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New Trends and Ideas

Holistic resource management for sustainable and reliable cloud computing: An innovative solution to global challenge

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ABSTRACT

Minimizing the energy consumption of servers within cloud computing systems is of upmost importance to cloud providers toward reducing operational costs and enhancing service sustainability by consolidating services onto fewer active servers. Moreover, providers must also provision high levels of availability and reliability, hence cloud services are frequently replicated across servers that subsequently increases server energy consumption and resource overhead. These two objectives can present a potential conflict within cloud resource management decision making that must balance between service consolidation and replication to minimize energy consumption whilst maximizing server availability and reliability, respectively. In this paper, we propose a cuckoo optimization-based energy-reliability aware resource scheduling technique (CRUZE) for holistic management of cloud computing resources including servers, networks, storage, and cooling systems. CRUZE clusters and executes heterogeneous workloads on provisioned cloud resources and enhances the energy-efficiency and reduces the carbon footprint in datacenters without adversely affecting cloud service reliability. We evaluate the effectiveness of CRUZE against existing state-of-the-art solutions using the CloudSim toolkit. Results indicate that our proposed technique is capable of reducing energy consumption by 20.1% whilst improving reliability and CPU utilization by 17.1% and 15.7% respectively without affecting other Quality of Service parameters.

1. Introduction

Commercial cloud providers such as Microsoft, Google, and Amazon heavily depend on datacenters to support the ever-increasing demand for computational requirements of their services. Such demand has subsequently increased operational costs of running large infrastructures, as well as producing substantial carbon emissions that negatively impact the environmental sustainability of cloud services (Buyya and Gill, 2018). Existing efforts to tackle this problem primarily focus on minimizing the energy consumption of servers via service consolidation to reduce the number of active servers and increase datacenter resource utilization (Buyya and Gill, 2018; Gill and Buyya, 2019; Mastelic et al., 2015). However, such approaches typically do not consider other core datacenter components, including the network, storage, and cooling systems, which constitute significant amount (32% approximately) of total Cloud DataCentres (CDC) power consumption (Barroso and Clidaras, 2013). Server consolidation unaware of the cooling system may increase the number of hot spots in the datacenter which subsequently increases the requirement of cooling capacity and reduces cooling efficiency (Li et al., 2014). Hotspot mitigation is performed via load balancing. However, load balancing can widely spread communicating Virtual Machines (VMs) across multiple hosts without considering their pairwise network traffic, increasing network cost and energy consumption (Kaur et al., 2018). Thus, to create cloud platforms that are

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energy efficient, a resource management approach capable of managing all these resources (network, storage, servers, memory and cooling components) in a holistic manner is required (Gill and Buyya, 2019).

While energy efficiency is critical, cloud providers must also provide highly available and reliable cloud services (Gill and Buyya, 2019). However, with the growing adoption of cloud, CDCs are rapidly expanding in terms of scale and system complexity, which has subsequently increased the frequency and diversity of failures (Garraghan et al., 2014). These failures range across Service Level Agreement (SLA) violation, data corruption, loss/premature execution termination, degrading cloud service performance and availability (Mastelic et al., 2015). In order to address this problem, one of the most common practices is to replicate cloud services frequently to minimize the risk of simultaneous failure (Gill et al., 2019). However, replicas require additional resource usage from servers within the CDC leading to extra resource usage which increases their respective power consumption (Garraghan et al., 2014). It has been reported that a huge quantity of base-load energy is consumed even when actual cloud resource usage is very low or even idle (Shuja et al., 2016; Sharma et al., 2016). This results in a potential conflict in resource management decision making within the CDC to balance between energy consumption and reliability (Chang et al., 2017; Taherizadeh et al., 2018). In order to minimize server power usage, it would be preferable to consolidate servers and power down idle machines (Gill et al., 2019). On the other hand, in order to maximize cloud service availability and reliability, replicas across additional machines are required (Gill and Buyya, 2018b). Therefore, a holistic resource management is not only required for managing all aforementioned components, but must also consider replication and coordination of services to enable reliable delivery of cloud services in a cost-efficient manner.

Heuristic methods such as evolutionary algorithm are a suitable candidate to tackle the complexity of this problem. Li et al. (2018a) suggested that scheduling algorithms equipped with a Cuckoo Optimization (CO) algorithm can be used in this regard because CO algorithm performs better than Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) in terms of accuracy, speed and convergence (Yang, 2014) for solving batch process and job scheduling problems (Rajabioun, 2011; Yang, 2014). The main motivation of this research work is to extend a conceptual model proposed in Gill and Buyya (2019), Buyya and Gill (2018) and Gill and Buyya (2018b) to develop a ***C****uckoo optimization based efficient* ***R****esource* ***U****tiliZation techniqu****E*** called ***CRUZE*** for holistic management of all resources (servers, network, storage, cooling systems) to improve the energy efficiency and reduce carbon footprint while minimizing service failure within hardware, service, and software to maintain required cloud service reliability. Our approach clusters the workloads based on their Quality of Service (QoS) parameters for provisioning of cloud resources and schedules the provisioned resources for workload execution using a Cuckoo optimization-based scheduling algorithm.

The rest of the article is structured as follows. Section 2 presents the related work of existing holistic resource management approaches. Section 3 presents the system model and design model of CRUZE. Section 4 proposes the resource provisioning and scheduling strategy. Section 5 describes the experimental setup and presents the results and analysis. Section 6 summarizes the paper and offers future research directions.

2. Related work

Holistic management of cloud resources is a challenging task due to dynamic requirements of cloud users (Singh and Chana, 2016). The majority of existing works study the energy management of servers alone without omitting other components, which consume substantial energy (Natu et al., 2016; Singh and Chana, 2013). This section describes the existing resource management techniques and their comparison with our proposed approach.

2.1. Energy-aware cloud resource scheduling

Li et al. (2018a) proposed an Energy-Aware Resource Scheduling (EARS) technique to execute workloads within virtual cloud environments. EARS technique models the power and failure profiles for CDC and implements them using event-based cloud simulator, and is an effective in reducing energy cost of cloud data center and improving task completion rate, however only considers homogeneous workloads. Similarly, Li et al. (2018b) proposed a VM Scheduling (VMS) technique to reduce energy consumption of servers and identifies the effect of energy consumption on SLA violation rate to improve user satisfaction. Balis et al. (2018) proposed a Holistic Approach (HA) for management of IT infrastructure to reduce execution cost and energy consumption. Pérez et al. (2018) proposed a Holistic Workload Scaling (HWS) technique to enable scaling of resources vertically as well as horizontally simultaneously and aids to reduce latency using multi-scaling approach without considering energy consumption of cloud resources. Luo et al. (2015) formulates energy consumption as a task-core assignment and scheduling problem and proposed a Holistic Energy Optimization Framework (HEOF) to reduce thermal effect as well as cooling cost simultaneously and HEOF framework focuses on powerful computation capability. Liu et al. (2014) proposed a Server-based Cloud-enabled Architecture (SCA) to improve the energy-efficiency of different hardware components such as memory, storage and processors. Furthermore, the performance of SCA is evaluated using a case study of video tracking application and experimental results show that SCA performs better in terms of memory utilization. Guzek et al. (2013) proposed a Holistic Model for Resource Management (HMRM) in virtualization based cloud datacenter to reduce the energy consumption of different resources such as memory, storage and networking. Ferrer et al. (2012) proposed a Holistic Approach for Cloud Service Provisioning (HACSP) to meet predicted and unforeseen changes in resource requirements dynamically and optimizes energy cost. Feller et al. (2012) proposed a Holistic approach for Energy Management (HEM) technique for effective management of virtual cloud resources using dynamic web workloads and saves the substantial amount of energy. Sitaram et al. (2015) proposed Energy Efficient Data Center Management (EEDCM) technique under availability constraints and outlines the importance of availability and designs a hill climbing algorithm to prevent failure zone. The experimental result shows that EEDCM technique reduces the energy consumption by the datacenter, but the trade-off between energy consumption and other important QoS parameters such as reliability, cost and execution time are omitted.

2.2. Reliability-aware cloud resource scheduling

Zhou et al., (2016) presented a Cloud Service Reliability Enhancement (CSRE) approach to utilization of network and storage resources. This approach stores the state of VM using service checkpointing, which is in executing state. Further, node failure predicator is designed to optimize the use of network resources. Li et al., (2016) developed a convergent dispersal based multi-cloud storage (CDStore) solution to offer reliable, secure and cost-efficient cloud service. The proposed solution offers deterministic-based deduplication approach to save network bandwidth and storage space. Moreover, CDStore uses two-stage deduplication to protect the system from malicious attacks. Azimzadeh and Biabani (2017) proposed a Multi-Objective

Table 1
Comparison of CRUZE with existing holistic resource management techniques.

Technique	Components of holistic resource management for cloud computing												
					Sustainability-aware and Reliability-aware Holistic Management								
	1	2	3	4	5	6	7	8	9	10	11	12	13
EARS (Li et al., 2018a)						✔		✔		✔			
HA (Balis et al., 2018)						✔		✔					
VMS (Li et al., 2018b)								✔			✔		
HWS (Pérez et al., 2018)						✔							
HEOF (Luo et al., 2015)	✔							✔	✔	✔		✔	✔
SCA (Liu et al., 2014)								✔					
HMRM (Guzek et al., 2013)								✔			✔		
HACSP (Ferrer et al., 2012)								✔					
HEM (Feller et al., 2012)								✔			✔		
CSRE (Zhou et al., 2016)			✔		✔						✔		
CDStore (Li et al., 2016)					✔	✔							
MORS (Azimzadeh and Biabani, 2017)					✔	✔							
AJIT (Poola et al., 2016)	✔				✔	✔							
HSIA (Qu et al., 2016)					✔	✔							
E-storm (Liu et al., 2017)					✔	✔							
DCLCA (Latiff et al., 2018)					✔	✔							
GTCO (Shahdi-Pashaki et al., 2015)				✔				✔			✔		
COTC (Sundarrajan et al., 2016)				✔				✔					
CORM (Abbasi and Mohri, 2016)				✔		✔		✔					
CSATS (Navimipour and Milani, 2015)				✔		✔							
CSMH (Madni et al., 2017)				✔		✔							
EEDCM (Sitaram et al., 2015)								✔					
ROCDC (Luo et al., 2016)					✔			✔					
CRUZE (proposed)	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔

Abbreviations: 1 – heterogeneous workloads, 2 – workload clustering, 3 – provisioning based scheduling, 4 – Cuckoo optimization scheduling, 5 – failures, 6 – application QoS, 7 – capacity planning, 8 – energy management, 9 – thermal-aware scheduling, 10 – cooling, 11 – virtualization, 12 – renewable energy and 13 – waste heat utilization.

Resource Scheduling (MORS) approach to increase the reliability of cloud service and optimize the execution time. Further, authors identify a trade-off between reliability and execution time for efficient execution of HPC (High Performance Computing) workloads. Poola et al. (2016) proposed an Adaptive and Just-In-Time (AJIT) scheduling approach using spot and on-demand instances to provide fault management mechanism. This approach uses resource consolidation to optimize execution time and cost and experimental results indicates that AJIT is efficient for execution of deadline-oriented workloads. Qu et al. (2016) proposed a Heterogeneous Spot Instances-based Auto-scaling (HSIA) approach to execute web applications in a reliable manager. Further, HSIA approach designed a fault tolerant system to improve the availability and reduce the execution cost and response time of cloud service. Liu et al. (2017) proposed a replication-based state management (E-Storm) approach actively maintains multiple state backups on different VMs during the execution of real-world and synthetic streaming applications. The performance of E-Storm is evaluated against checkpointing method and experimental results indicates that E-Storm achieves effective results in terms of latency and throughput. Shafie et al., (2018) proposed a Dynamic Clustering League Championship Approach (DCLCA) to minimize fault reduction in task failure during resource scheduling for workload execution. Luo et al. (2016) proposed a Resource Optimization method for Cloud Data Center (ROCDC), which designs a conceptual model to optimize the performance parameters reliability and energy while scheduling resources. However, this approach was not validated via simulation or experimentation.

2.3. Cuckoo optimization based energy-aware cloud resource scheduling

Shahdi-Pashaki et al. (2015) proposed a Group Technology-based model and Cuckoo Optimization (GTCO) algorithm to allocate resources for effective mapping of VMs to cloud workloads. GTCO reduces energy cost during execution of VMs and performs better than round robin based resource scheduling. Sundarrajan et al. (2016) proposed a Cuckoo Optimization based Task Scheduling (COTC) algorithm to schedule the tasks in cloud processing and improves the energy utilization for the execution of homogeneous workloads. Abbasi and Mohri, (2016) proposed a Cuckoo Optimization based Resource Management (CORM) mechanism for task scheduling, which improves load balancing to reduce energy cost. CORM improves energy-efficiency during execution of cloud resources and performs better than round robin based resource scheduling. Navimipour and Milani (2015) proposed a Cuckoo Search Algorithm based Task Scheduling (CSATS) technique for effective utilization of cloud resources. Authors just measured the fitness value (execution time) of CSATS with different values of probability to find the cloud resource for execution of workloads. Madni et al. (2017) proposed a Cuckoo Search Meta-Heuristic (CSMH) algorithm, which optimizes energy consumption of cloud workloads. The performance of COTC (Sundarrajan et al., 2016) and CSMH (Madni et al., 2017) have been evaluated using CloudSim (Calheiros et al., 2011) and both reduces energy cost of servers without focusing on other components of the cloud datacenter.

2.4. Comparison of CRUZE with existing resource scheduling techniques

Table 1 compares our proposed technique (CRUZE) with existing resource scheduling approaches discussed above. We identified that existing approaches for holistic resource management only consider one or two components simultaneously. The majority of existing work schedule resources for the execution of homogeneous workloads while others like EARS (Li et al., 2018a), HEOF (Luo et al., 2015) and AJIT (Poola et al., 2016) schedule resources for the execution of heterogeneous workloads as well. None of the existing works considers clustering of workloads

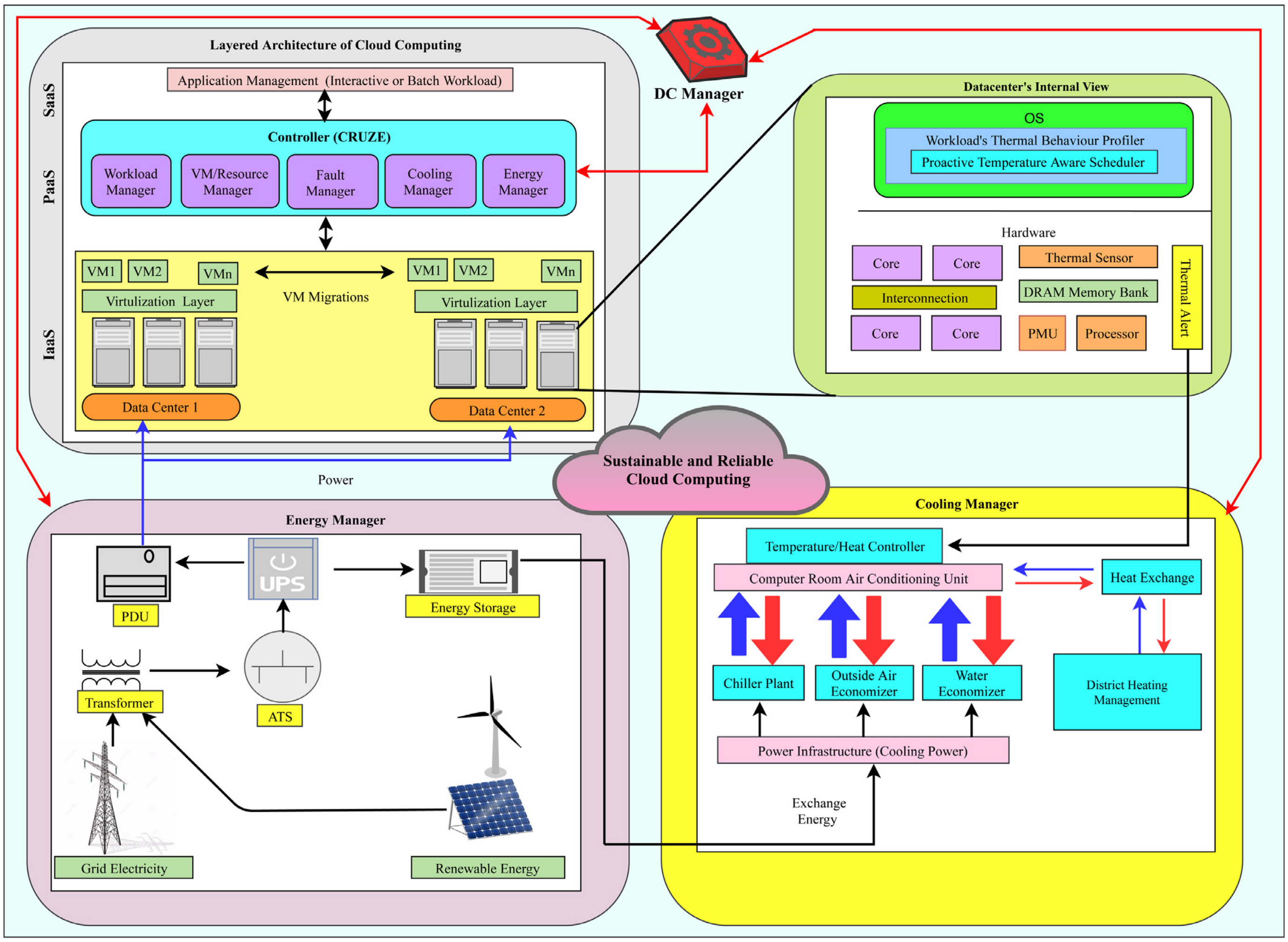


Fig. 1. System model.

for resource provisioning. Provisioning based resource scheduling is only considered in CSRE (Zhou et al., 2016). Cuckoo Optimization (CO) based scheduling is performed in GTCO (Shahdi-Pashaki et al., 2015), COTC (Sundarrajan et al., 2016), CORM (Abbasi and Mohri, 2016), CSATS (Navimipour and Milani, 2015) and CSMH (Madni et al., 2017), but scheduled resources only for homogenous cloud workload without any provisioning of resources. GTCO (Shahdi-Pashaki et al., 2015) optimizes energy cost and latency but COTC (Sundarrajan et al., 2016), CORM (Abbasi and Mohri, 2016), CSATS (Navimipour and Milani, 2015) and CSMH (Madni et al., 2017) only optimizes energy cost and execution time. **This is the first research paper which focuses on holistic management of all CDC components toward providing reliable and sustainable cloud services.** The proposed technique (CRUZE) schedules the provisioned resources for the execution of clustered and heterogeneous workloads to enable reliable and sustainable cloud services.

3. System model

As our proposed approach operates within a holistic CDC (Gill and Buyya, 2019), we present and describe all core components within the system as shown in Fig. 1. Our approach considers components within all levels of cloud service provisioning.

1. *Software as a Service (SaaS):* This layer handles the incoming user workloads (batch style or interactive) and forward those workloads (requests or user sessions) to workload manager as discussed in *Section 4.1*. Based on their QoS requirements such as deadlines and budget constraints, workload manager maintains the queue of workloads in a specific order based on their priorities.
2. *Platform as a Service (PaaS)*: This layer deploys a controller to handle the different functions of the system. Controller schedules the provisioned cloud resources efficiently with three main objectives: 1) maximize resource utilization, 2) minimize energy consumption and 3) improve the reliability and sustainability of cloud datacenters. Further, a controller (middleware) has five sub modules: cooling manager, energy manager, fault manager, VM/resource manager and workload manager and roles of sub modules is described below:
   a) *Workload manager* maintains the queue of arriving user workloads from the application manager and recognizes their QoS constraints and forward the QoS information to the next module i.e. VM/resource manager for provisioning and scheduling of resources.
   b) *VM/resource manager* schedules the provisioned resources for their execution using virtual or physical machines based on QoS requirements of workload.
   c) *Fault manager* performs fault detection and correction with the minimal performance degradation. We have considered three types of faults for this research work: VM creation failures, host failures (Processing Elements failure and

memory failure) and high-level failures like cloudlets failures (which are caused by any networking problem) (Gill and Buyya, 2018b). FIM-SIM (Nita et al., 2014) is integrated with CloudSim toolkit (Calheiros et al., 2011) to simulate failures as discussed in Section 5.

d) *Data Center (DC) Manager* acts as a broker to handle other modules such as *cooling manager* and *energy manager* for cooling and energy management respectively.

The working of controller (CRUZE) is discussed in *Section 4* in detail.

3. *Infrastructure as a Service (IaaS):* IaaS layer comprises of information related to cloud infrastructure such as VMs and CDCs. Furthermore, the virtualization layer enables workload balancing via VM migration. The variations of the temperature of different VMs running at different cores is measured, monitored and controlled by proactive temperature-aware scheduler. Power Management Unit (PMU) is deployed to provide and control the power for different components of cloud data centers. Check-pointing mechanism is provided by Dynamic Random-Access Memory (DRAM) by storing the current states of VMs (Gill et al., 2019). Thermal sensors monitor the value of temperature and forward to the *Thermal profiling and monitoring* module to analyze the temperature variations of cloud datacenters. When system generates thermal alert then *heat controller* takes a required action to control the temperature if it is higher than its threshold value and maintains the performance of datacenter. Uninterruptible Power Supply (UPS) is deployed to continue the power in case of power failure from main sources. For cooling management, the *district heating management* uses water economizer, outside air economizer and chiller plant to control the temperature of CDC. *Energy manager* manages the energy produced from renewable and non-renewable sources. Sustainable CDCs focuses more on renewable energy sources (solar and wind) (Gill and Buyya, 2019; Guitart, 2017). To provide reliable services, CDC can prefer grid energy for the execution of deadline-aware workloads. Automatic Transfer Switch (ATS) manages the electricity producing from renewable as well as non-renewable sources. Moreover, Power Distribution Unit (PDU) transfers the energy to all the devices of cloud datacenters and cooling components.

3.1. Design models

We have used following design models for holistic management of cloud resources:

a) **Energy Model**: The energy model is developed on the basis that resource utilization has a linear relationship with energy consumption (Li et al., 2018a; Balis et al., 2018; Gill and Buyya, 2018; Gill et al., 2019; Singh and Chana, 2016; Möbius et al., 2014). Energy Consumption (E) of a CDC can be expressed as Eq. (1):

$$E = E_{Processor} + E_{Storage} + E_{Memory} + E_{Network} + E_{Cooling} + E_{Extra} \quad (1)$$

$E_{Processor}$ represents the processor's energy consumption, which is calculated using Eq. (2):

$$E_{Processor} = \sum_{r=1}^{r=cores} \left(E_{dynamic} + E_{SC} + E_{Leakage} + E_{idle}\right) \quad (2)$$

where $E_{dynamic}$ represents dynamic energy consumption and calculated using Eq. (3), E_{SC} represents short-circuit energy consumption, $E_{Leakage}$ represents power loss due to transistor leakage current and E_{idle} represents the energy consumption when processor component is idle.

$$E_{dynamic} = CV^2\ f \quad (3)$$

where C is capacitance, f is frequency, and V is voltage.

$E_{Storage}$ represents the energy consumption of storage device, which performs data read and write operations and it is calculated using Eq. (4):

$$E_{Storage} = E_{ReadOperation} + E_{WriteOperation} + E_{idle} \quad (4)$$

where E_{idle} represents the energy consumption when storage component is idle.

E_{Memory} represents the energy consumption of the main memory (RAM/DRAM) and cache memory (SRAM), which is calculated using Eq. (5):

$$E_{Memory} = E_{SRAM} + E_{DRAM} \quad (5)$$

$E_{Network}$ represents the energy consumption of networking equipment such as routers, switches and gateways, LAN cards, which is calculated using Eq. (6):

$$E_{Network} = E_{Router} + E_{Gateway} + E_{LANcard} + E_{Switch} \quad (6)$$

$E_{Cooling}$ represents the energy is consumed by cooling devices (air conditioners (AC), compressors and fans) to maintain the temperature of cloud datacenter (Li et al., 2018a), which is calculated using Eq. (7).

$$E_{Cooling} = E_{AC} + E_{Compressor} + E_{Fan} \quad (7)$$

E_{Extra} represents the energy consumption of other parts, including the current conversion loss and others, which is calculated using Eq. (8):

$$E_{Extra} = E_{Motherboard} + \sum_{f=0}^{F} E_{connector,\ f} \quad (8)$$

where $E_{Motherboard}$ is energy consumed by motherboard (s) and $\sum_{f=0}^{F} E_{connector,\ f}$ is energy consumed by a connector (port) running at the frequency f.

For a resource r_k at given time t, the resource utilization $RESU_{t,\ k}$ is defined as (Eq. 9):

$$RESU_{t,k} = \sum_{i=1}^{m} ru_{t,k,i} \quad (9)$$

where m is the number of cloud workloads running at time t, $ru_{t,\ k,\ i}$ is the resource (VMs) usage of workload w_i on resource r_k at given time t. The actual energy consumption ($E_{consumption}$) is $ECON_{t,\ k}$ of a resource r_k at given time t is defined as (Eq. 10):

$$E_{consumption} = ECON_{t,k} = (E_{max} - E_{min}) \times RESU_{t,k} + E_{min} \quad (10)$$

where E_{max} is the energy consumption at the peak load (or 100% utilization) and E_{min} is the minimum consumption of energy in the idle/active mode (or as low as 1% utilization), which can be calculated using Eq. (1) through profiling.

b) **Reliability model:** Reliability of cloud services is the ability to provision correct service (Gill and Buyya, 2018b; Gill et al., 2019), and is calculated as (Eq. 11):

$$R_{service} = e^{-\lambda t} \quad (11)$$

where t is time for the resource to deal with its request for any workload execution and λ is the failure rate of the resource at the given time, which is calculated using Eq. (13).

The list of available SLAs = $<m_1, m_2 \ldots\ldots\ldots\ldots\ldots.m_n>$, where n is the total number of SLAs.

$$Failure\ (m) = \begin{cases} 1, & m \text{ is not violated} \\ 0, & m \text{ is violated}, \end{cases} \quad (12)$$

Failure rate (λ) is computed as a ratio of the summation of all the SLA violated to the total number of SLAs (Gill et al., 2019).

$$\lambda = \sum_{i=1}^{n} \left(\frac{\text{Failure}\ (m_i)}{n}\right) \quad (13)$$

c) **Capacity planning model:** The capacity model is defined in terms of memory utilization, disk utilization and network utilization at given time t (Kouki and Ledoux, 2012). The formula for calculating memory utilization ($M_{Utilization}$) in percentage is as follows [Eq. 14]:

$$M_{Utilization} = \frac{\text{Total Physical Memory} - (\text{Memory Free} + \text{Memory Buffers} + \text{Cache Memory})}{\text{Total Physical Memory}} \times 100 \tag{14}$$

The formula for calculating disk utilization ($D_{Utilization}$) in percentage is as follows (Eq. 16):

$$D_{Usage} = \frac{Total\ Used}{Total\ HD\ size} \times 100 \tag{15}$$

$$D_{Utilization} = \frac{Storage\ Allocation\ Units \times Storage\ Used}{Storage\ Allocation\ Units \times Storage\ Size} \times 100 \tag{16}$$

The formula for calculating network utilization ($N_{Utilization}$) in percentage is as follows (Eq. 17):

$$N_{Utilization} = \frac{data\ bits}{bandwidth \times interval} \times 100 \tag{17}$$

d) **Temperature model:** We used Computer Room Air Conditioning (CRAC) model and RC (where R and C are thermal resistance (k/w) and heat capacity (j/k) of the host respectively) thermal model (Moore et al., 2005; Zhang and Chatha, 2007; Qinghui et al., 2008; Lazic et al., 2018) to design temperature model for calculation of datacenter temperature ($Datacenter_{Temp}$). The following formula is used to calculate the temperature of datacenter (Eq. 18).

$$Datacenter_{Temp} = Temp_{inlet} + \sum_{i=1}^{n}\left(\frac{Temp_{CPU\,i}}{n}\right) + T_{\text{initial}} \times e^{-\text{RC}} \tag{18}$$

where CRAC model is used to calculate inlet temperature ($Temp_{inlet}$) and RC model is used to calculate CPU temperature ($Temp_{CPU}$). T_{initial} is the initial temperature of the CPU. $1 \le i \le n$, n is the number of CPUs.

e) **Renewable energy model:** A renewable energy model (Tschudi et al., 2010) is used in terms of Energy Reuse Effectiveness (ERE) and Eq. (19) is used to calculate its value.

$$\text{ERE} = \frac{E - Energy_{Reused}}{E} \tag{19}$$

The value of E is calculated using Eq. (1). $Energy_{Reused}$ is amount of energy reused by different IT equipment.

f) **Waste heat utilization model:** The district heating management based waste heat utilization model (Karellas and Braimakis, 2016) is used in terms of recirculation ratio (R_R) and it is defined as the following (Eq. 20):

$$R_R = \frac{W_m}{W_s} \tag{20}$$

where W_m = mass flow rate of the water entering the circulation system, kilograms per second (kg/s) and W_s = mass flow rate of the steam generated in the circulation system, kg/s. Resource manager utilizes the waste heat to generate renewable energy to reduce electricity costs and carbon emissions, which further improves the sustainability of CDC in an efficient manner.

g) **Cooling management model:** A Water based Cooling Management Model (Liu et al., 2012) is used in terms of Datacenter Cooling System (DCS) Efficiency or cooling effectiveness and it is defined as the following (Eq. 21):

$$\text{DCS Efficiency} = \alpha \frac{Heat_{Removed}\ (t)}{ENCN_{Cooling}} \tag{21}$$

$$\alpha = Temp_{\text{ExhaustingAir}} - Temp_{\text{OutsideAir}} \tag{22}$$

$Heat_{Removed}(t)$ is calculated as the heat absorbed by the heat pump per unit time t and $ENCN_{Cooling}$ is work done by the cooling devices (compressor, air conditioner and fan) of the heat pump to transfer the thermal energy. Where α is weight to prioritize components of the *DCS Efficiency* and it is the temperature difference between outside air temperature and the temperature of the (hot) exhausting air of CRAC model (Moore et al., 2005) as specified in Eq. (22). Outside air temperature is the temperature of data center room (Zhang and Chatha K, 2007; Qinghui et al., 2008; Lazic et al., 2018). The exhausting air is exhausted from server rack, which contains server fans, air conditioners and compressors for smooth functioning of CDC (Liu et al., 2012). Different from the outside air cooling, the chiller cooling effectiveness does not change much with temperature and the variation over different IT load is much smaller than that under outside air cooling.

4. Resource provisioning and scheduling

It is very challenging to schedule provisioned resources for workload execution and maintain reliability and sustainability of cloud service simultaneously (Li et al., 2018a; Guitart, 2017). Cloud resource scheduling is a tedious task due to the problem of finding the best match of resource-workload pair based on the user QoS requirements (Singh and Chana, 2015; Gill and Buyya, 2018; Gill et al., 2019). The problem can be expressed as: mapping a set of independent cloud workloads $\{w_1, w_2, w_3, \ldots, w_m\}$ to a set of heterogeneous and dynamic resources $\{r_1, r_2, r_3, \ldots, r_n\}$ has been taken. For continuous problem, $R = \{r_k \mid 1 \le k \le n\}$ is the collection of resources and n is the total number of resources. $W = \{w_i \mid 1 \le i \le m\}$ is the collection of cloud workloads and m is the total number of cloud workloads. Fig. 2 shows the resource provisioning and scheduling mechanism for execution of user workloads, which determines the most suited resources for a given workload. CRUZE operates by performing the following steps: 1) analyzes workload characteristics with respective QoS requirements, 2) categorizes workload based on their common QoS requirements, 3) provisions cloud resources for categorized workloads and 4) schedule the provisioned resources for workload execution.

4.1. Clustering of workloads

Table 2 lists the various types of workload and their QoS requirements (Gill and Buyya, 2018; Gill et al., 2019), which are considered for this research work.

Further, k-means based clustering algorithm is used for clustering the workloads for execution on different set of resources because k-means clustering has been demonstrating to be an effective means for cloud workload categorization (Moreno et al., 2014). The process of workload clustering using k-means clustering algorithm has been described in previous research work in

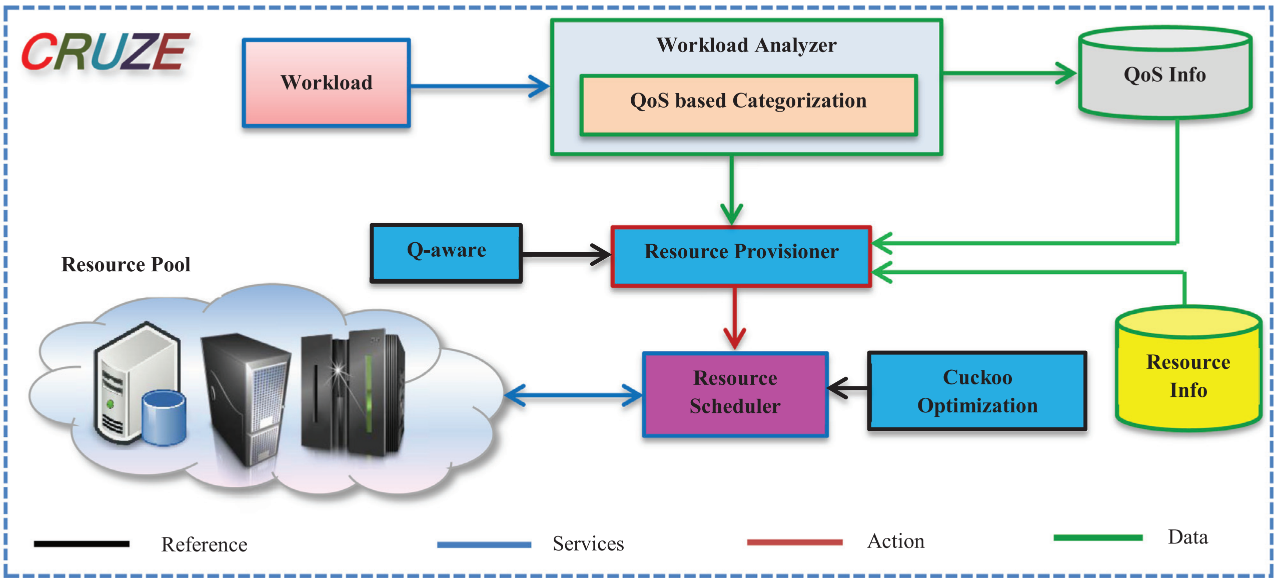


Fig. 2. Architecture of resource management in CRUZE.

Table 2
Cloud workloads and their key QoS requirements.

Workload name	QoS requirements
Technological computing	Computing capacity
Websites	High availability, High network bandwidth and Reliable storage
E-Commerce	Customizability and Variable computing load
Graphics Oriented	Visibility, Data backup, Latency and Network bandwidth
Backup and Storage Services	Persistence and Reliability
Endeavour Software	Correctness, High availability and Security
Productivity Applications	Security, Data backup, Latency and Network bandwidth
Critical Internet Applications	Usability, Serviceability and High availability
Mobile Computing Services	Portability, Reliability and High availability
Software/Project Development and Testing	Testing time, Flexibility and User self-service rate
Central Financial Services	Integrity, Changeability, High availability and Security
Online Transaction Processing	Usability, Internet accessibility, High availability and Security
Performance Testing	SLA Violation Rate, Resource Utilization, Energy, Cost and Time

Table 3
K-means based clustering of workloads.

Cluster	Cluster name	Workloads
C4	Administration	Graphics oriented, Software/Project development and testing, Productivity applications, Central financial services, Online transaction processing and endeavour software
C3	Communication	Mobile computing services, Critical internet applications and websites
C2	Storage	Backup and storage services and E-commerce
C1	Compute	Performance testing and technical computing

detail (Singh and Chana, 2015). Final set of workloads are shown in Table 3.

4.2. Resource provisioning

The resources are provisioned for clustered workload using a resource provisioning technique i.e. Q-aware (Singh and Chana, 2015) based on the requirement of workloads of different clusters as described in Table 3. After the provisioning of resources, workloads are submitted to resource scheduler. Then, the resource scheduler will ask to submit the workload for resources provisioned. After this, the resource scheduler returns results to the corresponding cloud user, which contains the resource information (Singh and Chana, 2015).

4.3. Cuckoo optimization based resource scheduling algorithm

Our proposed scheduling algorithm attempts to minimize overall cloud energy consumption whilst maximizing system reliability. Attaining these two objectives together is typically considered a trade-off; consolidating VMs onto fewer active servers minimizes system energy consumption, server failure can affect multiple VMs and reduce system reliability. In contrast, increasing the number of VM replicas maximizes system reliability, however also incurs additional energy costs due to greater computation requirements and active servers. To overcome this impact, a trade-off between energy consumption and reliability is required to provide cost-efficient cloud services. Specifically, whilst Dynamic Voltage and Frequency Scaling (DVFS) based energy management techniques can reduce energy consumption, response time and service delay are increased due to the switching of resources between high scaling and low scaling modes. Furthermore, reliability of the system component is also affected by excessive turning on/off servers. Power modulation decreases the reliability of server components such as storage devices, memory etc. Therefore, there is a need of new energy-aware resource management techniques to reduce power consumption whilst incurring minimal impact upon cloud service reliability (Sharma et al., 2016).

Cuckoo Optimization (CO) algorithm is a based resource scheduling technique is designed for execution of user workload considering both energy consumption and reliability. The goal of an objective function is to minimize system energy consumption and maximize server reliability simultaneously for finishing all n workloads. We define fitness function (F) in terms of energy consumption and reliability as specified in Eq. (23).

$$F = \theta\ E_{consumption} + \delta\ R_{service} \tag{23}$$

where $0 \leq \theta < 1$ and $0 \leq \delta < 1$ are weights to prioritize components of the fitness function. Energy consumption ($E_{consumption}$) and Reliability ($R_{service}$) is calculated using Eqs. (10) and (11) respectively. This objective function successfully captures the compromise among QoS parameters as specified in Eq. (23). Cuckoo Optimization (CO) algorithm is motivated by the life of the cuckoo bird (Rajabioun, 2011) as it adapts the features of a cuckoo and process of laying eggs. CO algorithm has both local and global search abilities and the performance of the CO algorithm has been demonstrated to be more effective in comparison to PSO and ACO in terms of accuracy, speed and convergence (Deb, 2019) for solving optimization problems such as batch process scheduling and job scheduling (Rajabioun, 2011; Yang, 2014). The mapping and execution of the workloads on suitable cloud resources is recognized to be an NP-complete problem and there is a need for novel algorithm for resource scheduling with maximum reliability and sustainability of cloud services (Li et al., 2018a). We have selected CO algorithm for scheduling of provisioned resources due to following reasons: a) capability to schedule resources for workload execution automatically, b) relatively straight forward integration with traditional optimization techniques, and c) easy modification in a dynamic cloud environment. *Resource Utilization* is a ratio of execution time of a workload executed by a particular resource to total uptime of that resource and it is specified in Eq. (24). The *total uptime* of resource is the amount of time that a resource from a resource set is available for execution of workloads.

$$R_U = \sum_{i=1}^{n}\left(\frac{execution\ time\ of\ a\ workload\ executed\ on\ i^{th}\ resource}{total\ uptime\ of\ \ i^{th}\ resource}\right) \tag{24}$$

where n is the no. of resources. A resource set consist of number of instances. Eq. (25) shows *ith resource* (R_i) contains instances *(I)*:

$$R_i = [I_{i1},\ I_{i2},\ \ldots\ldots\ldots\ldots I_{iX}],\ \text{where}\ I_{i1},\ I_{i2},\ \ldots\ldots\ldots\ldots I_{iX}\ \textit{are instances of}\ \ i\text{th resource and}\ x \leq 50 \tag{25}$$

The value of resource utilization depends on the number of instances of that resource are using to execute the workload. Resource utilization for i^{th} *resource* (R_i) is shown in Eq. (26).

$$R_U i = \frac{\sum_{a=1}^{x}(Execution\ Time\ of\ Workload\ on\ ath\ resource)}{\sum_{a=1}^{x}(total\ uptime\ of\ \ ath\ resource)} \tag{26}$$

where x is the number of instances and we have assumed the value of $x \leq 50$ for this research work. Fig. 3 shows the flowchart of CO algorithm based resource scheduling. Similar to the other evolutionary algorithms, this algorithm starts with an initial population. In this research work, we have modified the CO algorithm based on the requirements of cloud resource scheduling. We have considered as *Mature* cuckoos (existing provisioned resources) and their *Eggs* (new instances). Based on different values of resource utilization (R_U), initial population is considered as a resource set and different resources are sorted in decreasing order ($R_{U1} \geq\ R_{U2} \geq \ldots \geq\ R_{Un}$). There are new instances of those resources to be added to a specific resource for future execution of workloads and these instances will become part of resource after producing required performance ($E_{consumpton} < TV_E$ && $R_{Service} > TV_R$), where TV_E is a threshold value for energy and TV_R is a threshold value for reliability (which are decided based on the historic data of past execution of workloads (Singh and Chana, 2015; Gill et al., 2019)). The more number of instances are adding to a resource pool, the more profit is gained (in terms of resource utilization). Therefore, the improvement in resource utilization will be the definition that CO algorithm intends to optimize.

The main objective of CO the algorithm in this research work is to increase utilization of resources by selecting best resource based on their fitness value. Cuckoo search finds the most suitable resource to create more instances in order to maximize their resource utilization. After new instances performing as required, they come together to make new resources. Each instance has its resource to execute workloads. The best instance among all the instances will be the destination for the workloads for their execution. Then they move toward this best resource. They will inhabit near the best resource. Considering the number of instances each resource has and the resource's distance to the goal point (best resource), some range of resource (in terms of Egg Laying Radius (ELR)) is dedicated to it, and is calculated using Eq. (33). There is no obvious metric on the space of resource sets, as opposed to n-dimensional space. The next step is that a resource begins to create instances in a stochastic manner inside the resource range, defined by the value of ELR. This process lasts until the best resource with extreme value of profit (in terms of resource utilization) is obtained and most of the instances of resource are gathered around the same position.

The following are important functions of CO based resource scheduling algorithm:

a) *Initialize resource set*: Cuckoo Habitat as a resource set ($Resource_{Set}$) is considered in CO based resource scheduling algorithm. The resource set is an array of $1 \times q_{var}$ in q_{var}-dimensional optimization problem, the resource set is demonstrated as follows Eq. (26). Resource set contains different number of resources.

$$Resource_{Set} = [R_1,\ \ R_2,\ \ \ldots\ldots\ldots\ldots R_{\ q_{var}}],\ \ where\ R_1,\ \ R_2,\ \ \ldots\ldots\ldots\ldots R_{\ q_{var}}\text{are resources} \tag{27}$$

b) *Initialize instance set of resource*: Furthermore, every resource contains instances (I) as shown in Eq. (28).

$$R_{\ q_{var}} = \left[I_{\ q_{var}1},\ \ I_{\ q_{var}2},\ \ \ldots\ldots\ldots\ldots I_{\ q_{var}X}\right],\ \ where\ I_{\ q_{var}1},\ \ I_{\ q_{var}2},\ \ \ldots\ldots\ldots\ldots I_{\ q_{var}X}\ are\ instatnces\ and\ x\ \leq\ 50 \tag{28}$$

where x is the number of instances and we have assumed the value of $x \leq 50$ for this research work. $I_{\ q_{var}i} \in \{0,\ 1\}$, where $1 \leq i \leq 50$. The value *1* state that the particular instance is initialized and *0* represent the elimination of that instance from the final set.

c) *Determine profit:* The profit of a resource set is obtained by evaluation of profit function at a resource set ($R_1,\ \ R_2,\ \ \ldots\ldots\ldots\ldots R_m$). So, profit function is shown in Eq. (29):

$$\text{Profit} = R_U(Resource_{Set}) = R_U(R_1,\ R_2,\ \ldots\ldots\ldots\ldots R_{\ q_{var}}) \tag{29}$$

$$\text{Profit} = R_U((I_{11},\ I_{12},\ldots\ldots\ldots\ldots I_{1X}),\ (I_{21},\ I_{22},\ \ldots\ldots\ldots\ldots I_{2X}),\ldots\ldots\ldots\ (I_{\ q_{var}1},\ I_{\ q_{var}2},\ldots\ \ldots\ldots\ldots\ldots I_{\ q_{var}X})) \tag{30}$$

Maximize the profit in terms of cost ($-\ c_t$) for cost optimization of resource scheduling. To apply the CO algorithm to solve the minimization problems, it is sufficient to multiply the *minus sign* by cost function. A negative sign means that an improvement in the respective resource utilization results in a reduced cost. If the resource utilization reduces, then it results in an increased cost

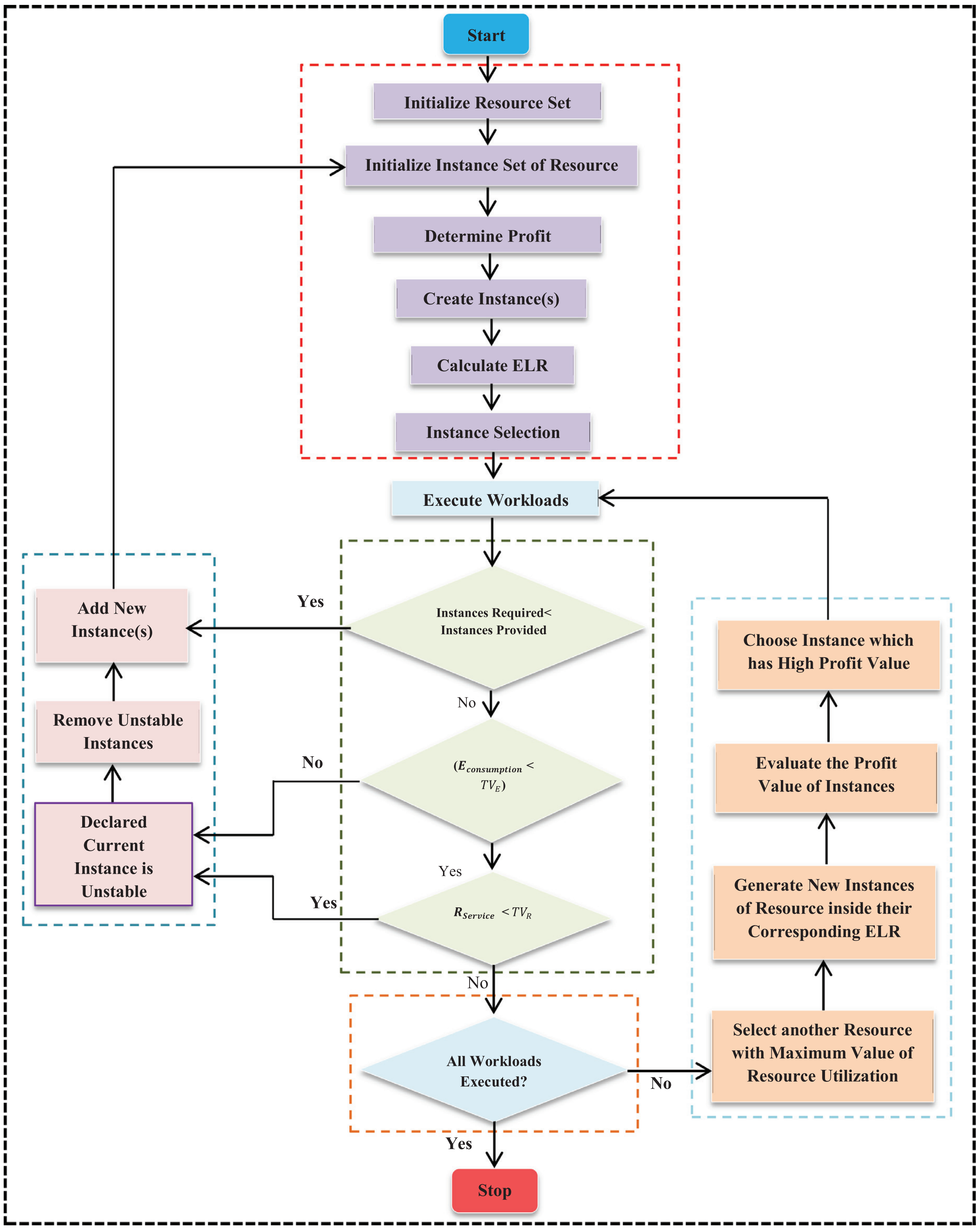

Start
Initialize Resource Set
Initialize Instance Set of Resource
Determine Profit
Create Instance(s)
Calculate ELR
Instance Selection
Execute Workloads
Instances Required< Instances Provided
Yes
No
Add New Instance(s)
Remove Unstable Instances
Declared Current Instance is Unstable
$(E_{consumption} < TV_E)$
No
Yes
$R_{Service} < TV_R$
Yes
No
All Workloads Executed?
Yes
No
Stop
Choose Instance which has High Profit Value
Evaluate the Profit Value of Instances
Generate New Instances of Resource inside their Corresponding ELR
Select another Resource with Maximum Value of Resource Utilization

Fig. 3. The working of CO based resource scheduling algorithm.

(because negative times negative results in a positive). The magnitude of the change is given by the value of the cost. The sign gives the direction of the change.

$$\text{Profit} = -Cost\,(Resource_{Set}) = -\ c_t\,(R_1,\quad R_2,\ \ldots\ldots\ldots.R_{\ q_{var}}) \tag{31}$$

$$\begin{aligned}\text{Profit} = -\ c_t\,(&(I_{11},\quad I_{12},\ \ldots\ldots\ldots\ I_{1X}),\\ &(I_{21},\quad I_{22},\ \ldots\ldots\ldots\ I_{2X}),\ldots\ldots\ldots\\ &(I_{\ q_{var}1},\quad I_{\ q_{var}2},\ \ldots\ldots\ldots\ I_{\ q_{var}X}))\end{aligned} \tag{32}$$

To begin the optimization algorithm, a candidate $Resource_{set}$ matrix of size $q_{pop} \times q_{var}$ is created, where q_{pop} is the value of an initial population considered in a resource set. Then some randomly produced number of instances is supposed for each of these initial resource sets.

d) *Create instance(s):* In this research work, each resource creates 1 to 50 instances. These values are used as the upper and lower limits of instance creation to each resource set at different iterations. In CO algorithm, instances are creating within a

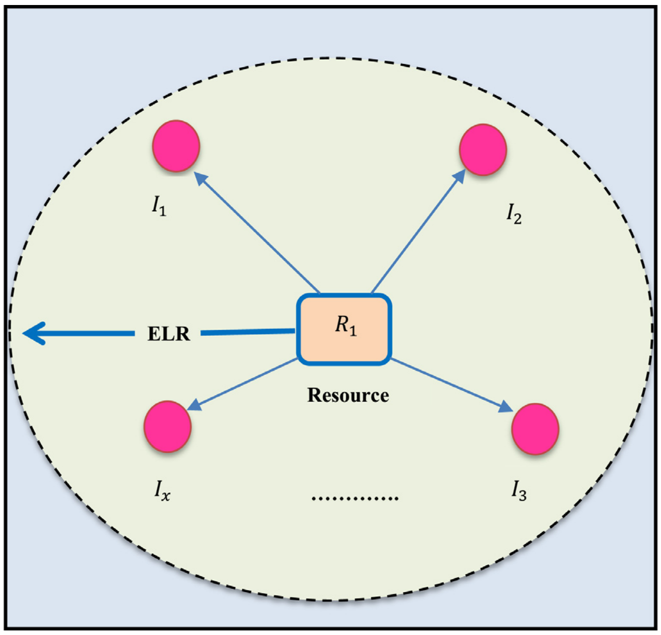


Fig. 4. Resource creating their instances within the region defined by ELR.

maximum distance from their resource set and this maximum range is known as Egg Laying Radius (ELR). Based on the ELR value, every resource generates instances as shown in Fig. 4. In a resource, there are two types of instances: stable and unstable. Stable instances are those which have maximum value in terms of resource utilization and fitness value (Eq. 23). Further, stable instance has also a capability to execute at least certain number of workloads. Otherwise, it is called as unstable instance.

e) *Calculate ELR:* ELR is defined as the ratio of number of instances of a current resource are executing a particular workload to the total number of active instances of that resource and it is described in Eq. (Kouki and Ledoux, 2012).

$$\mathrm{ELR} = \mu \times \left(\frac{number\ of\ instances\ of\ i^{th}\ resource\ executing\ a\ particular\ workload}{total\ number\ of\ active\ instances\ of\ i^{th}\ resource} \right) \times (\,var_U - \,var_L) \tag{33}$$

In an optimization problem with upper limit of $\mathrm{var_U}$ and lower limit of $\mathrm{var_L}$ for variables, each resource set has an ELR, which is proportional to the total number of instances of a resource set and also variable (var) limits of $\mathrm{var_U}$ and $\mathrm{var_L}$. μ is an integer, supposed to handle maximum value of ELR.

f) *Instance selection*: CO based resource scheduling algorithm (i) finds the number of unstable instances, (ii) selects the resource with minimum value of unstable instances, and (iii) create instances of selected resource to execute set of workloads. Instance is selected based on its Fitness Value (F), calculated using Eq. (33) and start execution of workloads.

g) *Monitor performance:* The performance of workload execution is monitored continuously and checks the instance requirement (whether the provided instances are sufficient for execution of current set of cloud workloads). The more number of instances are provided to continue execution if provided instances are less than required instances. It calculates the value of energy consumption and reliability. The value of energy consumption ($\mathrm{E_{consumption}}$) associated with it should be less than Threshold Value (TV_E) and the value of reliability ($\mathrm{R_{Service}}$) associated with it should be more than Threshold Value (TV_R) for successful execution of workloads. Otherwise, it declares the current instance as an unstable, eliminates unstable instance and add new instance using following steps: a) select another resource with maximum value of resource utilization, b) generate new instances of resource inside their corresponding ELR, c) evaluate the profit value of instances and d) choose instance which has higher profit value. The performance is monitored continuously until all the workloads are not executed.

The main steps of CO based resource scheduling algorithm are presented as a pseudo-code in Algorithm 1.

Initially, provisioned resources as an input for scheduling of resources to execute cloud workloads, and both workload and resource set contains integer values for our technique. Firstly, CO based resource scheduling algorithm initializes the resources. Further, it evaluates the resource utilization of all the resources using Eq. (24) to determine the profit and sorts the resources in decreasing order ($R_{U1} \geq\ R_{U2} \geq \ldots \geq\ R_{Un}$) based on their value of resource utilization. Then, it selects the best resource based on the maximum value of resource utilization ($\mathrm{R_U}$). Further, it creates some number of instances $[I_1,\ \ I_2,\ \ldots\ldots\ldots.\ I_X]$ for every resource and evaluates the value of the ELR for each resource using Eq. (33). Moreover, each resource generates instances inside their corresponding ELR and evaluate the Fitness Value (F) for all instances using Eq. (Shahdi-Pashaki et al., 2015) and determine the best individual with the best fitness value (which has maximum value of R_U and the value of energy consumption associated with it is less than a threshold value and the value of reliability is more than its threshold value). Further, CO based resource scheduling algorithm starts execution of workloads and it checks the execution status of workloads. If all the workloads are executed successfully then execution stops otherwise it continues execution of workloads. The performance is monitored continuously during execution of cloud workloads. It checks the instance requirement (whether the provided instances are sufficient for execution of current set of cloud workloads). The more number of instances are provided to continue execution if provided instances are less than required instances. It calculates the value of energy consumption and reliability. The value of energy consumption ($\mathrm{E_{consumption}}$) associated with it should be less than Threshold Value (TV_E) and the value of reliability ($\mathrm{R_{Service}}$) associated with it should be more than Threshold Value (TV_R) for successful execution of workloads. Otherwise, it declares the current instance as an unstable, eliminates unstable instance and add new instance using following steps: 1) select another resource with maximum value of resource utilization, 2) generate new instances of resource inside their corresponding ELR, 3) evaluate the profit value of instances and 4) choose instance which has higher profit value. The performance is monitored continuously until all the workloads are not executed.

5. Performance evaluation

We modeled and simulated a cloud environment using CloudSim (Calheiros et al., 2011), a prominent cloud computing simulation framework. Fig. 5 shows the interaction of different entities for simulation. Table 4 presents the resource configuration of the simulation as we used in our previous research work (Gill and Buyya, 2018; Gill et al., 2019). We used three Physical Machines (PMs) with different number of virtual nodes (6, 4 and 2) and virtual nodes are further divided into instances called Execution Components (ECs).

Algorithm 1
Cuckoo optimization based resource scheduling algorithm.

```
    Input: Set of Provisioned Resources
           Set of Workloads
    Output: Execute Workloads
1.  Start
2.  Initialize Resource Set  [$R_1$,  $R_2$, ........... $R_{q_{var}}$]
3.  Evaluate Resource Utilization ($\boldsymbol{R_U}$) using Eq. (24) for every resource to determine its Profit
4.  Rank the Resources ($R_{U1} \geq R_{U2} \geq \ldots \geq R_{Un}$) based on $\boldsymbol{R_U}$
5.  Select Best Resource with maximum $\boldsymbol{R_U}$
6.  Create instances of that resource $R_{q_{var}} = [I_1, I_2, \ldots\ldots I_X]$
7.  Evaluate ELR for each resource using Eq. (33)
8.  Each resource generates instances inside their corresponding ELR
9.  Evaluate the Fitness Value ($\boldsymbol{F}$) for all instances using Eq. (23)
10. Choose instance which has high $\boldsymbol{F}$
11. Execute Workloads using selected instance of resource
12. if (All Workloads Executed Successfully == FALSE) then
13.   While do
14.     Continue Execution
15.     Monitor Performance
16.     if (Instances Required $\geq$ Instances Provided) then
17.       While do
18.         Add New Stable Instance
19.         Calculate $E_{consumption}$ and $R_{Srtvice}$
20.         if ($E_{consumption} < TV_E$) then
21.           if ($R_{Service} > TV_R$) then
22.             break
23.           else
24.             Declare Current Instance is Unstable
25.             Remove Unstable Instance
26.             continue
27.           else
28.             continue
29.       else
30.         continue
31. else Stop
```

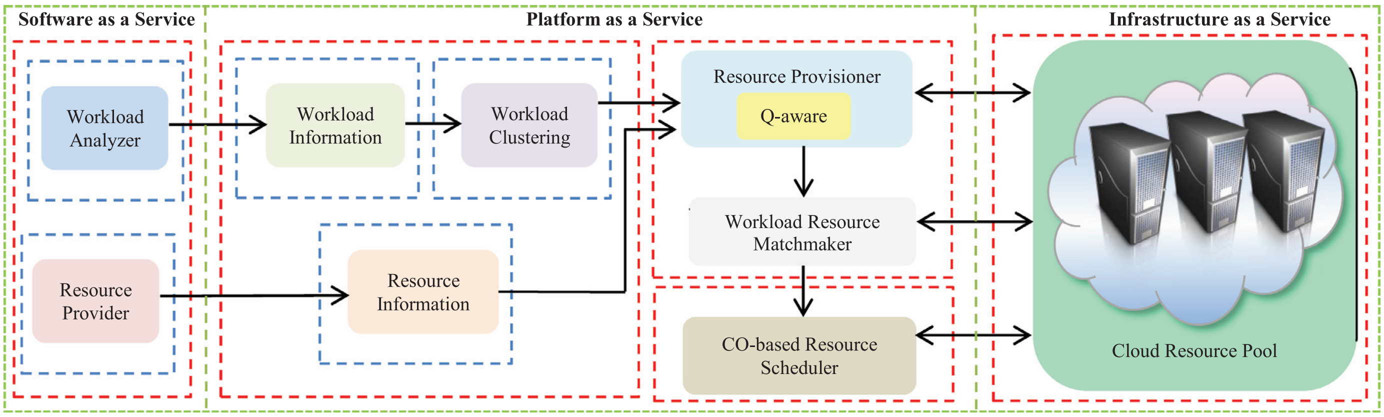


Fig. 5. Interaction of various entities in the simulated cloud environment.

Table 4
Configuration details.

Resource_Id	Configuration	Specifications	Core	Operating system	Number of virtual nodes	Number of ECs	Price (C$/EC time unit)
R1	Intel Core 2 Duo – 2.4 GHz	6 GB RAM and 320 GB HDD	2	Windows	6 (1 GB and 50 GB)	18	2
R2	Intel Core i5-2310- 2.9GHz	4 GB RAM and 160 GB HDD	2	Linux	4 (1 GB and 40 GB)	12	3
R3	Intel XEON E 52407-2.2 GHz	2 GB RAM and 160 GB HDD	2	Linux	2 (1 GB and 60GB)	6	4

Every EC contains their own cost of execution and it is measured with unit (C$/EC time unit (Sec)). EC measures cost per time unit in Cloud dollars (C$).

We have integrated temperature and cooling management model (Moore et al., 2005), renewable energy model (Tschudi et al., 2010), waste heat management model (Karellas and Braimakis, 2016), security manager (Gill and Buyya, 2018c) and Fault Injection Module (FIM-SIM) (Nita et al., 2014) to the CloudSim toolkit for simulation as shown in Fig. 6. We have integrated FIM-SIM (Nita et al., 2014) for fault management in CloudSim toolkit to simulate failures (VM creation failures and host failures) as discussed in Case-1 of *Section 5.3*. The detailed description about experimental setup is given in previous research work (Gill and Buyya, 2018; Gill et al., 2019).

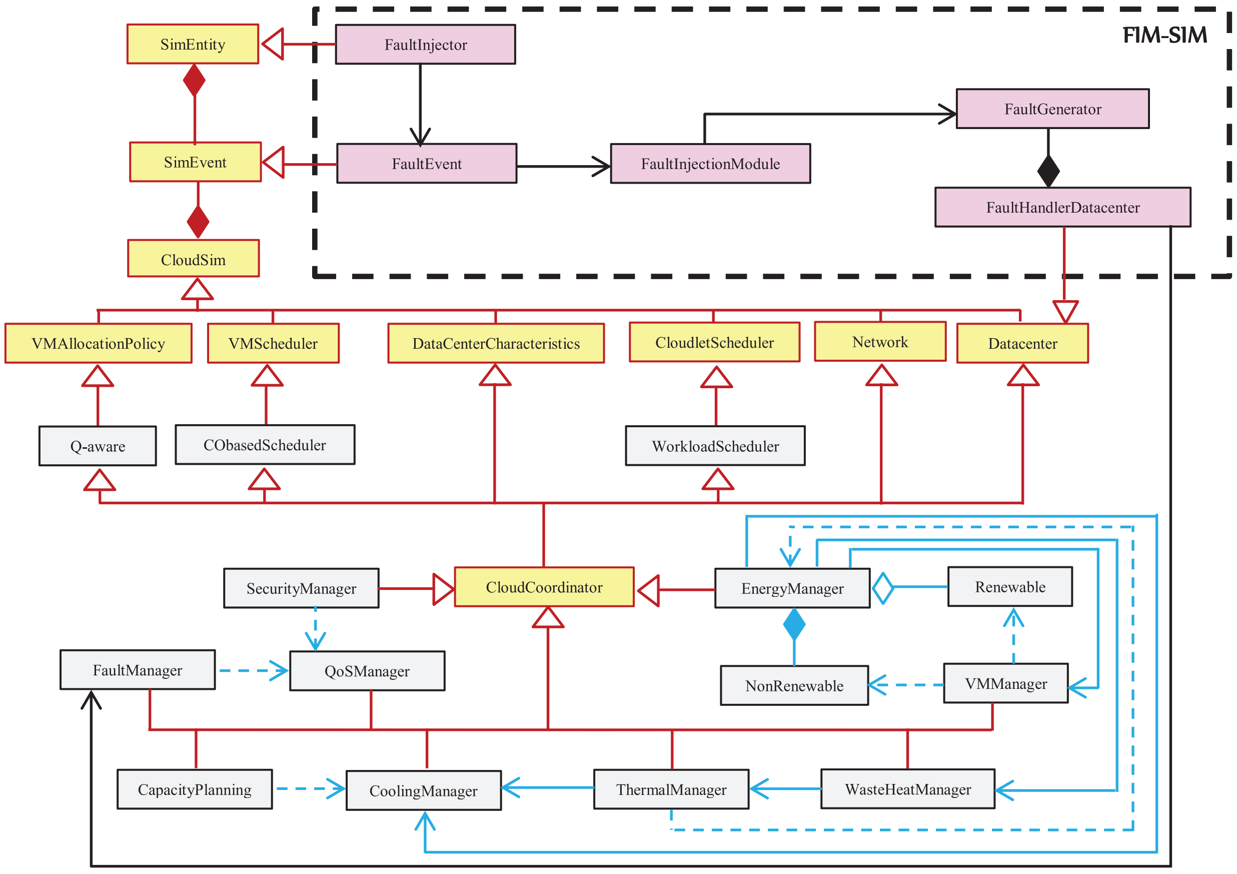


Fig. 6. Design description using class diagram.

For the execution of workloads in our experiments, we have chosen varied computational settings on top of heterogeneous resources. The variety comes in the number of cores at the CPU-level, the page levels of the main memory, switches at the network level and disk space at the storage level (Calheiros et al., 2011; Grozev and Buyya, 2013; Lebre et al., 2015). Cores is the number of Processing Element's (PE) required by the Cloudlet. Table 5 shows the simulation parameters utilized in the various experiments undertaken by this research work, also as identified from the existing empirical studies and literature such as fault management (Li et al., 2018a; Gill and Buyya, 2018; Gill et al., 2019), application's QoS (Gill and Buyya, 2018a; Gill and Buyya, 2018b; Gill and Buyya, 2018c; Gill et al., 2019; Singh and Chana, 2016), capacity planning (Kouki and Ledoux, 2012; Qinghui et al., 2008), energy management (Li et al., 2018a; Balis et al., 2018; Gill and Buyya, 2018b; Singh and Chana, 2016), waste heat utilization (Karellas and Braimakis, 2016; Qinghui et al., 2008), renewable energy (Tschudi et al., 2010; Liu et al., 2012), virtualization (Li et al., 2018a; Balis et al., 2018; Singh and Chana, 2016), thermal-aware scheduling (Moore et al., 2005; Lazic et al., 2018; Möbius et al., 2014) and cooling management (Liu et al., 2012; Qinghui et al., 2008; Lazic et al., 2018; Möbius et al., 2014). Experimental setup incorporated CloudSim to produce and retrieve simulation results.

5.1. Workload

For performance evaluation, we have selected four different types of cloud workload from every cluster of workloads as given in Table 3. Table 6 shows the different cloud workloads, which are considered to evaluate the performance of CRUZE. To find the experiment statistics, 500-3000 different workloads are executed. CRUZE processes different workloads using the different number of resources to evaluate its performance with different resource configuration.

We selected the Poisson Distribution (Singh and Chana, 2015) for workload submission in this research work due to following reasons: 1) evaluating the performance of workload execution for specific interval of time and 2) every workload is independent of all other workloads (number of workloads are arriving in first hour is independent of the number of workloads arriving in any other hour).

CRUZE also maintains the details of every executed workload and stores into workload database, which can be used to test the efficiency of CRUZE in future. For experimental results, we executed four different workloads [(i) Storage and Backup Data, (ii) Websites, (iii) Performance Testing and (iv) Software Development and Testing] with the same experimental setup.

5.2. Baseline resource scheduling approaches

In order to evaluate our approach, we have selected three state-of-the-art resource scheduling approaches from the literature (as discussed in *Section 2*). We have selected most relevant and recent similar work such as HMRM (Guzek et al., 2013), CSRE (Zhou et al., 2016) and CSMH (Madni et al., 2017) to evaluate the performance of our proposed approach. The other reasons of selection of these existing scheduling approaches are: HMRM (Guzek et al., 2013) manages cloud resources holistically by focusing on the energy consumption and CSRE (Zhou et al., 2016) executes workloads by improving the reliability of cloud service, while CSMH (Madni et al., 2017) schedule resources in an energy-efficient manner using Cuckoo search meta-heuristic algorithm.

Table 5
Simulation Parameters and their values.

Parameter	Value
Number of VMs (n)	36
Number of cloudlets (Workloads)	3000
Bandwidth	1000–3000 B/S
CPU MIPS	2000
Size of cloud workload	10000+ (10%–30%) MB
Number of PEs per machine	1
PE ratings	100-4000 MIPS
Cost per cloud workload	3 C$–5 C$
Memory size	2048-12576 MB
File size	300 + (15%–40%) MB
Cloud workload output size	300 + (15%–50%) MB
CPU temperature	10-27°C
Inlet temperature	15-40°C
W_m = mass flow rate of the water entering the circulation system	0.08-0.024 kg/s
W_s = mass flow rate of the steam generated in the circulation system	0.03-0.134 kg/s
Power (KW)	108-273 KW
Latency	20-90 Seconds
$Heat_{Removed}$	100-1,000 Joules/Second
Cache memory size	4 MB – 16 MB
Energy reused	40 – 85%
Power consumption by processor	130W – 240W
Power consumption by cooling devices	400 W – 900W
Power Consumption by RAM	10W – 30W
Power consumption by storage	35W – 110W
Power consumption by network	70W-180W
Power consumption by extra components	2W-25W
Equipment cost (E_i)	4-30 C$
Support contract cost (S_i)	5-15 C$
Administrative costs (A_i)	15-50 C$
Power cost per month (P_i)	12-30 C$
Rack cost per month (R_i)	3-12 C$
Communication cost (C_i)	2-17 C$

Table 6
Details of cloud workloads.

Workload	Cluster	Description
Performance testing	Compute (C1)	CRUZE processes and converts an image file (713 MB) to PNG format from JPG format. The change of a one JPG file into PNG is taken as a workload (in the form of Cloudlet).
Storage and backup data	Storage (C2)	Store a huge chunk of data (5 TB) and generates a backup of data is considered as a workload.
Websites	Communication (C3)	A large number of users are accessing a website of university during Admission Period is considered as a workload.
Software development and testing	Administration (C4)	Development and testing of an Agri-Info Software to find out the productivity of a crop is considered as a workload (Gill et al., 2017).

1) **HMRM** (**Guzek et al., 2013**)**:** Holistic Model for Resource Management (HMRM) approach is designed for virtual cloud environment to reduce energy consumption of different components of cloud datacenters such as storage and network without focusing on memory, processors, cooling systems. HMRM executes only homogeneous cloud workloads.
2) **CSRE** (**Zhou et al., 2016**)**:** Cloud Service Reliability Enhancement (CSRE) approach is developed to improve the storage and network resource utilization during execution of workloads. CSRE uses service checkpoint to store the state of all the VMs, which are currently processing user workloads. Further, a node failure predicator is developed to reduce the network resource consumption. CSRE executes only homogeneous workloads and considers only two types of resources such as storage and network without focusing on memory, processors, cooling systems.
3) **CSMH** (**Madni et al., 2017**)**:** Cuckoo Search Meta-Heuristic (CSMH) algorithm based resource scheduling approach is designed to optimize the energy consumption of cloud resources (processors only) for execution of homogeneous workloads without focusing on other resources such as networks, memory, storage, cooling systems.

Our proposed approach (CRUZE) focuses on holistic management of all resources (including servers, networks, memory, storage, cooling systems) to provide reliable as well as sustainable cloud services simultaneously, which schedules the provisioned resources using evolutionary algorithm (Cuckoo Optimization) for the execution of clustered and heterogeneous workloads within their specified deadline, budget and other important QoS parameters.

5.3. Experimental results

All the experiments utilized four different workloads described in Table 6. The various parameters are used to evaluate the performance of proposed approach for holistic resource management, which comprises of different categories such as fault management,

Table 7
Entitles of FIM-SIM and their functionalities.

FaultInjector	FaultEvent	FaultHandlerDatacenter
• Extends the *SimEntity* class • Starts at simulation startup along with the other entities from the system	• Extends the *SimEvent* class • Describes a fault event: source, destination, time and type; – tag type: HOST FAILURE, CLOUDLET FAILURE, CREATE VM FAILURE	• Extends the *Datacenter* class • Processes fault events sent by the *FaultGenerator*
• Responsible for inserting fault events at random moments of time		• Updates the cloudlet execution/status according to the fault event type
• The random generation of moments of time is based on a statistical distribution (We used Weibull Distribution (Gill et al., 2019) for this research work.)	• Created in the *Fault Injection Module.*	•Handles VM migration; – since host and VM are static entities, all its state modification should be processed by the datacenter.

application's QoS, capacity planning, energy management, waste heat utilization, renewable energy, virtualization, thermal-aware scheduling and cooling management. The temporal evaluations are conducted in a time period of 12 hours with 3000 workloads submitted. The performance of CRUZE is evaluated using following different test cases:

Case 1 – Fault management: We have evaluated the performance of CRUZE in terms of *reliability* and *fault detection rate* for fault tolerance and used Eq. (11) to measure the value of reliability. Fault detection rate is defined as the ratio of number of faults/failures (hardware, software, network) detected to the total number of faults/failures in the system (Gill et al., 2019). Fault Detection Rate (FDR) is calculated using Eq. (34).

$$\text{FDR} = \frac{\text{Number of Faults Detected}}{\text{Total number of Faults}} \tag{34}$$

Faults can be a network, software or hardware, which is detected based on the violation of SLA. The Software faults/failures can be occurred due to following reasons: 1) lesser storage space, 2) resource unavailability, 3) deadlocks and 4) unhandled exceptions. The reasons of hardware faults/failures can be problems in hardware parts such as hard disk, primary memory and processor. Network error can be breakage of network, scalability or physical damage.

FIM-SIM: We have integrated Fault Injection Module (FIM-SIM) (Nita et al., 2014; Gill et al., 2019) to inject faults automatically to test the reliability of CRUZE as shown in Fig. 6. FIM-SIM is working based on event-driven models and injects faults into the CloudSim (Calheiros et al., 2011) using different statistical distributions at runtime. A Weibull Distribution is used in order to model failures characteristics when injecting faults (Gill et al., 2019). We injected three types of faults: VM creation failures, host failures (Processing Elements failure and memory failure) and high-level failures like cloudlets failures (which are caused by any networking problem that CloudSim (Calheiros et al., 2011) cannot handle). The entities in CloudSim (Calheiros et al., 2011) communicate through messages. Since host and VM are static entities, each change in their state should be realized by the datacenter. The broker, based on the simulation configuration (number of cloudlets and their specification) will request the VM creation, cloudlet scheduling and it will wait to be informed by the datacenter when the cloudlets completion is realized. We have simulated VM creation failures, host failures (hardware failure) and cloudlets failures (network failure) by creating fault injector thread, which sends the failure event based on the following command: sendNow(dataCenter.getId(), FaultEventTags.HOST_FAILURE, host); and it generates the events based on statistical distribution using Weibull Distribution (Gill et al., 2019). The Fault Tolerance Module is extending the CloudSim core functions (see Fig. 6) with three entities (FaultInjector, FaultEvent and FaultHandlerDatacenter) as described in Table 7.

CRUZE uses the concept of Carburizer (Gill et al., 2018; Gill et al., 2019) to perform process of hardware hardening, which reduces the frequency of faults/failures. CRUZE replaces the new driver (harden driver) with original in case of fault and update the database regarding new faults to avoid future faults, which improves the fault detection rate in CRUZE as compared to HMRM, CSRE and CSMH. Fig. 7(a) shows the variation of fault detection rate for CRUZE, HMRM, CSRE and CSMH. Fault detection rate is decreasing as number of workloads increases for CRUZE, HMRM, CSRE and CSMH, but CRUZE performs better than HMRM, CSRE and CSMH. The average value of fault detection rate in CRUZE is 19.99%, 21.14% and 22.45% more than HMRM, CSRE and CSMH respectively. Dynamic Random-Access Memory (DRAM) provides the Check-pointing mechanism to store the current states of VMs in case of failure (Gill et al., 2019). Fig. 7(b) shows the variation of reliability for CRUZE, HMRM, CSRE and CSMH with different number of workloads (500-3000). The average value of reliability in CRUZE is 19.07%, 19.75% and 20.98% more than HMRM, CSRE and CSMH respectively.

Case 2 - Application QoS: We have considered three performance parameters for application's QoS**:** *execution cost, time and security* (Gill et al., 2018). *Execution cost* is defined as the total money that can be spent in one hour to execute the application successfully and execution cost is measured in Cloud Dollars (C$) (Gill and Buyya, 2019). We have used following formula to calculate Execution Cost (C) (Eq. 35).

$$C = E_t \times Price \tag{35}$$

where "price" of a resource is calculated using Table 4 and the value of E_t is calculated using Eq. (36). Fig. 7(c) shows the comparison of CRUZE, HMRM, CSRE and CSMH in terms of execution cost and cost is increasing with increase in number of workloads for CRUZE, HMRM, CSRE and CSMH, but CRUZE consumes less cost as compared to HMRM, CSRE and CSMH. The average value of cost in CRUZE is 14.41%, 14.91% and 15.46% less than HMRM, CSRE and CSMH respectively.

In resource scheduler, CRUZE considers the impact of other workloads on current workload during execution. CRUZE schedules provisioned resources using Q-aware (Gill et al., 2018), which clusters the workloads and execute within their specified deadline and budget. *Execution time* is the amount of time required to execute application successfully and execution time is measured in Seconds (Gill and Buyya, 2019). Eq. (36) is used to calculate Execution Time (E_t).

$$E_t = \sum_{i=1}^{m} \left(\frac{WC_i - WS_i}{m} \right) + \Delta t_i \tag{36}$$

Where WC_i is workload completion time and WS_i is workload submission time, Δt_i is time to restart the node and m is the number of workloads. Fig. 7(d) shows the variation of an execution time with different number of workloads and time is increasing with increase in number of workloads for both CRUZE, HMRM, CSRE and CSMH. The average value of execution time in CRUZE is 9.96%, 10.35% and 12.11% less than HMRM, CSRE and CSMH respectively

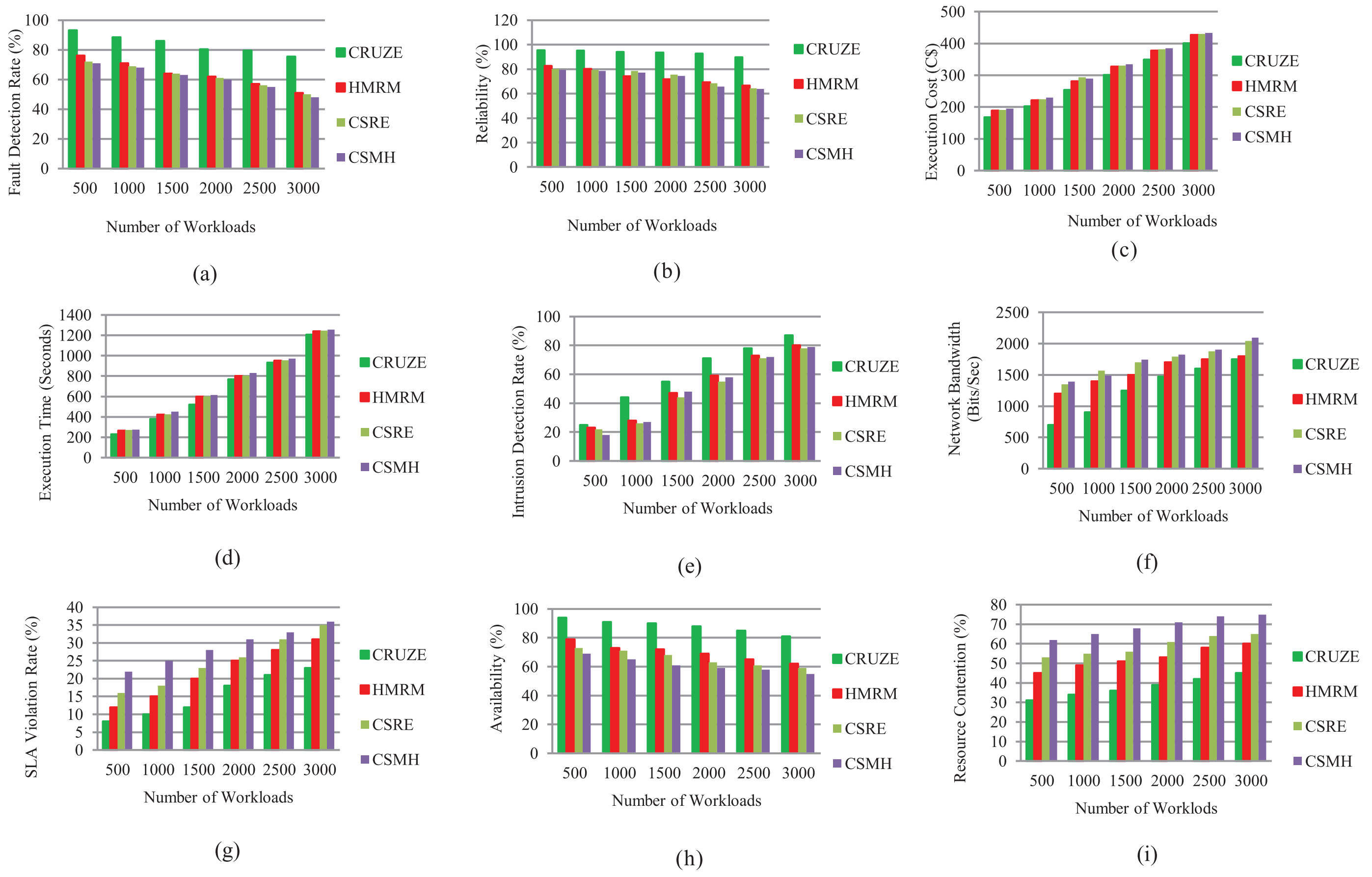


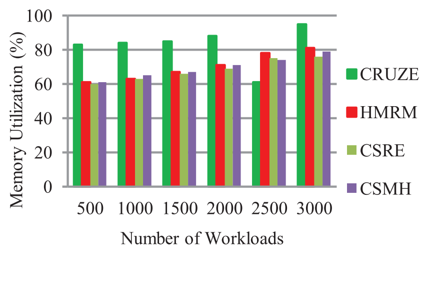
Fig. 7. Comparison of algorithms: (a) Fault detection rate, (b) Reliability, (c) Execution cost, (d) Execution time, (e) Intrusion detection rate, (f) Network bandwidth, (g) SLA violation rate, (h) Availability, (i) Resource contention. Note: We have considered 36 resources for these results.

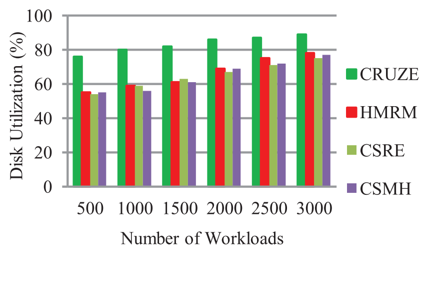
because CRUZE tracks the resource states automatically for effective decisions. *Security* is an ability of the computing system to protect the system from malicious attacks and measured in terms of Intrusion Detection Rate (IDR) (Gill and Buyya, 2018c). IDR is described in Eq. (37), which is the ratio of total number of true positives to the total number of intrusions.

$$IDR = \frac{Total\ Number\ of\ True\ Positives}{Total\ Number\ of\ Intrusions} \tag{37}$$

IDR considers the number of detected and blocked attacks. CRUZE deploys security agents on different computing systems, which trace unknown attacks (using an anomaly-based detector) and known attacks (using a signature-based detector). It captures new anomalies based on existing data stored in the central database (SNORT DB). CRUZE captures and detects anomalies using the Intrusion Detection System and labels it as anomalous or normal traffic data by comparing its signatures with the signatures of known attacks (Gill and Buyya, 2018c). A State Vector Machine-based security agent detects the new anomalies and stores the information into the database to maintain a log about attacks. CRUZE protects from security attacks: DDoS (HTTP Flood and Zero-Day Attack), Probing (NMAP and Ports sweep), U2R (Buffer Overflow and Rootkits), R2L (IMAP, Guess password and SPY) and DoS (Teardrop, SYN Flood, LAND and Smurf) as discussed in previous research work (Gill and Buyya, 2018c). Fig. 7(e) shows the comparison of CRUZE, HMRM, CSRE and CSMH in terms of intrusion detection rate with different number of workloads. The value of intrusion detection rate is increasing with increase in number of workloads, but CRUZE performs better than HMRM, CSRE and CSMH. The value of intrusion detection rate in CRUZE is 19.20%, 21.45% and 20.86% more than HMRM, CSRE and CSMH respectively, because CRUZE uses an anomaly detector component i.e. SNORT (Gill and Buyya, 2018c). It is a signature based system to detect known attacks automatically and stores the signature of attack into database if attack is unknown.

We have measured other important QoS parameters such as network bandwidth, SLA violation rate, availability, resource contention to test the performance of CRUZE with different number of workloads and formulas to calculate the value of these QoS parameters is described in previous research work (Singh and Chana, 2015; Gill et al., 2018; Gill et al., 2019). Fig. 7(f) shows the value of network bandwidth in CRUZE is 14.44%, 16.31% and 18.73% less than HMRM, CSRE and CSMH respectively. This is because, CRUZE identifies the network faults automatically and it also prevents system from security attacks as discussed above, which improves the network bandwidth of CRUZE as compared to HMRM, CSRE and CSMH. Fig. 7(g) shows the value of SLA violation rate in CRUZE is 23.68%, 24.42% and 27.45% less than HMRM, CSRE and CSMH respectively. This is because, CRUZE uses admission control and reserve resources for execution of workloads in advance based on their QoS requirements specified in the SLA document. Further, CRUZE outperforms as it regulates the resources at runtime based on the user's new QoS requirements during its execution to avoid SLA violation. Fig. 7(h) shows the value of availability in CRUZE is 12.45%, 13.91% and 15.34% more than HMRM, CSRE and CSMH respectively. This is expected as the recovering faulty task manages the faults efficiently in CRUZE, which further improves the availability of cloud services. Fig. 7(i) shows the value of resource contention in CRUZE is 17.56%, 18.79% and 19.42% less than HMRM, CSRE and CSMH respectively. This is expected as the





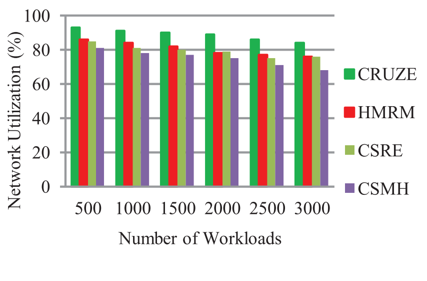


Fig. 8. Comparison of algorithms: (a) Memory utilization, (b) Disk utilization, (c) Network utilization. Note: We have considered 36 resources for these results.

workload execution is done using CRUZE, which is based on QoS parameters based resource provisioning policy (Q-aware). Based on deadline and priority of workload, clustering of workloads is performed, and resources are provisioned for effective scheduling. This is also because of the low variation in execution time across various resources as the resource list that is obtained from the resource provisioning unit is already filtered using Q-aware (Singh and Chana, 2015).

Case 3 – Capacity planning: We have considered memory, disk and network utilization as a performance parameter for capacity planning and it is measured in percentage (%) using Eqs. (14) and (16) and Eq. (17) respectively. Fig. 8(a) shows the memory utilization during workload execution for CRUZE, HMRM, CSRE and CSMH and CRUZE executes the same number of workloads with better memory utilization. The value of memory utilization in CRUZE is 24.78%, 25.45% and 25.91% more than HMRM, CSRE and CSMH respectively. Fig. 8(b) shows the disk utilization during workload execution for CRUZE, HMRM, CSRE and CSMH and CRUZE executes the same number of workloads with better disk utilization. The value of disk utilization in CRUZE is 18%, 18.5% and 19.18% more than HMRM, CSRE and CSMH respectively. CRUZE gives higher memory and disk utilization as the algorithm consumes resources dynamically based on the requirement of current workloads and unused resources are scaled back to the resource pool. CRUZE keeps only the required number of resources active, thus increasing its utilization efficiency. Fig. 8(c) shows the network utilization during workload execution for CRUZE, HMRM, CSRE and CSMH and CRUZE executes the same number of workloads with better network utilization. The value of network utilization in CRUZE is 12.77%, 11.68% and 12.25% more than HMRM, CSRE and CSMH respectively because CRUZE performs data transmission with the least packet loss when network utilization reaches at its higher value. CRUZE has FIM-SIM based fault manager (as discussed in Case-1) to detect faults at runtime, which further reduces the occurrence of same network faults in future and it improves network utilization.

Case 4 – Energy management: We have evaluated the performance of CRUZE in terms of energy consumption for energy management and used Eq. (10) to measure the value of energy consumption, which is measured in kilo Watt hour (kWh). Fig. 9(a) shows the variation of energy consumption with different number of workloads and the average value of energy consumption in CRUZE is 17.35%, 18.71% and 20.10% less than HMRM, CSRE and CSMH respectively. This is because CRUZE executes clustered workloads instead of individual workloads, which minimizes the network traffic and number of switches and further reduces energy consumption.

Case 5 – Virtualization: We have evaluated the performance of CRUZE in terms of *CPU utilization* and *VM Co-Location Cost* for virtualization. Fig. 9(b) shows the variation of CPU utilization with different number of workloads for CRUZE, HMRM, CSRE and CSMH. The experimental result show that the average value of CPU utilization in CRUZE is 11.12%, 14.45% and 15.69% more than HMRM, CSRE and CSMH respectively because best resources are identified using resource provisioning technique for scheduling. Provisioning based scheduling of resources consumes slightly more time initially and then it avoids underutilization and overutilization of resources during scheduling. VM Co-Location Cost is the total cost of VM migration from one cloud datacenter to another (Oxley et al., 2018; Youn et al., 2017) and it is calculated using Eq. (38).

$$VM\ CoLocation\ Cost = \sum_{i=1}^{n} (E_i + S_i + A_i + P_i + R_i + C_i) \tag{38}$$

Where E_i is Equipment cost (installation cost), S_i is Support contract cost (maintenance cost per month), A_i is Administrative costs (includes server, storage, network cost per month), P_i is Power cost per month (to run CDC), R_i is Rack cost per month, C_i is communication cost and n is the number of VMs. Fig. 9(c) shows the comparison of VM Co-Location Cost for CRUZE, HMRM, CSRE and CSMH to execute different number workloads. The average value of VM Co-Location Cost in CRUZE is 6.25%, 6.91% and 7.15% less than HMRM, CSRE and CSMH respectively because CRUZE identifies the nearest CDC, which consumes more renewable energy as compared to other CDCs. The migration of VM to nearest CDC also reduces the communication cost, which further optimize the value of VM Co-Location Cost.

Case 6 – Renewable energy: We have evaluated the performance of CRUZE in terms of Energy Reuse Effectiveness for renewable energy. Energy Reuse Effectiveness is the ratio of energy (reused) consumed by Cooling, Lighting and IT devices to the total energy consumed by IT devices (Tschudi et al., 2010) and described in Eq. (19). Fig. 9(d) shows the amount of renewable energy reused during the execution of different number of workloads. The value of energy reuse effectiveness in CRUZE is 17.56%, 19.45% and 20.99% greater than HMRM, CSRE and CSMH respectively because CRUZE mainly selects the CDC which are utilizing more renewable energy as compared to grid energy. CRUZE manages the energy produced from renewable and non-renewable sources and sustainable CDCs focuses more on renewable energy sources (solar and wind). To provide reliable services, CDC can prefer grid energy for the execution of deadline-aware workloads.

Case 7 –Thermal-aware scheduling: We used Computer Room Air Conditioning (CRAC) model based temperature model (Moore et al., 2005) to test the performance of CRUZE in terms of *datacenter temperature* for thermal-aware scheduling. Datacenter Temperature is the operating temperature of CDC and it is measured in degree Celsius (°C) as described in Eq. (20). The variations of the temperature of different hosts (PMs) is measured, monitored and controlled by proactive temperature-aware scheduler. We used an analytical model (Zhang and Chatha K, 2007; Qinghui et al., 2008; Lazic et al., 2018) for the CRAC to measure the temperature of different PMs. Fig. 9(e) shows the comparison of datacenter (CDC) temperature with different number of workloads. The average value of temperature in CRUZE is 13.76%, 14.91%

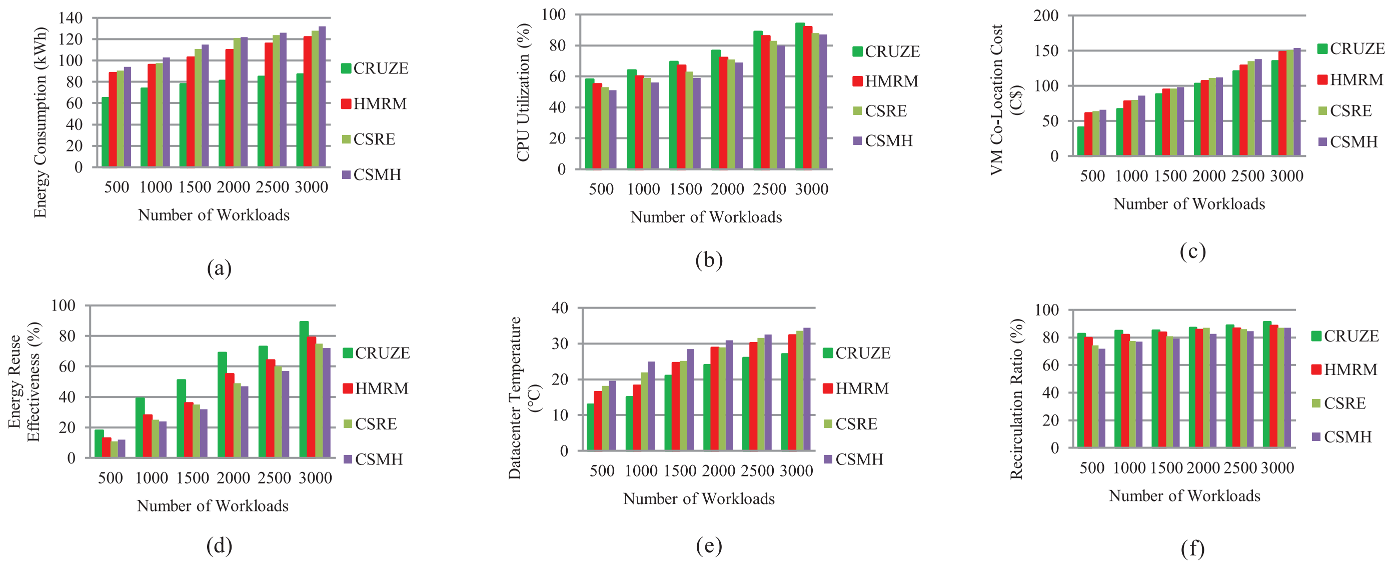


Fig. 9. Performance of different scheduling algorithms: (a) Energy consumption, (b) CPU utilization, (c) VM co-location cost, (d) Energy reuse effectiveness, (e) Datacenter temperature, (f) Recirculation ratio. Note: We have considered 36 resources for these results.

and 15.30% less than HMRM, CSRE and CSMH respectively. This is because CRUZE optimizes the resource utilization, avoids underloading and overloading of resources and uses minimum energy consumption by reducing the number of components such as number of switches, adapters etc. The other reasons of optimized temperature are effective CRAC-based cooling management (Moore et al., 2005) and dynamic capacity planning for workload execution. CRUZE automatically switched-off the idle resources in CDC, which also reduces the heat and temperature.

Case 8 – Waste heat utilization: We have evaluated the performance of CRUZE in terms of Recirculation Ratio. Recirculation Ratio is the amount of waste-water that flows through the advanced pretreatment component divided by the amount of waste-water that is sent to the final treatment and dispersal component (Karellas and Braimakis, 2016) and it is described in Eq. (20). Fig. 9(f) shows the value of recirculation ratio for CRUZE, HMRM, CSRE and CSMH during the execution of workloads and the average value of recirculation ratio in CRUZE is 3.42%, 4.77% and 4.97% more than HMRM, CSRE and CSMH respectively. CRUZE performs effective than HMRM, CSRE and CSMH because CRUZE has capability to reuse waste heat in district heating, which further reduces the cost of utilization of waste heat.

Case 9 – Cooling management: We have evaluated the performance of CRUZE in terms of Datacenter Cooling System (DCS) Efficiency. DCS Efficiency is the amount of cooling capacity to remove heat per unit of energy it consumes to maintain the cooling of CDC (Liu et al., 2012) and is described in Eq. (21). For cooling management, the district heating management uses water economizer, outside air economizer and chiller plant to control the temperature of CDC. Fig. 10 shows the variation of DCS Efficiency with execution of different number of workloads for CRUZE, HMRM, CSRE and CSMH. The average value of DCS Efficiency in CRUZE is 9.98%, 10.23% and 11.56% more than HMRM, CSRE and CSMH respectively because CRUZE uses district heating management module for effective management of cooling. Fig. 11 shows the variation of cooling energy (Eq. 7) with the execution of different number of workloads for CRUZE, HMRM, CSRE and CSMH. The average value of cooling energy in CRUZE is 15.66%, 18.31% and 22.65% less than HMRM, CSRE and CSMH respectively because CRUZE dynamically switched-on/off the cooling components for different workload intensity, which further reduces the cooling power. Note: We have considered 36 resources for these results.

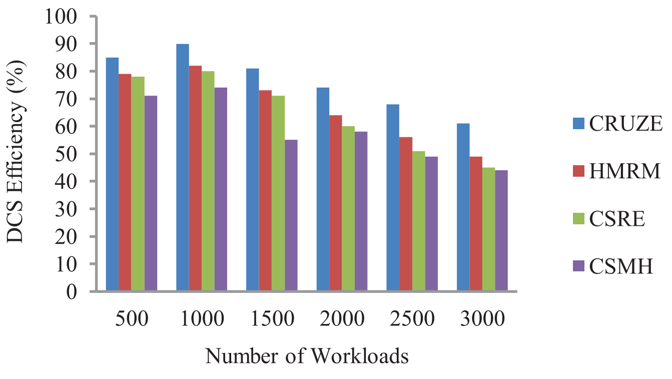


Fig. 10. DCS efficiency vs. number of workloads.

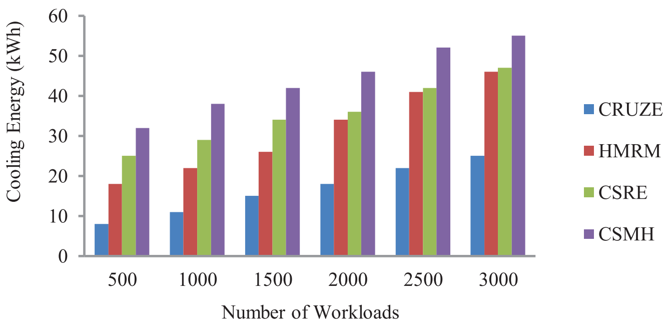


Fig. 11. Cooling energy vs. number of workloads.

5.3.1. Comparison of algorithms for different time intervals

We have compared the performance of proposed algorithm with existing algorithms for different time intervals. Fig. 12(a) demonstrates that memory utilization during execution of workloads for CRUZE, HMRM, CSRE and CSMH and the value of memory utilization in CRUZE is 27.77%, 28.11% and 29.12% more than HMRM, CSRE and CSMH respectively for different time period. Fig. 12(b) shows the variation of energy consumption with different time interval and the average value of energy consumption in CRUZE is 14.46%, 15.35% and 18.86% less than HMRM, CSRE and CSMH respectively. Fig. 12(c) demonstrates the variation of

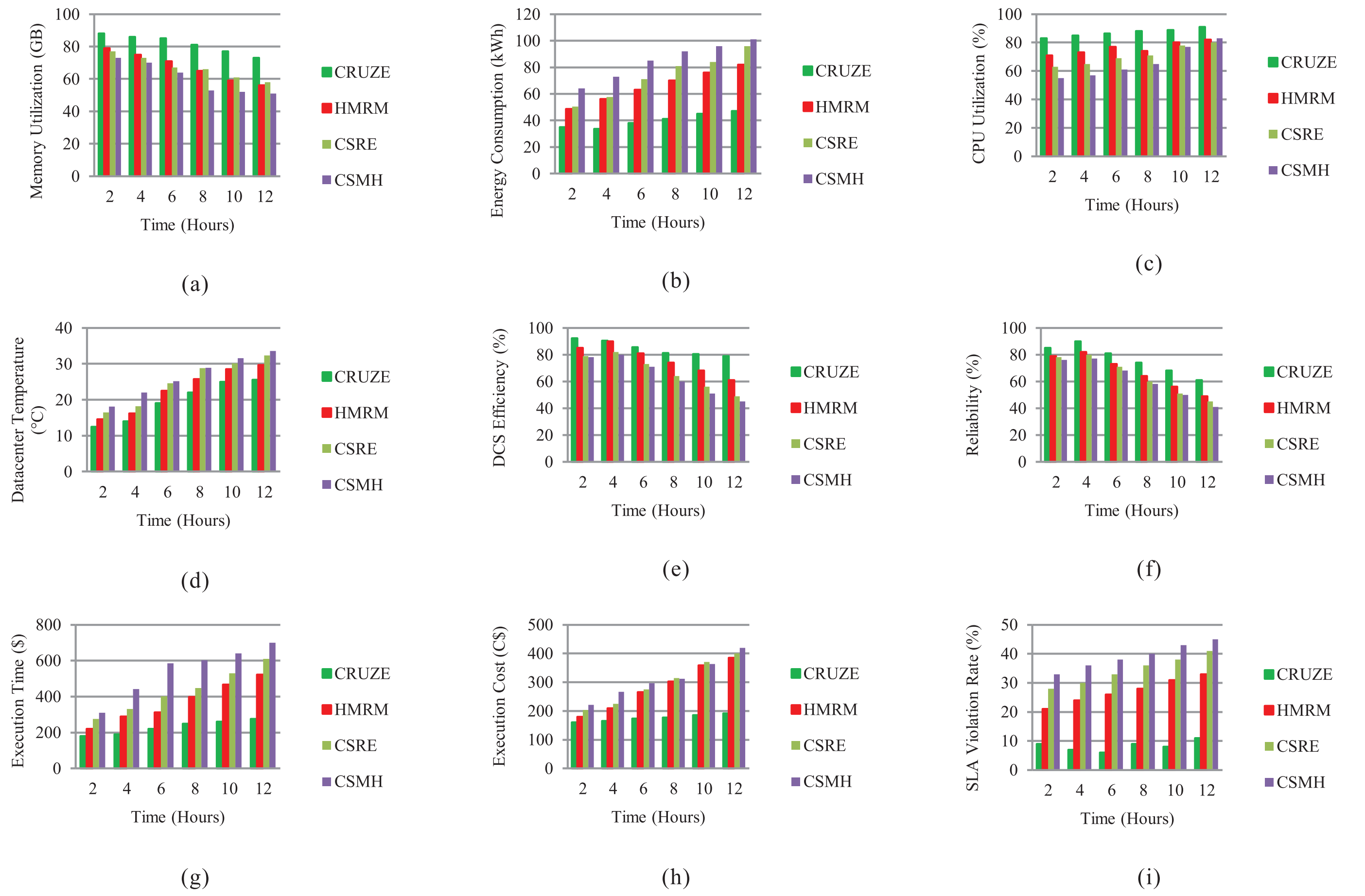


Fig. 12. Comparison of algorithms for different time intervals: (a) Memory utilization, (b) Energy consumption, (c) CPU utilization, (d) Datacenter temperature, (e) DCS efficiency, (f) Reliability, (g) Execution time, (h) Execution cost, (i) SLA violation rate.

CPU utilization with different number of workloads for different scheduling techniques. The experimental result show that the average value of CPU utilization in CRUZE is 12.55%, 13.91% and 14.04% more than HMRM, CSRE and CSMH respectively. This is expected as the workload execution is performed based on QoS-aware resource provisioning policy (Q-aware). Based on deadline of workload, clustering of workloads is performed, and resources are provisioned for effective scheduling. This is also because of the low variation in execution time across various resources as the resource list that is obtained from the resource provisioning unit is already filtered using Q-aware (Singh and Chana, 2015). Based on QoS requirements of a specific workload, resource provisioning consumes little more time to find out the best resources (Singh and Chana, 2015), but later it increases the overall performance of CRUZE. Therefore, underutilization and overutilization of CPU will be assuaged or avoided, which reduces the further queuing time. Fig. 12(d) presents the comparison of datacenter (CDC) temperature for different time intervals. The average value of temperature in CRUZE is 8.46%, 10.45% and 13.33% less than HMRM, CSRE and CSMH respectively. Fig. 12(e) shows the variation of DCS Efficiency for different resource scheduling approaches with different time interval. The average value of DCS Efficiency in CRUZE is 11.46%, 12.75% and 13.01% more than HMRM, CSRE and CSMH respectively. Fig. 12(f) shows the variation of reliability for different algorithms with different value of time interval. The average value of reliability in CRUZE is 9.21%, 9.99% and 10.21% more than HMRM, CSRE and CSMH respectively. Fig. 12(g) presents the comparison of execution time for different time intervals. The average value of execution time in CRUZE is 17.65%, 18.95% and 19.63% less than HMRM, CSRE and CSMH respectively. Fig. 12(h) shows the variation of execution cost for resource management approaches with different time interval. The average value of execution cost in CRUZE is 15.89%, 17.72% and 19.81% less than HMRM, CSRE and CSMH respectively. Fig. 12(i) shows the variation of SLA violation rate for different resource scheduling algorithms with different time interval. The average value of SLA violation rate in CRUZE is 24.35%, 27.29% and 31.42% less than HMRM, CSRE and CSMH respectively. Note: We have considered 36 resources and 3000 workloads for these results.

5.3.2. *Trade-off among different performance parameters*

Fig. 13 shows the trade-off among energy consumption, reliability and CPU utilization for execution of workloads using CRUZE. With increasing energy consumption, the value of CPU utilization and reliability is decreasing while reliability of cloud service is increasing with increase in CPU utilization. It is clearly shown that energy consumption is inversely proportional to reliability and CPU utilization, while reliability is proportional to CPU utilization. Note: We have considered 36 resources and 3000 workloads for these results.

Fig. 14(a) shows the variation of intrusion detection rate for CRUZE, HMRM, CSRE and CSMH. The value of reliability is increasing as Intrusion detection rate increases for all the approaches, but CRUZE performs better than HMRM, CSRE and CSMH. The average value of Intrusion detection rate in CRUZE is 70%.

Latency (L) is defined as a difference between expected execution time and actual execution time. We have used following

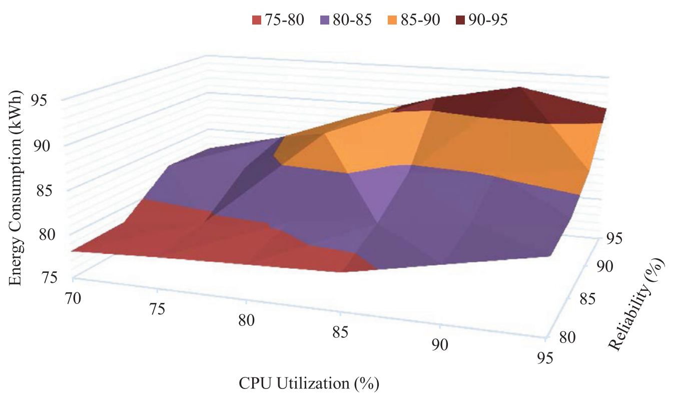


Fig. 13. Trade-off among energy consumption, reliability and CPU utilization.

Table 8
A 10 × 6 subset of the ETC matrix.

Workloads	r_1	r_2	r_3	r_4	r_5	r_6
$\boldsymbol{w}_1$	212.14	341.44	336.65	109.66	150.46	185.58
$\boldsymbol{w}_2$	152.61	178.26	149.78	114.26	198.92	148.69
$\boldsymbol{w}_3$	147.23	190.23	180.26	121.65	141.65	152.69
$\boldsymbol{w}_4$	103.62	159.63	192.85	107.69	139.89	139.36
$\boldsymbol{w}_5$	178.65	171.35	201.05	127.65	169.36	201.66
$\boldsymbol{w}_6$	193.62	142.65	205.36	132.26	188.33	207.72
$\boldsymbol{w}_7$	187.24	138.23	217.58	147.69	112.39	210.98
$\boldsymbol{w}_8$	124.13	110.65	212.39	141.26	135.88	169.35
$\boldsymbol{w}_9$	138.56	123.65	170.26	181.65	116.61	142.87

formula to calculate Latency (Eq. 39):

$$L = \sum_{i=1}^{n} (Expected\ Execution\ Time_i\ - Actual\ Execution\ Time_i) \tag{39}$$

Where n is number of workloads. The value of *[Number of workloads × number on resources]* for every workload on resources is calculated from Expectable Time to Compute (ETC) matrix (Gill et al., 2019). Columns of ETC matrix demonstrate the estimated execution time for a specific workload while rows on ETC matrix demonstrate the execution time of a workload on every resource. In this research work, the ETC benchmark simulation model is used, which has been introduced in (Braun et al., 2001) to address the problem of resource scheduling. The expected execution time of the workloads can be derived from workload task length or historical trace data (Gill et al., 2019). A high variation in execution time of the same workload is generated using the gamma distribution method. In the gamma distribution method, a mean workload execution time and coefficient of variation are used to generate ETC matrix (Ali et al., 2000). Table 8 shows a 10 × 6 subset of the ETC matrix and results provided in this research work used the matrix of size 90 × 36. These are then used to find out the best resource to execute workload with minimum time.

Fig. 14(b) shows the variation of SLA violation rate for CRUZE, HMRM, CSRE and CSMH with different values of latency. The value of SLA violation rate is increasing as latency increases for all the algorithms, but CRUZE performs better than other algorithms. The average value of SLA violation rate is 67%, which is quite less than HMRM, CSRE and CSMH. Fig. 14(c) shows the variation of latency for CRUZE, HMRM, CSRE and CSMH with different value of fault detection rate. Latency is increasing as the value of fault detection rate decreases for all resource scheduling techniques, but CRUZE performs better than other techniques. The average value of latency in CRUZE is 8.32%, 8.49% and 9.31% less than HMRM, CSRE and CSMH respectively. The reduction in failure rate, latency and improvement in fault detection rate increases the reliability in CRUZE.

Fig. 14(d) shows the impact of network bandwidth (bits/seconds) on reliability. The value of reliability is increasing as network bandwidth increases for all the approaches, but the average value of network bandwidth in CRUZE is 9.26%, 10.55% and 11.62% less than HMRM, CSRE and CSMH respectively. Fig. 14(e) shows the impact of datacenter temperature (°C) on reliability. The value of reliability is increasing as datacenter temperature decreases for CRUZE, HMRM, CSRE and CSMH, but CRUZE gives better results as compared to other algorithms. The value of datacenter temperature is 13°C in CRUZE at 95% reliability and the average value of temperature is 21°C in CRUZE. Fig. 14(f) shows the variation of energy consumption for different scheduling techniques with different value of intrusion detection rate. The value of energy consumption is increasing as the value of intrusion detection rate decreases for CRUZE, HMRM, CSRE and CSMH, but CRUZE gives better results and the average value of energy consumption in CRUZE is 79.5 kWh.

Fig. 14(g) shows the trade-off between energy consumption and reliability for all the algorithms and the value of energy consumption is increasing as the value of reliability increases, but CRUZE has better outcome as compared to existing algorithms. The average value of energy consumption in CRUZE is 7.47%, 9.42% and 10.95% less than HMRM, CSRE and CSMH respectively. Fig. 14(h) shows the impact of execution time on energy consumption for different scheduling algorithms and the value of energy consumption is decreasing as the value of execution time increases for all approaches, but CRUZE consumes less energy as compared to existing techniques. Fig. 14(i) shows the variation of energy consumption for CRUZE, HMRM, CSRE and CSMH with different value of execution cost. The value of execution cost is increasing as the value of energy consumption increases and the average value of energy consumption in CRUZE is 64 kWh approximately. Overall CRUZE performs better than other techniques. The variation of energy consumption with different value of latency is shown in Fig. 14(j) and it measures the impact of latency on energy consumption and the consumption of energy is increasing as the value of latency decreases for all the resource scheduling approaches, but CRUZE performs better than others. Fig. 14(k) shows the trade-off between energy consumption and SLA violation rate and the value of energy consumption is increasing as the value of SLA violation rate decreases for all the approaches, but CRUZE performs better than HMRM, CSRE and CSMH. The impact of network bandwidth on energy consumption is measured in Fig. 14(l) and the value of energy consumption is increasing as the value of network bandwidth increases. The value of network bandwidth in CRUZE is 16.68%, 17.35% and 17.99% less than HMRM, CSRE and CSMH respectively.

5.3.3. Straggler analysis

Due to the increased complexity of modern large-CDCs, certain emerging phenomena, which can directly affect the performance of these systems occur (Garraghan et al., 2016). This is also known as the Long Tail Problem, or the scenario where a small number of task stragglers, negatively affect the time of the workload completion. Task stragglers can occur within any highly parallelized system, which processes workloads consisting of multiple tasks. We have analyzed the performance the effect of various parameters on probability of stragglers. Note: We have considered 36 resources and 3000 workloads for these results. Fig. 15(a) shows the probability of stragglers for different percentage of SLA Violation Rate (SVR). The probability of stragglers is increasing as the value of SVR increases for CRUZE, HMRM, CSRE and CSMH, but CRUZE performs better than other resource scheduling techniques. Fig. 15(b) shows the probability of stragglers for different value of energy consumption. The probability of stragglers is increasing as the value of

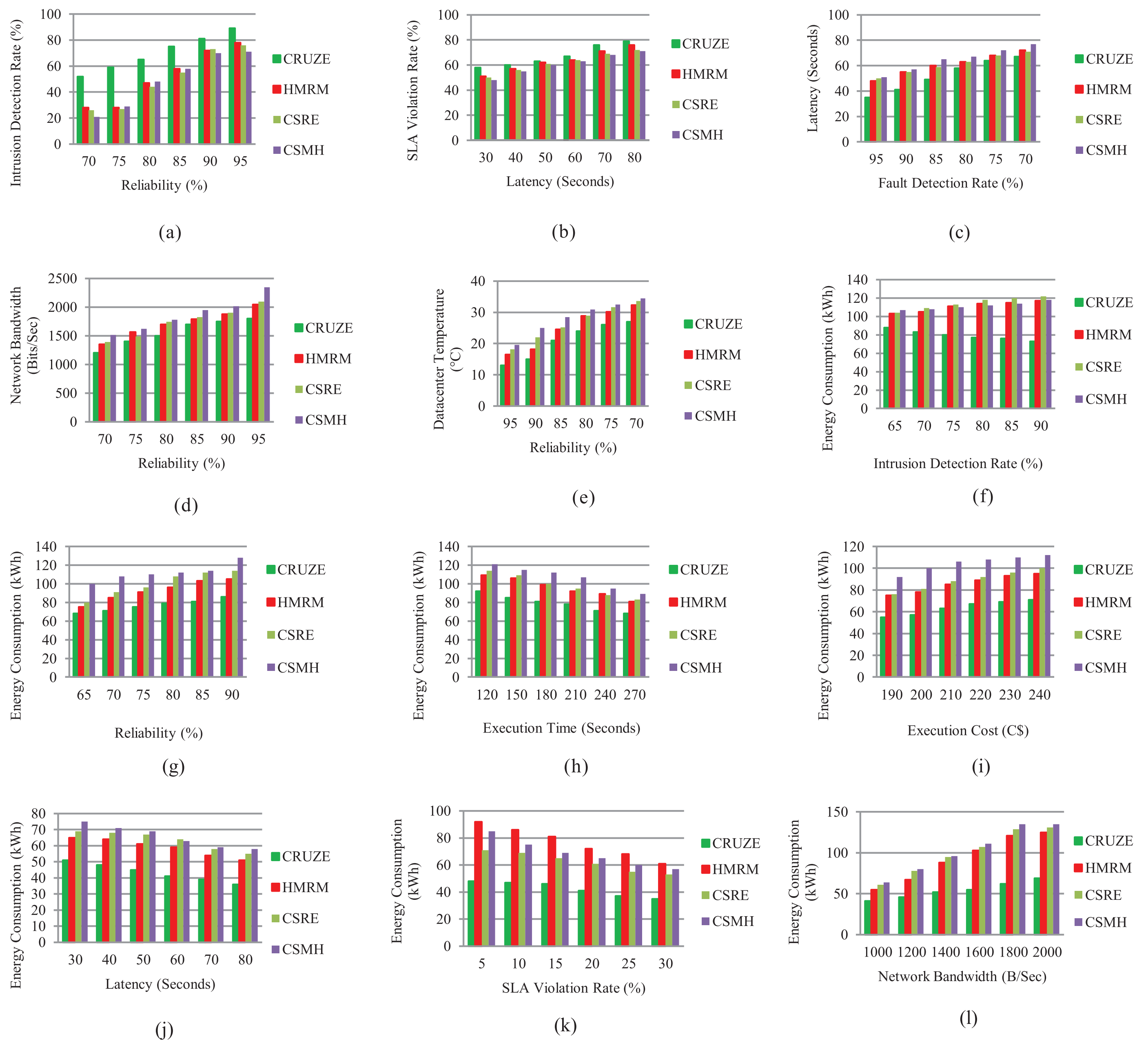


Fig. 14. Trade-off between different performance parameters: (a) Intrusion detection rate vs. reliability, (b) SLA violation rate vs. latency, (c) Fault detection rate vs. latency, (d) Network bandwidth vs. reliability, (e) Datacenter temperature vs. reliability, (f) Energy consumption vs. intrusion detection rate, (g) Energy consumption vs. reliability, (h) Energy consumption vs. execution time, (i) Energy consumption vs. execution cost, (j) Energy consumption vs. latency, (k) Energy consumption vs. SLA violation rate, (l) Energy consumption vs. network bandwidth.

energy consumption increases for all the algorithms, but the value of straggler probability in CRUZE is 5.45%, 5.95% and 6.36% less than HMRM, CSRE and CSMH respectively.

Fig. 15(c) shows the probability of stragglers for different percentage of CPU utilization and its average value in CRUZE is 0.24 and it shows the probability of stragglers is increasing as the value of CPU utilization increases for all the resource scheduling techniques, but CRUZE performs better than others. The probability of stragglers is measured for different value of memory utilization as shown in Fig. 15(d) and probability of stragglers is decreasing as the value of memory utilization increases for different scheduling techniques, but CRUZE performs better than other techniques. Fig. 15(e) shows the probability of stragglers for different value of reliability and it is increasing as the value of reliability increases for CRUZE, HMRM, CSRE and CSMH, but CRUZE gives better results than others. The probability of stragglers for different value of latency is measured in Fig. 15(f) and it shows the probability of stragglers is increasing as the value of latency increases for CRUZE, HMRM, CSRE and CSMH, but CRUZE performs better than other scheduling techniques. The average value of probability of stragglers in CRUZE is 0.41. Fig. 15(g) shows the probability of stragglers for different percentage of network bandwidth and CRUZE gives better results than other techniques but the probability of stragglers is increasing as the value of network bandwidth increases for all the scheduling techniques. Fig. 15(h) shows the probability of stragglers for different percentage of fault detection rate. The probability of stragglers is decreasing as the value of fault detection rate increases for CRUZE, HMRM, CSRE and CSMH, but CRUZE performs better than others. Fig. 15(i) shows the probability of stragglers for different percentage of intrusion detection rate. The

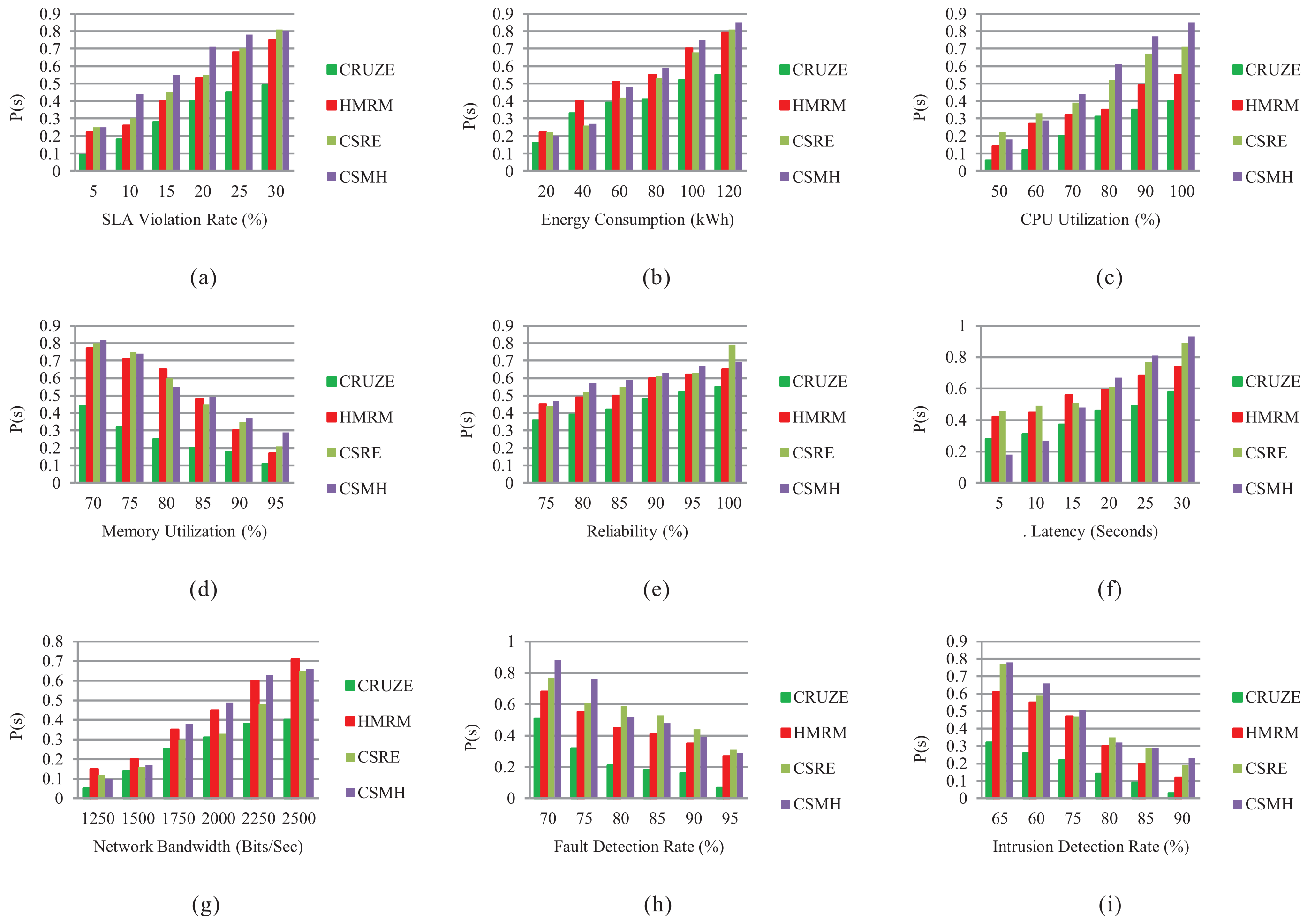


Fig. 15. Analysis of the effect of various performance parameters on Probability of Stragglers (P(s)): (a) SLA violation rate, (b) energy consumption, (c) CPU utilization, (d) Memory utilization, (e) Reliability, (f) Latency, (g) Network bandwidth, (h) Fault detection rate, and (i) Intrusion detection rate.

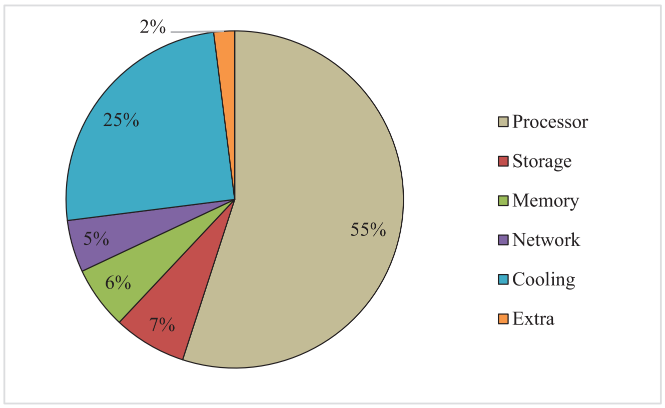


Fig. 16. Energy consumption of different components of CDC in CRUZE.

average value of probability of stragglers in CRUZE is 0.17 and the probability of stragglers is decreasing as the value of intrusion detection rate increases for every approach, but CRUZE performs better than others. The average value of straggler probability in CRUZE is 11.22%, 14.01% and 15.77% less than HMRM, CSRE and CSMH respectively.

5.3.4. *Energy consumption analysis*

Fig. 16 shows the consumption of energy by different components of CDC such as processor, storage, memory, network, cooling and extra using CRUZE as per Eq. (1). The processor is most power hungry component of CDC followed by cooling component. The remaining components (storage, memory, network and extra) consumes energy between 2-7% of total energy consumption by CDC. Note: We have considered 36 resources and 3000 workloads for these results.

5.3.5. *Convergence of CO algorithm*

Fig. 17 plots the convergence of total energy consumed by CO algorithm over the number of iterations for different value of Reliability: 95%, 90% and 85% by executing different number of workloads. Initially the workloads are randomly initialized. Therefore, the total initial energy consumption is very high at 0th iteration. As the algorithm progresses, the convergence is drastic and achieves global minima very quickly. The number of iterations required for the convergence is seen to be 30-45, for our simulated cloud environment. Note: We have considered 36 resources and 3000 workloads for these results.

Table 9 describes summary of experiment statistics and percentage of overall improvement of different performance parameters.

5.3.6. *Statistical analysis*

Statistical significance of the results has been analyzed by Coefficient of Variation (*Coff. of Var.*), a statistical method. Coff. of Var. is used to compare to different means and furthermore offer an overall analysis of performance of the framework used for creating the

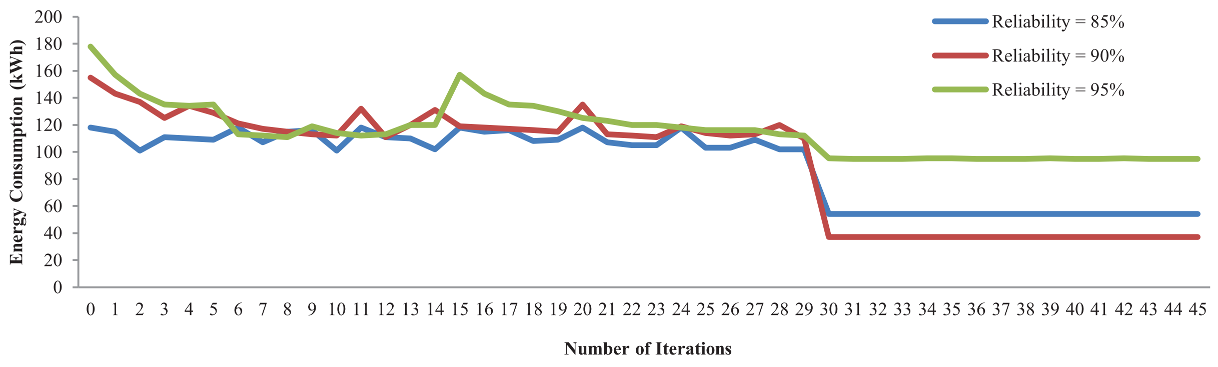


Fig. 17. The trend of convergence of CO with the number of iterations for different value of reliability.

Table 9
Summary of experimental statistics and overall improvement.

Type of experiment	Performance parameter	Overall improvement (%)			Average improvement (%)
		HMRM	CSRE	CSMH	
(Number of Workloads)	Fault detection rate	19.99	21.14	22.45	21.2
	Reliability	19.07	19.75	20.98	19.9
	Execution cost	14.41	14.91	15.46	14.9
	Execution time	9.96	10.35	12.11	10.8
	Intrusion detection rate	19.20	21.45	20.86	20.5
	Network bandwidth	14.44	16.31	18.73	16.49
	SLA violation rate	23.68	24.42	27.45	25.18
	Availability	12.45	13.91	15.34	13.9
	Resource contention	17.56	18.79	19.42	18.59
	Memory utilization	24.78	25.45	25.91	25.38
	Disk utilization	18	18.5	19.18	18.56
	Network utilization	12.77	11.68	12.25	12.23
	CPU utilization	11.12	14.45	15.69	13.75
	Energy consumption	17.35	18.71	20.10	18.8
	VM co-location cost	6.25	6.91	7.15	6.8
	Datacenter temperature	13.76	14.91	15.30	14.7
	Energy reuse effectiveness	17.46	19.45	20.99	19.3
	Recirculation ratio	3.42	4.77	4.97	4.4
	DCS efficiency	9.98	10.23	11.56	10.6
(Time in Hours)	Memory utilization	27.77	28.11	29.12	28.3
	Energy consumption	14.46	15.35	18.86	16.2
	CPU utilization	12.55	13.91	14.04	13.5
	Datacenter temperature	8.46	10.45	13.33	10.8
	DCS Efficiency	11.46	12.75	13.01	12.4
	Reliability	9.21	9.99	10.21	9.8
	Execution time	17.65	18.95	19.63	18.74
	Execution cost	15.89	17.72	19.81	17.8
	SLA violation rate	24.35	27.29	31.42	27.68

statistics. It states the deviation of the data as a proportion of its average value, and is calculated as follows (Eq. 40):

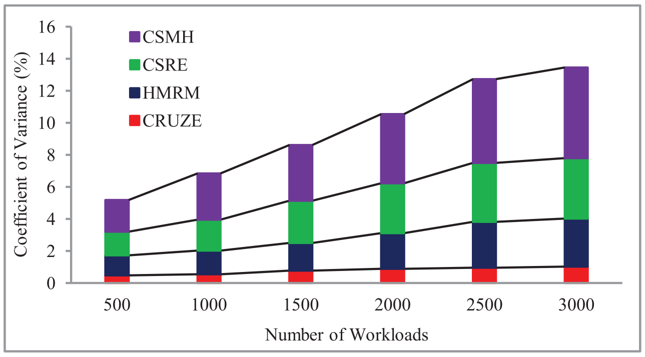
$$Coff.\ of\ Var.\ = \frac{SD}{\mathrm{M}} \times 100 \tag{40}$$

where SD is a standard deviation and M is a mean. *Coff. of Var.* of waiting time of CRUZE, HMRM, CSRE and CSMH is shown in Fig. 18(a). Range of *Coff. of Var.* (0.48% - 1.03%) for energy consumption approves the stability of CRUZE.

Coff. of Var. of reliability of CRUZE, HMRM, CSRE and CSMH is shown in Fig. 18(b). Range of *Coff. of Var.* (0.63% - 1.33%) for reliability approves the stability of CRUZE. Value of *Coff. of Var.* increases as the number of workloads is increasing. Small value of *Coff. of Var.* signifies CRUZE is more efficient and stable in resource management in the situations where the number of cloud workloads are changing. CRUZE attained the better results in the cloud for energy consumption and reliability has been studied with respect to number of workloads. This research work is a practical implementation of the conceptual models that we proposed in our previous research work (Gill and Buyya, 2019; Gill and Buyya, 2018b).

6. Summary and conclusions

We proposed a Cuckoo Optimization (CO) algorithm based resource scheduling approach called CRUZE, for holistic management of all resources (spanning servers, networks, storage, cooling systems) to improve the energy efficiency and reduce carbon footprints in cloud datacenters and whilst maintaining cloud



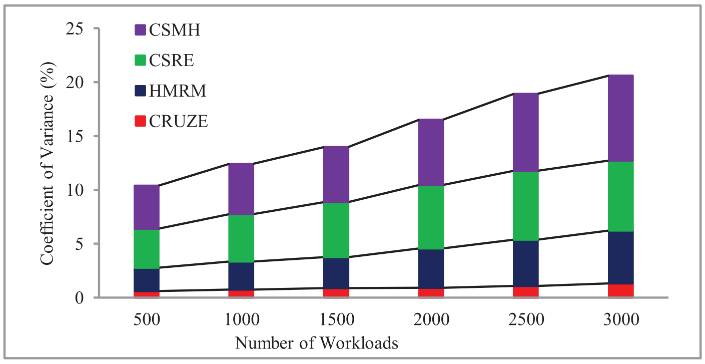


Fig. 18. Coefficient of variation for algorithms (a) energy consumption, (b) reliability.

service reliability by managing the failures (hardware, service, software or resource) dynamically. Furthermore, CRUZE schedules provisioned resources for heterogeneous workload execution and it adjusts the resources at runtime according to the QoS requirements of workloads, which can avoid or assuage under-utilization and over-utilization of resources. Experimental results demonstrate that CRUZE improves the fault detection rate by 15.42%, reliability by 17.11%, intrusion detection rate by 20.46%, CPU utilization by 15.69%, memory utilization by 25.91%, disk utilization by 19.18%, network utilization by 12.25%, energy reuse effectiveness by 20.56%, recirculation ratio by 4.97% and DCS Efficiency by 11.56% and it reduces the latency by 8.32%, execution cost by15.46%, execution time by 12.11%, energy consumption by 20.10%, VM Co-Location Cost by 7.15% and datacenter temperature by 15.30% as compared to existing resource management approaches. Finally, the trade-off among energy consumption, reliability and resource utilization for execution of workloads is described.

6.1. Future research directions and open challenges

In the future, we shall explore the applicability of the present model and any potentially needed extensions in the following main directions.

First, the modeling components for workflows analysis and QoS based characterization shall be extended with knowledge of the external context that may inform our holistic management approach. This may require to use additional modeling constructs that help capture the non-functional requirements of each particular application. This is similar to the common technique of prioritization of jobs, for example, depending on the usage context the same workflow can be launched with different priorities.

Second, we shall study possible extensions of the model to include exchange of information and actual hardware, networking, software, storage, heat, and other resources with any other resources from the environment (Gill and Buyya, 2019). For example, micro-data centers may be placed in blocks of flats, and the actual heating, ventilation, and air conditioning HVAC (Heating, Ventilation and Air Conditioning) systems (Buyya and Gill, 2018) may actually use the thermal energy generated by the micro-data center. Moreover, jobs scheduling could happen during periods that inhabitants usually spend at home, which in turn may define the hourly rate for hosting computations (Mastelic et al., 2015). An economy of resources like these may be facilitated by recent development in the area of Blockchain and Smart Contracts, but, it is still necessary to study the theoretical foundations which may potentially lead to energy efficient management of highly distributed Fog computing environments.

Third, many new applications rely on the Internet of Things (IoT) and have particular focus on Big Data management. There is the necessity to implement Big Data pipelines starting from the IoT via Fog and Cloud nodes up to High-Performance Data Centers (Li et al., 2018a; Balis et al., 2018). This requires the streaming of significant amounts of data over the network, which in turn represents various management challenges, involving energy efficiency, time-critical operations, and similar (Kaur et al., 2018). Some of these aspects were tackled by the present study, nevertheless, more in-depth simulations are necessary to study the various arrangements of system components that lead to quasi-optimal states.

Fourth, the unplanned downtime can violate the SLA and affects the business of cloud providers. To solve this problem, proposed technique (CRUZE) should incorporate dynamic scalability to fulfill the changing demand of user applications without the violation of SLA, which helps to improve the sustainability and reliability of cloud services during peak load. Further, the scalability provides operational capabilities to improve performance of cloud computing applications in a cost-effective way, yet to be fully exploited. However, holistic resource management mechanisms need to be able to strategically use these capabilities.

Finally, relationship between theory and practice is very important. Benchmarking is an important starting point, which may try to relate the holistic aspects studied in our simulation in real-world practice. For example, various workflow-based applications performing similar calculations, could be related among each other by analyzing the entire hardware and software stack, including virtualization. This may lead to additional improvements of the theoretical basis.

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References

Abbasi, M.J., Mohri, M., 2016. Scheduling tasks in the cloud computing environment with the effect of Cuckoo optimization algorithm. SSRG Int. J. Comput. Sci. Eng. (SSRG - IJCSE) 3 (August 8), 1–9.

Ali, S., Siegel, H.J., Maheswaran, M., Hensgen, D., Ali, S., 2000. Representing task and machine heterogeneities for heterogeneous computing systems. Tamkang J. Sci. Eng. 3 (3), 195–207.

Azimzadeh, F., Biabani, F., 2017. Multi-objective job scheduling algorithm in cloud computing based on reliability and time. In: 2017 Third International Conference on Web Research (ICWR). IEEE, pp. 96–101.

Balis, B., Brzoza-Woch, R., Bubak, M., Kasztelnik, M., Kwolek, B., Nawrocki, P., Nowakowski, P., Szydlo, T., Zielinski, K., 2018. Holistic approach to management of IT infrastructure for environmental monitoring and decision support systems with urgent computing capabilities. Fut. Gener. Comput. Syst. 79, 128–143.

Barroso, L.A., Clidaras, J., Hoelze, U., 2013. The datacenter as a computer: an introduction to the design of warehouse-scale machines. Synth. Lect. Comput. Architect. (July).

Braun, T.D., Siegel, H.J., Beck, N., Bölöni, L.L., Maheswaran, M., Reuther, A.I., Robertson, J.P., et al., 2001. A comparison of eleven static heuristics for mapping a class of independent tasks onto heterogeneous distributed computing systems. J. Parallel Distrib. Comput. 61 (6), 810–837.

Buyya, R., Gill, S.S., 2018. Sustainable cloud computing: foundations and future directions.. Bus. Technol. Digital Transform Strat. Cutter Consortium 21 (6), 1–10.

Calheiros, R.N., Ranjan, R., Beloglazov, A., De Rose, C.A.F., Buyya, R., 2011. CloudSim: a toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms. Softw.: Pract. Exp. 41 (1), 23–50.

Chang, C.W., Liu, C.-Y., Yang, C.-Y., 2017. Energy-efficient heterogeneous resource management for wireless monitoring systems. J. Syst. Softw. 131, 168–180.

Deb, K., 2019. Constrained multi-objective evolutionary algorithm. In: Evolutionary and Swarm Intelligence Algorithms. Springer, Cham, pp. 85–118.

Feller, E., Rohr, C., Margery, D., Morin, C., 2012. Energy management in IaaS clouds: a holistic approach. In: 2012 IEEE Fifth International Conference on Cloud Computing (CLOUD). IEEE, pp. 204–212.

Ferrer, A.J., HernáNdez, F., Tordsson, J., Elmroth, E., Ali-Eldin, A., Zsigri, C., Sirvent, R., et al., 2012. OPTIMIS: a holistic approach to cloud service provisioning. Fut. Gener. Comput. Syst. 28 (1), 66–77.

Garraghan, P, Solis Moreno, I., Townend, P., Xu, J., 2014. An analysis of failure-related energy waste in a large-scale cloud environment. IEEE Trans. Emerg. Top. Comput. 2 (2), 166–180.

Garraghan, P., Ouyang, X., Yang, R., McKee, D., Xu, J., 2016. Straggler root-cause and impact analysis for massive-scale virtualized cloud datacenters. IEEE Trans. Serv. Comput..

Gill, S.S., Buyya, R., 2018a. Resource provisioning based scheduling framework for execution of heterogeneous and clustered workloads in clouds: from fundamental to autonomic offering. J. Grid Comput. 1–33.

Gill, S.S., Buyya, R., 2018b. Failure management for reliable cloud computing: a taxonomy, model and future directions. Comput. Sci. Eng. IEEE doi:10.1109/MCSE.2018.2873866.

Gill, S.S., Buyya, R., 2018c. SECURE: Self-Protection Approach in Cloud Resource Management. IEEE Cloud Comput. 5 (1), 60–72.

Gill, S.S., Buyya, R., 2019. A taxonomy and future directions for sustainable cloud computing: 360 degree view. ACM Comput. Surv. 51 (5), 104.

Gill, S.S., Chana, I., Buyya, R., 2017. IoT based agriculture as a cloud and big data service: the beginning of digital India. J. Org. End User Comput. (JOEUC) 29 (4), 1–23.

Gill, S.S., Chana, I., Singh, M., Buyya, R., 2018. CHOPPER: an intelligent QoS-aware autonomic resource management approach for cloud computing. Cluster Comput. 21 (2), 1203–1241.

Gill, S.S., Chana, I., Singh, M., Buyya, R., 2019. RADAR: self-configuring and self-healing in resource management for enhancing quality of cloud services. Concurrency Comput. Pract. Exp. (CCPE) 31 (1), 1–29.

Grozev, N., Buyya, R., 2013. Performance modelling and simulation of three-tier applications in cloud and multi-cloud environments. Comput. J. 58 (1), 1–22.

Guitart, J., 2017. Toward sustainable data centers: a comprehensive energy management strategy. Computing 99 (6), 597–615.

Guzek, M., Kliazovich, D., Bouvry, P., 2013. A holistic model for resource representation in virtualized cloud computing data centers. In: 2013 IEEE Fifth International Conference on Cloud Computing Technology and Science (CloudCom), 1. IEEE, pp. 590–598.

Karellas, S., Braimakis, K., 2016. Energy–exergy analysis and economic investigation of a cogeneration and trigeneration ORC–VCC hybrid system utilizing biomass fuel and solar power. Energy Convers. Manage. 107, 103–113.

Kaur, A., Singh, V.P., Gill, S.S., 2018. The future of cloud computing: opportunities, challenges and research trends. In: Second International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud). IEEE, pp. 213–219.

Kouki, Y., Ledoux, T., 2012. Sla-driven capacity planning for cloud applications. In: 2012 IEEE Fourth International Conference on Cloud Computing Technology and Science (CloudCom). IEEE, pp. 135–140.

Shafie, A.L.M., Madni, S.H.H., Abdullahi, M., 2018. Fault tolerance aware scheduling technique for cloud computing environment using dynamic clustering algorithm. Neural Comput. Appl. 29 (1), 279–293.

Lazic, N., Boutilier, C., Lu, T., Wong, E., Roy, B., Ryu, M.K., Imwalle, G., 2018. Data center cooling using model-predictive control. In: Advances in Neural Information Processing Systems, pp. 3814–3823.

Lebre, A., Legrand, A., Suter, F., Veyre, P., 2015. Adding storage simulation capacities to the SIMGRID toolkit: Concepts, models, and api. In: 2015 Fifteenth IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing. IEEE, pp. 251–260.

Li, X., Jiang, X., He, Y., 2014. Virtual machine scheduling considering both computing and cooling energy. In: 2014 IEEE Intl Conf on High Performance Computing and Communications, 2014 IEEE Sixth Intl Symp on Cyberspace Safety and Security, 2014 IEEE Eleventh Intl Conf on Embedded Software and Syst (HPCC, CSS, ICESS),. IEEE, pp. 244–247.

Li, M., Qin, C., Li, J., Lee, P.P.C., 2016. CDStore: toward reliable, secure, and cost–efficient cloud storage via convergent dispersal. IEEE Internet Comput. 20 (3), 45–53.

Li, X., Garraghan, P., Jiang, X., Wu, Z., Xu, J., 2018b. Holistic virtual machine scheduling in cloud datacenters towards minimizing total energy. IEEE Trans. Parallel Distrib. Syst. 29 (6), 1317–1331.

Li, X., Jiang, X., Garraghan, P., Wu, Z., 2018a. Holistic energy and failure aware workload scheduling in Cloud datacenters. Fut. Gener Comput. Syst. 78, 887–900.

Liu, Z., Chen, Y., Bash, C., Wierman, A., Gmach, D., Wang, Z., Marwah, M., Hyser, C., 2012. Renewable and cooling aware workload management for sustainable data centers. ACM SIGMETRICS Perform. Eval. Rev. 40 (1), 175–186 ACM.

Liu, B., Chen, Y., Blasch, E., Pham, K., Shen, D., Chen, G., 2014. A holistic cloud-enabled robotics system for real-time video tracking application. In: Future Information Technology. Springer, Berlin, Heidelberg, pp. 455–468.

Liu, X., Harwood, A., Karunasekera, S., Rubinstein, B., Buyya, R., 2017. E-Storm: replication-based state management in distributed stream processing systems. In: Proceedings of the Forty-Sixth International Conference on Parallel Processing, ICPP 2017. USA, Bristol, UK. IEEE CS Press August 14-17.

Luo, C., Yang, L.T., Li, P., Xie, X., Chao, H.-C., 2015. A holistic energy optimization framework for cloud-assisted mobile computing. IEEE Wirel. Commun. 22 (3), 118–123.

Luo, L., Li, H., Qiu, X., Tang, Y., 2016. A resource optimization algorithm of cloud data center based on correlated model of reliability, performance and energy. In: 2016 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C), Vienna, pp. 416–417.

Möbius, C., Dargie, W., Schill, A., 2014. Power consumption estimation models for processors, virtual machines, and servers. IEEE Trans. Parallel Distrib. Syst. 25 (6), 1600–1614.

Madni, S.H.H., Shafie, A.L.M., Abdulhamid, S.M., 2017. Optimal resource scheduling for IaaS cloud computing using Cuckoo search algorithm. Sains Humanika 9 (1-3).

Mastelic, T., Oleksiak, A., Claussen, H., Brandic, I., Pierson, J.-M., Vasilakos, A.V., 2015. Cloud computing: survey on energy efficiency. ACM Comput. Surv. 47 (2), 33.

Moore, J.D., Chase, J.S., Ranganathan, P., Sharma, R.K., 2005. Making scheduling. In: USENIX Annual Technical Conference, General Track Cool: Temperature-Aware Workload Placement in Data Centers., pp. 61–75.

Moreno, I.S., Garraghan, P., Townend, P., Xu, J., 2014. Analysis, modeling and simulation of workload patterns in a large-scale utility cloud. IEEE Trans. Cloud Comput. 2 (2), 208–221.

Natu, M., Ghosh, R.K., Shyamsundar, R.K., Ranjan, R., 2016. Holistic performance monitoring of hybrid clouds: complexities and future directions. IEEE Cloud Comput. 3 (1), 72–81.

Navimipour, N.J., Milani, F.S., 2015. Task scheduling in the cloud computing based on the cuckoo search algorithm. Int. J. Model. Optim. 5 (1), 44.

Nita, M.C., Pop, F., Mocanu, M., Cristea, V., 2014. FIM-SIM: fault injection module for CloudSim based on statistical distributions. J. Telecommun. Inf. Technol. 4, 14.

Oxley, M.A., Jonardi, E., Pasricha, S., Maciejewski, A.A., Siegel, H.J., Burns, P.J., Koenig, G.A., 2018. Rate-based thermal, power, and co-location aware resource management for heterogeneous data centers. J. Parallel Distrib. Comput. 112, 126–139.

Pérez, J.F., Chen, L.Y., Villari, M., Ranjan, R., 2018. Holistic workload scaling: a new approach to compute acceleration in the cloud. IEEE Cloud Comput. 5 (1), 20–30.

Poola, D., Ramamohanarao, K., Buyya, R., 2016. Enhancing reliability of workflow execution using task replication and spot instances. ACM Transactions on Autonomous and Adaptive Systems (TAAS), 10. ACM Press, New York, USA ISSN:1556-4665.

Qinghui, T., Gupta, S.K.S., Varsamopoulos, G., 2008. Energy-efficient thermal-aware task scheduling for homogeneous highperformance computing data centers: a cyber-physical approach. IEEE Trans. Parallel Distrib. Syst. 19 (11), 1458–1472.

Qu, C., Calheiros, R.N., Buyya, R., 2016. A reliable and cost-efficient auto-scaling system for web applications using heterogeneous spot instances. In: Journal of Network and Computer Applications (JNCA), 65. Elsevier, Amsterdam, The Netherlands, pp. 167–180. ISSN: 1084-8045.

Rajabioun, R., 2011. Cuckoo optimization algorithm. Appl. Soft Comput. 11 (8), 5508–5518.

Shahdi-Pashaki, S., Teymourian, E., Kayvanfar, V., Komaki, G.H.M., Sajadi, A., 2015. Group technology-based model and cuckoo optimization algorithm for resource allocation in cloud computing. IFAC-PapersOnLine 48 (3), 1140–1145.

Sharma, Y., Javadi, B., Si, W., Sun, D., 2016. “Reliability and energy efficiency in cloud computing systems: survey and taxonomy. J. Netw. Comput. Appl. 74, 66–85.

Shuja, J., Gani, A., Shamshirband, S., Ahmad, R.W., Bilal, K., 2016. Sustainable cloud datacenters: a survey of enabling techniques and technologies. Renewable Sustainable Energy Rev. 62, 195–214.

Singh, S., Chana, I., 2015. Q-aware: quality of service based cloud resource provisioning. Comput. Electr. Eng. 47, 138–160.

Singh, S., Chana, I., 2015. QRSF: QoS-aware resource scheduling framework in cloud computing. J. Supercomput. 71 (1), 241–292.

Singh, S., Chana, I., 2016. A survey on resource scheduling in cloud computing: issues and challenges. J. Grid Comput. 14 (2), 217–264.

Singh, S., Chana, I., 2016. EARTH: energy-aware autonomic resource scheduling in cloud computing. J. Intell. Fuzzy Syst. 30 (3), 1581–1600.
Sitaram, D., Phalachandra, H.L., Gautham., S, Swathi, H.V., Sagar, TP, 2015. Energy efficient data center management under availability constraints. In: 2015 Annual IEEE Systems Conference (SysCon) Proceedings, Vancouver, BC, pp. 377–381.
Sundarrajan, R., Vasudevan, V., 2016. An optimization algorithm for task scheduling in cloud computing based on multi-purpose Cuckoo seek algorithm. In: International Conference on Theoretical Computer Science and Discrete Mathematics, Cham. Springer, pp. 415–424.
Taherizadeh, S., Jones, A.C., Taylor, I., Zhao, Z., Stankovski, V., 2018. Monitoring self-adaptive applications within edge computing frameworks: a state-of-the-art review. J. Syst. Softw. 136, 19–38.
Tschudi, B.I.L.L., O.T.T.O. Vangeet, J. Cooley, and D. Azevedo. "ERE: a metric for measuring the benefit of reuse energy from a data center." White Paper29 (2010).
Gill, S.S., Garraghan, P., Buyya, R., 2019. ROUTER: Fog Enabled Cloud based Intelligent Resource Management Approach for Smart Home IoT Devices. J. Syst. Softw. 154, 125–138.
Singh, S., Chana, I., 2013. Consistency verification and quality assurance (CVQA) traceability framework for SaaS. In: 3rd IEEE International Advance Computing Conference (IACC). IEEE, pp. 1–6.
Yang, X.-S., 2014. Swarm intelligence based algorithms: a critical analysis. Evol. Intell. 7 (1), 17–28.
Youn, C.-H., Chen, M., Dazzi, P., 2017. Cloud Broker and Cloudlet for Workflow Scheduling. Springer, Singapore.
Zhang, S, Chatha, K S, 2007. Approximation algorithm for the temperature aware scheduling problem. In: Proceedings of International Conference on Computer-Aided Design, pp. 281–288.
Zhou, A., Wang, S., Zheng, Z., Hsu, C.-H., Lyu, M.R, Yang, F., 2016. On cloud service reliability enhancement with optimal resource usage. IEEE Trans. Cloud Comput. 4 (4), 452–466.

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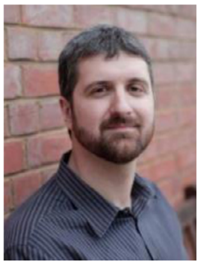
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