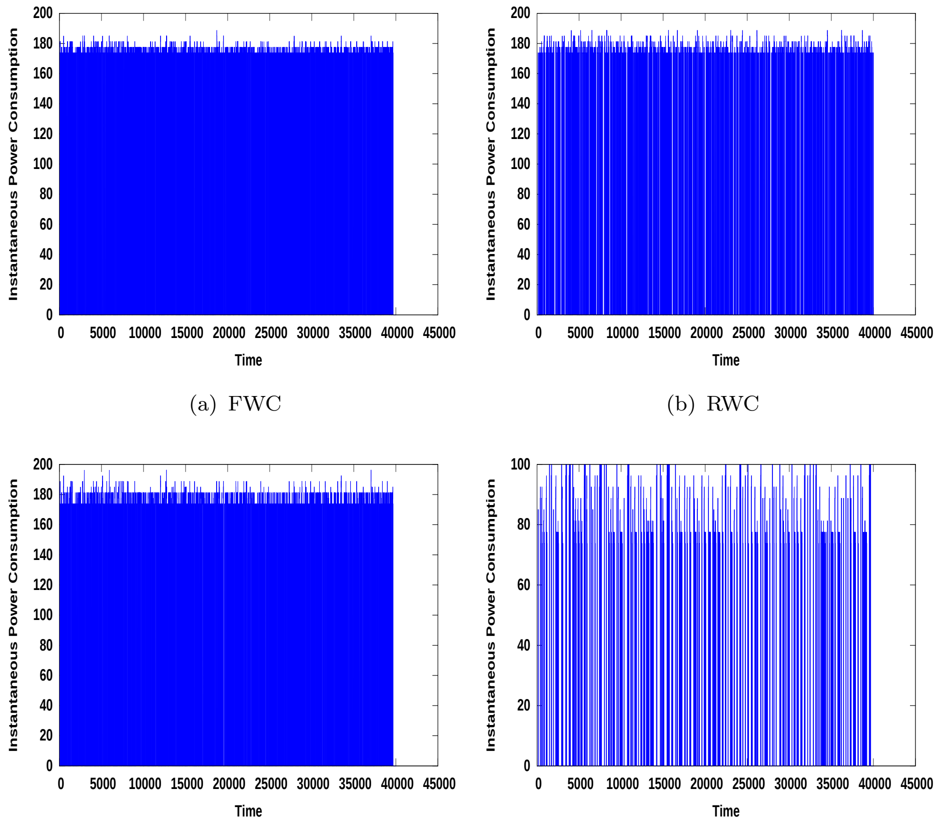
Deadline scheme	**Parameter values**
Random	$Z_{max} = 1000$
Gaussian	$\mu = 10, \sigma = 5$
Increasing	$k = 3$
Decreasing	$k = 3$
Common	$D = 10205$

Table 3.3: Different experimental parameter values for deadline schemes

σ) values e.g. $(10, 5), (20, 10), (30, 15)$ and $(40, 20)$ for generating this arrival pattern. Each experiment is conducted with 1000 number of tasks and results are averaged over 10 such sets. As stated in Section 3.4.1, we have used four different distributions and two functions for modeling the execution time of tasks. Values of different parameters for these schemes are listed in Table 3.2. We have also used five types of deadline schemes and parameter values for these schemes are listed in Table 3.3.

3.8.2.3 Migration overhead

In a compute system, total migration overhead is determined by many factors, which includes i) working set size, (ii) path of migration, (iii) migration frequency, (iv) migration count etc. And the overhead is typically expressed in terms of i) an increase in overall execution time, (ii) a degradation in overall performance of the system (measured using loss in instructions per cycle or millions instructions per second). Literature reported these overheads an average of 2 to 3 % per migration and an average of 0.1% per context switch [90, 118, 119, 120]. Since we are dealing with the energy consumption of the system, we have considered it to be 2.5% and 0.1% of the per-thread power consumption for one migration and



(a) FWC (b) RWC

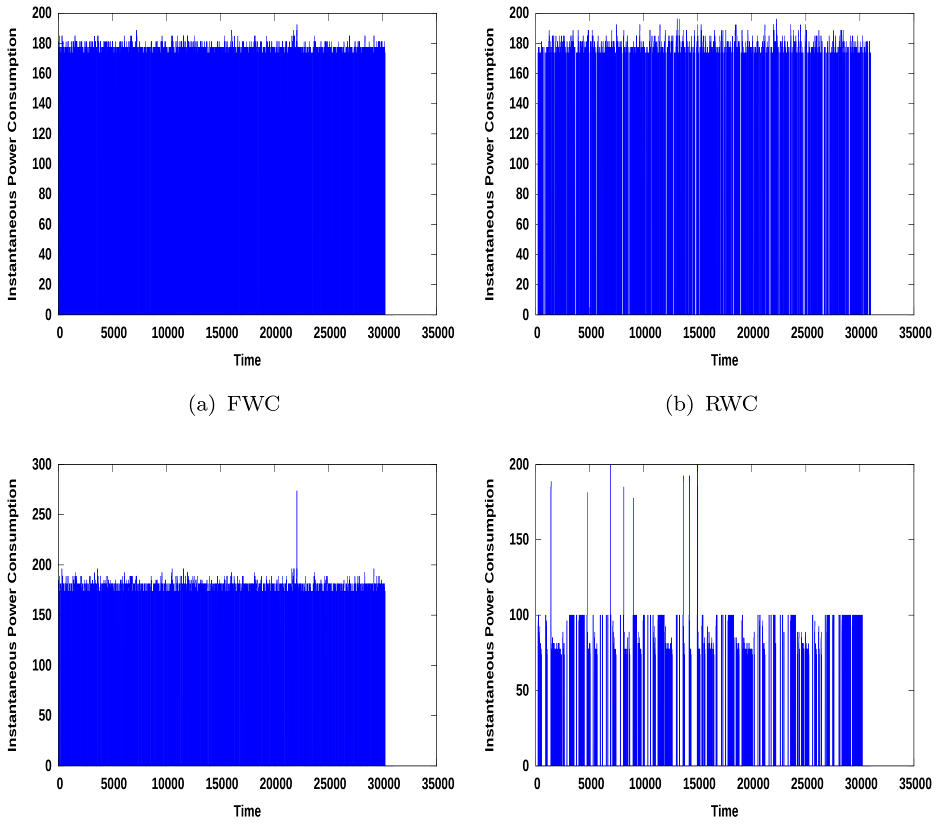
(c) UBA (d) Smart

FIGURE 3.9: Instantaneous power consumption verses time under Scheme2 (Gaussian) deadline scheme (μ = 40 and σ = 20, and execution scheme is random)

one preemption respectively. Thus the total overhead increases with their count. But these overhead were not included for the utilization based scheduling policy as the policy is mainly of theoretical interest and suffers from an infinitely large number of preemption and migration (already discussed in Section 3.6).

3.8.3 Instantaneous power consumption

The instantaneous power consumption of the system for different scheduling policies under deadline scheme 2 (execution scheme is random) is shown in Figure 3.9. Similarly, Figure 3.10 shows the same for the random execution time scheme with random deadline scheme. We observe that our proposed policy (Smart) shows an attractive power consumption behavior as compared to others and we see many gaps in the power consumption graph (Figures 3.9(d) and 3.10(d)). These gaps indicate zero instantaneous power consumption value for that time instant. The Figures also established the fact system does not consume any power until the



(a) FWC (b) RWC

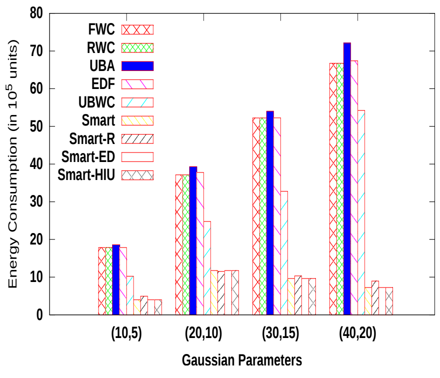
(c) UBA (d) Smart

FIGURE 3.10: Instantaneous power consumption verses time for different scheduling policies under random execution time scheme ($\mu = 30$ and $\sigma = 15$), and deadline scheme is random

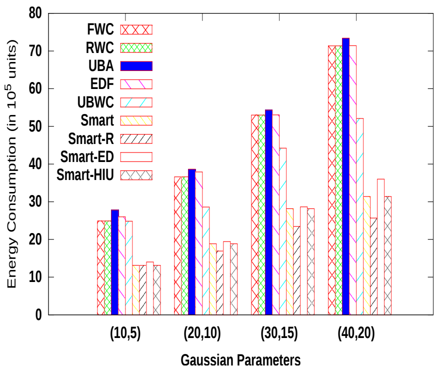
first task becomes urgent and this is true for both smart scheduling policy and rear workload consolidation policy. Thus they behave same for the initial period.

3.8.4 Results and discussions

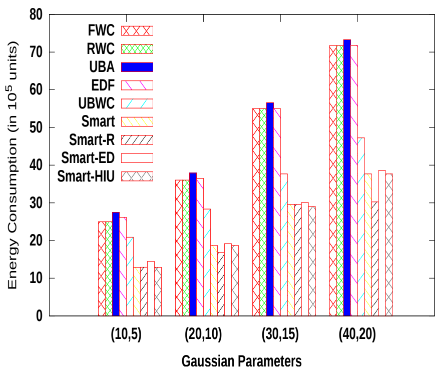
Figure 3.11(a), 3.11(b), 3.11(c), 3.11(d), 3.11(e) and 3.11(f) show the overall energy consumption of 1000 aperiodic tasks (averaged over 10 such sets) which are executed on LMTMPS using various scheduling techniques for synthetic data under (i) random distribution, (ii) Gaussian distribution, (iii) Poisson distribution, (iv) Gamma distribution, (v) increasing, and (vi) decreasing execution time schemes respectively. We observe that the proposed policies (smart, smart-ED, smart-R and smart-HIU) perform better than all other baseline policies for all the execution time schemes. The results are reported considering deadline scheme 1 and we observe similar behavior for the other four schemes. Similarly, Figure 3.12(a),



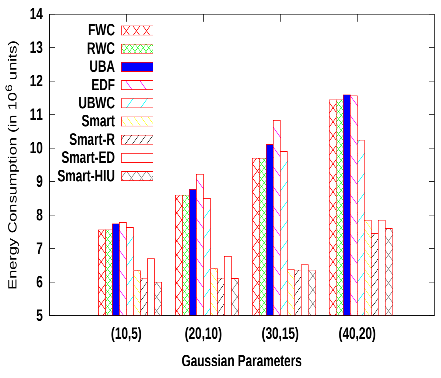
(a) Random distribution ($R_{max} = 100$)



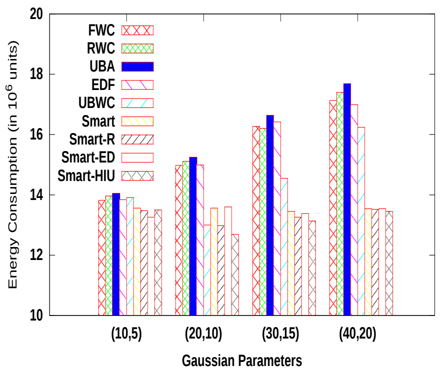
(b) Gaussian distribution ($\mu = 100, \sigma = 20$)



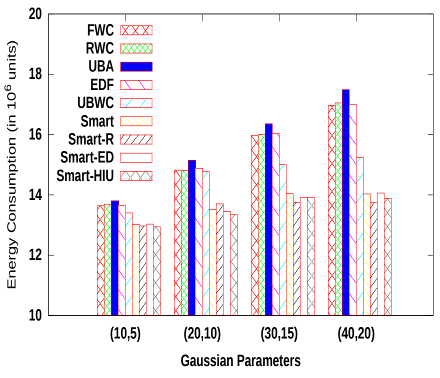
(c) Poisson distribution ($\mu = 100$)



(d) Gamma distribution ($\alpha = 50, \beta = 10$)



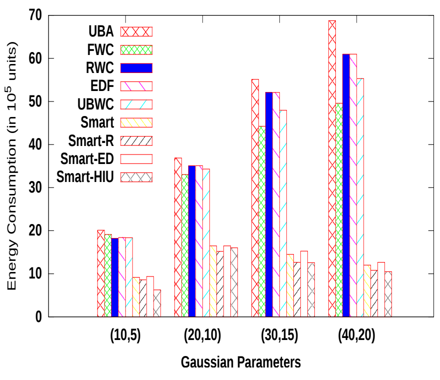
(e) Increasing ($k = 2$)



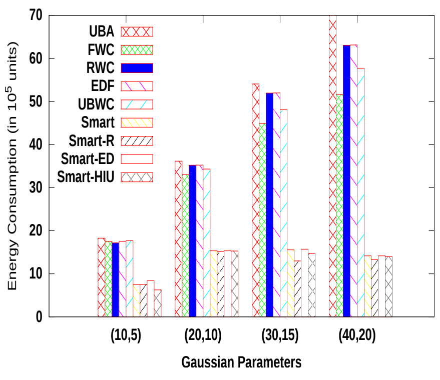
(f) Decreasing ($k = 2$)

FIGURE 3.11: Energy consumption for different scheduling policies under different execution time schemes with random deadline distribution

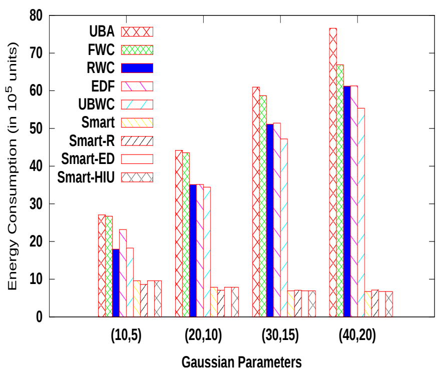
3.12(b), 3.12(c), 3.12(d) and 3.12(e) show the overall energy consumption of the system under five different deadline schemes (considering random execution time scheme). We can clearly observe that the energy consumption under our proposed policies is significantly lesser than all other baseline policies for all kinds of task models.



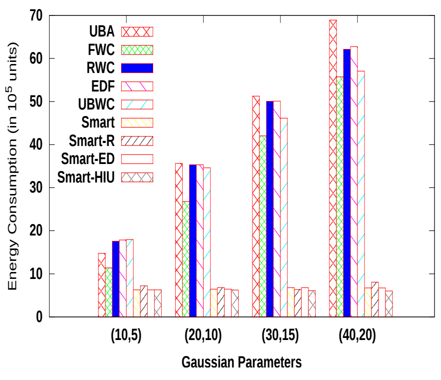
(a) Randomly distributed deadline



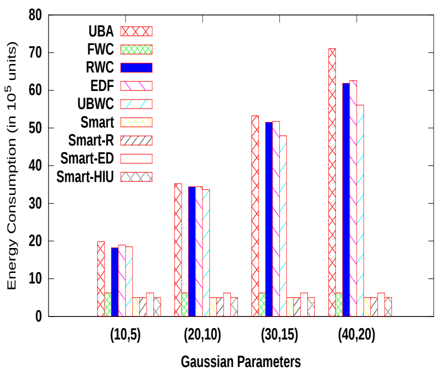
(b) Gaussianly distributed deadline



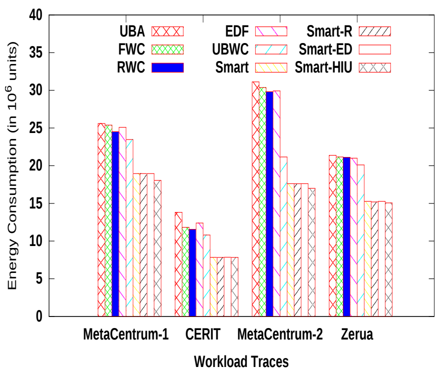
(c) Increasing deadline



(d) Decreasing deadline



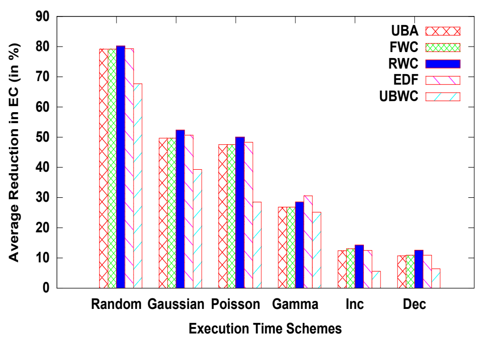
(e) Common deadline



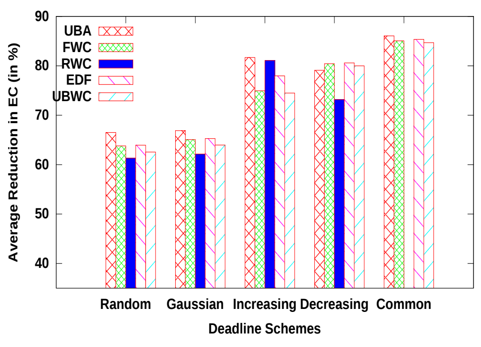
(f) Real data sets

FIGURE 3.12: Energy consumption in case of deadline centric synthetic data and real data sets

The tasks arrive at the system in an online fashion and the inter-arrival time between two consecutive tasks follows a Gaussian distribution. When the Gaussian parameter (μ and σ) values are less, inter-arrival time of consecutive tasks is also less. In such case, our proposed scheduling policy cannot fully utilize the idea for saving energy. Thus the energy reduction with respect to other scheduling policies is comparatively lesser. But with an increase in μ and σ values, the

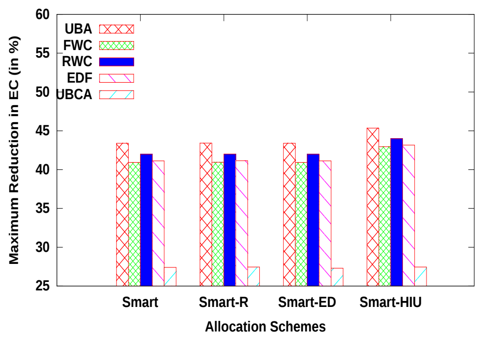


(a) Execution time schemes

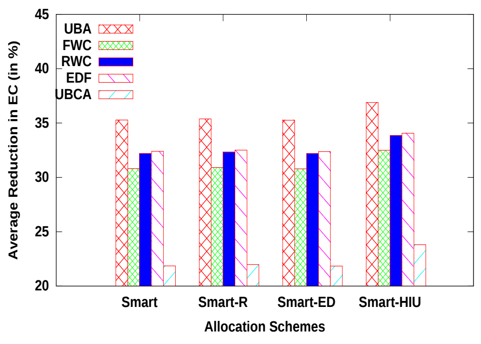


(b) Deadline schemes

FIGURE 3.13: Average energy reduction of smart policy compared to baseline policies for synthetic data



(a) Maximum



(b) Average

FIGURE 3.14: Energy reduction of proposed policy as compared to baseline policies for real-world trace data

time difference also increases. In such case, smart can take full benefit of it. As the tasks become sparser, energy reduction in smart policy becomes more. The experimental results also establish our claim that Smart-R and Smart-HIU can further reduce the energy consumption of the system almost in all the cases. But the total energy consumption for Smart-ED is same or little higher than Smart. The motivation behind introducing Smart-ED policy was to avoid the sharp jump in the power consumption value. As already explained in Section 3.7.2 with an example, this policy distributes the power consumption value across the time axis.

Figure 3.13(a) shows the average (across Gaussian parameters) energy reduction of our proposed scheduling technique with respect to the baseline policies for different execution time schemes. The proposed technique achieves an energy reduction of 37% (average) as compared to others. Similarly, Figure 3.13(b) shows the average energy reduction of our proposed scheduling technique with respect to the baseline policies for different deadline schemes. The proposed technique achieves an energy reduction of 55% (average) as compared to others. Based on this experimental result, we can firmly say that our proposed policies reduce system energy consumption by a significant margin for the synthetic workload with all the considered variations in execution time and the deadline of tasks.

3.8.5 Experiments with real workload traces

To establish the importance and effectiveness of our work, the experiments were performed for real-world trace data. The experiments were performed for four different workloads: MetaCentrum-1, CERIT-SC, MetaCentrum-2 and Zewura data sets. CERIT-SC and Zewura contain job descriptions of 17900 jobs (same as tasks) and 17256 jobs respectively. We have considered the execution of all the jobs for both the CERIT-SC and Zewura workload traces. On the other hand, MetaCentrum-1 and MetaCentrum-2 workload traces contains job descriptions of 495299 jobs and 103656 job respectively. Since it is relatively difficult to conduct experiments with such large numbers, we have taken first 15000 jobs in our experiments. Each record contains the job id (represented as task number in our work), arrival time, execution time along with other information. Deadline of a task is taken as *arrival time* + *execution time* + *Rand_Int*; where *Rand_Int* is a random integer, varies in the range 0 to 1000.

Energy consumption for real-world trace data under different scheduling policies is shown in Figure 3.12(f). It is seen that our proposed policies perform significantly better than all other policies. Figures 3.14(a) shows the maximum energy reduction of our proposed smart scheduling policies Smart, Smart-ED, Smart-R and Smart-HIU with respect to the baseline policies for real workload traces. Our proposed policies achieve maximum energy reduction up to 44% as compared to all baseline policies. Similarly 3.14(b) shows the average energy reduction of our proposed smart scheduling policies as compared others for real workload traces. The proposed policies achieve energy reduction of 30% (average) as compared to the baseline policies. Experimental results show that the energy reduction in case of real workload trace is lesser (compared to synthetic data). This is because the inter-arrival time among consecutive tasks in case of real-world trace data is lesser (similar to the case with low μ and σ values) and the smart policy cannot take the benefit by switching the processors off for a longer time.

Scheduling policies →		UBA	FWC	RWC	UBWC	EDF	Smart	Smart-ED	Smart-R	Smart-HIU
Data sets ↓	(μ, σ)									
Random ES	(10,5)	∞	0	0	442	0	0	0	0	0
	(20,10)	∞	0	0	810	0	0	2	2	4
	(30,15)	∞	0	0	1065	0	7	5	0	9
	(40,20)	∞	0	0	571	0	1	9	5	0
Gaussian ES	(10,5)	∞	0	0	4331	0	11	0	0	0
	(20,10)	∞	0	0	2463	0	42	9	2	0
	(30,15)	∞	0	0	2216	0	15	1	0	1
	(40,20)	∞	0	0	1825	0	15	9	2	3
Poisson ES	(10,5)	∞	0	0	2152	0	7	2	2	0
	(20,10)	∞	0	0	1348	0	5	1	1	0
	(30,15)	∞	0	0	1350	0	0	2	0	0
	(40,20)	∞	0	0	1388	0	0	2	0	0
Gamma ES	(10,5)	∞	0	0	31575	0	132	48	26	19
	(20,10)	∞	0	0	28019	0	7	28	22	12
	(30,15)	∞	0	0	22141	0	8	12	20	7
	(40,20)	∞	0	0	17994	0	12	9	2	7
Increasing ES	(10,5)	∞	0	0	27708	0	9	28	22	14
	(20,10)	∞	0	0	26213	0	10	19	12	10
	(30,15)	∞	0	0	24965	0	40	17	11	13
	(40,20)	∞	0	0	24757	0	24	19	12	14
Decreasing ES	(10,5)	∞	0	0	27066	0	15	9	13	9
	(20,10)	∞	0	0	25587	0	24	5	7	9
	(30,15)	∞	0	0	25004	0	24	20	4	9
	(40,20)	∞	0	0	24141	0	24	17	15	17
Random DS	(10,5)	∞	0	0	524	0	2	0	7	5
	(20,10)	∞	0	0	602	0	7	9	2	4
	(30,15)	∞	0	0	577	0	3	2	0	0
	(40,20)	∞	0	0	599	0	12	9	7	4
Gaussian DS	(10,5)	∞	0	0	539	0	7	9	2	0
	(20,10)	∞	0	0	677	0	12	9	2	0
	(30,15)	∞	0	0	527	0	9	9	2	1
	(40,20)	∞	0	0	424	0	15	9	2	3
Increasing DS	(10,5)	∞	0	0	501	0	0	0	0	0
	(20,10)	∞	0	0	497	0	0	0	0	0
	(30,15)	∞	0	0	627	0	0	0	0	0
	(40,20)	∞	0	0	599	0	0	0	0	0
Decreasing DS	(10,5)	∞	0	0	587	0	17	7	5	9
	(20,10)	∞	0	0	594	0	7	9	2	2
	(30,15)	∞	0	0	498	0	5	9	2	7
	(40,20)	∞	0	0	425	0	0	9	2	5
Common DS	(10,5)	∞	0	0	505	0	9	9	2	4
	(20,10)	∞	0	0	621	0	7	9	2	1
	(30,15)	∞	0	0	701	0	7	9	2	3
	(40,20)	∞	0	0	657	0	7	9	2	4
RWDTD	CERIT-SC	∞	0	0	19505	0	74	39	73	29
	MetaCentrum-1	∞	0	0	26214	0	24	55	67	49
	Zewura	∞	0	0	17201	0	52	20	24	49
	MetaCentrum-2	∞	0	0	24257	0	29	52	55	37

TABLE 3.4: Number of migrations occurred in different scheduling policies for different data sets (ES: Execution time Scheme, DS: Deadline Scheme, RWDTD: Real-World Trace Data)

3.8.6 Migration count

Table 3.4 shows the number of migrations with different scheduling policies both for the synthetic dataset and real-world trace data. As already explained earlier, UBA is of theoretical interest and has an unlimited number of migrations. FWC and RWC are of non-preemptive nature and do not require any migration but they lack in the overall energy consumption with respect to the proposed policies. We have considered a non-preemptive implementation of EDF and thus the number of migrations, in this case, is also 0. Energy consumption in case of UBWC is in general lesser than that of UBA, FWC, and RWC but this policy incurs a significant number of migrations. It can be lucidly seen from the experimental data that our proposed policies not only reduce overall energy consumption by a substantial margin, but also the number of migrations in these policies is within a reasonable range. Thus it can be concluded that even in case of high migration overhead system, the proposed policies will achieve a significant energy reduction.

3.9 Summary

Recent compute systems comprise of multiple processors and each processor consists of multiple threads within it. Thus the processing capabilities of these systems are adequate to handle high-end real-time applications. With the increase in the processing capability of the systems, the energy consumption also increases. As the real-time applications consume a significant amount of resources, it yields a significant amount energy consumption and the existing energy-efficient scheduling considering power construct at a lower granularity is not sufficient. Thus the energy-aware scheduling at a coarser granularity level has become essential for the large multi-threaded multiprocessor systems. In this work, we have devised an elegant power consumption model for such large systems with multi-threaded features in processors and proposed an online energy-efficient task scheduling technique, namely, *smart scheduling policy* for executing a set of online independent aperiodic real-time tasks. We have then proposed three variations of this policy to reduce the energy consumption further and to efficiently handle different situations which might occur at runtime. The experimental result shows that our proposed policies perform significantly better than all other five baseline policies for both synthetic data sets and real workload traces.

Chapter 4

Scheduling Online Real-Time Tasks on Virtualized Cloud

This chapter first presents a power consumption model for the cloud system considering both the static and the dynamic components of it. The model assumes a nonlinear relationship between the power consumption and the utilization of the hosts. Then the concept of *urgent* points of real-time tasks in the context of a heterogeneous cloud computing environment are introduced. Then the chapter presents two proposed energy-efficient scheduling approaches, named *UPS* and *UPS-ES* for executing a set of online aperiodic real-time tasks in the virtualized cloud environment.

4.1 Introduction

In the previous chapter, we considered scheduling a set of real-time tasks in a non-virtualized computing environment. In this chapter, we consider a virtualized cloud environment. Virtualization is a popular technique where multiple VMs of different types and specifications are placed on a physical machine with the help of virtualizer to improve the resource utilization of the system and thereby reduces the overall hardware cost. Cloud has emerged as a promising virtualized computing environment of recent time [121]. Cloud has attracted the users from various domains by providing exciting features such as the pay-as-you-go pricing model, scalability, reliability, etc. As the demand for the cloud system increase, several companies have also started to render the service. Cloud system not only provides exciting features to its user, it also offers similar features to the service

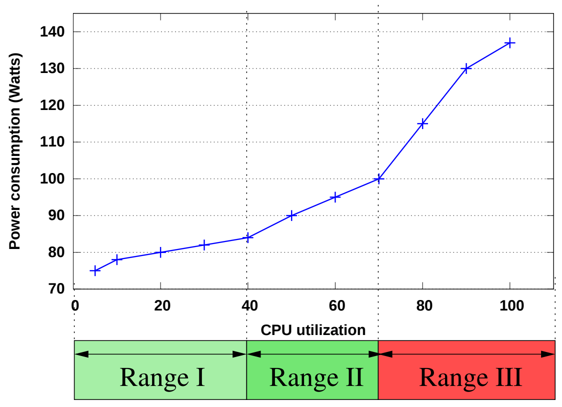


FIGURE 4.1: Power consumption of a server versus the utilization of the host as reported in [4]

providers. Elasticity is one of the feature where VM can be added to and removed from the hosts seamlessly as and when required by the service providers to meet the user's need [121, 63].

Cloud has proved itself as a perfect platform for various high-end scientific applications [27, 30]. These applications exhibit a unique characteristic, that is the variation of their resource requirements. However, traditional computing platforms, such as grid and clusters are not adequate to handle such high resource intensive applications and the variation in their resource requirement. Thus the cloud is proved to be a promising computing platform to meet the demand of these applications [27, 24].

To support the high demand at times, the cloud systems are over-provisioned with resources. It is observed that one of the major reason for high energy consumption is the poor utilization of the hosts. As the scheduling deals with the utilization of the host and it impacts the overall performance of the system, energy consumption has become one of the major optimality criteria of scheduling. These are termed as energy-efficient scheduling or power-aware scheduling [75, 122]. Each physical machine hosts a number of virtual machines (VM) and the VMs executes user tasks. These VMs are of different types, sizes, and capacities. Thus the execution time of a task depends on the VM which runs it. In this work, we consider scheduling of real-time tasks and completing their execution before the deadline is essential.

We address two conflicting parameters regarding the energy consumption of a host in the cloud system. The first parameter is the utilization of the hosts, and the second parameter is the number of active hosts. With an increase in the utilization, the temperature of the system increases. It is reported in [60] that with an increase in every 10°C in temperature, the failure rate of an electronic device doubles. Thus the first parameter puts a restriction on the utilization of the hosts. As the utilization of the hosts moves above some threshold value, the performance of the VMs starts getting deteriorated [108, 88]. Thus to maintain the performance of the system, hosts should not be overloaded, and that implies that their utilization should be kept below some threshold value. On the contrary, to save the energy consumption, we should use the minimum number of hosts in the system. In order to minimize the active host count, the utilization of the hosts should be kept high.

Now, if we observe the power consumption pattern of the servers, we see an interesting pattern. Dayarathna *et al.* [48] presented a survey paper which contains the description of several power models. The power consumption of a host is typically expressed as a function of host utilization, frequency, VM power consumption, etc. Lien *et al.* [4] presented a nice study and measured the power consumption of the server for six different workloads. As per their study, the power consumption varies non-linearly with utilization. Figure 4.1 shows the power consumption of a server versus the host utilization as reported in [4]. We can roughly divide the graph in three ranges, where utilization varies: (i) 0% to 40% (denoted as Range-I), (ii) 40% to 70% (denoted as Range-II), and (iii) 70% to 100% (denoted as Range-III). We can observe that when the host is switched on, it consumes 70W of power. Then the power consumption increase rate is less with respect to the utilization of Range-I. In case of Range-II, the increase rate is more than Range-I but not too high. The increase is significantly high in case of Range-III. To the best of our knowledge, the existing energy-efficient scheduling algorithms of real-time tasks for the cloud computing domain do not sufficiently consider this interesting power consumption behavior of the hosts.

We can now interestingly link the "restriction on the utilization of hosts" and "the power consumption behavior of the servers" together in scheduling. We define a threshold on the utilization of the host when the power consumption takes a sharp jump from Range-II to Range-III. The target of the scheduler is to usually keep the host at this utilization (in between Range-I and Range-II). This will prevent the system from performance degradation as we are not utilizing 100% of the computing resources of the hosts. On the other hand, we are dealing with real-time tasks and meeting the deadline of the tasks is a must. Thus we allow the hosts to accommodate more tasks (i.e. VMs) and to exceed the threshold when it becomes necessary to meet task deadline.

Here we summarize the contribution of this chapter as follows.

- First, an energy consumption model for the cloud system is presented which considers both static and dynamic energy consumption of the cloud hosts and assumes a nonlinear relationship between the power consumption and the utilization of the processor.
- Next, we propose two energy-efficient scheduling policies, (i) urgent point aware scheduling (*UPS*), and (ii) urgent point aware scheduling - early scheduling (*UPS-ES*), for executing online aperiodic real-time tasks on the cloud system.
- Next, we present the idea of urgent points for the real-time tasks in the context of heterogeneous compute systems and design strategies for the proposed scheduling policies *UPS* and *UPS-ES* to (i) enable scheduling of critical tasks, (ii) activate VM consolidation to reduce the number of active hosts, (iii) efficiently use live VMs for executing tasks to reduce the overhead for VM creation and deletion.
- At last, we evaluate the effectiveness of *UPS* and *UPS-ES* policies by comparing them with a state of the art scheduling policy EARH [41] and two simple scheduling approaches: immediate and delayed. The comparison is done for the real-world trace data (Google tracelog and Metacentrum) and a synthetic data sets comprising of three variations in deadline schemes for the tasks.

4.2 System Model

The logical view of the considered cloud computing system comprises of three layers: a physical layer, a VM layer, and an application layer. The physical layer consists of an infinite set of heterogeneous machines (or hosts) $\boldsymbol{H} = \{h_1, h_2, h_3, h_4, \cdots\}$. These hosts are typically characterized by their compute capacity, amount of RAM, and storage capacity, base power consumption, etc. Compute capacity of a host is defined in terms of MIPS (million instructions per second). We define a set of active hosts as $H_{active} \subseteq \boldsymbol{H}$. These are the hosts which are switched on. They might be idle (does not contain any active VM) or busy (contains some active VMs). Each host h_k can accommodate a set of VMs, $VM_k = \{v_{1k}, v_{2k}, \ldots, v_{|V_k|k}\}$. Each VM consumes a portion of its host's compute capacity, RAM, and storage. The portion of the resources assigned to a VM does not get changed during its lifetime. Moreover, we consider a fully elastic cloud where VMs can be dynamically added and removed from the hosts based on the requirement.

When a VM executes a task, it consumes a portion of the resources of the physical machine it is hosted on. Each VM v_{jk} (j^{th} VM on k^{th} host) has some compute capacity (expressed in MIPS) and it represented as $CP(v_{jk})$. Thus the VMs are of heterogeneous nature (specially, in their compute capacity and power consumption). For simplicity, we assume that the compute capacity of the VMs lie within a range: $\Big[minCP, maxCP\Big]$. The $minCP$ and $maxCP$ indicates the minimum and maximum compute capacity of the VMs respectively. Without any loss of generality, we assume that the utilization associated with an active VM (running some task) is proportional to its compute capacity. For, a VM v_{jk}, the corresponding utilization u_{jk} can be expressed as

$$u_{jk} = \frac{CP(v_{jk})}{CP(h_k)} \times 100\,\% \tag{4.1}$$

where $CP(h_k)$ is the compute capacity of the host h_k.

As the VM finishes the task assigned to it, it becomes idle and the corresponding utilization of the VM becomes negligible and we ignore this in our work. We further assume that a VM hosted on one host can be migrated to another host if required.

4.3 Task Model

In our work, we consider a set of online aperiodic independent real-time tasks, $T = \{t_1, t_2, t_3, \cdots\}$. Each task t_i is characterized by three-tuple (a_i, l_i, d_i) where a_i is the arrival time, l_i is the length, and d_i is the deadline of the task. The length of the tasks is expressed in million instructions (MI). All the tasks are assumed to be sequential and uni-VM, that is, a task is executed by only one VM. We assume that the inter-arrival time of the tasks follows the Poisson distribution.

Suppose a task t_i is executed by a VM v_{jk}. Then, the task requires $l_i/CP(v_{jk})$ amount time for its completion. This becomes the execution time of task t_i on VM v_{jk} and it is represented by e_{ijk}. Mathematically, it can be written as:

$$e_{ijk} = \frac{l_i}{CP(v_{jk})} \tag{4.2}$$

We define the ready time of a VM, $rt(v_{j,k})$ as:

$$rt(v_{jk}) = st(v_{jk}) + e_{ijk} \tag{4.3}$$

where, $st(v_{jk})$ is the start time of the VM which indicates the time instant when the VM v_{jk} has started executing the task t_i.

We define a VM v_{jk} as a candidate VM for executing a task t_i if the following condition is satisfied.

$$rt(v_{jk}) \leq d_i - e_{ijk} \tag{4.4}$$

Now we introduce maximum execution time $(et_{max}(t_i))$ and minimum execution time $(et_{min}(t_i))$ of a task t_i as follows.

$$et_{max}(t_i) = \frac{l_i}{minCP}; \qquad et_{min}(t_i) = \frac{l_i}{maxCP} \tag{4.5}$$

Then slack of a task can be defined as $slk(t_i) = d_i - et_{max}(t_i) - a_i$.

We assume the task sets with three different types of deadline schemes: **Random**, **Tight**, and **Relax**. In **Random** deadline scheme, the slack of the tasks are generated from a random distribution; where $slk(t_i)$ varies in the range from R_{min} to R_{max}. In case of **Tight** deadline scheme, the time difference between the deadline and execution time of the task is short. This can be written as: $slk(t_i) \leq D_{max}$. In **Relax** deadline scheme, the time difference between the deadline and execution time of task is long; where $slk(t_i) \geq D_{min}$. Here, R_{min}, R_{max}, D_{min}, and D_{max} are user defined deadline threshold values.

4.4 Energy Consumption Model

A cloud computing system comprises various components, such as the computation nodes, storage, network equipment, etc. Out of these components, the major portion of the power is drowned by the computation node, i.e., the host. Thus, in this work, we consider the energy consumption model of the host only. The power consumption of a host has two parts: static power consumption and dynamic power consumption. A significant amount of research in the area of real-time task scheduling considered only the dynamic power consumption [33, 30, 52, 67]. But static power consumption plays the vital role, and it contributes almost 60% to 70% of the total power consumption [45, 43]. Thus in our work, we consider both static and dynamic power consumption of the hosts of the cloud system. The summation of the power consumption over the total time interval produces the energy consumption of the system. Thus, it can be written as, $E = \int_{t=0}^{\infty} PC_t.dt$, where PC_t is the total instantaneous power consumption of the system at time t.

Now, the power consumption of a host is expressed as a function of its total utilization. For a host h_k, at any time instant, the total utilization U_k is defined as

$$U_k = \sum_{j=1}^{VM_k} u_{jk} \tag{4.6}$$

where, u_{jk} is the resource utilization of the VM v_{jk}.

As mentioned in the Section 4.1 and reported in Figure 4.1, we have considered three different ranges for the power consumption of a host and this can be written as

$$\begin{aligned} P_{total} &= P_{static} + \alpha_1 \times U_k, \quad \text{if } U_k \leq 40\% \text{ (in Range-I)} \\ &= P_{static} + \alpha_2 \times U_k, \quad \text{if } 40\% < U_k \leq 70\% \text{ (in Range-II)} \\ &= P_{static} + \alpha_3 \times U_k, \quad \text{if } U_k > 70\% \text{ (in Range-III)} \end{aligned} \tag{4.7}$$

where, $\alpha_3 > \alpha_2 > \alpha_1$ and $\alpha_3 > (\alpha_1 + \alpha_2)$

Now, the energy consumption of a host can be expressed as

$$E_{h_k} = \int_{t=0}^{\infty} P_{total} \cdot dt \tag{4.8}$$

Thus the energy consumption of the cloud system can be expressed as

$$E_{total} = \sum_{k=1}^{|H_{active}|} E_{h_k} \tag{4.9}$$

As demonstrated in the Figure 4.1 and formulated in the Equation 4.7, the slope of the power function is much higher when the utilization of the host moves above 70%. Keeping this into consideration, we have used two threshold values TH_{U1} and TH_{U2} in our work. TH_{U1} indicates the boundary of the second region (i.e., when the utilization of the host moves above 70%) and TH_{U2} indicates the maximum permissible utilization for a host which is taken as 100%. Usages of these thresholds are described in the Section 4.6.

The power consumption model indicated by Equation 4.7 used in our work assumes that there is a local power optimization module (DVFS or DPM) at each host. The local optimization module at a host controls the frequency and the sleep slate the compute system which may have more then one compute components. As a whole, the power consumption is depended on the utilization of the host. We can safely assume that whenever the host runs at the highest utilization, it is running at its highest capable frequency of operation, and the frequency of operation of a host is proportional to the utilization of the host.

4.5 Objective in the Chapter

In this chapter, we wish to design energy-efficient scheduling policies for online aperiodic independent real-time tasks for the virtualized cloud system (as described

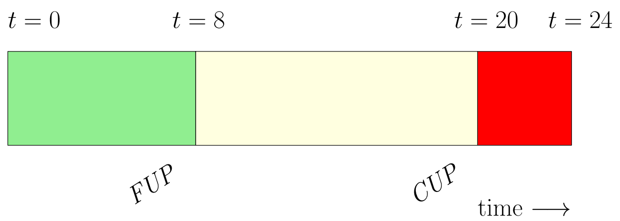


FIGURE 4.2: Urgent points of a task with deadline 24

in Section 4.2) under the considered energy consumption model (as described in Section 4.4) such that all the tasks meet their deadline constraints and the overall energy consumption of the cloud system is minimized.

4.6 Scheduling Strategies

In this section, we first introduce the concept of the urgent point for a real-time task in the context of a virtualized cloud system. As already stated in the Section 4.3 that a task t_i is characterized by its arrival time (a_i), length (l_i) and deadline (d_i). Now, to meet the real-time constraint of the task t_i, it must be finished on or before d_i. For a task t_i with execution time e_i, urgent point can be defined as

$$UP(i) = d_i - e_i \tag{4.10}$$

However, in our considered model, the actual execution time of the task depends on the compute capacity of the VM it is executed by. Whenever the task is executed by a VM of minimum compute capacity, its execution time becomes longest. On the other hand, if the task is executed by a VM of maximum compute capacity, its execution time becomes shortest. Figure 4.2 shows an example to demonstrate this. The arrival time and the deadline of the shown task are 0, and 20 seconds. The length of the task is 80 MI (million instructions). The minimum compute capacity and the maximum compute capacity of the VMs of the example cloud system is assumed to be 5 MIPS and 20 MIPS. If the task is executed by a VM of compute capacity of 5 MIPS, then the execution time of the task becomes 16 (= 80/5) second. In this case, the task must start its execution latest by 8 (= 24 − 16) second. We name this time instant as *first urgent point* (*FUP*). Again if the task is executed by a VM of compute capacity of 20 MIPS, then the execution time of the task becomes 4 (= 80/20) second. In this case, the task execution must begin latest by 20 ($= 24 - 4$) second. We name this time instant as *critical urgent point* (*CUP*). Now we present a series of approaches, which together perform the scheduling operation by efficiently utilizing the *FUP* and *CUP* of tasks.

Figure 4.3 depicts the schematic view of the cloud system for the proposed scheduling approaches. The scheduler consists of the main scheduling agent (*UPS* or *UPS-ES*) and three supporting agents: *SCUP* (Scheduling at Critical Urgent Point), *STC* (Scheduling at Task Completion), and *SWC* (Scheduling With Consolidation). The system maintains a common waiting queue for the tasks, called global waiting queue (*GWQ*). The tasks in this queue are kept in the sorted order of their *CUP* values. In addition to this waiting queue, each VM maintains its individual local waiting queue. The scheduling process is invoked upon the arrival of a task to the cloud system. The basic steps of the scheduling operation can be explained as below.

Main scheduling agent: The scheduling agent always maintains updated information about the cloud resources. Upon arrival of a task, the scheduling agent checks whether the incoming task can be placed on any of the local queues of the running VMs so that the deadline constraint of the task can be met. If so, the task is added to the local queue of the VM. If multiple VMs can execute the task, then the task is placed in the local queue of the VM with the lowest power consumption.

Supporting scheduling agent: If the placement of the task to the local queue of the VMs remains unsuccessful, then it is added to the GWQ. GWQ is accessed by the agents SCUP (Scheduling at Critical Urgent Point), STC (Scheduling at Task Completion), and SWC (Scheduling at Workload Consolidation). When a task waiting in GWQ reaches its CUP value, SCUP scheduling agent immediately schedules the task. The agent STC runs to re-use the VM whenever a task finishes its execution and releases the VM. It also consults the GWQ to select an appropriate task for execution. When the total required compute capacities of the workload in the system is significantly lesser than the total compute capacities of the active hosts, we say that the system resources are poorly utilized. Then the SWC performs its operation. In the first phase, the agent tries to re-use the idle VMs by assigning tasks from GWQ. In the next phase, unused VMs are switched off and de-allocated from hosts. And then the running VMs are consolidated into a fewer number of hosts, and idle hosts are switched off.

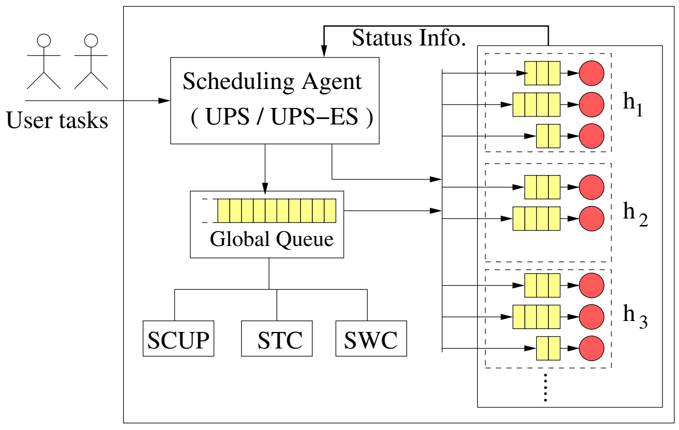


FIGURE 4.3: Schematic representation of the cloud system for the proposed scheduling polices

4.6.1 Urgent point aware scheduling (UPS)

Algorithm 2 shows the pseudocode of the *UPS* policy. This algorithm acts as a scheduling agent which runs on the arrival of a task to the cloud system. Once a task arrives at the system, the scheduling policy first checks whether the running VMs on the system can execute the task. A set of eligible VMs (**candidateVMSet** in the pseudocode) are listed which can meet the deadline constraint of the task maintaining the utilization threshold of the corresponding host below TH_{U1}. The target of the policy is to keep the utilization of the hosts close to TH_{U1}. If an existing VM can execute the task satisfying its deadline constraint, then the task is placed in the local queue of the VM. In case, multiple VMs can execute the task, the policy selects the VM with the least energy consumption. Line numbers 4 to 9 of the Algorithm 2 represents these steps. If the attempt fails, then the task is added to the global waiting queue (GWQ). The scheduling window of the task is set as: $[FUP(t_i), CUP(t_i)]$; where $FUP(t_i)$ is the first urgent point of the task, and $CUP(t_i)$ is the critical urgent point of the task. This means that the task can be scheduled at any time instant from $FUP(t_i)$ to $CUP(t_i)$. Once the tasks are added to GWQ (if current system state cannot handle) under this scheduling policy, they can be further handled by policies which scan the queue. These policies are described in the Sections 4.6.1.1, 4.6.1.2 and 4.6.1.3. The target of UPS scheduling policy is to delay the execution of an incoming task if the current system state cannot execute the task energy-efficiently.

Algorithm 2 Urgent Point aware Scheduling (UPS)

```
On arrival of a task $t_i(a_i, l_i, d_i)$
 1: Calculate the $FUP(t_i)$ and $CUP(t_i)$
 2: $findVMFlag \leftarrow FALSE$
 3: Find the candidateVMset for the task maintaining host utilization threshold
    $TH_{U1}$
 4: if candidateVMset is not $NULL$ then
 5:     Select the VM such that host utilization remains closest to $TH_{U1}$
        (best fit policy)
 6:     if Multiple VM exists then Select the VM with least power consumption
 7:     Schedule the task $t_i$ at current ready time of the VM
 8:     Update ready time of the VM
 9:     $findVMFlag \leftarrow TRUE$
10: if $findVMFlag = FALSE$ then
11:     Add the task to $GWQ$
12:     Set the scheduling window for the task: $[FUP(t_i), CUP(t_i)]$
```

4.6.1.1 Scheduling at urgent critical point (*SCUP*)

Algorithm 3 shows the pseudocode for scanning the *GWQ* looking for the tasks whose *CUP* is reached. The tasks in *GWQ* are sorted based on their deadline. If such a task is found. the scheduler first checks whether there is any idle VM in the system and whether the VM is a candidate for the task. If such VM exists, the scheduler selects the VM with the least energy consumption. If no such VM exists, then a new VM with the minimum required compute capacity is created and the VM is tried to place on an active host. As the task is critically urgent, we allow the host utilization to go up to TH_{U2}. If multiple active hosts can accommodate the VM, the scheduler selects the VM such that the utilization of the host after addition of the VM remains close to threshold TH_{U1}. If an active host can accommodate the VM, then it is placed on the host, and the task is assigned to the VM. If the scheduler fails to find a host, then a consolidation operation is performed on the active set of hosts to create sufficient space (i.e., utilization) for the new VM. The algorithm achieves this via a procedure call to *createSpace*(). The pseudocode for *createSpace*() is shown using the Procedure *creatSpace*(). The procedure migrates VMs from lowly utilized hosts to the highly utilized hosts. The procedure returns the host once it gets a host which can accommodate the VM. Until this point, the scheduler tried to get a host from the active set only. If it fails, then a new host is switched on and then it is added to the list of the active set of hosts. After the task is assigned to the VM and the VM is placed on the host, the scheduler then fills the remaining utilization of the newly switched-on

Algorithm 3 Scheduling at Critical Urgent Point ($SCUP$)

```
1: for each task $t_i$ in $GWQ$ do
2:     if $currentTime = CUP(t_i)$ then
3:         $findVMFlag \leftarrow FALSE$
4:         if any idle VM in the system can execute the task then
5:             Assign the task to the VM
6:             Update the ready time of the VM
7:             $findVMFlag \leftarrow TRUE$
8:         if $findVMFlag = FALSE$ then
9:             Create a VM, $v$ with minimum required compute capacity so that
               the deadline constraint of the task is met
10:            Choose the host from $H_a$ such that after the addition of the VM
               its utilization is close to threshold $TH_{U1}$
               (if multiple hosts exist)
11:            if Success then
12:                Assign the task to the VM and place the VM on the host
13:                Update the ready time of the VM
14:                $findVMFlag \leftarrow TRUE$
15:            if $findVMFlag = FALSE$ then
16:                $h_k \leftarrow createSpace(v)$
17:                if $h_k$ is not $NULL$ then
18:                    Assign the task to the VM and place the VM on the host
19:                    Update the ready time of the VM
20:                    $findVMFlag \leftarrow TRUE$
21:            if $findVMFlag = FALSE$ then
22:                Start a new host $h_k$
23:                Place the VM on the host and assign the task to the VM
24:                Set ready time of the VM
25:                Call procedure fillHost($h_k$)
26: end for
```

processor by placing new VMs on it. Procedure *fillHost*() shows the pseudocode for this. The process of VM placement is repeated until the utilization of the host reaches the target utilization threshold TH_{U1}.

4.6.1.2 Scheduling at task completion (*STC*)

As the tasks are assigned to the VMs and the executions start, the mapping remains the same and eventually, the tasks finish their executions and the corresponding VMs become idle. Now the motivation of the scheduler is to re-use the VMs for executing the other tasks. Algorithm 4 shows the pseudocode for this

```
1: procedure $createSpace(v)$
2:     Sort the active host set $H_a$ in increasing order of their utilization
3:     $migrationFlag \leftarrow FALSE$;
4:     $sourceHost \leftarrow NULL$
5:     for each host $h_k$ in $H_a$ do
6:         Find the VM $v_j$ with least utilization in $h_k$ s.t. it can accommodate
           $v$ after removal of $v_j$
7:         for each host $h_i$ in $H_a$ (considered in descending order) do
8:             if $h_i$ can accommodate $v_j$ then
9:                 Perform the migration of VM $v_j$ from host $h_k$ to $h_i$
10:                return $h_k$
11:        end for
12:    end for
13:    return $NULL$
14: end procedure
```

```
1: procedure $fillHost(h_k)$
2:     Set the utilization threshold of the host $h_k$ as $TH_{U1}$
3:     while $U_k < TH_{U1}$ do
4:         Calculate the maximum possible MIPS for the remaining host
           utilization
5:         Scan GWQ and find the feasible set of tasks for this
6:         Choose the task with closest $CUP$ value
7:         Create a VM with required compute capacity for executing the task
8:         Set the ready time of the VM
9: end procedure
```

Algorithm 4 Scheduling at Task Completion (*STC*)

```
On completion of a task $t_i$
1: Get the corresponding VM $v$ and its compute capacity $CP(v)$
2: Scan through the $GWQ$ and find a task $t_j$ so that $currentTime$ lies in the
   scheduling window and $v$ is a candidate VM for the task and the required
   compute capacity is close to $CP(v)$
3: if Successful then
4:     Assign the task $t_j$ to the VM
5:     Update the ready time of the VM
```

operation. This algorithm runs whenever a task finishes its execution. The algorithm runs through GWQ and finds the task which best fits the compute capacity of the VM released by the completed task.

Algorithm 5 Scheduling With Consolidation (SWC)

```
1: Sort the tasks in the global waiting queue $GWQ$ in increasing order of their $CUP$ value
2: for each host $h_k$ in $H_a$ do
3:     for each idle VM $v_{jk}$ in $h_k$ do
4:         Scan through $GWQ$ to find a candidate task for the VM $v_{jk}$
5:         if Success then
6:             Assign the task to the VM $v_{jk}$
7:             Update the ready time of $v_{jk}$
8:     end for
9:     if $U_k \geq TH_{U1}$ then Set $fullFlag(h_k) \leftarrow TRUE$
10: end for
11: Destroy all the idle VMs of the system.
12: Sort the hosts in ascending order of their utilization
13: for each host $h_k$ in $H_a$ do
14:     for each VM $v_{jk}$ in $h_k$ do
15:         for each host $h_i$ in $H_a$ do
16:             if $h_i$ can host $v_{jk}$ and $fullFlag(h_i) = FALSE$ and $h_i \neq h_j$ then
17:                 Migrate $v_{jk}$ from host $h_k$ to host $h_i$
18:         end for
19:     end for
20: end for
21: Hosts without any active VMs are switched off and removed from set $H_a$
```

4.6.1.3 Scheduling with consolidation (SWC)

The target of the scheduling policies is to keep the host utilization at TH_{U1}. This threshold is revoked in case a task has reached its CUP. Here we present a modified version of the basic consolidation operation of literature. A basic consolidation operation first simply removes the idle VMs from the host, then migrates the VMs from one host to another to reduce the number of active hosts. In addition, they switch off the idle hosts. But in this modified consolidation procedure, we first give an opportunity to the waiting tasks in the system to re-use the idle VM. We scan through GWQ and find if there is any feasible task in the queue for an idle VM. Once the tasks are given opportunity, then the migration of VMs takes place.

4.6.2 UPS - early scheduling ($UPS - ES$)

We present a variation of the *UPS*. In *UPS*, an incoming task is added to the GWQ if the currently running VMs in the system cannot execute the task meeting its

Algorithm 6 Urgent Point aware Scheduling - Early Scheduling ($UPS-ES$)

```
On arrival of a task $t_i(a_i, l_i, d_i)$
 1: Find the candidateVMset-I for the task maintaining host utilization
    threshold $TH_{U1}$
 2: if candidateVMset-I is not $NULL$ then
 3:     Select the VM such that host utilization remains closest to $TH_{U1}$
        (best fit policy)
 4:     if Multiple VM exists then Select the VM with least power consumption
 5:     Schedule the task $t_i$ at current ready time of the VM
 6:     Update ready time of the VM
 7:     $findVMFlag \leftarrow TRUE$
 8: if $(FUP(t_i) - currentTime) < TH_{VMCDT}$ then
 9:     Find the candidateVMset-II for the task considering host utilization
        $TH_{U2}$
10:     if candidateVMset-II is not $NULL$ then
11:         Select the VM with minimal power consumption
12:         Schedule the task $t_i$ at current ready time of the VM
13:         Update ready time of the VM
14:         $findVMFlag \leftarrow TRUE$
15:     else
16:         Start a new host $h_k$
17:         create a new VM $v_{jk}$ on $h_k$ with minimal compute capacity such that
            the task deadline can be met
18:         Place the VM on the host and assign the task to the VM
19:         Set ready time of the VM
20:         Call procedure fillHost($h_k$)
21: else
22:     Add the task to the Global Waiting Queue $Q$
23:     Set the scheduling window for the task: $[FUP(t_i), CUP(t_i)]$
```

deadline constraint. But in this policy, we first check whether the deadline of the incoming task is close. The policy first tries to put an incoming task to the local queue of an existing VM if the VM can execute satisfying the deadline constraint of the task. This step is similar to that of policy UPS. If this step fails, then the scheduling policy checks whether the deadline of the task is near. If yes, then the policy tries to schedule the task by allowing the host utilization to go up to the next threshold level TH_{U2}. We determine the nearness by comparing the difference between the FUP and the current time with a pre-defined threshold TH_{VMCDT}. We take the value of the threshold TH_{VMCDT} as the summation of the creation time and the deletion time of a VM. If the occurrence of the FUP is not near, then the scheduler puts the task to GWQ with the scheduling window from the *FUP* to *CUP*. In case the task is having a tight deadline, the scheduler lists a set of eligible VMs for the task (**candidateVMSet-II** as mentioned in the pseudocode of Algorithm 6) and selects the VM with least power consumption. If the scheduler fails to find any such VM, then a new host is switched on. A new VM is created with the minimum required MIPS. And then the task is assigned to the VM and the execution starts immediately. To fill up the remaining utilization, the procedure *fillHost()* is called for the newly created host. Algorithm 6 shows the pseudocode for this scheduling policy. The policy also acts as a scheduling agent that runs on the arrival of a task in the cloud system.

Once the tasks are added to GWQ with the appropriate scheduling window, the rest of the processing happens similar to that of *UPS* scheduling policy.

4.7 Performance Evaluation

In this section, we present the performance indices of the two proposed scheduling policies, named UPS and $UPS - ES$, for different task characteristics. To show the effectiveness of our work, we have implemented state of the art energy-efficient policies, namely, *EARH* [30]. In addition, we implement two simple approaches, called *immediate* scheduling, and *delayed* scheduling.

Immediate scheduling: Under this approach, a task starts its execution immediately after its arrival at the cloud system; thus the name. If no idle VM exists in the system, a new VM is created with the minimum required MIPS. If any active host can accommodate the VM, then the VM is placed on that host. Otherwise, a new host is switched on, and the VM is placed on it. If multiple resources are available (VM or host), the selection is made using a *random* policy.

Delayed scheduling: Under this approach, the execution of all the tasks are delayed as long as possible. All the tasks start their execution at their *CUP* even if sufficient resource is available. If idle VM with required MIPS is available at the *CUP* of a task, the task is assigned to the VM. Otherwise, a new VM is created for the task. If required, a new host is created to run the task.

Parameter	Values
Task count	$10,000$
Task length (MI)	Randomly distributed from $10,000$ to $100,000$
Task arrival	$\lambda = 10, \ 20, \ 50$
Deadline parameters	$R_{min} = 100$, $R_{max} = 1000$, $D_{max} = 200$, $D_{min} = 1000$
Thresholds	$TH_{U1} = 70\%$, $TH_{U2} = 100\%$
Compute capacities:Host	$1000, 1500, 2000$ (MIPS)
Compute capacities:VM	$minCP = 100$, $maxCP = 500$ (MIPS)

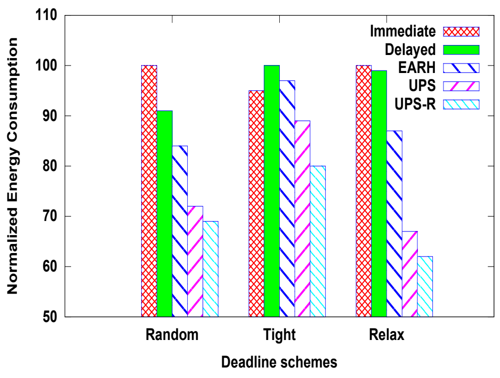
Table 4.1: Different experimental parameter values

4.7.1 Simulation environment and parameter setup

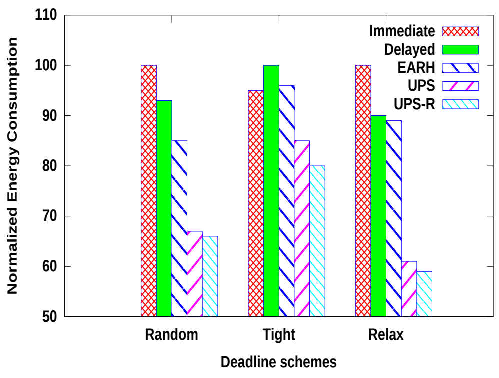
To evaluate the performance of our scheduling policies, a set of comprehensive simulations and experiments are conducted using cloudSim toolkit [123]. We have made necessary changes in the simulator to include different parameters. Table 4.1 lists the important parameters along with their considered value for our experiments. We have performed the experiments for $10,000$ tasks and considered three different deadline schemes. Length of the tasks is expressed in million instructions (MI). The experiments are performed for 10 such sets to minimize the system error, and the average result is reported in the following section.

4.7.2 Experiments with synthetic data

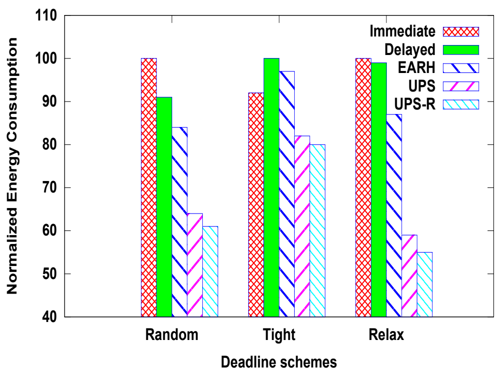
Figure 4.4 shows the overall energy consumption (normalized) of $10,000$ aperiodic real-time tasks (averaged over 10 such sets) when executed in the simulated cloud environment. The results were produced for two different values of arrival parameter, $\lambda = 10$, $\lambda = 20$, and $\lambda = 50$. Figures show the energy consumption for three different types of deadline schemes: Random, Tight, and Relax. We observe that the proposed scheduling policies (*UPS* and *UPS-ES*) perform significantly better than all other baseline policies for all the deadline schemes and the energy consumption pattern remains similar for different values of λ. In case of the random deadline scheme, the proposed policies consume around 15% lesser energy than *EARH*. In case of the tight deadline, the reduction is around 10%. And in case of the relax deadline, the reduction is around 24%. The reduction in energy increases with an increase in the arrival parameter value. For $\lambda = 20$, the corresponding reduction in energy consumption are around 18%, 11%, and 29% and for $\lambda = 50$, the corresponding reduction in energy consumption are around 22%, 15%, and 37%.



(a) $\lambda = 10$



(b) $\lambda = 20$



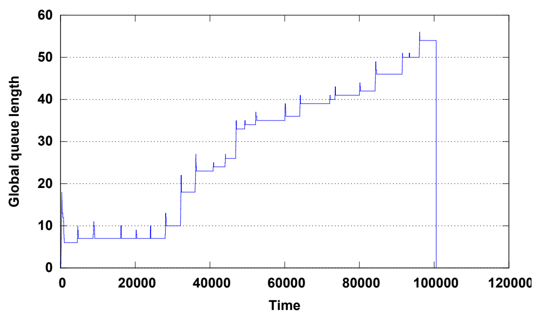
(c) $\lambda = 50$

FIGURE 4.4: Normalized energy consumption of various scheduling policies for synthetic dataset

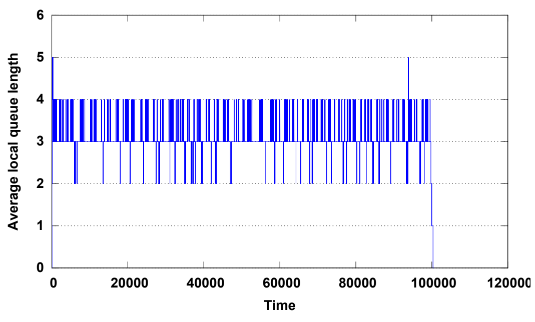
In addition to measuring the energy consumption, we have also reported the length of the global waiting queue, the average length of the local queues of the VMs, and the total number of active VMs present in the cloud system for different time instants. Figure 4.5(a) shows the instantaneous length of the global waiting queue versus time. Similarly, Figure 4.5(b) shows the average length of the local queues of the VMs. Figure 4.5(c) show the total number of active VMs of the considered cloud system. As most of the time GWQ contains a smaller number of tasks (10 to 55), they are efficiently handled by the SCUP, STC and SWC agents to schedule in an energy-efficient way.

4.7.3 Experiments with real-world data: Metacentrum

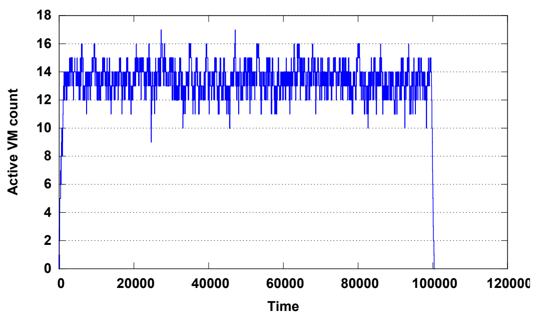
In addition to the synthetic real-time tasks with many variations in their arrival pattern and deadline, we consider four variations of MetaCentrum trace data [111]. The detailed description of these trace files is already given in Chapter 3. Energy



(a) Global waiting queue

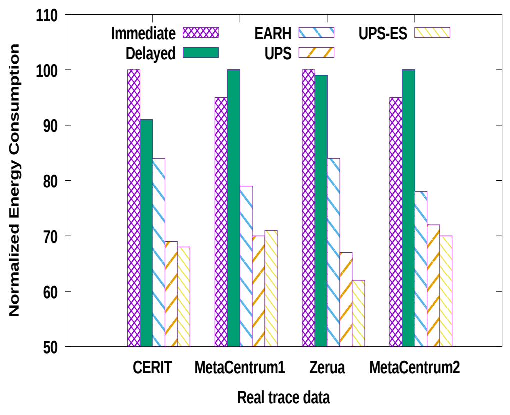


(b) Local waiting queue of VMs

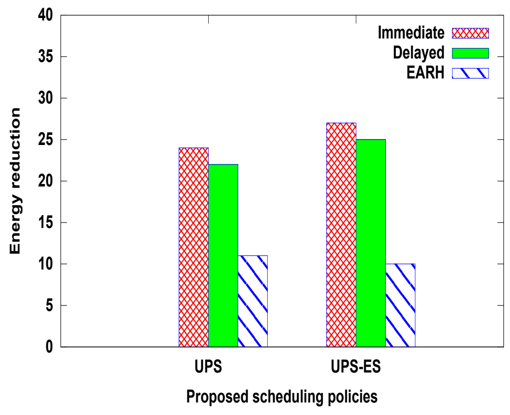


(c) Active VM count

FIGURE 4.5: Task and VM information for $\lambda = 10$



(a) Metacentrum



(b) Google trace

FIGURE 4.6: Energy reduction of the proposed policies for real-trace data

consumption (normalized) for these trace data set when executed on the considered cloud system is represented using Figure 4.6(a). We observe that the proposed policies *UPS* and *UPS-ES* perform better than the baseline policies for all the trace data. In case of CERIT, the energy reduction is around 30% with respect to Immediate and around 15% with respect to EARH. In case of MetaCentrum-1, these reductions are around 25% and 9%. In case of Zerua, the reductions are around 30% and 17% and for MetaCentrum-2, these are around 24% and 6%. We further see that the energy reduction in case of CERIT and Zerua is comparatively more than MataCentrum-1 and MataCentrum-2. We believe that this is because the inter-arrival time in case of CERIT and Zerua is comparatively more than that of MataCentrum-1 and MataCentrum-2.

4.7.4 Experiments with real-world data: Google tracelog

We also perform our experiments for Google cloud tracelog [124]. The tracelog contains over 25 million tasks and 925 users span a period of 1 month. It is difficult to perform experiments in a simulated environment with such an enormous task count. Thus we have decided to consider first $10,000$ tasks of the day 18 as day 18 is reported as a sample day in [125]. We have also made the trivial assumptions regarding the task execution and failure as reported in [30, 125]. Length of a task is not directly reported in the trace and it is calculated from the start and end time of the task. Deadline of the tasks are assigned similar to the synthetic tasks and we have assumed Random distribution only. In Figure 4.6, we have plotted the reduction in energy consumption of the two proposed policies with respect to all three baseline policies. We see that *UPS* scheduling policy achieves an energy reduction of 24%, 22%, and 11% with respect to *Immediate*, *Delayed*, and *EARH* respectively. On the other hand, *UPS-ES* achieves an energy reduction of 27%, 25%, and 10% with respect to *Immediate*, *Delayed*, and *EARH* respectively.

4.8 Summary

Cloud computing environment has evolved as a popular and promising utility-based computing paradigm of the recent time. As a result, applications from various domains are getting deployed in the cloud system. But these applications consume an enormous amount of resources and hence the energy-efficient scheduling has become crucial. The scheduling operation becomes more challenging when both static and dynamic power consumption of the hosts are considered in the power consumption model. In this work, we have devised a power consumption model for the cloud system based on the utilization of the hosts. We have then introduced the concept of an urgent point in the context of a heterogeneous computing environment. Then two scheduling techniques, *UPS*, and *UPS-ES* are proposed based on the urgent point of the tasks. We have also designed three other supporting procedures as complementary policies to the primary scheduling policies. We have performed an extensive simulation work to validate our work with different task parameters. Results show that the proposed scheduling policies reduce energy consumption by an average of almost 24% for synthetic data as compared to the baselines. For MetaCentrum trace data, the average energy reduction is almost 12% and for Google tracelogs, it is around 10%.

Chapter 5

Scheduling Real-Time Tasks on VMs with Discrete Utilization

This chapter presents scheduling strategies for efficiently executing a set of offline real-time tasks on a virtualized cloud system where the hosts of the system offer VMs with discrete utilization values. Generally, time triggered activities generate offline tasks. Examples include tasks in air-traffic control system, digital signal processing, etc. Here we first calculate a utilization value for which the energy consumption of the hosts of the cloud system is minimum. We term it as *critical utilization.* The target of the scheduling policies is to keep the utilization of the hosts close to the *critical utilization.* The problem is divided into four different subproblems and a solution is proposed for each subproblem.

5.1 Introduction

In the last chapter, we discussed scheduling online real-time tasks for a virtualized cloud system where the compute capacities of the VMs are considered to be continuous. As a VM with certain compute capacity is created on a host, the VM starts utilizing a proportionate amount of resources of that host. This results in a certain increase in the utilization of the host. Because the compute capacities of the VMs are considered to be continuous, the corresponding utilization values are also continuous. Accordingly, several studies [126, 30, 45] on the energy-efficient scheduling have been done in the context of cloud computing environment and these studies also consider a continuous compute capacity of the VMs.

When the cloud service providers offer Infrastructure as a service (IaaS) [127, 128], they provide virtualized resources in the form of VMs to the users. Each VM has different CPU, memory, storage and bandwidth capacities. Users select the VM instance based on the requirement. For instance, Amazon EC2 [129] offers configurations, such as small, medium, large, extra-large, etc. The compute capacities of these configurations are discrete. As the compute capacity of a VM corresponds to the resource utilization, the resource utilization of the VMs for the hosts becomes discrete. In this chapter, we consider that the VMs are specified with utilization values. Bigger VMs have higher host utilization requirement and smaller VMs are having smaller host utilization requirement. The purpose of this work is to propose approaches to select a suitable type of VM for each user requested real-time task and to allocate the selected VMs to hosts. The tasks are scheduled on their respective VMs. Bigger VM (i.e., VM having higher utilization) executes the task faster then the smaller VMs and the execution time of task on a VM is inversely proportional to the utilization of VM. We consider the cloud system provides k discrete types of VMs and each VM type is specified with host utilization requirement, where the cloud system consists of an infinitely large number of homogeneous hosts.

The main aim of this work is to schedule a set of real-time aperiodic tasks on the cloud environment. The scheduler chooses VM for each task. Resulting VM allocation must consume the minimum amount of energy, and all the tasks must complete before their respective deadlines. Such a scheduling approach comes with following complementary challenges.

1. Meeting deadlines - each task comes with a deadline and its execution time at maximum utilization. Using these two values, we need to find a minimum value of utilization at which a task must be executed so that it meets its deadline.

2. Minimizing energy consumption- whenever a physical machine is active, it consumes some amount of energy. Energy consumption depends on the time for which the host is active and utilization of host during its active period.

These two factors are contradicting because when a task executes at higher utilization, although it completes earlier, but consumes more power. On the other hand, at lower utilization, power consumption is lower but the task takes more time to complete and in the worst case it may miss its deadline. Our objective is to find an optimal or near-optimal solution to this problem.

The *UPS* and *UPS-ES* scheduling policies discussed in the last chapter makes use of two threshold values of host utilization. One threshold was used while scheduling the non-urgent tasks, and the other one was used when scheduling an urgent task. But in this work, we have formally computed an optimum value of host utilization at which the host consumes the minimum amount of energy known as critical utilization (described later in Section 5.3 in detail). Depending on the specification of the task and the value of critical utilization, we allocate a VM of suitable type to each task, so that, no deadline is missed and minimum amount of energy is consumed. For scheduling the selected VMs to the available physical hosts, we have divided our problem into several cases and solved each case separately. We thus summarize the contribution of this chapter as follows.

- First, we calculate the critical utilization value for the cloud host where the energy consumption is minimum.
- Next, we put forward an analysis regarding two choices while allocating a task. These are (i) to increase the utilization of a running host, and (ii) switching on a new host.
- Then, we divide the problem of scheduling into four different subproblems based on the task characteristics and propose a solution for each subproblem.

5.2 System Model

In most of the cloud systems, the user tasks get executed on virtual machines and the virtual machines get allocated to physical hosts. So the natural way to model the cloud system is a three-layer system and these layers are the task layer, virtual resource layer, and physical layer. Cloud consists of physical machines which host the virtual resources to satisfy the needs of user requested tasks.

These layers can be described as follows:

- **Physical Layer**: The cloud system that we are considering consists of a set of m homogeneous physical machines (or hosts) $PM = \{h_1, h_2, h_3, \cdots, h_m\}$. We specially consider that the compute capacities and the hardware specification of the hosts are same. Several virtual machines can be placed on a single host and the resource utilization of a host gets shared among the hosted virtual machines depending on their types. The utilization of a host

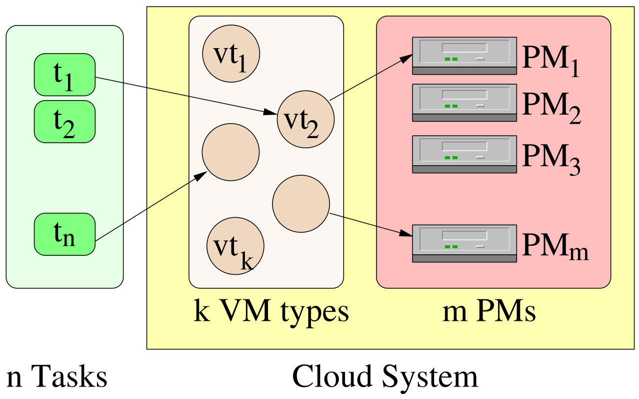


FIGURE 5.1: System model

is the maximum when it is utilized to its maximum compute capacity. For a host h_k, its utilization $U(h_k)$ ranges in between 0 and 1. These hosts consume energy which depends on the total utilization of the host. All the hosts possess one more property that is critical utilization, u_c. It is the utilization at which energy consumption is minimum (this is defined formally in next section).

- **Virtual Resource Layer**: This layer constitutes virtual machines which need to be hosted on physical machines for task execution. The utilization of a VM is proportional to its compute capacity and it expressed in MIPS (million instructions per second). We have taken k types of VMs based on the values of utilization they provide to a task. The set of VM types is denoted by $VT = \{vt_1, vt_2, \cdots, vt_k\}$. The compute capacity offered to the tasks by these VM types is not continuous. For each VM type, there is no limit on the number of VMs. These VM types are characterized by the amount of CPU utilization (proportional to the compute capacity) they provide to a task when hosted to a physical machine, also when the VM with utilization u runs on top a host, it consumes u fraction of compute (CPU) resource of the host. For a VM type vt_j, there is a constant u_j, which is the amount of utilization that vt_j will provide for the task. The value of u_j is between 0 and 1 that is $0 < u_j \leq 1$. When VMs are allocated to a host at a particular time, the sum of their total utilization must be less than or equal to 1, which is $\sum_{j=1}^{\nu} u_j \leq 1$, where ν is the number of VMs allocated to that host and u_j is the utilization of vm_j.

For the sake of simplicity, we have considered five types of VMs ($k = 5$) : tiny (T), small (S), medium (M), large (L) and extra large (XL) with discrete utilization values $u_T = 0.2$, $u_S = 0.4$, $u_M = 0.6$, $u_L = 0.8$, and $u_{XL} = 1.0$

respectively. But the work can be easily extended for any value of k. For instance, the compute capacity of a tiny type VM placed on a host with compute capacity of 1000 MIPS will be $CP(VM_T) = 1000 \cdot u_T = 1000 \cdot 0.2$ = 200 MIPS. Similarly, the compute capacities of S, M, L and XL type VMs will be 400, 600, 800, and 1000 MIPS respectively.

- **Task Layer** : The users send requests to the cloud system in form of tasks. The set or bag of n tasks is denoted by $T = \{t_1, t_2, \cdots, t_n\}$. The tasks in user requests are independent. Each task is an indivisible unit which needs to be executed on one VM (and one host) only. Any such task t_i can be described using 3-tuple: $t_i = (a_i, e_i, d_i)$, where a_i is arrival time, e_i is the execution time when run at maximum utilization ($u_{max} = 1$) and d_i is the deadline for the task. We are considering synced tasks to be scheduled ($a_i = 0$ for all the tasks). Therefore, tasks can be represented using 2-tuple in our case $t_i = (e_i, d_i)$.

  The execution time of a task is expressed in seconds and this can be calculated from the length of the task. For a task t_i with length l_i, the execution time e_i can be expressed as

$$e_i = \frac{l_i}{CP(VM_{XL})} \tag{5.1}$$

  where $CP(VM_{XL})$ is the compute capacity of the VMs of type XL. When the task is executed by a VM of other type, its execution time will increase; but it is dependent on its length l_i.

  The minimum value of utilization required by t_i is $u_i = \frac{e_i}{d_i}$. Therefore, if we execute the task at utilization u_i, it finishes exactly at d_i. But the utilizations of the VMs available in the system are discrete (equi-spaced on utilization line). Let $u_{LF}(t_i)$ be the utilization of the least feasible VM type among the available k VM types for a task $t_i(e_i, d_i)$. Then this can be written as

$$u_{LF}(t_i) = \tfrac{1}{k}\lceil \tfrac{e_i}{d_i} \cdot k \rceil \tag{5.2}$$

  where k is the number of VM types available in the system. This formula works for the cases when utilizations provided by VM types is equally distributed over the range $(0, 1.0]$. All the VM types with utilization value greater than or equal to u_{LF} (as computed by Equation 5.2) are suitable for the task t_i. We do not allow a task with utilization requirement more than 1 in our system. We assume that the VM creation and deletion time is negligible in our work. Thus as soon as a task gets scheduled for execution to a VM of a particular type, the execution of the task can immediately start. Moreover we assume that the tasks are specified with the

5.3 Energy Consumption Model

A user task is allocated to a suitable VM type, and the selected VM is then hosted on the physical machine of the cloud system. When the tasks execute, physical machines consume some energy. Energy consumption E is the amount of total power consumption during the active period of the physical machine. Which can be written as $E = \int_{0}^{t_{total}} P(t)dt$, where $P(t)$ is the power consumed by the host at time t and t_{total} is the total time for which that host is active. $P(t)$ has two components: static power consumption and dynamic power consumption. Static power consumption P_{min} (same as P_{static} or P_{base} in earlier chapters) is the minimum amount of power consumed when a host is switched on. Static power consumption depends on the host's internal activities and maintenance of tasks. Dynamic power consumption ($P_{dyn}(t)$) varies with the current frequency of the host machine. So the total power consumption can be written as $P(t) = P_{min} + P_{dyn}(t)$ and as stated in [48], dynamic power consumption be formulated as $P_{dyn}(t) \propto f(t)^3$, where $f(t)$ is the frequency of the host at time t. For single processor systems, we may safely assume that frequency is directly proportional to the utilization u of the host. So, $f(t) \propto u(t)$, where $u(t)$ is the utilization of the host at time t as stated in [48]. Therefore, we can say

$$P(t) = P_{min} + \alpha u(t)^3, \tag{5.3}$$

where α is a constant.

$\frac{e}{u}$ is the actual execution time of a task when running on VM with utilization u. Therefore, if we assume that utilization does not vary throughout the execution of the task, then, energy consumed by the host can be computed as

$$E = \Big(P_{min} + \alpha u^3\Big) \cdot \frac{e}{u} = e \cdot \Big(\frac{P_{min}}{u} + \alpha u^2\Big) \tag{5.4}$$

Figure 5.2 shows energy consumption of tasks executed at different utilization values of a host with $P_{min} = 100$ and $\alpha = 70$. The resultant plot is an inverted

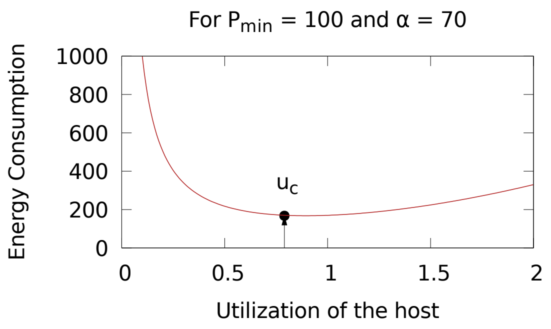


FIGURE 5.2: Energy consumption versus total utilization of the host

bell curve. The lowermost point shows the minimum energy consumed by the host and the corresponding utilization is called critical utilization, u_c.

At critical utilization u_c, $\frac{dE}{du} = 0$, from Equation 5.4

$$\frac{dE}{du} = e.\Big(\frac{P_{min}}{u} + \alpha u^2\Big) = 0, \Rightarrow e.\Big(-\frac{P_{min}}{u^2} + 2\alpha u\Big) = 0$$

$$\Rightarrow u_c = \sqrt[3]{\frac{P_{min}}{2\alpha}} \tag{5.5}$$

So, we can see that the value of the critical utilization is independent of the execution time (i.e. the length) of task executed the system. It only depends on the values of P_{min} and α.

From Equation 5.5, we get

$$P_{min} = 2\alpha u_c^3 \tag{5.6}$$

Substituting the value of P_{min} in Equation 5.3, we get

$$E = \Big(2\alpha u_c^3 + \alpha u^3\Big) \cdot \frac{e}{u}$$

Thus the total energy consumption of a host can be expressed as

$$E = \alpha(2{u_c}^3 + u^3) \cdot \frac{e}{u} \tag{5.7}$$

As mentioned in the previous chapter, the power model used in this chapter also assumes that there is a local power optimization module (DVFS or DPM) at each host. The local optimization module at a host controls the frequency and sleep state of the compute system which may have more then one compute components. As the power consumption is dependent on the utilization of the host, we can safely assume when the host is running at highest utilization, it is running at the highest capable frequency of operation and the frequency of operation of the host is proportional to the utilization of the host.

5.4 Objective in the Chapter

Given a set of user tasks $T = \{t_1, t_2, ..., t_n\}$, of size n, this chapter aims to find a set of suitable VM type for each task and allocate all the resulting VMs to physical machines. The objective of the resulting schedule is to minimize the amount of energy consumed without missing the deadline of any task.

As u_c is the critical utilization for each host, we try to maintain the utilization for each active host closest to u_c. If ν is the number of VMs allocated to a host, then the sum of values of utilization of these VMs is maintained to be approximately equal to u_c for every instant of time.

$$\sum_{j=1}^{\nu} u_j \approx u_c, \tag{5.8}$$

The tasks that need utilization above u_c, are exceptions to this because if they are executed at lower utilization, they won't meet their deadlines. Hence, they should be scheduled on separate hosts individually using a suitable VM type. Now, the problem gets reduced to finding a combination of VMs with $u_i \approx u_c$, which can be allocated to the same host while minimizing the amount of energy consumption.

The scheduling policies discussed in this chapter tries to minimize the number of active hosts along with maintaining the host utilization close to u_c such that no task misses its deadline.

5.5 Classification of cloud systems

We have analyzed the energy consumption characteristics of the hosts of the cloud system which are based on the value of critical utilization, u_c (as calculated in Equation 5.5). The value of u_c depends on the values of P_{min} and α. Since we are considering a homogeneous cloud system, these values are same for all the hosts. Based on this, we have categorized our problem into three types of systems, out of which two fall in the category of systems with extreme static power consumption and the third type refers to the systems with general specifications. In general systems, we classify the cloud system based on host or physical machine characteristics into three categories and these categories or types are:

- **Type 1**: Host with negligible static power consumption and in this type of cloud, the P_{min} of the host is negligible with respect to αu^3 and the critical utilization of the hosts is 0 (i.e. $u_c = 0$).
- **Type 2**: Host with significantly high static power consumption, and critical utilization of the host is above 1 (i.e. $u_c > 1$).
- **Type 3**: This is the most common type of cloud, where the host critical utilization u_c lies between 0 and 1.

Scheduling approaches for type 1 and type 2 systems are described in Subsections 5.5.2 and 5.5.3, respectively and for type 3 systems, the scheduling approach is described in Section 5.6.

For the case when $0 < u_c \leq 1$, both static and dynamic power consumption play significant roles. The value of critical utilization lies in the range $(0, 1.0]$. But the VMs available within the system can provide only discrete values of utilization i.e., $u_T = 0.2$, $u_S = 0.4$, $u_M = 0.6$, $u_L = 0.8$, and $u_{XL} = 1.0$ for T, S, M, L, and XL types of VM respectively. So when more than one task run in parallel on a host, the total value of utilization may not be exactly equal to u_c. Hence, we calculate a value of utilization u_t by which the utilization can be increased when the exact value of u_c cannot be reached.

As seen in Section 5.3, for a single physical machine, when only one task is executing, energy consumption is minimum at its critical utilization, u_c. If more than one task gets scheduled to a machine, they should execute for approximately same time, so that, total utilization of the host remains same throughout the time for

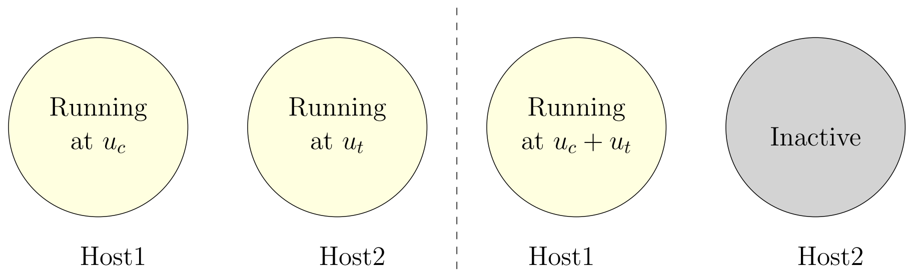


Figure 5.3: Options for scheduling the new task

which it is active (basic assumption while computing the value of u_c). Moreover, if this is not the case, CPU cycle wastage will be there.

As mentioned earlier that the utilization of the active hosts should be approximately equal to the critical utilization to minimize the total energy consumption of the system. But the overall energy consumption of the system also depends on the number of active hosts. Reducing the number of active hosts may help in decreasing the total energy consumption of the system. So, instead of switching on a new host, we may prefer an active host to schedule the available tasks. This may result in increasing the utilization of that host by a small amount but the total energy consumption can get lesser as compared to energy consumption in case of more number of active physical hosts.

Let u_t be the value of utilization which serves as an upper limit on the amount of utilization by which utilization of a host can exceed u_c. So, $u_c + u_t$ can be referred to as the hot threshold of a host. The hot threshold of a host is the value of utilization above which the host becomes over-utilized and we do not get any benefits in term of energy reduction by scheduling more tasks on it.

5.5.1 Calculation of hot thresholds for the hosts

As we define $u_c + u_t$ as the hot threshold for the hosts, in this section, we are interested in calculating the value of u_t in terms of u_c. Suppose one host is running at utilization u_c and a new task needs to be scheduled with utilization requirements u_t. To choose whether (a) to switch on a new host and schedule the task on it or (b) to schedule the task on the already active host, we need to compare the energy consumption in both the cases and chooses the one with least amount of energy consumption. Figure 5.3 depicts the two choices for scheduling the new task.

Let E_1 and E_{new} be the energy consumption of an already active PM and the new PM switched on for the incoming task, when the task is scheduled on new

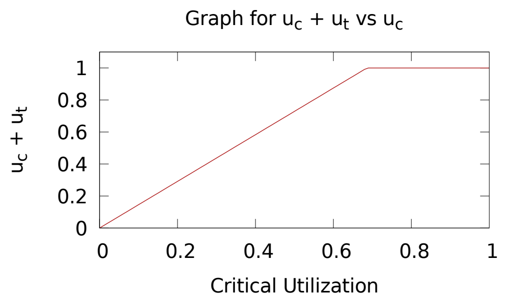


FIGURE 5.4: Hot threshold $(u_c + u_t)$ versus u_c

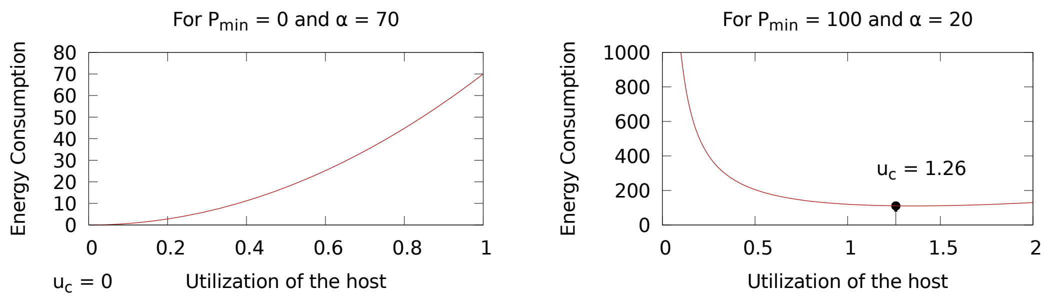
PM (as shown in left side of Figure 5.3). Also E_1' be the energy consumption of the already active host when the incoming task gets scheduled to the active host instead of a new host (as shown in right side of Figure 5.3). Also, $u_t \in (0, 1.0]$. Let t be the execution time of the tasks. Then the energy consumption E_1, E_{new} and E_1' can be written as $E_1 = t(P_{min} + \alpha {u_c}^3)$, $E_{new} = t(P_{min} + \alpha {u_t}^3)$ and $E_1' = t(P_{min} + \alpha(u_c + u_t)^3)$ respectively. The incoming task will be scheduled on already active hosts, if it is beneficial in term of energy consumption as compared to switching on a new host (even if it makes total utilization of the host, $u > u_c$), which is $E_1' < E_1 + E_{new}$. So

$$\begin{aligned} t(P_{min} + \alpha(u_c + u_t)^3) &< t(P_{min} + \alpha {u_c}^3 + P_{min} + \alpha {u_t}^3) \\ \Rightarrow 3\alpha u_c u_t (u_c + u_t) &< P_{min} \\ \Rightarrow u_c {u_t}^2 + {u_c}^2 u_t &< \tfrac{2}{3} {u_c}^3 \;\; [P_{min} = 2\alpha {u_c}^3, \;\; Eqn\, 5.5] \end{aligned}$$

This is a quadratic Equation in u_t. Thus, $u_t < \frac{(\sqrt{33}-3)u_c}{6}$ and this can be simplified to

$$u_t < 0.4574 u_c \tag{5.9}$$

Figure 5.4 shows a graph for variation of the value of hot threshold $(u_c + u_t)$ with respect to u_c. Since u_t is the value of utilization by which we can exceed the total utilization above u_c, therefore, while allocating VMs we should target for $u_c + u_t$ as total utilization. Whenever $u_c + u_t > 1$, we round off its value to 1.



(a) Energy consumption versus utilization for negligible P_{min} ($u_c = 0$)

(b) Energy consumption versus utilization with $u_c > 1$

FIGURE 5.5: Energy consumption versus utilization of extreme cases

Algorithm 7 Scheduler for system with $u_c = 0$

```
Require: Schedule for real-time tasks
Ensure: All the tasks meet their deadline and minimum energy gets consumed
1: for Each task $t_i$ in task set $T = \{t_1, t_2, ..., t_n\}$ do
2:     Take the VM type with utilization just above or equal to $u_i = \frac{e_i}{d_i}$
3:     Host the resulting VM on a new host and execute the tasks on their selected
       VM.
4: end for
```

5.5.2 Hosts with negligible static power consumption ($u_c = 0$)

Figure 5.5(a) shows the variation of energy consumption of a host with respect to its total utilization. The host has negligible static power consumption. When P_{min} is negligible as compared to αu^3, we can take its value to be 0 for all the hosts. As a result, we get $u_c = 0$ from Equation 5.5. To maintain total utilization values as close as possible to u_c, that is 0 in this case, we should allocate a suitable VM type with least utilization value to a task and schedule them on separate hosts. A suitable VM type for task t_i is the one which completes the task before the deadline when the task is allocated to it, that is, the VM type with utilization greater than $\frac{e_i}{d_i}$, which is the least feasible VM type and this can be calculated using Equation 5.2. The total energy spent will only depend on the squares of utilization of the hosts. Beloglazov *et al.* [130] have considered only the current utilization as the deciding factor for scheduling the user requests. But such systems fall in the category of systems with extreme specifications which can be solved trivially.

The pseudocode of the scheduler is shown in Algorithm 7. The scheduler simply chooses the least feasible VM type for each task in the task set $T = \{t_1, t_2, ..., t_n\}$, which can complete the task before its deadline. After that, it allocates all the selected VMs to separate physical machines and execute the tasks on their respective allocated VMs. This schedule is based on the fact that the value of u_c is 0 for each physical machine and we want its total utilization to be as close as possible to u_c. Thus, using the least feasible VM will give us the schedule with minimum energy consumption. Also, energy consumption of a host is directly proportional to the square of total utilization in this case (Equation 5.4 with $P_{min} = 0$). As we know, given a set of n positive utilization values, say $\{u_1, u_2, ..., u_n\}$, the sum of squares of these values will be less than the square of summation of these values.

$$u_1{}^2 + u_2{}^2 + ... + u_n{}^2 \leq (u_1 + u_2 + ... + u_n)^2$$

So, we should schedule the selected VMs on separate hosts. Let the value of utilization of the least feasible VM be u_i for task t_i, then, the energy consumption in executing all the tasks can be computed as follows:

$$E = \sum_{i=1}^{n} (P_{min} + \alpha u_i^3) \cdot \frac{e_i}{u_i} \Rightarrow E = \sum_{i=1}^{n} (0 + \alpha u_i^3) \cdot \frac{e_i}{u_i}$$

$$\Rightarrow E = \alpha \sum_{i=1}^{n} (e_i \cdot u_i{}^2) \tag{5.10}$$

where e_i is the execution time of task t_i, when run at maximum utilization. The value of e_i is given as input with each task.

5.5.3 Hosts with significantly high static power consumption ($u_c > 1$)

Figure 5.5(b) shows the energy consumption versus utilization curve of a host with the value of the critical utilization more than one. But for any system, the total value of utilization can never exceed one, so we should take $u_c = 1$ and schedule the tasks on separate host taking $u_c = 1$. The reason behind choosing $u_c = 1$ is that the value of energy consumption strictly decreases with an increase in the value of utilization until the value of u reaches u_c. As the minimum value of the energy consumption can be obtained at the utilization value 1 among all the possible utilization values, choosing $u_c = 1$ gives the best possible result.

5.6 Scheduling Methodology for the Systems with General Specifications $(0 < u_c \leq 1)$

Scheduling and analysis of the tasks for the general specifications are tricky and difficult. Thus, we divide the problem into four sub-problems and solved separately. Based on the type of tasks in the request, the energy-efficient scheduling of real-time tasks can be done by dividing them into four sub-problems (e and d refer to the execution time of the task at maximum utilization and the deadline of the task, respectively). The considered cases of sub-problems are:

1. Case 1: All the n tasks are of same type i.e. $t_i(e_i = e, d_i = d)$.
2. Case 2: Two type of tasks with different execution times but same deadline i.e. $t_i(e_i \in \{e_1, e_2\}, d_i = d)$.
3. Case 3: Tasks with different execution times but same deadline i.e. $t_i(e_i, d_i = d)$.
4. Case 4: All the n tasks having their own e_i and d_i, i.e. $t_i(e_i, d_i)$.

The reason behind choosing this set of cases is that, the scheduling approach of every case is dependent on the scheduling approach for the previous one (except for the first case, which depends on the scheduling approach for base case). And we can apply the solution approach of one case to generate the solution approach of the next case. This will be clear from the detailed discussion of scheduling approaches for these cases described in next subsections.

5.6.1 Scheduling n tasks of same type (Case 1: (e, d))

This case refers to the requests with n tasks having same specifications $t_i(e, d)$. An iterative approach has been followed to solve this problem. We start with a suitable VM type with least utilization value that complete the task within the deadline. Then we check whether the VM type with the next higher utilization performs better. If u_c is the critical utilization of the hosts and tasks require a VM with utilization u, the number of VMs that can be scheduled per host are $\beta = \lceil \frac{u_c}{u} \rceil$ or $\gamma = \lfloor \frac{u_c}{u} \rfloor$. For example, when $u_c = 0.7$ and $u_T = 0.2$, the values of β and γ are 4 and 3 respectively. Suppose β gets chosen out of these two, then, we have these two following cases for the number of tasks getting scheduled:

1. If n is a perfect multiple of β then all the tasks are scheduled according to our method and the number of hosts required to execute all the tasks will be $m = \frac{n}{\beta}$, where n is the number of tasks in the request.
2. If n is not multiple of β then $m = \lfloor \frac{n}{\beta} \rfloor - 1$ number of hosts will execute $m\beta$ tasks and the remaining tasks $(n - m\beta)$ are scheduled according to the base case. The remaining number of tasks are guaranteed to be less than 2β.

For scheduling the tasks in the base case, we have used a first fit method. For this, we have sorted the tasks in decreasing order of their utilization requirements and the VMs are allocated to hosts using the first-fit approach for bin packing. Instead of taking bin capacities as 1, we take these as $u_c + u_t$. Moreover, in this case, the tasks have the same specifications, so, we do not need to sort them. Also, the maximum value of β can be 5 (when the least feasible VM type is tiny with $u_T = 0.2$), the maximum number of tasks that will be in the base case is 10.

Energy consumption in this case is given by,

$$E = m.\frac{e}{u}.\alpha(2{u_c}^3 + (u\beta)^3) + E_{base} \tag{5.11}$$

where m is the number of active hosts, $\frac{e}{u}$ is the execution time of a task (or we can say the time for which the hosts are active), $\alpha(2{u_c}^3 + (u\beta)^3)$ is the amount of power consumption of each host and E_{base} is the energy consumption for scheduling of the tasks that are in base case.

We have a set of suitable VM types for a task which can complete the task before its deadline. For choosing the best VM type among the suitable VM types, we have computed certain relation through which we can make the decision based on the value of u_c of the hosts.

1. **Relation between β and γ for same VM type:** Let u be the utilization provided by current VM type and n_1 and n_2 be the total number of hosts needed with β and γ number of VMs per host, respectively. Schedule with γ number of VMs per host consumes lesser energy than the schedule with β number of VMs per host when total energy consumption in former case is lesser as compared to total energy consumption in the latter case (can be derived from Equation 5.11). The high number (γ) of VMs per host is preferable if The high number (γ) of VMs per host is preferable if

$$n_2.\frac{e}{u}.\alpha(2{u_c}^3 + (u\gamma)^3) < n_1.\frac{e}{u}.\alpha(2{u_c}^3 + (u\beta)^3)$$
$$2n_2{u_c}^3 - 2n_1{u_c}^3 < n_1(u\beta)^3 - n_2(u\gamma)^3$$

$$u_c < u\sqrt[3]{\frac{n_1\beta^3 - n_2\gamma^3}{2(n_2 - n_1)}} \tag{5.12}$$

For example, when the least feasible VM type is S ($u_S = 0.4$) and $u_c \in (0.40, 0.49]$, the resulting values of β and γ are 2 and 1, respectively. And in this case, schedule with one VM per host consumes lesser energy as compared to the schedule with two VMs per host.

2. **Relation between two different VM types:** Let u_1 and u_2 be the values of utilizations provided by the two VM types which we need to compare. The corresponding number of tasks per host be β_1 and β_2, as a result of above relation. Let m_1 and m_2 be the corresponding number of hosts and $u_1 < u_2$. Choosing the VM with higher utilization will give lesser energy consumption when

$$m_1.\frac{e}{u_1}.\alpha(2{u_c}^3 + (\beta_1 u_1)^3) > m_2.\frac{e}{u_2}.\alpha(2{u_c}^3 + (\beta_2 u_2)^3)$$
$$m_1 u_2(2{u_c}^3 + (\beta_1 u_1)^3) > m_2 u_1(2{u_c}^3 + (\beta_2 u_2)^3)$$

$$2{u_c}^3(u_1 m_2 - u_2 m_1) < m_1 u_2(\beta_1 u_1)^3 - m_2 u_1(\beta_2 u_2)^3 \tag{5.13}$$

For example, when the least feasible VM type is S and $u_c \in (0.50, 0.69]$, schedule using L type of VMs consumes lesser energy as compared to the schedule using S type of VMs.

Pseudo-code for scheduling the single type of tasks is shown in Algorithm 8. We start with finding the minimum utilization required by the tasks. Based on the minimum utilization required, we select the VM type with the least utilization among the set of suitable VM types. We call the utilization of this VM type u_1. This can also be calculated as $u = \left\lceil \frac{e}{d} \cdot 5 \right\rceil / 5$. Then, we check the satisfiability of the relation given in Equation 5.12 to choose the number of tasks per host to execute. If it gets satisfied then schedule with γ VMs per host performs better than the schedule with β VMs per host. The chosen number of VMs per host is set as β_1 and the corresponding number of hosts is assigned to m_1. Similarly, for the next VM type with utilization u_2, find the values of β_2 and m_2. Now, we check which of the two VM types gives us better results. For this, we check

Algorithm 8 Scheduling single type of tasks $S(e, d, n)$

```
1: Allocate the VM with minimum utilization required by the task from T, S, M,
   L and XL. Let it be $u$.
2: Number of tasks per host when total utilization is more than $u_c$, $\beta \leftarrow \lceil \frac{u_c}{u} \rceil$
3: Number of tasks per host when total utilization is less than $u_c$, $\gamma \leftarrow \lfloor \frac{u_c}{u} \rfloor$
4: Find the number of hosts in each case. Let they be $n_1$ and $n_2$, respectively
5: if $u_c < u \cdot \sqrt[3]{\frac{n_1\beta^3 - n_2\gamma^3}{2(n_2 - n_1)}}$ then
6:     $\beta_1 \leftarrow \gamma$                          ▷ $\gamma$ VMs per host consumes less energy
7:     Number of hosts, $m_1 \leftarrow n_2$
8: else
9:     $\beta_1 \leftarrow \beta$                          ▷ $\beta$ VMs per host consumes less energy
10:    Number of hosts, $m_1 \leftarrow n_1$
11: $u_1 \leftarrow u$
12: Similarly choose $\beta_2$ and $m_2$ for $u_2 = u_1 + 0.2$ if $u_1 \leq 0.8$
13: if $2{u_c}^3(u_1m_2 - u_2m_1) < n_1u_2(\beta_1u_1)^3 - n_2u_1(\beta_2u_2)^3$ then
14:     $u_f \leftarrow u_2$, $\beta_f \leftarrow \beta_2$ and $m_f \leftarrow m_2$
15:     $u \leftarrow u_2$ goto step 2
16: else
17:     $u_f \leftarrow u_1$, $\beta_f \leftarrow \beta_1$ and $m_f \leftarrow m_1$
18: Allocate VMs with utilization $u_f$ to the tasks.
19: Schedule $\beta_f$ number of VMs on each host.
20: Schedule the remaining number of tasks i.e. $n - m_f\beta_f$ according to base case.
```

whether the relation given in Equation 5.13 gets satisfied. If yes, the higher VM type with utilization u_2 gives better result than the VM type with utilization u_1 and continue with u_2 as u. Otherwise, u_1 performs better than u_2. Store the final utilization values as u_f, β_f and m_f, where u_f is the utilization provided by the selected VM type, β_f is the number of VMs to be scheduled on one host and m_f is the total number of hosts required (without considering the tasks that fall into base case). Then we allocate the tasks to VMs with utilization u_f and schedule β_f VMs on a host and the remaining tasks are scheduled according to the base case.

Algorithm 8 gives the schedule with the lowest energy consumption, but, we have some special cases, where the two relations in Equation 5.12 and 5.13, can be simplified further. They would not make any change to the decision made by the algorithm, so, whenever the task set of user request falls in one these cases, we can safely replace the relations with the resulting ones. These special cases are:

- **Relation between energy consumption with β and γ number of tasks per host when total number of tasks is a multiple of both:** Let n be the number of tasks in user request which satisfies $n\%\beta = 0$ and

$n\%\gamma = 0$. Let n_1 and n_2 be the number of hosts in case of β and γ number of VMs per host, respectively. Then $n_1 = \frac{n}{\beta}$ and $n_2 = \frac{n}{\gamma}$. Energy consumption is lower with γ number of VMs per host when a VM with utilization u is used if the following condition is satisfied

$$\begin{aligned}
&\frac{n}{\gamma}.\frac{e}{u}.\alpha(2{u_c}^3 + (u\gamma)^3) < \frac{n}{\beta}.\frac{e}{u}.\alpha(2{u_c}^3 + (u\beta)^3)\\
\Rightarrow&\frac{2{u_c}^3 + (u\gamma)^3}{\gamma} < \frac{2{u_c}^3 + (u(\gamma+1))^3}{\gamma+1}\ [as\ \beta = \gamma + 1]\\
\Rightarrow&(\gamma+1)(2{u_c}^3 + (u\gamma)^3) < \gamma(2{u_c}^3 + (u(\gamma+1))^3)\\
\Rightarrow&2{u_c}^3 + (u\gamma)^3 < \gamma u^3(3\gamma^2 + 3\gamma + 1)
\end{aligned}$$

$$\Rightarrow u_c < \sqrt[3]{\frac{\gamma u^3(2\gamma^2 + 3\gamma + 1)}{2}}. \tag{5.14}$$

So if the above Equation is satisfied then the γ number of VMs per host is allocated to have minimum energy consumption, otherwise β number of VMs per host have lesser energy consumption.

- **Comparing energy consumption by two different VM types when number of tasks is a multiple of both β_1 and β_2:** Let n is the number of tasks and u_1 and u_2 ($u_1 < u_2$) be the values of utilization provided by the two VM types that need to be compared. If β_1 and β_2 are the respective number of tasks per host and n satisfies $n\%\beta_1 = 0$ and $n\%\beta_2 = 0$, then energy consumption is lower at u_2 if:

$$\begin{aligned}
\frac{n}{\beta_2}.\frac{e}{u_2}.\alpha(2{u_c}^3 + (u_2\beta_2)^3) &< \frac{n}{\beta_1}.\frac{e}{u_1}.\alpha(2{u_c}^3 + (u_1\beta_1)^3)\\
u_1\beta_1(2{u_c}^3 + (u_2\beta_2)^3) &< u_2\beta_2(2{u_c}^3 + (u_1\beta_1)^3)\\
2{u_c}^3(u_1\beta_1 - u_2\beta_2) &< u_2\beta_2(u_1\beta_1)^3 - u_1\beta_1(u_2\beta_2)^3\\
2{u_c}^3(u_1\beta_1 - u_2\beta_2) &< u_1u_2\beta_1\beta_2\\
&\quad((u_1\beta_1)^2 - (u_2\beta_2)^2)\\
2{u_c}^3(u_1\beta_1 - u_2\beta_2) &< u_1u_2\beta_1\beta_2(u_1\beta_1 - u_2\beta_2)\\
&\quad(u_1\beta_1 + u_2\beta_2)
\end{aligned}$$

The final relation depends on the value of $(u_1\beta_1 - u_2\beta_2)$.

$$\begin{cases}
2{u_c}^3 > u_1u_2\beta_1\beta_2(u_1\beta_1 + u_2\beta_2) & (u_1\beta_1 - u_2\beta_2) < 0\\
2{u_c}^3 < u_1u_2\beta_1\beta_2(u_1\beta_1 + u_2\beta_2) & \text{else}
\end{cases}$$

$$\Rightarrow \begin{cases} u_c > \sqrt[3]{\frac{u_1 u_2 \beta_1 \beta_2 (u_1\beta_1 + u_2\beta_2)}{2}} & (u_1\beta_1 - u_2\beta_2) < 0 \\ u_c < \sqrt[3]{\frac{u_1 u_2 \beta_1 \beta_2 (u_1\beta_1 + u_2\beta_2)}{2}} & \text{else} \end{cases} \tag{5.15}$$

- **When β_1 and β_2 are equal in the above case:** This case refers to a situation where both values of utilization result in same β values. Since $u_2 > u_1$ and $\beta_1 = \beta_2$, say β, the value of $u_1\beta_1 - u_2\beta_2$ will always be less than 0. Therefore, $\sqrt[3]{\frac{1}{2}u_1u_2\beta\beta(u_1\beta + u_2\beta)}$ can be written as $\beta\sqrt[3]{\frac{1}{2}u_1u_2(u_1 + u_2)}$. So if the following condition

$$u_c > \beta\sqrt[3]{\frac{1}{2}u_1u_2(u_1 + u_2)} \tag{5.16}$$

  is satisfied then, the VM type with higher utilization will consume lesser amount of energy as compared to the VM type with lesser utilization value.

5.6.2 Scheduling approach for two types of tasks having same deadline (Case 2: (e_1, d) and (e_2, d))

This case refers to the requests where there are only 2 types of tasks. They may have any one of the two available execution times but they ought to have the same deadline. Let n_1 and n_2 be the number of tasks with specification (e_1, d) and (e_2, d), respectively. These tasks may run independently on separate hosts or may run in together on the same host. When the tasks run individually, the problem gets reduced to case 1, but when they run together, total energy consumption will have two components:

1. Energy consumption of the hosts where both types of tasks reside.
2. Energy consumption of the hosts where a single type of tasks resides.

The second component occurs when one type of task is much higher in number than the other type of tasks, and all the former type of tasks could not be combined with the latter type.

As discussed in the previous case, the tasks running on the same host must have approximately the same execution time so that the total utilization of the host remains the same throughout its active period. For achieving this, we allocate the least feasible VM type to all the tasks and to approximate their execution time

Algorithm 9 Scheduling two types of tasks with same deadline ($D(e_1, e_2, d, n_1, n_2)$)

```
1: Let $u_1$ and $u_2$ be the utilization of VM types which satisfies the minimum
   requirements of tasks with specification $(e_1, d)$ and $(e_2, d)$, respectively
2: Compute $(\beta_1, \beta_2)$ such that total utilization is approximately equal to $u_c$ and
   should not be more than $u_c + u_t$.
3: for each combination $c$ of $(\beta_1, \beta_2)$ do
4:     if $\lfloor \frac{n_1}{\beta_1} \rfloor > \lfloor \frac{n_2}{\beta_2} \rfloor$ then
5:         swap the two types of tasks.
6:     number of hosts with both type of tasks, $numHosts_c \leftarrow \lfloor \frac{n_1}{\beta_1} \rfloor$
7:     Remaining second type task $NR_c \leftarrow n_2 - \lfloor \frac{n_1}{\beta_1} \rfloor \beta_2$
8:     $E_c \leftarrow \lfloor \frac{n_1}{\beta_1} \rfloor d(2{u_c}^3 + (u_1\beta_1 + u_2\beta_2)^3) + E_{part} + S(e_2, d, NR_c)$
9: end for
10: $E_{single} \leftarrow S(e_1, d, n_1) + S(e_2, d, n_2) + E_{part}$
11: Compare energy consumption in all the cases and choose least one.
```

to deadline d. The reason behind choosing the least feasible VM type is that it completes the task just before its deadline. All the tasks have the same deadline in this case, so, if we allocate them to their least feasible VM type, the execution time of all the tasks will be approximately equal to deadline d.

Now, let u_1 and u_2 be the utilization of the VM types allocated to the two types of tasks and β_1 and β_2 be the non-zero number of tasks of each type on a host. When either of the two is zero, the tasks run individually. Also, based on the values of u_c, u_1 and u_2, the pair (β_1, β_2) may assume several values. The decision on whether to run the tasks individually or in one of the combinations need to be made. For this, we compare the total energy consumption in each case and choose the one with the least value.

The pseudo-code for scheduling two type of tasks with the same deadline is given in Algorithm 9. We first find the least feasible VM that can be allocated to both the task types. Let u_1 and u_2 be the utilization of selected VM types. To obtain total utilization of the hosts approximately equal to u_c (preferably higher), these VM types can be scheduled together. Let β_1 and β_2 be the corresponding number of VMs on one host when they are scheduled together. Also, there is an option for scheduling both the type of tasks individually ($S(e_1, d, n_1)$ and $S(e_2, d, n_2)$ scheduled described in Algorithm 8). So, for all the available options, we compute the energy consumption and choose the best one out of these options. As we are comparing all the cases exhaustively and choose the best one, we always get the result with the minimum energy consumption.

5.6.3 Scheduling approach for the requests with multiple number of task types having same deadline (Case 3: (e_i, d))

This case refers to the requests where tasks may take different execution times at utilization 1 but have the same deadline. For each task, we initially allocate the least feasible VM type as done in the previous case. This way the tasks get classified into 5 categories based on the category of the VM type allocated to them. These categories contain tasks that need T, S, M, L and XL VM types respectively.

One important observation for solving this problem is that *there cannot be VMs from more than two categories on the same host as the number of discrete VM types is 5 where all VM types are equi-spaced in terms of utilization.* This can be seen from the following example, that even with $u_c = 1.0$, which is the highest among all the possible values of u_c, not more than two types of VMs can be combined. There are at most five possible combinations of VM types for any value of u_c (sum of utilization values of three least powerful VMs T, S and M is $0.2 + 0.4 + 0.6 = 1.2 > 1.0$). These permissible combinations are: (a) one VM of type T with one VM of type L ($u_T + u_L \leq 1.0$), (b) two VMs of type T with one VM of type M ($2u_T + u_M \leq 1.0$), (c) one VM of type S with one VM of type M ($u_S + u_M \leq 1.0$), (d) three VMs of type T with one VM of type S ($3u_T + u_S \leq 1.0$), and (e) one VM of type T and two VMs of type S ($u_T + 2u_S \leq 1.0$). Even if we execute them separately, the total utilization will never be 1.0 except for $u = 0.2$. As we can see, even with the highest value of utilization only five combinations are possible, so the number of combinations will be even lesser with smaller values of utilization. So, we can exhaustively check each of the possible cases and choose the best option. *For each of the possible combinations, we use the approach used for solving case 2, as both the problems are same, i.e., two types of tasks having the same deadline.*

Scheduling approach for case 3 is given in Figure 5.6. We start with all the five categories of tasks which have been allocated to VMs of types T, S, M, L, and XL, respectively. Since the XL VMs cannot be scheduled with any other VMs, therefore, tasks of that category get scheduled individually on separate hosts (which is shown in Figure 5.6 as $Schd_{ind}\ XL\ VMs$). The combination of VM types depends on the value of critical utilization, so, depending on the values of u_c, there are several possible flows and we choose the one which consumes the

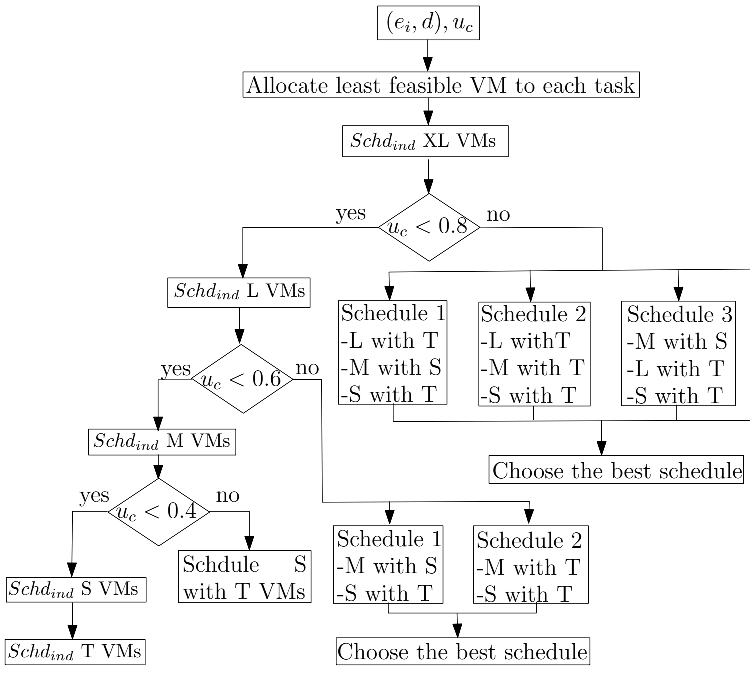

$(e_i, d), u_c$
Allocate least feasible VM to each task
$Schd_{ind}$ XL VMs
yes
$u_c < 0.8$
no
$Schd_{ind}$ L VMs
Schedule 1 -L with T -M with S -S with T
Schedule 2 -L withT -M with T -S with T
Schedule 3 -M with S -L with T -S with T
Schedule 4 -M with T -L with T -S with T
yes
$u_c < 0.6$
no
Choose the best schedule
$Schd_{ind}$ M VMs
yes
$u_c < 0.4$
no
Schdule S with T VMs
Schedule 1 -M with S -S with T
Schedule 2 -M with T -S with T
$Schd_{ind}$ S VMs
$Schd_{ind}$ T VMs
Choose the best schedule

FIGURE 5.6: Scheduling approach for case 3: $SC3(e_i, d, n)$

least amount of energy. The tasks with VM types L and XL were given preference in scheduling order because they can only be combined with tasks allocated to T and S types of VMs. And if we schedule the latter ones first, we would not have any tasks to combine with tasks having higher utilization requirements.

As shown in the flowchart, we consider these four conditions and based on that we decide about scheduling of VMs and these cases are

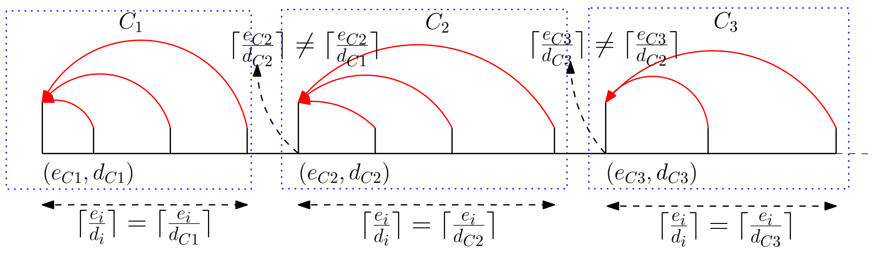
- Case ($0.8 \leq u_c < 1$): We select one the four schedules (a) L type VM combined with T type VM, followed by M type VM combined with S type VM and followed by S type VM combined with T type VMs, (b) L type VM combined with T type VM, followed by M type VM combined with T type VM and followed by S type VM combined with T type VMs, (c) M type VM combined with S type VM, followed by L type VM combined with T type VM and followed by S type VM combined with T type VMs and (d) M type VM combined with T type VM, followed by S type VM combined with S type VM and followed by S type VM combined with T type VMs. The combination schedule are specified in the flowchart (shown in Figure 5.6), among all these schedules which has the least value of total energy consumption (ties are broken arbitrarily) gets selected. While proceeding in one schedule, only the tasks left in one step goes to the next. Also, we aim to schedule all the tasks with higher VM type in one step and the remaining tasks with lower VM types, if any, goes to the next steps.

- Case ($0.6 \leq u_c < 0.8$): In this case, we schedule L type VMs individually on separate hosts and further check whether the value of $u_c \leq 0.6$. For $u_c > 0$, we have two possible schedules (a) M type VM combined with S type VM, followed by S type VM combined with T type VM, and (b) M type VM combined with T type VM, followed by S type VM combined with T type VMs. We compare the total energy consumption in both cases and choose the schedule with the least energy consumption.
- case ($0.4 \leq u_c < 0.6$): In this case, the M type VMs get scheduled individually in separate hosts and check for running the two types of VMs in parallel, with respect to the schedule for case 2 (using $D(e_1, e_2, d, n_1, n_2)$ as described in Algorithm 8) and scheduled accordingly.
- Case ($u_c < 0.4$): In this case, we schedule T and S type of VMs on separate hosts, and this minimized the energy consumption of the hosts of the cloud system.

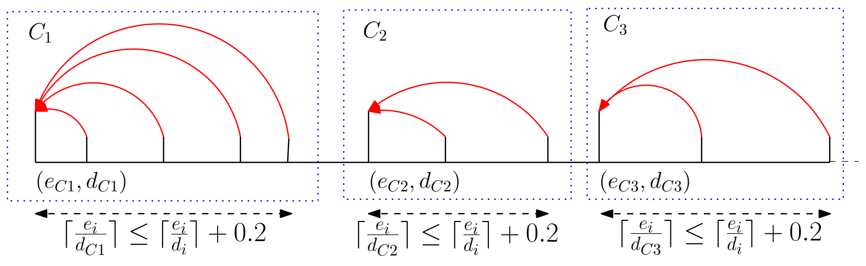
5.6.4 Scheduling approach for general synced real-time tasks (Case 4: (e_i, d_i))

This is the general case where there is no restriction on the values of execution time and the deadline of the tasks. For solving this, we want to divide the tasks in several task sets having same deadlines, so that, we can schedule all the sets according to the schedule for case 3 ($SC(e_i, d, n)$ as given in flowchart of Figure 5.6), separately. For this, we first sort the task set in increasing order of their deadlines and then select the VM with the least utilization value from the set of suitable VM types. To divide the task set into clusters, we have applied one of the methodologies described below to the task set such that tasks belonging to same cluster map to the same value of deadline which may not be the actual deadline of the tasks. Each cluster is then executed according to case 3 (($SC(e_i, d, n)$ as given in flowchart of Figure 5.6)) where the tasks may have different execution times but the same deadline. We have designed and used four methodologies for clustering the tasks according to their deadline are described as follows:

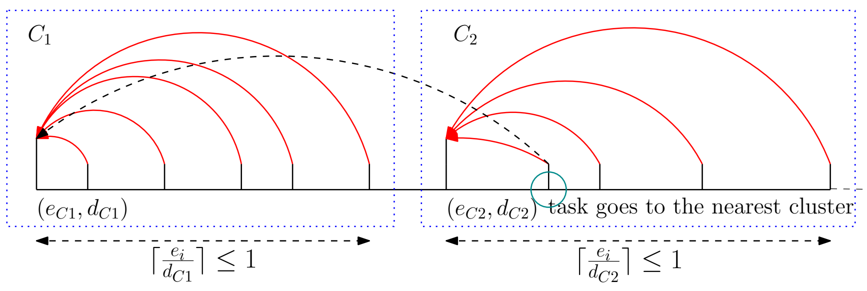
1. **Clustering method 1 (CLT1): No change in utilization requirements of the tasks:** Figure 5.7(a) describes this clustering technique. The


C_1
C_2
C_3
$\lceil \frac{e_{C2}}{d_{C2}} \rceil \neq \lceil \frac{e_{C2}}{d_{C1}} \rceil$
$\lceil \frac{e_{C3}}{d_{C3}} \rceil \neq \lceil \frac{e_{C3}}{d_{C2}} \rceil$
(e_{C1}, d_{C1})
(e_{C2}, d_{C2})
(e_{C3}, d_{C3})
$\lceil \frac{e_i}{d_i} \rceil = \lceil \frac{e_i}{d_{C1}} \rceil$
$\lceil \frac{e_i}{d_i} \rceil = \lceil \frac{e_i}{d_{C2}} \rceil$
$\lceil \frac{e_i}{d_i} \rceil = \lceil \frac{e_i}{d_{C3}} \rceil$

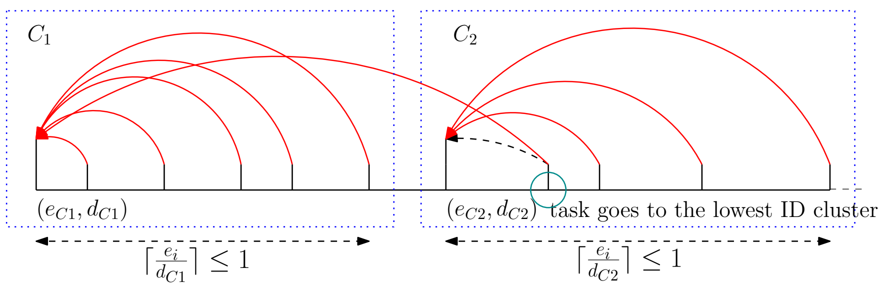
(a) CLT1


C_1
C_2
C_3
(e_{C1}, d_{C1})
(e_{C2}, d_{C2})
(e_{C3}, d_{C3})
$\lceil \frac{e_i}{d_{C1}} \rceil \leq \lceil \frac{e_i}{d_i} \rceil + 0.2$
$\lceil \frac{e_i}{d_{C2}} \rceil \leq \lceil \frac{e_i}{d_i} \rceil + 0.2$
$\lceil \frac{e_i}{d_{C3}} \rceil \leq \lceil \frac{e_i}{d_i} \rceil + 0.2$

(b) CLT2


C_1
C_2
(e_{C1}, d_{C1})
(e_{C2}, d_{C2})
task goes to the nearest cluster
$\lceil \frac{e_i}{d_{C1}} \rceil \leq 1$
$\lceil \frac{e_i}{d_{C2}} \rceil \leq 1$

(c) CLT3


C_1
C_2
(e_{C1}, d_{C1})
(e_{C2}, d_{C2})
task goes to the lowest ID cluster
$\lceil \frac{e_i}{d_{C1}} \rceil \leq 1$
$\lceil \frac{e_i}{d_{C2}} \rceil \leq 1$

(d) CLT4

FIGURE 5.7: Description for clustering techniques

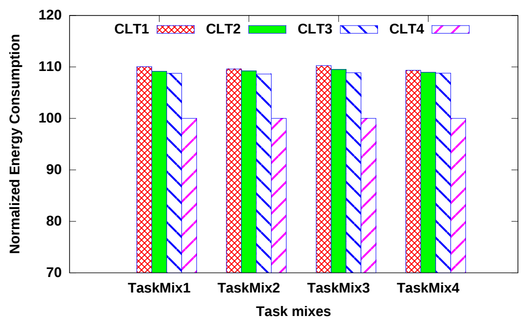
horizontal axis represents the time axis and tasks are plotted at their respective deadlines. Vertical lines in the time axis (x-axis) represent the task deadlines. We initialize the first cluster with the first task. Let the deadline of the cluster be the same as the deadline of this task. We keep on adding tasks to the cluster until they need a higher VM type than their initial allocated one (their actual deadline of the added task is changed to the deadline of the cluster, by shifting deadline of the task towards left in the time axis).

We start a new cluster whenever such a task is found. This process is repeated until all the tasks are mapped to some cluster or the other. When the deadline of a task is shifted toward the left side of the time axis, the absolute deadline time of a task is decreased, so the utilization requirement of the task is increased. Suppose a task requires utilization 0.12 (T type VM). Then the deadline can be shifted left of the time axis until the utilization requirement the task is equal to less than the 0.2 (same T type VM). Thus the deadline for all the tasks belonging to a cluster is same, which is taken as the deadline of the cluster. We write $\lceil \frac{e_i}{d_i} \rceil = \lceil \frac{e_i}{d_{C1}} \rceil$. Again the deadlines of two different clusters are different.

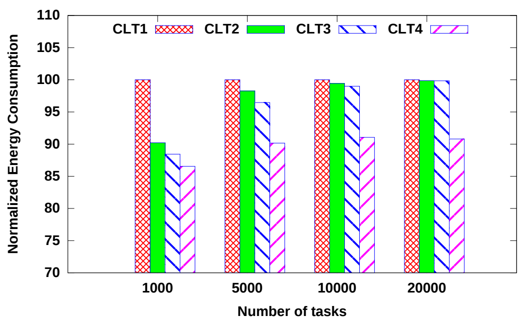
2. **Clustering method 2 (CLT2): Utilization requirement of the task changes by at most 1 level:** The process is same as above with a small change that tasks may be allocated the next higher VM type if required, that is up-gradation of VM types is allowed but only by one step. Figure 5.7(b) describes this clustering technique. For a task $t_i(e_i, d_i)$, we can write $\lceil \frac{e_i}{d_{C1}} \rceil \leq \lceil \frac{e_i}{d_i} \rceil + 0.2$.

3. **Clustering method 3 ((CLT3)): Utilization requirement may change up to $u_i = 1$ and task is allocated to the nearest cluster:** In this technique, VM up-gradation to the best type is allowed. The remaining process is same as in the above two clustering techniques. Figure 5.7(c) describes this clustering technique. The marked task is eligible for both clusters C1 (marked with dotted line) and C2, but this clustering technique chooses C2 for the task as it is the cluster with the closest deadline.

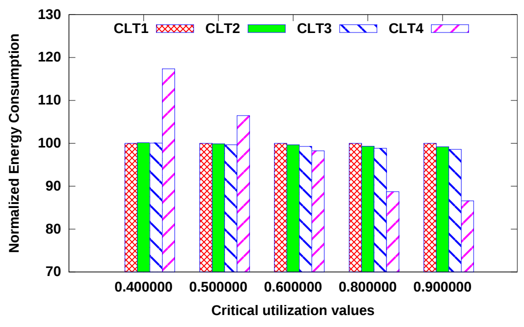
4. **Clustering method 4 (CLT4): Utilization requirement may change up to $u_i = 1$ and task is allocated to the cluster with lowest ID:** Initialize the first cluster with the first task. Let the deadline of the cluster be same as the deadline of this task. Iterate over all the tasks and check if they can be allocated to the current cluster. Start the new cluster from the first task which could not be allocated to the previous cluster. Repeat until all the tasks are covered in one cluster or the other by considering only uncovered tasks in each iteration. Proceeding this way, the tasks cannot go into a cluster of higher ID even if it satisfies the requirements. Figure 5.7(d) describes this clustering technique. The marked task is eligible for both clusters C1 and C2 (marked with dotted line), but this clustering technique chooses C1 for the task as it is the cluster with lowest ID.



(a) Different task mixes



(b) Different number of tasks



(c) Different u_c

FIGURE 5.8: Energy consumption of cloud system

5.7 Performance Evaluation

In the previous section, we described four clustering techniques for dividing the task set into clusters with the same deadline. In this section, we compare the total energy consumed by the task set when clustered according to these techniques. The task set is generated by randomly computing their execution time at utilization 1 and deadline. The tasks are then sorted according to their deadline. This sorted task set is given as input to each of the clustering techniques, which schedules the resulting clusters according to case 3 ($SC(e_i, d, n)$ as given in flowchart of Figure 5.6).

Since we are using a homogeneous cloud system, all the hosts have the same specifications. These hosts are characterized by the value of critical utilization, u_c. Therefore, the cloud system itself can also be characterized by this value. We have performed our experiments with different variations which are stated below.

1. Keeping the number of tasks fixed, we have computed the energy consumption for different set of tasks. Figure 5.8(a) shows a comparison of energy

consumption values between all the four clustering techniques for the same cloud system. We have taken $u_c = 0.73$ in this case. As we can see, clustering techniques CLT4 gives us the least energy consumption for all the task mixes.

2. Figure 5.8(b) shows a comparison of energy consumption values between all the four clustering techniques when the requests have different number of tasks. We have normalized the energy consumption of all the clustering techniques with respect to CLT1 for same task set. This comparison is done for same cloud system with $u_c = 0.73$. As we can see, a similar pattern is being followed for all the task sets. Here CLT4 is giving the least energy consumption in all the cases.

3. Keeping the task set same, Figure 5.8(c) shows a comparison of energy consumption values between all the four clustering techniques on a different cloud system. Here also, we have compared the normalized values of energy consumption with respect to CLT1 for the same cloud system. Clustering techniques CLT1, CLT2, and CLT3 produced better results than CLT4 when the value of the critical utilization (u_c) is less than 0.6, whereas, for the value of $u_c > 0.6$, CLT4 produced a better result.

From the above results, we can say that choosing the clustering techniques does not depend on the user request but on the specification of the cloud system. As the value of u_c is known for a cloud system, we can choose the clustering technique, without looking at the task mix. For cloud systems with lower critical utilization values, that is $u_c \leq 0.6$, choose any one of CLT1, CLT2 or CLT3, as they all produce comparable results. For systems with a higher u_c, it is better to choose CLT4 as the clustering technique to minimize the energy consumption of the system.

5.8 Summary

In this chapter, we investigate the problem of energy-efficient scheduling of a set of offline real-time tasks in a virtualized cloud environment. The virtual resource layer of the cloud system consists of a set of different type of VMs, where each VM type is specified by its utilization. We assume that the bigger VMs (having higher compute capacity and thus requires lesser time to execute a task) provide higher utilization and smaller VMs (having lesser compute capacity and thus requires more time to execute a task) provide lower utilization to the host. In this chapter, we have carefully used the energy consumption versus the utilization characteristics of the hosts of the cloud system to minimize the overall energy consumption of the system. We first calculate critical utilization value when the host energy is minimum and the target of the scheduling policy is to keep the host utilization close to the critical utilization. We categorize the problem of energy-efficient scheduling of a set of real-time tasks into four subproblems and then solve them individually.

Chapter 6

Scheduling Scientific Workflows on Virtualized Cloud System

This chapter presents a series of energy-efficient scheduling techniques for executing a set of online dependent tasks, represented as scientific workflows. Each task in a workflow requires multiple VMs to execute and we use two different VM allocation approaches for this. We consider three different migration policies: no migration, limited migration, and full migration in designing our scheduling approaches. Extensive simulation experiments are conducted on Cloudsim toolkit to establish the superiority of the proposed work as compared to a state-of-art energy-efficient scheduling policy.

6.1 Introduction

The overwhelming popularity of the cloud system has attracted the users from different domains to host their applications at an affordable cost. The availability of high-end resources in the cloud has made itself a better choice for the scientific applications [95]. The elasticity feature added advantage to the cloud domain to efficiently handle the variation in the resource requirement of these scientific applications. These scientific applications often come from fields, such as astronomy, astrophysics, bioinformatics, high energy physics, etc., and they are modeled as scientific workflows [24, 25, 41].

Because of the significant cost of the compute servers of the cloud system, most of the cloud system provider does not procure all the servers (or hosts) of their cloud system in one go; instead, they purchase servers in phases and add them to their existing cloud system. In fact, a data center might contain multiple generations of hardware [86]. Thus, in most of the cases, cloud systems are bound to be heterogeneous. But for the cloud user, this heterogeneity gets hidden by the virtualization layer and user's requests require machines in terms of VMs and most of the cases the requests are for homogeneous VM. So to cater this particular behavior of cloud system, in this work, we have considered scheduling of workflows to be run on top of a set of homogeneous virtual machines while the cloud system essentially consists of heterogeneous servers (hosts).

Scientific workflows are typically expressed as a precedence constraint graph. But the graphs are structured in such a way that most of them can also be represented as a chain of tasks [131, 132]. Each task in the chain represents a collection of sub-tasks. Each task has also its individual execution time or length. A collection of VMs (in case of a virtualized system) or a set of threads (in case of a non-virtualized system) together execute a task where each VM or thread executes a sub-task. Thus in case of a virtualized cloud system, a task of a scientific workflow requires multiple VMs for its execution. In this chapter, we consider the scheduling of this structured scientific workflows for the cloud system. Now there may be two different types of VM allocations for a task of a workflow: (i) non-splittable VM allocation (NSVM), and (ii) splittable VM allocation (SVM). In case of NSVM, all the required VMs of a task must be placed on one host. And in case of SVM, the VMs can be placed on different hosts. In our work, we have considered scheduling of a set of online scientific workflows so as to reduce the energy consumption where each workflow has a deadline and the schedule must satisfy the deadline constraint.

A substantial amount of research has already been done to schedule scientific workflows in the cloud system in an energy-efficient manner [102, 103, 61, 41, 95, 99]. For instance, Durillo *et al.* [102] has developed a multi-objective energy-efficient list-based workflow scheduling algorithm, called *MOHEFT* (Multi-Objective HEFT) where they present a trade-off between the energy consumption and the makespan time. In [28], Bousselmi *et al.* partitioned the workflow to reduce the data communication among them, thereby reduced the network energy consumption. Then they used the cat swarm optimization based heuristic to schedule each partition on a set of VMs in an energy-efficient manner. Chen *et al.* [104] designed an online scheduling algorithm, called, energy-efficient online scheduling *EONS* to schedule tasks from different workflows. In this approach, system resources are dynamically adjusted to maintain the weighted square frequencies of the hosts.

Recently, Li *et al.* [61] has considered reducing both the energy consumption and the execution cost of workflow while guaranteeing deadline constraints. They considered only the dynamic energy consumption of the hosts and used DVFS technology to utilize the slack time of a task. Xu et al. [41] considered the execution of scientific workflows to minimize the energy consumption of cloud resources. They transformed a workflow into a set of sequential tasks and each task arrives at the system with a predefined start time. Their considered cloud system consists of heterogeneous hosts and a set of homogeneous VMs placed on those hosts execute the tasks.

In this chapter, we consider similar kinds of environment (homogeneous VMs on heterogeneous hosts) as considered in [41] to schedule a set of online scientific workflows in the cloud system. But we do not consider the static partition of the tasks; instead, the start time of each task of a workflow is calculated dynamically based on the usages of the slack time of the workflow. We summarize the contributions of this chapter as follows.

- An energy consumption model for the cloud is presented catering to both static and dynamic energy consumption.
- Two different VM allocation techniques (splittable and non-splittable) is presented
- Three different slack distribution and utilization technique is presented.
- A series of energy-efficient online scheduling techniques are presented for executing a set of online scientific workflows in the cloud environment.
- Trade-off between the energy consumption, the number of migrations and number of splits is addressed.

6.2 System Model

The considered virtualized cloud system accepts a set of online workflows. Each workflow is represented by a chain of tasks. These tasks are to be executed on some virtual machines (VMs) which are hosted on a set of physical machines. The physical layer of the cloud system consists of a sufficiently large number (can be considered as infinite) of physical machines (or hosts), $\boldsymbol{H} = \{h_1, h_2, h_3, h_4, \cdots\}$.

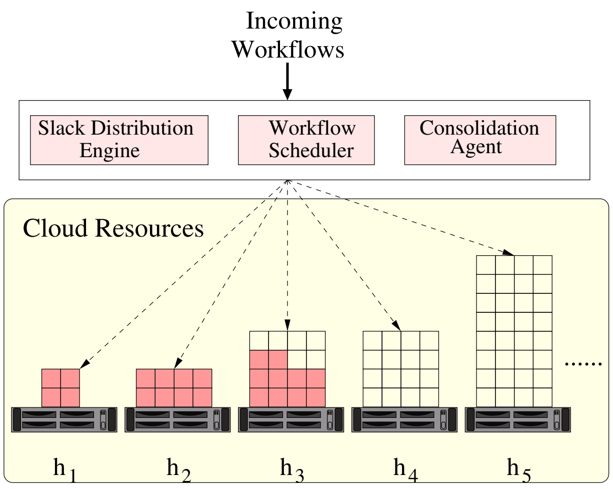


FIGURE 6.1: System architecture

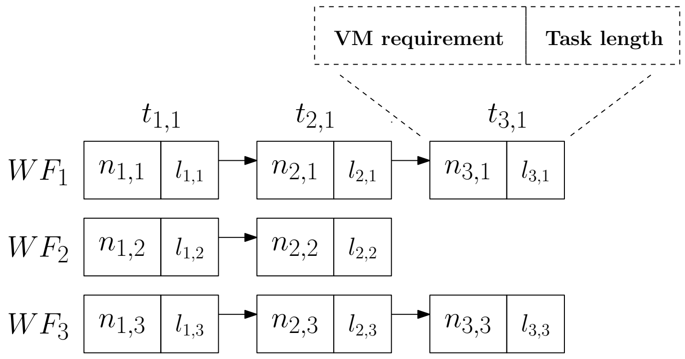


FIGURE 6.2: Application model

These hosts are heterogeneous in nature and they are mainly characterized by their compute capacity, amount of RAM, and storage capacity. Compute capacity of a host is defined in terms of MIPS (million instructions per second). We define a set $H_{active} \subseteq \boldsymbol{H}$ as the active hosts that are switched on. Each physical machine (i.e. host) h_k accommodates a set of VMs, $VM_k = \{v_{1k}, v_{2k}, \ldots, v_{|V_k|k}\}$. Each VM consumes a portion of its host's compute capacity, RAM, and storage. VMs can be added and removed from the physical machines (PMs) dynamically as and when required. They can also be migrated from one PM to another to facilitate consolidation. The compute capacity of a VM v_{jk} (j^{th} VM on k^{th} host) is written as $CP(v_{jk})$

The system model can be illustrated using Figure 6.1. The example cloud system has five hosts: h_1, h_2, h_3, h_4, and h_5 where hosts h_1, h_2, and h_3 are active hosts. The VM capacity of host h_1 is 4 that is, it can accommodate maximum 4 VMs. Similarly, VM capacity of h_2, h_3, h_4 and h_5 are 8, 16, 16 and 32 respectively. All the VMs in h_1 and h_2 are executing some tasks of some workflows while only 10 VMs in h_3 are busy executing some tasks; and h_3 can host another 6 VMs. As the workflows enter the cloud system, they pass through the slack distribution engine. The job of the slack distribution engine is to distribute the whole slack of a workflow among different tasks of that workflow. The next phase is the workflow scheduling phase. The job of the workflow scheduler is to efficiently schedule the tasks of an incoming workflow on the existing state of the cloud resources such that the overall energy of the cloud system is minimized (considering the energy consumption model described in Section 6.4). The system consists of a consolidation agent and the job of the agent is to consolidate the VMs to a minimum number of hosts to reduce the total number of active hosts in the system.

6.3 Application Model

The application model consists of a set of online workflows $\boldsymbol{WF} = \{WF_1, WF_2, \cdots\}$. Each workflow WF_p is represented by a sequence of tasks $\{t_{1,p}, t_{2,p}, \cdots, t_{|WF_p|,p}\}$ with a chain constraint among them [131, 132]. Each workflow WF_p has its arrival time a_p. Each task $t_{i,p}$ of a workflow WF_p is characterized by two parameters: (a) VM requirement of the task $n_{i,p}$, and (b) the length of the task ($l_{i,p}$); where i is the task sequence number in the workflow and p is the workflow number. VM requirement of a task means total number of parallel VMs needed at the same time to execute the task. The length of the task is expressed as million instructions (MI).

Figure 6.2 shows an example of such workflow system consisting of 3 different workflows or chains WF_1, WF_2, and WF_3 having 3, 2, and 3 tasks respectively. A task of a workflow can not start execution before complete execution of its predecessor tasks of the same workflow. We assume that there is no dependency among different workflows and thus execution of one workflow can overlap with others.

Suppose a task $t_{i,p}$ requires only one VM for its execution and it is executed by a VM v_{jk}. Then it will require $l_{i,p}/CP(v_{jk})$ amount time for its completion. This becomes the execution time of task $t_{i,p}$ on VM v_{jk} and is represented by e_{ipjk}. Mathematically, it can be written as:

$$e_{ipjk} = \frac{l_{i,p}}{CP(v_{jk})} \tag{6.1}$$

We also define the ready time of a VM, $r(v_{j,k})$ as:

$$rt(v_{jk}) = st(v_{jk}) + e_{ipjk} \tag{6.2}$$

where, $st(v_{jk})$ is the start time of the VM which indicates the time instant when the VM v_{jk} has started executing the task t_{ip}.

Every workflow has a user-defined deadline d_p; that is execution of all the tasks in the workflow must finish their execution by time d_p. Deadline of a workflow WF_p satisfies the relation $d_p \geq \sum_{i=1}^{|WF_p|} e_{ipjk} + a_p$.

The time difference between the deadline and the summation of execution time for all the tasks of a workflow WF_p is called the slack time slk_p and this can be represented as

$$slk_p = d_p - a_p - \left(\sum_{i=1}^{|WF_p|} e_{ipjk} \right) \tag{6.3}$$

where slk_p is the total amount of slack time for the workflow WF_p, $|WF_p|$ indicates the length of the workflow (or chain) that is the total number of tasks for the workflow WF_p. In case of homogeneous VMs, slk_p can be calculated beforehand.

6.4 Energy Consumption Model

Cloud system consists of many power consuming components but a major portion of the power in a cloud data center is consumed by the host (or compute node) itself. Again the host power consumption is mainly driven by that of the processor (CPU), memory, network interface and disk storage. Power consumption of a host has two components: *static* and *dynamic*. A large volume of research has already been done considering only the dynamic power consumption of the host, specially when scheduling of real-time tasks was considered [33, 30, 52, 67]. But research also reveals the fact that static power consumption of a host is nearly 60% to 70% of the total power consumption [45, 43] which is significant and should not be ignored.

Thus in our work, we have considered both the static and dynamic power consumption of the host to schedule a set of scientific workflows in the cloud where each workflow consists of a chain of real-time tasks. The summation of these power consumption values over the total time interval gives the energy consumption of the system. Mathematically, it can be written as $E = \int_{t=0}^{\infty} PC_t.dt$, where PC_t is the total power consumption of the system at time t. Total energy consumption of an active host h_k can be expressed as follows.

$$E_{h_k} = E_{h_k\_s} + E_{h_k\_d} \tag{6.4}$$

where, E_{h_k} is the total energy consumption of a host h_k, $E_{h_k\_s}$ is the static energy consumption of the host, and $E_{h_k\_d}$ is the dynamic energy consumption of the host.

Thus total energy consumption of the cloud system can be expressed as

$$E_{total} = \sum_{k=1}^{|H_{active}|} E_{h_k} \tag{6.5}$$

We assume that all non-active hosts are switched off and they do not consume any energy.

In this work, we considered that the hosts in the cloud system are heterogeneous and their base power (or energy) consumptions are different, similar to the energy consumption model considered in [41]. Base (or static) energy consumption of a host h_k can be written as

$$E_{h_k\_s} = ECR_{base_k}.t \tag{6.6}$$

where, ECR_{base_k} is the base energy consumption rate of host h_k and t is the total active time for host h_k.

The base energy consumption rate of the hosts can be taken as the function of their VM capacity which is explained in details with example in Section 6.10. Accordingly, the base energy consumption rate of hosts in the system model (Figure 6.1) can be expressed as follows.

$$ECR_{base_1} \leq ECR_{base_2} \leq ECR_{base_3} \leq ECR_{base_4} \leq \cdots \tag{6.7}$$

which means the base energy consumption rate of host h_1 is less than or equal to the base energy consumption rate of host h_2, which is tern less or equal to the base energy consumption rate of host h_3 and so on. This is because the VM capabilities of host h_1 is less than VM capabilities of host h_2, which is less than VM capabilities of host h_3, and so on.

Again the dynamic energy consumption of a host is basically contributed by the active VMs when they execute some tasks. In our work, we considered the dynamic energy consumption model similar to [30]. Suppose VM v_{jk} executes task $t_{i,p}$. Then the energy consumption of the VM, $E_{v_{ipjk}}$ can be written as follows.

$$E_{v_{ipjk}} = ECR_{v_{jk}}.e_{ipjk} \tag{6.8}$$

where, $ECR_{v_{jk}}$ is the energy consumption rate of VM v_{jk}, e_{ipjk} is the time taken by VM v_{jk} to execute task $t_{i,p}$.

Now the total dynamic energy consumption of a host can be represented as

$$E_{h_k\_d} = \sum_{j=1}^{|VM_k|} \sum_{i=1}^{|WF_p|} E_{v_{ipjk}} \tag{6.9}$$

In order to achieve energy efficiency, the workflow scheduler always try to put the tasks of workflows in the hosts with lower energy consumption.

6.5 Objective in the Chapter

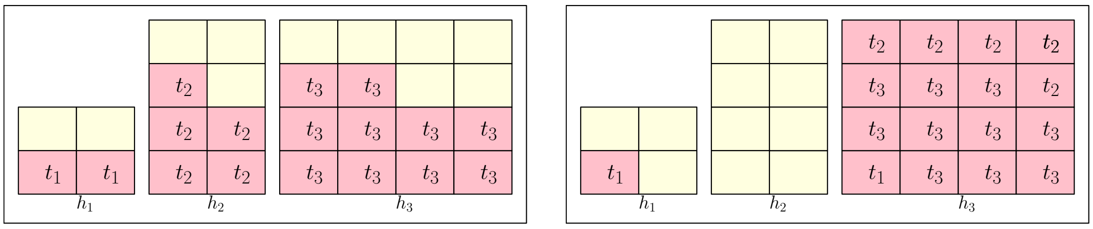
The chapter aims to schedule a set on online workflows, represented by $\boldsymbol{WF} = \{WF_1, WF_2, WF_3, \cdots\}$ onto a virtualized cloud system, represented by an infinite set of physical machines (or hosts), $\boldsymbol{H} = \{h_1, h_2, h_3, h_4, \cdots\}$ such that the overall energy consumption of the cloud data center is minimized and the deadline constraints of all the workflows are met. Each workflow consists of a chain of tasks where each task has its own VM requirement and length (described in details in Section 6.3). We assumed that all the hosts reside in a single data center and they are heterogeneous in their compute capacity and energy consumption. In this chapter, we have considered all the VMs are homogeneous by their computing capabilities. Thus the execution time of two tasks with the same length happens to be the same even if different VMs execute them on different hosts.

6.6 Scheduling Options and Restrictions in Workflow Scheduling

Any scheduling policy primarily addresses three parameters: "which" task to execute, "where" to execute the task and "when" to execute the task. In our work, we are considering a set of online scientific workflows for scheduling in a cloud system and the scheduling procudure is invoked upon arrival of a workflow to the system. In case of arrival of multiple workflows at the same time, they are considered in any arbitrary order. Again, a workflow consists of a chain of tasks and these tasks are executed sequentially. This is how the "which" parameter is addressed. The "where" parameter of scheduling deals with two things: (i) selecting a proper host (or a set of hosts because we have considered multi-VM tasks) and (ii) placing VMs on the selected host (or a set of hosts). The scheduler selects the host or a set of hosts in an energy-efficient way which is explained in Section 6.7. The VM placement is described in Subsection 6.6.1. The third parameter **when** specifies the time at which the selected task is sent for execution to the selected host. We have exploited this parameter by efficiently utilizing the slack time of a workflow and is explained in the following Subsection.

6.6.1 VM placement

VM placement refers to mapping virtual machines to physical machines (or hosts) of the cloud system. In this work, we consider online mapping of VMs to hosts and this problem is proved to be NP-complete [133]. Various approaches such as constraint programming, linear programming, genetic algorithm, bin packing, etc. have been applied for efficiently placing the VMs on the hosts [134, 135, 136,



(a) Allocation under non-splittable VM category (b) Allocation under splittable VM category

FIGURE 6.3: System state with different VM allocation type

137, 56, 138]. Best fit decreasing order (BFD) and first fit decreasing order (FFD) are two effective heuristics when the problem is mapped to bin packing problem [41, 43]. In our work, we have used a variation of BFD and combination of BFD and FFD depending on the VM allocation type and migration planning.

A task t_i in the system is specified with its length l_i and VM requirement n_i. Thus a task may require more than one VM for its execution and a host might fail to accommodate the task. Keeping this scenario into consideration, we have used two types of VM allocation in our work.
(1) **Non-splittable VMs (NSVM)**: In this category, the VM allocation for a single task cannot be split; thus the name. All the required VMs of a task must be hosted on the same physical machine of the cloud system for the entire duration of the task execution. A task can be scheduled on a host only if it can accommodate the task completely, i.e. the idle number of VMs of a host must be greater than or equal to the number of VMs required by the task for its execution.
(2) **Splittable VMs (SVM)**: In the second category, the VM allocation for a task can be split. That is the required VMs of a task can be hosted on more than one physical machines of the cloud system. A task can be scheduled when a set of hosts in the system can collectively satisfy the VM requirement of the task.

In case of the non-splittable VM allocation category, the system might experience a poor utilization of the resources. This is illustrated using Figure 6.3. For instance, let there be 3 types of hosts with VM capacities 4, 8 and 16 respectively. Let us assume that base power consumptions of the hosts are 50W, 75W and 100W respectively. Now we suppose that there are 3 tasks with VM requirements 2, 5, and 7 which are to be placed on the hosts. In this case, the system will remain underutilized and there will be a wastage of 39% of the VM capacity. Figure 6.3(a) represents the system state after scheduling these tasks. The power consumption will be 50 + 75 + 100 + 17x10 = 395W (assuming per VM power consumption is 10W).

On the other hand, relaxation on VM placement condition in case of splittable type provides an opportunity to the scheduler to utilize the system resources more effectively. Now the scheduler searches for a collection of hosts which can collectively satisfy the VM requirement of a task. We see that for the given example, the total VM requirement of the tasks is $17(= 2 + 5 + 10)$ and this can be met only by only two hosts (h_1 and h_3). Host h_2 can be put in switched-off mode and this will not consume any power. Figure 6.3(b) represents the system status after this schedule. This reduces the number of active hosts; which in turn reduces the overall energy (or power) consumption of the system. Power consumption of the system under this allocation type is $50 + 100 + 17\text{x}10 = 320$W. But whenever, the VMs of a single task reside in different hosts, they need to communicate among themselves. The energy consumption due to this communication can be modeled as shown below which is considered similar to [41].

$$EC_{comm} = \sum_{i=1}^{|H_{active}|} \sum_{j=1}^{|H_{active}|} \frac{D_{i,j}}{bw_{i,j}} ECR_{comm} \tag{6.10}$$

where $D_{i,j}$ represents the total data transferred from host h_i to h_j, $bw_{i,j}$ is the network bandwidth between h_i and h_j, and ECR_{comm} is energy consumption rate for communication between two different hosts.

This extra energy will be added to the total energy consumption of Equation 6.5 in order to find the overall energy consumption of the system.

6.6.2 Migration

The workflow scheduler described in Section 6.1 has a consolidation agent. The job of the consolidation agent is to run through the active hosts and to migrate VMs from the hosts with lower utilization value to the hosts with higher utilization value. For this operation, we define a threshold called *MigThreshold*. Consolidation operation can be performed on a host if its utilization value falls below the *MigThreshold*. Under this setups, we outline three approaches as described below.

- **No migration (NM):** Under this approach, the consolidation operation is not performed. Thus the existing mappings between a task to VM and VM to host do not get changed during the course of execution. Whenever a new task of a workflow arrives at the cloud system, the scheduler performs scheduling of this task only and finds the best mapping for the task. The scheduler does not consider already scheduled tasks while scheduling the current task. Hence the number of migrations in this approach is zero; thus the name no migration.

- **Limited migration (LM):** Whenever a workflow arrives, it is scheduled on the cloud system without changing the mapping of the already scheduled tasks. Under this setup, the utilization of a host changes only when a task finishes its execution, thus releases the corresponding VM. Then consolidation agent checks whether the host utilization falls below the *MigThreshold* value. The agent performs the consolidation operation only if the host utilization falls below the threshold. After the consolidation operation is performed, the agent marks the active hosts without any active VMs on them and then it puts such hosts in switched off mode.
- **Full migration (FM):** Under this approach, the consolidation operation is performed along with the scheduling operation. Thus the existing mapping of tasks to VMs and VMs to hosts might get changed. The newly arrived tasks and the existing tasks in the system (both running and waiting) are considered to be fresh tasks and energy-efficient scheduling policies are applied to get new mappings. As per the new mapping, if the associated VMs of a task are mapped to their previous hosts, then no migration is required. Otherwise, the system needs to migrate VMs from the current host to the newly mapped hosts.

6.6.3 Slack distribution

Here the slack time of the task (or workflow) plays an important role. Suppose a workflow consists of m number of tasks and slack time for the workflow is z. If we consider discrete scheduling time, then the first task in the workflow can have $m.z$ choices to utilize the slack. Suppose, the task fails to utilize the slack. Then in the worst case, the second task in the workflow will have $m.z$ choices and this continued till the last task of the workflow. Thus in case of brute force approach, the total number of choice for utilizing the slack time will be exponential. In our work, we have used three simple but effective heuristics to utilize this slack time efficiently in our proposed scheduling techniques.

(1) **Slack to first task (SFT)**: Only the first task of every workflow enjoys

the advantage of using the slack time of that workflow. This is the simplest of all three.

(2) **Slack forwarding (SFW)**: The first task of a workflow gets the highest preference to use the slack time. If the task does not use the slack completely, then the remaining slack is forwarded to the next task of the same workflow, and this is continued until the last task of the workflow.

(3) **Slack division and forwarding (SDF)**: In this case, the total slack time of a workflow gets distributed among all the tasks of the workflow. If a task does not utilize the assigned slack time completely, then the remaining amount will be forwarded to the next task of the same workflow as in the former category. Here the tasks in a workflow are ranked based on their length and VM requirement and the slack time is distributed accordingly. A task with a greater value of length and VM requirement gets a greater portion of the slack time. For this, we calculate a factor called *total length-VM* (TLV) as

$$TLV_{WF_p} = \sum_{i=1}^{|WF_p|} (l_{i,p} \times n_{i,p}) \tag{6.11}$$

where, TLV_{WF_p} is the total length-VM factor of workflow WF_p, $l_{i,p}$ and $n_{i,p}$ are the length and VM requirement of the tasks of that workflow respectively.

Then we calculate individual portion of the slack time for each tasks in the workflow as follows.

$$slk_{i,p} = \frac{(l_{i,p} \times n_{i,p})}{TLV_{WF_p}} \times slk_p \tag{6.12}$$

where $slk_{i,p}$ is the individual slack time to be assigned for the i^{th} task of workflow WF_p. slk_p is the total slack time for the workflow WF_p as calculated by Equation 6.3.

These slacks are initially assigned to every task of the workflow. Whenever a task do not utilize its share of slack completely, it is forwarded to the following task. Thus the effective slack time of an task $t_{i,p}$ will be as follows which is calculated dynamically.

$$slk_{i,p} = slk_{i,p} + remainingSlack_{i-1,p} \tag{6.13}$$

where, $remainingSlack_{i-1,p}$ is the unused slack of the predecessor task $t_{i-1,p}$.

Vm allocation	**Migration**	**Slack distribution**
Non splittable (NSVM)	No migration (NM)	Slack to first task (SFT)
Splittable (SVM)	Limited migration (LM)	Slack forwarding (SFW)
	Full migration (FM)	Slack division and forwarding (SDF)

TABLE 6.1: Parameters determining scheduling policies

Algorithm 10 Scheduling workflow in a cloud system

```
On arrival of a workflow $WF_p(a_p, d_p)$
1: for each task $t_{i,p}$ of $WF_p$ do
2:     Calculate its permissible slack time $slk_{i,p}$ based on the policies
       described in Section 6.6.3
3:     Schedule task $t_{i,p}$ in an energy-efficient manner
4:     Update the remaining slack if any
5:     Update system information
6: end for
```

Table 6.1 listed the above stated scheduling options and restrictions which are combined to produce a series of scheduling policies. In the next section, we present these energy-efficient scheduling policies.

6.7 Scheduling Policies

In the previous section, we have discussed three different parameters which determine the overall working and performance of scheduling policy. In this section, we have proposed a series of scheduling policies where these parameters are combined in different ways. Algorithm 10 depicts the common steps involved in our proposed scheduling policies. A workflow WF_p enters the cloud system with an arrival time a_p and a deadline d_p. Then the slack slk_p can be calculated using equation 6.3. As explained in the previous section, this slack will be utilized by the tasks in the workflow. As mentioned in Section 6.1, tasks of a workflow pass through the slack distribution engine before they reach the workflow scheduler. The slack distribution engine determines the amount of slack individual task of a workflow gets. In the following subsections, we first present scheduling policies under the non-splittable VM allocation category and then we discuss scheduling policies under splittable VM allocation category. With each VM allocation category, we have associated the migration policy and the slack distribution approach to make it complete.

6.8 Scheduling with Non-splittable VM Allocation ($NSVM$)

In this section, we present scheduling approaches with the restriction that all the VMs executing a task of a workflow must reside on the same host. A variation of best fit decreasing order policy is used to put the VMs on the hosts. The scheduler maintains the host list in non-decreasing order of their base power consumption and the job of the scheduler is to find the host with lowest base power consumption such that the host can hold all the VMs required by the task. In the following subsections, we present different scheduling policies considering non-splittable VM allocation.

6.8.1 Non-splittable VMs without migration ($NSVM_{NM}$)

This scheduling technique is described using Algorithm 11. For each task of the workflow, the algorithm first calculates its individual slack time. Then it inspects the current system state and finds the best time to schedule the task in the system. For this, the algorithm calls a Procedure *findBestSlack()*. This procedure inspects all the active hosts in sorted order to find a host which can satisfy the VM requirement of the task. As soon as such a host is found, the procedure returns the host with the best slack time when the host becomes available for executing the task with minimum energy consumption. If no active host can hold the task within the slack range, the procedure returns a NULL value. These steps are stated in Procedure $findBestSlack()$.

Then the Algorithm 11 schedules the task using another Procedure $schedule()$. If any active host can hold the task, the task gets scheduled on the VMs of that host whenever it can hold (line number 4). If no active host can hold the task, then a new host with minimum base power consumption is switched on such that it can hold the task completely. Then the task is scheduled immediately without wasting any slack time. This scheduling policy does not change the mapping of the already scheduled tasks. Thus the execution of tasks are continuous and there is no migration of tasks (or VMs). Now depending on the slack distribution logic, the individual slack assigned to a task varies. For SFT slack distribution logic, $slk_{i,p}$ happens to be 0 for $i \geq 2$.

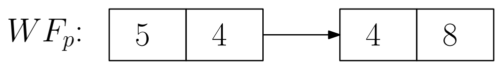


FIGURE 6.4: WorkFlow ($WF_p(a_p = 10, d_p = 33)$) to be scheduled on the system

6.8.1.1 Slack to first task (SFT_NSVM_{NM})

Figure 6.5 describes an example of the working of the scheduling policy when applied with SFT slack distribution logic. 6.5(a) shows the system state with three active hosts having VM capacity of 4, 8 and 16 respectively. Each filled cell of a host indicates a VM and the values inside represents the running task and the ready time for that VM. A blank cell indicates free slot for new VM. We assume that the hosts are in sorted in increasing order of their base power consumption. All the VMs of host h_1 is busy in executing task $t_{1,1}$ and their ready time is 20. VMs in host h_2 is executing two tasks $t_{1,2}$ and $t_{2,4}$ and their ready times are 15 and 12 respectively. Host h_2 can instantiate two more VMs on it. And in host h_3, ready time for eight VMs are 22 and it can instantiate another 8 VMs on it.

Now let us consider a workflow with two tasks as shown in Figure 6.4 with arrival time 10 and deadline 33. *As all the VMs in our cloud system is assumed to be homogeneous, the length of a task can easily be taken as the execution time for the task.* Thus slack is calculated by Equation 6.3 as $33 - 10 - (4 + 8) = 11$. The first task of the workflow requires 5 VMs to execute and currently host h_3 can easily hold the task. But the scheduler does not schedule the task in h_3. As the slack value is 11, the scheduler can schedule the task any time from time 10 to 21 ($= 10 + 11$). Scheduler checks that the VMs of the host can hold the task h_2 also and it prefers to schedule on h_2 only because the base power consumption of h_2 is lesser than that of h_3. But h_2 can hold 5 VMs only at time 15. As it lies in the slack range, the scheduler schedules the task on host h_2 to schedule at time instant 15, rather than immediate scheduling it on h_3 (though enough active resource is available). Figure 6.5(b) shows the system state after scheduling the first task of the workflow. Now scheduling of remaining tasks of the workflow will immediately start from time 19 because the finish time of the first task becomes $19(= 15 + 4)$. There is only one task remaining to be scheduled in the workflow and it is to be scheduled at time 19. VM requirement of this task is 4. Thus it has only one choice and the scheduler accordingly schedules the task on host h_2. Figure 6.5(c) shows the system state after this schedule.

Algorithm 11 NSVM without migration ($NSVM_{NM}$)

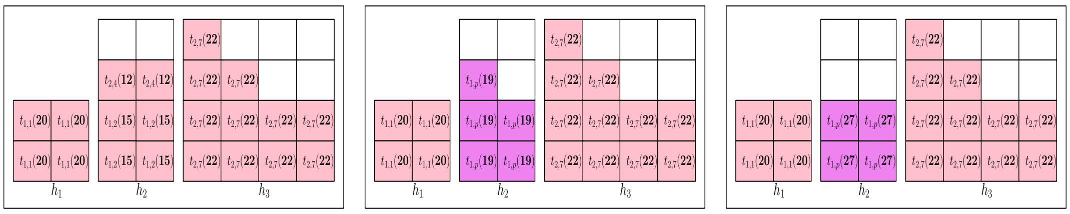
```
On arrival of a workflow $WF_p(a_p, d_p)$
 1: Calculate the slack time $slk_p$ by Equation 6.3
 2: $leftSlack \leftarrow 0$
 3: $schdTime \leftarrow a_p$
 4: for each task $t_{i,p}$ in $WF_p$ do
 5:     Calculate its permissible slack time $slk_{i,p}$ based on the policies
        described in Section 6.6.3
 6:     $slk_{i,p} \leftarrow slk_{i,p} + leftSlack$
 7:     $< h_k, bestSlk > \leftarrow findBestSlack(t_{i,p}, schdTime, slk_{i,p})$
 8:     $schedule(t_{i,p}, h_k, schdTime, bestSlk)$
 9:     $schdTime \leftarrow schdTime + e_{ipjk}$
10:     $leftSlack \leftarrow slk_{i,p} - bestSlk$
11: end for
```

```
 1: procedure $findBestSlack(t_{i,p}, startTime, slack)$
 2:     Sort the hosts in ascending order of their base power consumption
 3:     for each host $h_k$ in $H_{active}$ do
 4:         for $t = 0$ to $slack$ do
 5:             $idleVm \leftarrow 0$
 6:             for each VM $v_{jk}$ of $h_k$ do
 7:                 if $r(v_{jk}) \leq (t + startTime)$ then
 8:                     $idleVm \leftarrow idleVm + 1$
 9:             end for
10:             if $idleVm \geq n_{i,p}$ then
11:             return $< h_k, t >$
12:         end for
13:     end for
14:     return $< NULL, 0 >$
15: end procedure
```

6.8.1.2 Slack forwarding (SFW_NSVM_{NM})

From the stated example of the previous case, we see that the first task did not utilize the slack completely and 6 units of slack time were left after scheduling the first task. We also see that the VMs in host h_1 becomes ready at time 20 whose base power consumption is lesser than that of h_2. But as the second task was to be scheduled immediately, the scheduler was bound to schedule it on higher power consuming host h_2. This issue is addressed in this scheduling technique with slack forwarding (SFW_NSVM_{NM}). Under this approach, the remaining slack of a task is forwarded to its successor task for utilization. If we execute the same workflow as shown in Figure 6.4 with the same system state as of 6.5(a), scheduling of the first task remains same and is represented by Figure 6.5(b).

```
1: procedure $schedule(t_{i,p},\ h_k,\ schdTime, bestSlk)$
2:     $effSchdTime \leftarrow schdTime + bestSlk$
3:     if $h_k$ is not $NULL$ then
4:         Schedule $t_{i,p}$ on host $h_k$ at time $effSchdTime$
5:         Set ready time of the selected VMs of $h_k$ as
           $effSchdTime + e_{ipjk}$
6:     else
7:         Get the first host $h_m$ from the sorted order s.t. $|V_m| \geq n_{i,p}$
8:         Switch-on the host and initiate $n_{i,p}$ number of VMs
9:         Add $h_m$ to the active host list
10:        Schedule $t_{i,p}$ on $h_m$ at time $schdTime$
11:        Set ready time for VMs of $h_m$ as $schdTime + e_{ipjm}$
12: end procedure
```


$t_{2,7}(22)$
$t_{2,4}(12)$ $t_{2,4}(12)$ $t_{2,7}(22)$ $t_{2,7}(22)$
$t_{1,1}(20)$ $t_{1,1}(20)$ $t_{1,2}(15)$ $t_{1,2}(15)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$
$t_{1,1}(20)$ $t_{1,1}(20)$ $t_{1,2}(15)$ $t_{1,2}(15)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$
h_1 h_2 h_3
$t_{2,7}(22)$
$t_{1,p}(19)$ $t_{2,7}(22)$ $t_{2,7}(22)$
$t_{1,1}(20)$ $t_{1,1}(20)$ $t_{1,p}(19)$ $t_{1,p}(19)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$
$t_{1,1}(20)$ $t_{1,1}(20)$ $t_{1,p}(19)$ $t_{1,p}(19)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$
h_1 h_2 h_3
$t_{2,7}(22)$
$t_{2,7}(22)$ $t_{2,7}(22)$
$t_{1,1}(20)$ $t_{1,1}(20)$ $t_{1,p}(27)$ $t_{1,p}(27)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$
$t_{1,1}(20)$ $t_{1,1}(20)$ $t_{1,p}(27)$ $t_{1,p}(27)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$ $t_{2,7}(22)$
h_1 h_2 h_3

(a) **Initial state ($t = 10$)** (b) After scheduling first task ($t = 15$) (c) **After scheduling second task ($t = 19$)**

FIGURE 6.5: System state at different time (t) instant under SFT_NSVM_{NM} scheduling policy

But for the second task, the scheduler will not schedule it on host h_2 at time 19. Rather it will look for better option from time 19 to time $25(= 19 + 6)$. On the other hand, host h_1 becomes available at time 20 and its base power consumption is lesser. Moreover, it has sufficient VM capacity to execute the task. Thus the scheduler will schedule the task on host h_1 only at time 20. Figure 6.6 shows the system state after scheduling the task $t_{2,p}$ of the workflow WF_p.

6.8.1.3 Slack division and forwarding (SDF_NSVM_{NM})

Here we present another variation of our algorithm. We can observe from the previous algorithm that the order of the tasks in workflow was the only parameter which was used in slack sharing. The first task of a workflow gets the complete liberty of using the whole slack of the workflow. And in general initial tasks get more priority of using the slack than later tasks in the workflow. But this might not be beneficial for few workflows, specially with a longer chain and with variety in VM requirement of tasks in a workflow. Thus we present an approach where

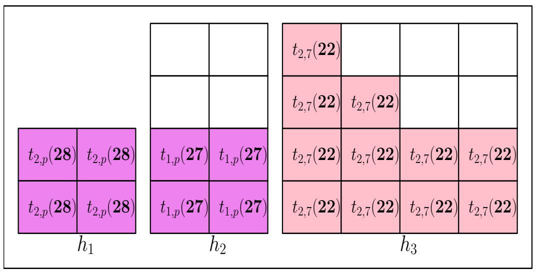


FIGURE 6.6: System state after scheduling second task ($t = 20$) in SFW_NSVM_{NM} scheduling policy

the length and the VM requirement of a task together decide the percentage of slack it gets. Initially, the whole slack of a workflow is distributed among the tasks of that workflow using Equation 6.12. However, if the assigned slack time to a given task is not used completely, then the remaining amount is forwarded to the next task of the same workflow and this process continues till the last task of the workflow.

Under the non-splittable VMs category without migration ($NSVM_{NM}$), for all the stated scheduling policies (SFT_NSVM_{NM}, SFW_NSVM_{NM}, SDF_NSVM_{NM}), whenever a host remains idle for more than a preset threshold time, the scheduler puts the host in switched off mode.

6.8.2 Non-splittable VMs with limited migration ($NSVM_{LM}$)

This scheduling policy is similar to the already discussed policy $NSVM_{NM}$. But in case of $NSVM_{NM}$, the consolidation operation is not performed and thus there is no migration of VMs from one host to another. However, in case of $NSVM_{LM}$, consolidation operation is performed separately. As mentioned in the Section 6.6, whenever the utilization of a host falls below *MigThreshold*, the host is selected and the consolidation operation is fired for that host. The consolidation agent checks whether all the VMs of a task (of the selected host) can be accommodated to a host with higher utilization. If multiple hosts can accommodate, then the host with the lowest base energy consumption rate is chosen as the target host. Then the migration operation from the selected host to the target host. This process is repeated for all the hosts whose utilization falls below *MigThreshold*. Then the hosts with no active VMs are switched off. The consolidation operation reduces the number of active hosts in the cloud system. Thus the total energy consumption of the system is also reduced as compared to $NSVM_{NM}$.

Algorithm 12 SVM without migration (SVM_{NM})

```
On arrival of a workflow $WF_p(a_p, d_p)$
1: Sort the hosts in ascending order of their base power consumption
2: Calculate the slack time $slk_p$ by Equation 6.3
3: $nextSchdTime \leftarrow a_p$
4: for each task $t_{i,p}$ in $WF_p$ do
5:     $flag \leftarrow FALSE$
6:
7:     Calculate its permissible slack time $slk_{i,p}$ based on the
       policies described in Section 6.6.3
8:     $slack \leftarrow slk_{i,p} + remainingSlack_{i-1,p}$
9:     $E_{minMap} \leftarrow \infty$
10:    while $slack > 0$ do
11:        $H_{select} = findMapping(nextSchdTime, n_{i,p})$
12:        $E_{map} \leftarrow 0$
13:        for each host $h_k$ in $H_{select}$ do
14:            Calculate $E_{h_k}$ by Equation 6.4
15:            $E_{map} \leftarrow E_{map} + E_{h_k}$
16:        end for
17:        if $E_{map} < E_{minMap}$ then
18:            $E_{minMap} \leftarrow E_{map}$
19:            $H_{minEnergy} \leftarrow H_{select}$
20:            $nextSchdTime \leftarrow t$
21:            $flag \leftarrow TRUE$
22:    if $flag = FALSE$ then
23:        $H_{minEnergy} = findMapping(nextSchdTime, n_{i,p})$
24:    Schedule the task $t_{i,p}$ on $H_{minEnergy}$ at $nextSchdTime$
25:    Set the ready time for the VMs in $H_{minEnergy}$
26:    Update $nextSchdTime$
27:    Update remaining slack for task $t_{i,p}$
28: end for
```

6.8.3 Non-splittable VMs with full migration ($NSVM_{FM}$)

This scheduling policy is similar to EnReal [41] which is taken as a baseline policy in our work. Here every time, a fresh task set is generated comprising of newly arrived tasks and the currently running tasks. Then the scheduler finds an energy-efficient mapping for the entire task set. This policy differs from EnReal in the slack distribution logic. EnReal uses a static time partition among the tasks of a workflow and $NSVM_{FM}$ uses a dynamic partition in the form of slack distribution.

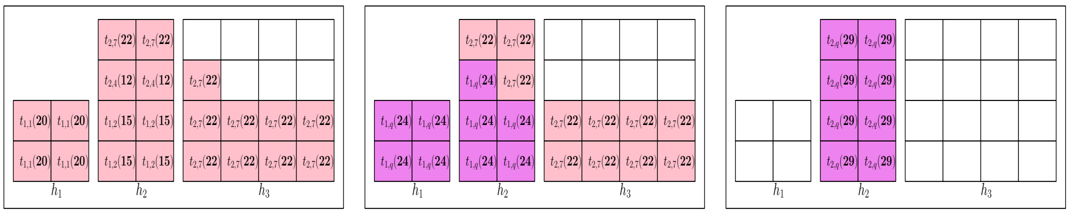
```
1: procedure $findMapping(t, n_{i,p})$
2:     $H_{select} \leftarrow NULL$
3:     for each host $h_k$ in host list do
4:         for each VM $v_{jK}$ in host $h_k$ do
5:             if $r(v_{jk} \leq t)$ then
6:                 $idleVmCount \leftarrow idleVmCount + 1$
7:                 Add $h_k$ in $H_{select}$
8:         end for
9:         if $idleVmCount \geq n_{i,p}$ then
10:            return set of hosts $H_{select}$
11:    end for
12: end procedure
```

6.9 Scheduling with Splittable VM Allocation (SVM)

In the last section, we described scheduling policies considering that all the required number of VMs of a task must reside in the same physical machine. But that restriction does not hold good here. Introducing this relaxation to the scheduling policy might reduce the energy consumption of the system significantly. This was already explained using an example in Subsection 6.6.1. In the following subsections, we present different scheduling policies considering splittable VM allocation.

6.9.1 Splittable VMs without migration (SVM_{NM})

Algorithm 12 shows the pseudocode for the SVM_{NM} policy. The policy basically aims to find a set of minimum energy consuming hosts such that the VM requirement of a task is satisfied. To achieve this, the hosts are initially sorted based on their base (or static) power consumption value. To get a mapping of the minimum energy consumption, the scheduler performs this checking for the entire permissible slack time for a task. Then the scheduler runs through the sorted hosts to select a set such that the total idle VM count in the set reaches the VM requirement. A VM becomes idle whenever its ready time is less than or equal to the scheduling time. Procedure $findMapping()$ encloses the steps to search for such collection of hosts. Then the scheduler selects the set with the minimum energy consumption and schedules the task to that set of hosts. In this case, also, we



(a) Initial state ($t = 10$) (b) After scheduling first task ($t = 20$) (c) After scheduling second task ($t = 24$)

FIGURE 6.7: System state at different time (t) instant under SFT_SVM_{NM} scheduling policy

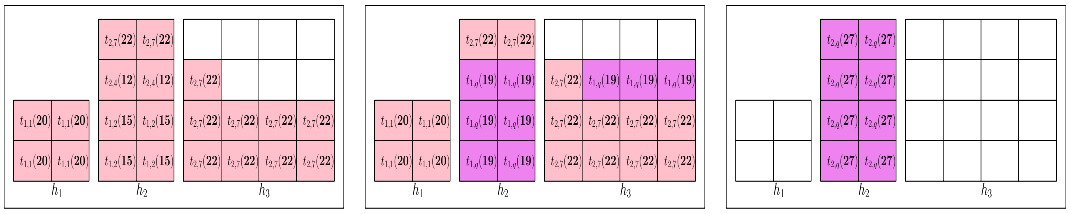
have considered three different ways to handle the slack time among the tasks of the workflow. This is similar to the approach as described in the previous section.

6.9.1.1 Slack to first task (SFT_SVM_{NM})

To understand the working of this scheduling policy, let us take an example system state as represented by Figure 6.7(a) and suppose a workflow (represented by Figure 6.9) is to be scheduled using SFT_SVM_{NM} scheduling approach. The first task in the workflow requires 9 VMs. Now we see that host h_2 contains 2 free VMs and host h_3 contains 5 free VMs. Hence currently the task cannot be scheduled in any active host. But at time 12, another two VMs will become free in host h_2. At this point, the task can be scheduled combining both host h_2 and h_3. But the scheduler does not schedule this way. Rather it checks whether low power consuming hosts become available within the slack range and it finds that h_2 becomes free at time 15 and h_1 becomes free at time 20. Thus it can schedule the task at time 20 on hosts h_1 and h_2. Figure 6.7(b) reflects the system state after this schedule. As slack is given only to the first task, the next task must be scheduled at time 24. This task requires 8 VMs and the scheduler schedules this task on host h_2 at time 24. Figure 6.7(c) represents the system state at time 24.

6.9.1.2 Slack forwarding (SFW_SVM_{NM})

The slack handling technique for this scheduling policy is same as SFW_NSVM_{NM}. The unused slack for one task gets forwarded to the successor task of the same workflow. But this policy differs from SFW_NSVM_{NM} in the sense that a task need not be scheduled on the VMs of the same host; rather it can be scheduled on the VMs which are placed on different hosts.



(a) Initial state ($t = 10$) (b) After scheduling first task ($t = 15$) (c) After scheduling second task ($t = 22$)

FIGURE 6.8: System state at different time (t) instant under SDF_SVM_{NM} scheduling policy

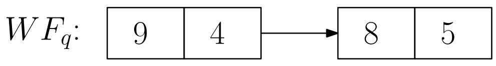


FIGURE 6.9: WorkFlow ($WF_q(a_p = 10, d_q = 30)$) to be scheduled on the system

6.9.1.3 Slack division and forwarding (SDF_SVM_{NM})

This approach is similar to that of SDF_NSVM_{NM}, i.e., the total slack of a workflow is initially distributed among all the tasks of that workflow using Equation 6.12. Then upon scheduling of one task, the remaining slack is forwarded to successor task of the same workflow. The effective slack of a task is dynamically calculated using Equation 6.13.

Let us consider the same workflow as shown in Figure 6.9 to be scheduled using SDF_SVM_{NM} policy where the current system state is shown in Figure 6.8(a). Slack of the whole workflow is calculated as 11 (by Equation 6.3). Then the initial individual slack times for all the tasks in that workflow are calculated by Equations 6.11 and 6.12. So, TLV becomes 76 ($= 9 \times 4 + 8 \times 5 = 76$). The first task of the workflow will get only 5 units of slack ($\frac{9 \times 4}{76} \times 11 = 5$). Thus it is to be scheduled from time 10 to 15 (arrival time of the workflow is 10). The task requires 9 VMs to execute and the current set of active hosts cannot execute this task. But the scheduler checks that two VMs will be ready on h_2 at time 12 and another four at time 15. Thus at time 15, the task can be scheduled where h_2 will hold 6 VMs and another 3 VMs will be hosted on h_3. Figure 6.8(b) represents the system state at time 15. Then for the second task, its individual slack time is 6 and since its predecessor forwards no slack, its effective slack remains 6 only. This task can be scheduled at any time instant from 19 to 25. The scheduler checks that if the task can be scheduled on h_2 and h_3 at time 19 but it can be on h_1 and h_2 at time 20. Further at time 22, the task can be scheduled only on host h_2. Now, the energy consumption for all the options are compared (h_2 and h_3 combined, h_1 and h_2

combined, and only h_2) and the scheduler chooses the lowest energy consumption set and in this case, it is h_2 alone. Accordingly, the task is scheduled on host h_2 at time 22. Figure 6.8(c) represents the system state after scheduling the second task of the workflow.

6.9.2 Splittable VMs with limited migration (SVM_{LM})

All three scheduling policies discussed in the previous subsection are of non-migratory nature, that is once a task is scheduled to a host, it executes in the same for the entire duration. But in SVM_{LM} scheduling, the scheduler occasionally performs a consolidation operation whenever the utilization of a host falls below *MigThreshold*. Whenever a task finishes its execution, the VMs associated with the task becomes free. These VMs might reside in different hosts. Thus the completion of one task might create spaces for VMs in different hosts. The consolidation agent migrates the VMs of the host to the hosts with higher utilization (target hosts are considered as decreasing order of their utilization). Then the consolidation agent finds all the idle hosts in the system and puts them in switched off mode. Rest of the scheduling operation is same as that of the SVM_{NM}.

6.9.3 Splittable VMs with full migration (SVM_{FM})

In the previous section, we have discussed scheduling policies where the VM allocation was splittable and the consolidation agent performs occasional consolidation operations to migrate the VMs from the lower utilized hosts to the higher utilized host. Scheduling policies also did not interfere the already running tasks of the system while scheduling a new task. All the existing mapping of tasks to the VMs and VMs to the hosts remained unchanged. This can not ensure that all the VMs will be running in lower power consuming hosts. But in this scheduling policy, a fresh task set is formed consisting of all the existing running tasks and the newly arrived task. Then the VMs are placed to the hosts with minimum energy consumption. We have used a combination of best fit decreasing order and first fit decreasing order heuristics for allocating VMs to hosts. As a workflow enters the cloud system, the slack distribution engine calculates the permissible slack for each task in that workflow. Then the scheduler finds the best time for the new task to schedule and accordingly creates a scheduling event at that time. This time is referred as the best scheduling point for the task. There can be various ways to find the best scheduling point of a task. We have used the time when

Algorithm 13 SVM with full migration (SVM_{FM})

On arrival of a workflow $WF_p(a_p, d_p)$

```
 1: Calculate the slack time $slk_p$ by Equation 6.3
 2: for each task $t_{i,p}$ in $WF_p$ do
 3:     Calculate the best slack for the task $bestSlk_{i,p}$
 4:     Schedule the task at $scheduleTime = currentTime + bestSlk_{i,p}$
 5:     if $currentTime = scheduleTime$ then
 6:         Form the task set $Q$ with the new tasks and the existing running tasks
 7:         Calculate total number of VMs requirement $vmNo$
 8:         $H_{select} = selectHost(vmNo)$
 9:         Sort the hosts in $H_{select}$ in ascending order of their VM capacity
10:         Sort the tasks in $Q$ in descending order of their VM requirement
11:         for each task $t_i$ in $Q$ do
12:             Allocate $t_i$ to the first host $h_j$ which can hold the task
13:             Update the VM information of $h_j$
14:             Delete $t_i$ from $Q$
15:             if idle VM count of $h_j$ becomes zero then
16:                 delete $h_j$ from $H_{select}$
17:         end for
18:         if $Q$ is not $NULL$ then
19:             Sort the hosts in $H_{select}$ in descending order of their remaining VM
                capacity
20:             Sort the tasks in $Q$ in descending order of their VM requirement
21:             for each task $t_i$ in $Q$ do
22:                 Split the task $t_i$ into two sub tasks $t_j$ and $t_k$
23:                 Set VM requirement of $t_j$ is as the remaining VM capacity of
                    first host $h_j$
24:                 Set VM requirement of $t_k$ is as the difference of VM requirements
                    of $t_i$ and $t_j$
25:                 Allocate task $t_j$ to host $h_j$
26:                 Update the VM information of $h_j$
27:                 Delete $t_i$ and $t_j$ from $Q$
28:                 Add $t_k$ to $Q$
29:                 if idle VM count of $h_j$ becomes zero then
30:                     delete $h_j$ from $H_{select}$
31:             end for
32: end for
```

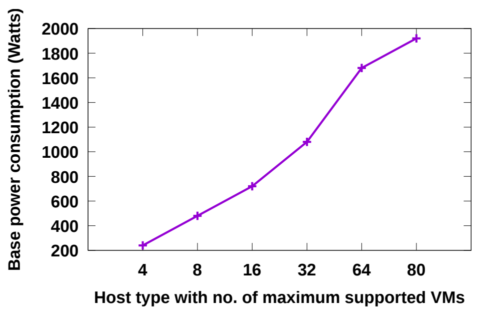
the system will execute minimum number of VMs on the hosts. Once the best scheduling point is selected, the scheduler forms a task set with the newly arrived tasks and the already running tasks where the running tasks are also treated as fresh tasks but possibly with lesser length. For example, suppose a task with actual execution time (indicates length) of 79 minutes have executed for 5 minutes and a rescheduling happens. Then it will be treated as a fresh task with execution

```
1: procedure $selectHost$ $(vmNo)$
2:     $remVmNo \leftarrow vmNo$
3:     while $remVmNo \geq 0$ do
4:         $remVmNo = remVmNo - vmCapacity(h_{max})$
5:         Add one new host to $H_{select}$ with maximum VM capacity
6:     while $remVmNo \geq 0$ do
7:         $h_i \leftarrow findCandidateHostType(remVmNo)$
8:         $option1 \leftarrow getPower(h_i, remVmNo)$
9:         $VmReq = remVmNo - vmCapacity(h_{i-1})$
10:        $option2 \leftarrow getPower(h_{i-1}, vmCapacity(h_{i-1}))$
           $+getPower(findCandidateHostType(VmReq), VmReq)$
11:        Choose the option with minimum power consumption
           And add the corresponding host in $H_{select}$
12:        Update $remVmNo$
13:    return $H_{select}$
14: end procedure
```

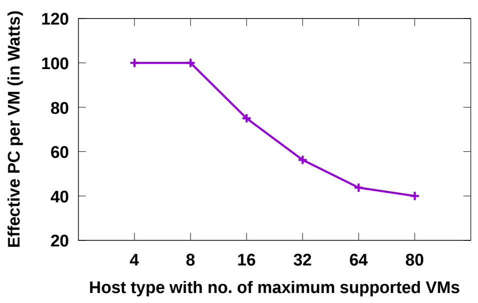
time 74 = (79 − 5) minutes.

Algorithm 13 captures the important steps for this scheduling policy. Once the task set is formed (in step 7 of the Algorithm), the scheduler calculates the total number of VM requirement for the tasks in the task set. And then it calls a Procedure *selectHost*(). This procedure selects a set of hosts such that the total power consumption of the hosts is minimum and the summation of their VM capacity is at least equal to the total VM requirement. When the total VM requirement is sufficiently high (more than the maximum VM capacity of hosts), the scheduler selects hosts with maximum VM capacity only. This is because effective power consumption per VM decreases with increase in VM capacity of hosts. And this is minimum in case of a host with maximum VM capacity. Then for the remaining VM requirement, the scheduler checks all possible options to find out the hosts with minimum power consumption. Line number 6 to 12 of Procedure *selectHost*() captures the same.

Once the hosts are selected, scheduler places the VMs on the hosts in two steps. In the first step, it tries to put the VMs without any split. Best fit decreasing order heuristic is applied for the same. Line number 9 to 17 of the Algorithm 13 reflects the same. Then in the second step, the hosts are sorted in descending order of their remaining VM capacity and tasks are also sorted in descending order of their VM requirements. In this step, no task can directly be placed on the hosts and thus a split is required. For a task, the scheduler goes through the host list and places VMs as per the idle VM slots for the host. If a task requires n VMs and



(a) Base power consumption of different host types



(b) Effective power consumption per VM in different host types

FIGURE 6.10: Power consumption of hosts and VMs

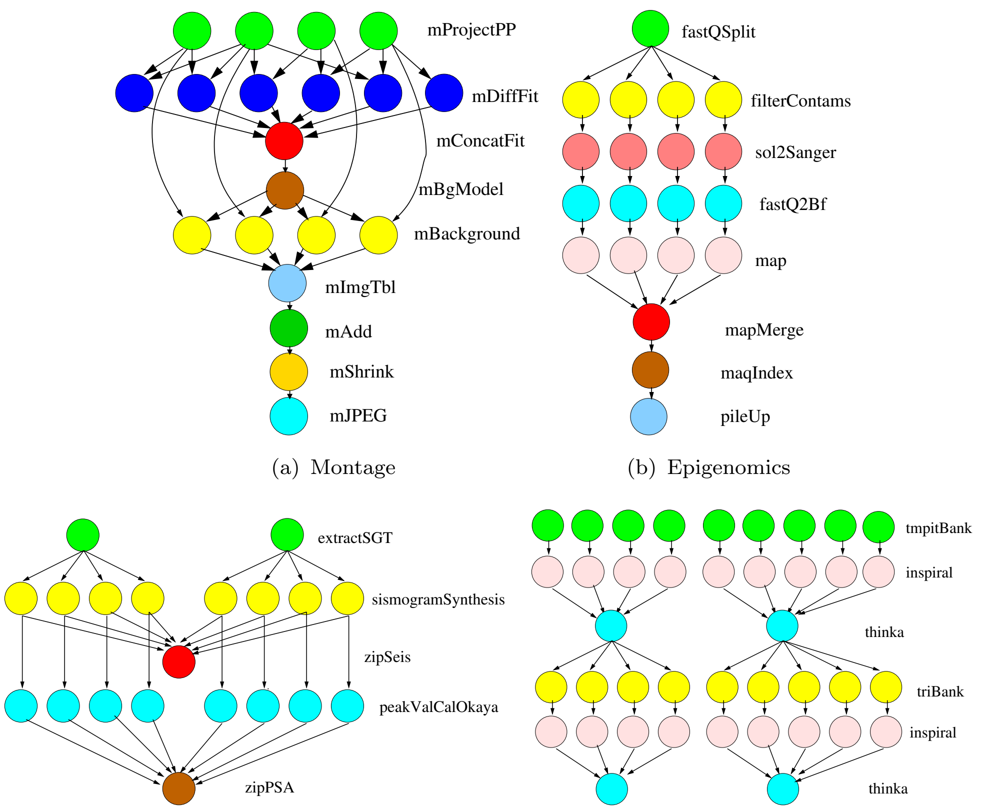
the first host has m free VMs ($m \leq n$), then a new task is created with m VM requirement and it is placed on the host. For the remaining VM requirement, the next host is tried and the process goes on.

6.10 Performance Evaluation

In this work, we have evaluated the performance of six scheduling policies $NSVM_{NM}$, $NSVM_{LM}$, $NSVM_{FM}$, SVM_{NM}, SVM_{LM}, and SVM_{FM}. We have also combined these policies with three different slack distribution approaches and analyzed their performances. To show the effectiveness of our work, we have also implemented a state of art energy-efficient scheduling policy for scientific workflow, namely, EnReal [41] and compared performances of the proposed policies.

6.10.1 Simulation platform and parameter setup

To evaluate the performance of our proposed approaches, a set of comprehensive simulations and experiments are conducted. We have used CloudSim toolkit [123] as the simulation platform and we did necessary changes to support multi-VM tasks. Observing the power consumption pattern of some real systems, we set the parameter values for our simulation. For instance, blade or rack server systems with 4, 8, 16, 32, 64, 80 hardware threads need to be installed with approximately 400W, 800W, 1200W, 1800W, 2800W and 3200W power supply respectively. A hardware thread can host one VM and in a rack, i.e. a host with 16 hardware threads can host 16 homogeneous VMs seamlessly.



(a) Montage (b) Epigenomics

(c) CyberShake (d) Inspiral

FIGURE 6.11: Examples of scientific workflows

In our experiment, we have considered six different types of hosts which can support 4, 8, 16, 32, 64, 80 number of VMs respectively. Figure 6.10(a) shows the base power consumption (BPC) of different host types considered in our work. BPC is taken as 60% of the total power consumption. BPC increases with an increase in the number of maximum supported VMs in the hosts. But the effective power consumption per VM decreases with an increase in the number of maximum supported VMs in the hosts. Effective power consumption for a VM is more in case of a smaller host and it is less in case of a bigger host. Figure 6.10(b) shows the relationship between the effective power consumption per VM with the host type.

6.10.2 Real scientific work-flow

We have used many scientific workflows such as CyberShake, Epigenomics, Montage, Inspiral, Sipht and many others to carry out our experiments [25]. **Montage** workflow was created by NASA/IPAC. It was used to create custom mosaics of the sky by stitching together multiple input images taken by satellite. **CyberShake** workflow was used to characterize earthquake hazards by the Southern Calfornia

Earthquake Centre. **Epigenomics** workflow was used in genome sequence processing by automating various operations. It is created by USC Epigenome Centre and the Pegasus team. In the **LIGO Inspiral** workflow model, data collection has been done by combining the compact binary systems to generate and analyze gravitational waveform. The **SIPHT** workflow was developed at Havard for bio-informatics project which helps to check for bacterial replications in the NCBI database by automating the search for untranslated RNAs (sRNAs). Descriptions of these scientific workflows can be found in [25].

Directed acyclic graph (DAG) is generally used to represent the scientific workflows. But most of the workflows have the structure that can be represented as chain of multi-processor (or multi-VM) tasks. Figure 6.11 shows the Montage, Epigenomic, CyberShake and Inspiral workflows. We can see from the Montage workflow that it has nine tasks: mProjectPP, mDiffFit, mConcatFit, mBgModel, mBackground, mImgTbl, mAdd, mShrink, and mJPEG. These tasks have 4, 6, 1, 1, 4, 1, 1, 1 and 1 number parallel subtasks within them respectively. These tasks can be run in parallel on multiple VMs. Execution time for these tasks are 14, 11, 1, 2, 11, 2, 3, 4, and 1 respectively. These values are obtained by reading and parsing the XML descriptions of $Montage\_25.xml$ file available in the website mentioned in [139]. Similarly, attributes for other workflows are obtained by processing the respective XML files for the workflows.

To perform our experiments, we have generated our benchmark with a mix of these scientific workflows. Each benchmark mix contains a random combination of 10 workflows which are of different sizes. We have two additional parameters for each workflow: *arrival time* and *deadline*. As we are considering online arrival, the arrival time of a workflow is known after they actually arrive at the system. Deadline of a workflow is taken as the summation of the execution time of all the tasks of the workflow plus the *slack time* where the *slack time* is a random number varies from 1 to 100.

6.10.3 Impact of slack distribution

In our work, we have used three different slack distribution approaches for the tasks of a workflow. Figure 6.12 shows the normalized energy consumption of the cloud system under proposed scheduling policies when it executes a mix of scientific workflows. The figure describes the impact of different slack distribution

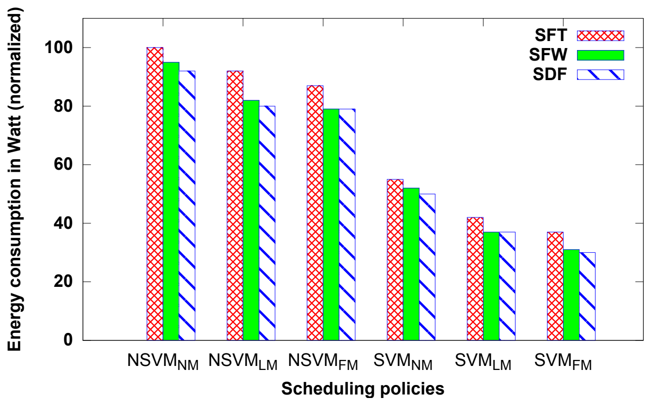


FIGURE 6.12: Impact of slack distribution on energy consumption

approaches when they are merged with scheduling policies. The energy consumption of the system for slack to first task (SFT) approach is more compared to the other two approaches. But SFT approach is the simplest one and incurs lesser overhead on the online scheduler. On the other hand, SFW and SDF approaches perform almost similar. This pattern remains the same for all the policies. The figure also reveals that the energy consumption of the system is comparatively lesser in case of splittable VM allocation compared to non-splittable allocation.

6.10.4 Trade-off between energy consumption, migration count and split count

Here we present three different output parameters, that is energy consumption, migration count and split count together under the same graph. The split count in case of scheduling with non-splittable VM allocation is zero because all the required VMs of a task is allocated on one host and thus the task is not split. But the energy consumption under these approaches is relatively higher. When all the VMs of a task t cannot be placed on one host, we need to divide the task into subtasks; and we treat the subtasks as new tasks with lesser VM requirement. The number of split increases with each such division. On the other hand, whenever the VMs executing a task need to migrate from one host to another, the migration count is increased by one.

Figure 6.13 shows the normalized values for energy consumption, migration count and split count for different scheduling policies when a mix of scientific workflows is executed in the cloud system. All the proposed policies applied SDF slack distribution approach. We make the following observations from the graph.

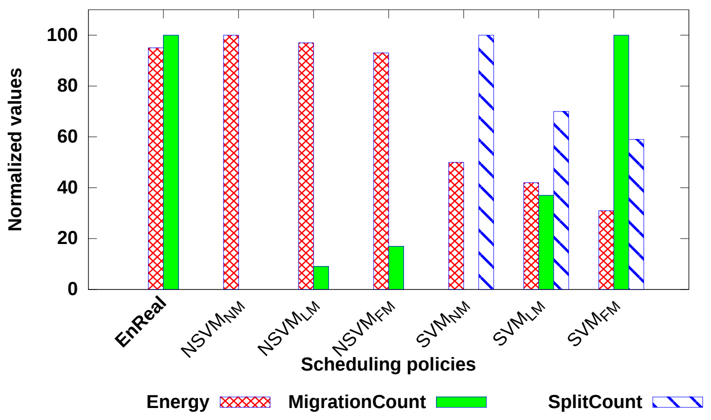


Figure 6.13: Normalized values of energy consumption, migration and split count

- Scheduling policies under non-splittable VM allocation policy perform similarly to the state-of-art policy, EnReal; but the proposed policies beat EnReal in terms of the number of migrations. $NSVM_{LM}$ and $NSVM_{FM}$ incur approximately 90% and 80% lesser number of migrations respectively than EnReal.
- Scheduling policies under splittable VM allocation policy perform significantly better than splittable VM allocation policies regarding energy consumption. Reduction in energy consumption in case of SVM_{NM}, SVM_{LM}, and SVM_{FM} are approximately 50%, 60%, and 64% respectively as compared to EnReal.
- In case of splittable policies, tasks are split, and we observe a significant split count as compared to non-splittable policies and EnReal. Systems need to incur additional overhead for a split.

6.10.5 Different mixes of scientific workflows

To ascertain the performances of the proposed policies, we have performed our experiments with 5 different benchmark mixes (MIX_1, MIX_2, MIX_3, MIX_4, MIX_5) which were generated from the scientific workflows as described in 6.10.2. Figure 6.14 shows the energy consumption of the cloud system for 5 different mixes under different scheduling policies along with EnReal. Slack distribution and forwarding (SDF) technique are applied to distribute the slack time among the tasks of a workflow. We observe similar energy consumption pattern for all the benchmark mixes. Splittable policies reduce energy consumption by approximately 60% as compared to EnReal.

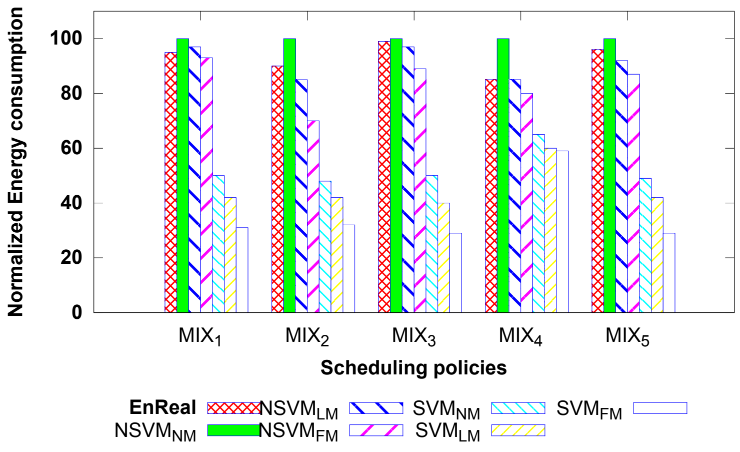


FIGURE 6.14: Energy consumption of the system (normalized) for different benchmark mixes

6.11 Summary

The high availability of high-end computing resources has made the cloud system a popular choice for hosting the scientific applications. Another inherent characteristic of these applications is the sharp variation in their resource requirement and the elasticity feature of the cloud system can efficiently handle this. As these applications consume a significant amount of resources, energy-efficient execution of these applications in the cloud becomes essential. These applications are modeled as scientific workflows where there is a dependency between the tasks.

We describe the scheduling of a set of online dependent tasks, represented as scientific workflows in the cloud environment and proposes a series of energy-efficient scheduling techniques considering both the static and dynamic energy consumption. The chapter describes several approaches regarding three important factors: VM allocation, migration, and slack distribution which affects the performance of scheduling. Extensive simulation is carried out in Cloudsim toolkit and performance is compared with a state of art energy-efficient scheduling technique EnReal [41] and found that the energy consumption of the proposed policies under splittable VM category is significantly lesser than EnReal. The proposed policies under non-splittable VM allocation performs at par with the state-of-art policy, but with a smaller number of migrations. All the proposed policies meet the deadline constraints of the workflows.

Chapter 7

Conclusion and Future Work

In recent time, the growing energy consumption of the large computing systems has gained the attention of the scientific community. At the same time, these computing platforms become a perfect choice for the high-end scientific applications which are often of real-time nature. The energy-efficient execution of these applications is essential because these applications consume a significant amount of computing resources for a substantial amount of time. It is observed that a major portion of the energy gets wasted due to poor utilization of the system. As scheduling can potentially improve the utilization of a system, designing energy-efficient scheduling techniques for the large system becomes important where these applications will be executed both energy and performance efficient way.

Any scheduling problem is typically represented by the machine environment, the task environment and the objective function. In our work, machine environment consists both virtualized and non-virtualized system with a large number of processors. For the task environment, we consider both independent and dependent real-time task set. We set the optimality criteria as the minimization of energy consumption without missing the deadline of any task. We summarize the contributions of the thesis as follows.

7.1 Summary of Contributions

We solved four different scheduling problems in our thesis. This section contains the summary of our work.

- At first, we have considered a non-virtualized system having a large number of processors and each processor is equipped with the multi-threaded feature. The task set consists of online independent aperiodic real-time tasks. We exploit the power consumption pattern of some recent multi-threaded processors and derive a simple but elegant power consumption model where the total power consumption of a processor is expressed as a function of the number of active threads of that processor. We then design four energy-efficient scheduling policies to reduce the energy consumption of the system maintaining the deadline constraints of all the tasks. Experiments are conducted for a wide range of synthetic data and real-world trace. We consider a variety of deadline and execution time schemes in the synthetic workload. Experimental results show that the proposed policies show an average energy reduction of around 47% for the synthetic workload and around 30% for the real-world traces.

- In the second contribution of the thesis, we have considered a heterogeneous virtualized cloud system where a host accommodates a number of VMs. A user task is assigned to a VM and the VM is placed on a host. Heterogeneity is mainly determined by the compute capacity and the energy consumption. Under this setup, we have considered a region based non-linear power consumption model for the hosts derived from the power consumption pattern of a typical server. We have designed two energy-efficient scheduling approaches, (i) Urgent Point aware Scheduling (*UPS*), and (ii) Urgent Point aware Scheduling - Early Scheduling (*UPS-ES*). These approaches are based on the urgent points of a task, and dynamically used two threshold values. We have performed our experiments in the CloudSim toolkit by making necessary changes. Experimental results show that the proposed policies achieve an average energy reduction of around 24% for the synthetic data, and around 11% for the real-trace data.

- We have considered scheduling a set of real-time tasks on the VMs having discrete utilization. For a host, we have first calculated the critical utilization value where the energy consumption happens to be the minimum. We have designed scheduling approaches by dividing the problem into four sub-problems. At first, we put forward the solution of the task set where all the tasks have the same length and same deadline. Then we target the problem of scheduling task set with two different lengths but the same deadline. To solve this sub-problem, we have used the solution of the previous solution. The third sub-problem deals with tasks having arbitrary lengths but same deadline, which is solved using the solution method of second sub-problem. Finally, we have designed the solution approach for arbitrary lengths and arbitrary deadlines of tasks. For the last sub-problem, we classified the task set into different classes and we concluded that this classification technique can be determined from the system parameters.

- In the last contribution of the thesis, we have considered scheduling a set of dependent real-time tasks on a cloud system. The task set is taken as scientific workflows, where each workflow has an end-to-end deadline. The tasks in the workflow are multi-VM tasks; thus they need multiple VMs simultaneously for their execution. We have designed a series of scheduling policies to execute an incoming workflow efficiently. We have considered several options and restrictions in the context of VM allocation, migration, and slack distribution. In addition to the energy consumption, we have also considered migration count and split count. Experiments are conducted on CloudSim toolkit by adding necessary functionalities to it. The proposed policies under non-splittable VM allocation category reduces the migration count significantly (for $NSVM_{NM}$, it is 0) compared to the state-of-art policy with almost same amount energy consumption. In case of splittable VM allocation category, we have achieved an energy reduction up to 64% as compared to the state-of-art policy with reasonable migration count and split count.

7.2 Scope for Future Work

The contributions of this thesis can be extended in a number of ways. Some of these possible future research directions are listed below:

- **Hierarchical organization of hosts:** In our work, we have considered the energy consumption for the processors assuming that all the processors are connected in one level. But in practice, they are often connected in a hierarchical order. A server contains multiple chassis, a chassis contains multiple racks, a rack contains different containers, and cores are placed on containers. Considering power consumption at each level while designing scheduling policies for real-time tasks will be an interesting research direction. This will make the setup more realistic. Furthermore, instead of reporting the migration count, a location-based cost matrix can be used to measure the impact of migration for such a hierarchical arrangement.

- **Resource provisioning based on the application behavior and arrival pattern:** Another future research of the thesis can be toward usages of some machine learning based techniques to predict the future the resource requirement and to prepare the system accordingly. Idle VMs and idle hosts are generally switched off to reduce the energy consumption. But deletion and creation of VMs, waking up a host from the sleep state has some inherent penalties. Making a trade-off between the overheads and the energy saving based on the application behavior and arrival pattern can be an interesting problem to solve.

- **Study as multi-objective function:** In our last contribution of scheduling workflows, we have observed that different policies perform better in different directions: energy consumption, number of migrations, and number of splits. Migration count and split count have overheads associated with them. Designing scheduling policies combining all these three factors can be a challenging research direction, where the objective function will be expressed as a combination of energy consumption, migration count, and split count.

- **Imrovement on VM splitting:** When a task requires multiple VMs to execute and the VMs are placed on different hosts (splittable VM allocation), the VMs need to communicate among them. This results in some extra energy consumption. Based on the placement location of the VMs (belonging to the same task), energy consumption will vary. We see a promising research direction to study the splitting criteria and the placement of the VMs while designing scheduling techniques for multi-VM tasks.

- **Trade-off between energy consumption and SLA violation:** All the scheduling policies designed in the thesis considered hard real-time tasks and thus the deadline constraints of all the tasks are met. But in case of soft real-time tasks, violation of the deadline constraints of a few tasks may be allowed. But this imposes some additional penalty. It will be an interesting research direction where some penalty can be associated with the violation of SLA of the tasks (or applications) while minimizing the energy consumption or the overall cost of execution.

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Bio-data and Publications

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Publications: published

- **M. Ghose**, A. Sahu, S. Karmakar, "Energy Efficient Online Scheduling of Real Time Tasks onto Large Multi-threaded Multiprocessor Systems," in *The Journal of Information Science and Engineering*, $34(6) : 1599 - 1615, 2018$.
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