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Energy-Cost Efficient of Secure Dynamic Data Virtualization in Multi-Tenant Data Centers

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ABSTRACT: The rapid growth in the data storage and data processing demands the energy consumption of data centers. Recently it became a major issue in large data centers due to financial and environmental concerns. Virtual Machine (VM) allocation for multiple tenants is an important and challenging problem to provide efficient infrastructure services in cloud data centers. Tenants run applications on their allocated VMs and the network distance between a tenants'. VMs may considerably impact the tenant's Quality of Service (QoS). Existing two greedy approximation algorithms like Minimum Energy virtual machine Scheduling algorithm (MinES) and Minimum Communication virtual machine Scheduling algorithm (MinCS) had been proposed to reduce the consumption of energy in data centers. But in this, network cost is more and it has to satisfy the Quality of Service while shifting the load between data centers. In order to overcome this drawback, we proposed secure Dynamic Data Virtualization (DDV) algorithm, which reduces the *CPU utilization, energy consumption* in data centers, *cost* and more number of requests can be sent to the server is demonstrated. The performance of the DDV algorithm with the real-time constraint of both VMs and Physical Machines (PMs).
Keywords: Cost, Energy, Multi-Tenants, Real-time, Virtual machine, Physical machine

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I. INTRODUCTION

The wider approval of Cloud and virtualization technologies has led to the arrangement of huge scale data centers that consume extreme energy and have considerable carbon footprints, where energy efficiency is appropriately growing essential for cloud and data centers [1]. Cloud computing has come forward as a very flexible service standard by allowing Cloud Service Providers (CSPs) and users to involve Virtual Machine (VM) resources on-demand and to supply VM resources via a pay-as-you-go model. The problem of allocating efficient VM resources to Physical Machines (PMs) with the goal of reducing the consumption of energy is solved. On the other hand, even if energy-proportional PMs are equipped with the cloud systems [2]. The security office of US condition evaluated that in 2006 about 1.5 percent of the cumulative US power consumption is utilized in order to manage data centers. This accounts for a gross 61 billion kWh and costs the dazzling US $4.5 billion. By 2010, this number had as of now achieved 2 percent in the US and 1.3 percent on the whole and in 2013 US data centers are said to have devoured 91 billion kWh equal to about US$10 billion.

The Energy consumption of a data center is an outcome of several resources such as CPU utilization, power supply units, memory utilization, cooling systems and disk storage boxes. The energy measured in terms of Joule's. According to a Google study, idle servers consume around 50% of their peak power and it is reported that the energy consumed by data centers worldwide has risen by 56% from 2005 to 2010 and it is about 1.5% of the global electricity use in 2010. Furthermore, the percentage will be doubled by 2020, if the current trends continue. High energy consumption not only means tremendous energy-related costs but also has negative impacts on the environment to reduce energy consumption in industry after reporting that Information and Communication Technology (ICT) is responsible for about 2% of the global carbon emissions, equivalent to aviation. To save power, it is therefore important to switch servers to the sleep mode when they are not in use. This requires the development of novel techniques that can monitor PMs and effectively decide whether and when they need to be put in sleep mode [3].

Considering that a typical data center is underutilized (precisely 5 to 20% of server utilization) much of the time, the energy cost can be greatly reduced by consolidating service requests and/or running applications into as few servers as possible and shutting down the surplus servers [4]. In general, pursuing energy efficiency conflicts with maintaining the adherence to the Service Level Agreement (SLA). Despite the lack of a unified definition for the SLA, the most used are based on the percentage of available VMs with respect to those requested [5], [6].

The computing resources can be organized as a service to support the users' demand. Therefore, the computing service in cloud computing can be accessed efficiently and flexible. Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) are the general service levels provided for users. IaaS is one of the common approaches used in the cloud computing, where the virtualization technology is adopted effectively [7]. Server virtualization allows applications to share the underlying hardware by running in isolated Virtual Machines (VMs) [5], which is configured with a certain amount of computing resources (such as CPU, memory, and I/O). For efficient resource usage, the capacity of VMs belonging to different applications needs to be adjusted dynamically to match the time-varying resource demands [8], [9]. Cloud data centers typically make extensive use of virtualization technology, in order to ensure isolation of applications while at the same time allowing a healthy utilization of physical resources. Good VM allocation helps to serve as many customer requests as possible with the given set of resources, and thus amortizing the expenses related to purchasing, operations, and maintenance of the equipment (computing, network, and storage elements, as well as the physical data center infrastructure with cooling, redundant power supplies, etc.). Data virtualization is an agile data integration approach organizations use to gain more insight from their data, respond faster to ever changing analytics and BI needs and saves 50-75% over data replication and consolidation. An effective means to save energy conservation to achieve energy efficient data center in the cloud is to adopt the optimal load balancing techniques, which try to improve the performance by evenly distributing the workload to minimize the enormous energy consumption of overloaded servers in cloud data centers [10]. Multi-tenant VM allocation in cloud data centers is a type of NP-hard problem. Tenants run applications on their allocated VMs and the network distance between a tenants' VMs may significantly impact the tenant's QoS. A recent study by Cisco predicts that cloud traffic will grow 12-fold by 2015.

1.1 Motivation

This paper was motivated by the problem of reducing the energy consumption in multi-tenant cloud data centers to assess their performance for different metrics. Existing algorithms such as MinES and MinCS in the presence of bandwidth guarantees as an integer programming problem [5]. There is still a lack of a methodology that empowers users for instant access to all the data they want, the way they want it and which also allows the scheduler to assign multiple requests possibly coming from different users to the same PM. The user requests are thus referred to as Virtual Machine (VM) requests. To fill this gap in algorithms for the maximum utilization of resources and communication between VMs, a technique called Dynamic Data virtualization (DDV) is proposed to achieve the above-said requirements in the cloud data center. The real-time constraint of both VMs and PMs, which is often neglected in writing, is considered.

1.2 Contribution

Contributions of this paper are: proposing an algorithm for reducing the consumption of energy in a data center and achieving good resource utilization that enhances cloud computing by allowing creation of multiple virtual machines over the underlying hardware; focusing on lowering of power consumption where existing algorithms (MinES and MinCS) still lack; designing and implementing a novel efficient secure technique is called as Dynamic Data Virtualization (DDV) combining real-time resource information. Data Virtualization offers the following novel features:

1) Providing an essential system mechanism which has good flexibility, security, fault tolerance, easy management including data centers, VMs, and physical machines.
2) Provides the opportunity to use an auto-scaling technique that dynamically allocates computational resources of the services to precisely match their current loads, thereby removing resources that would otherwise remain idle
3) Also, allows the scheduler to assign multiple requests possibly coming from different clients to the same PM.

***Organization*:** This paper is structured as follows. In section II, we discuss the related work. The problem definition is presented in section III. The system model is introduced in section IV. The analysis of the algorithm is as shown in section V. The performance evaluation is described in section VI. Finally, the conclusions is drawn in section VII.

II. RELATED WORK

We analyze the various energy, cost efficiency and virtual machine in different methods.

Parikh *et al*., [11] observe that from a user point of view cloud computing make able to use and install their applications from wherever on this globe and interest at focused QoS (Quality of Service) necessities. To provide these services on demand constantly, internally it uses many technologies like virtualization, terminal service, clustering, application server and more. Cloud computing environment contains data center which has enormous resources and a list of applications that are willing to use them by creating and allocating a virtual machine to the exact application which provides resources to the application. VM allocation algorithm allocates the virtual machines to the host of the data center, the task allocation algorithm act as load balance policy. Jiaxin Li *et al*., [3] observe the problem in existing methods generally result in significant differences in the QoS among multiple tenants and low utilization of cloud data centers. To solve this problem, based on the Layered Progressive Multiple Knapsack Problems resource allocation algorithm called LP-MKP is proposed. In this, the multi-tenant VM allocation problem in cloud data centers, considering the VM requirements of different tenants is defined and initiating the allocation goal of lowering the sum of the VMs network diameters of all tenants. The LPMKP algorithm uses a layered multi-stage progressive process for multi-tenant VM allocation and efficiently handles unprocessed tenants at each stage. This decreases the differences in the QoS among tenants, reduces resource fragmentation in cloud data centers and enhances tenants overall QoS in cloud data centers [12].

Beloglazov *et al*., [13] solves the host overload detection problem in the online setting by maximizing the mean inter-migration time, while meeting the QoS goal are generally heuristic based or rely on statistical analysis of historical data. The limitations of these approaches are that they lead to suboptimal results and do not allow explicit specification of a QoS goal. A novel approach that for any known stationary workload and a given state configuration optimally solves the problem of host overload detection by maximizing the mean inter-migration time under the specified QoS goal based on a Markov chain model is displayed. Heuristically the algorithm to handle unknown on stationary workloads using the multi-size sliding window workload estimation technique is adapted. Kumbhare *et al*., [14] motivated the need for online monitoring and adaptation of continuous data flow applications to meet their QoS constraints in the presence of data and infrastructure variability. Develop the concept of dynamic data flows which utilize alternate tasks as additional control over the data flow's cost and QoS [15]. Two greedy heuristics, centralized and shared, based on the variable-sized bin-packing algorithm and compare against a Genetic Algorithm (GA) based heuristic that gives a near-optimal solution is put forward. Constraints while maximizing its value, experimental results show that the continuous adaptation heuristics which makes use of application dynamism can reduce the execution cost by up to 27.5% on clouds while also meeting the QoS constraints.

Alasaad *et al*., [7] studies the problem of resource allocations for media streaming applications in the cloud to choose on both the right quantity of resources kept in the cloud and their reservation time which minimizes the financial cost. A plain easy to implement an algorithm for resource reservation that maximally reduces discounted rates presented in the tariffs while ensuring that adequate resources are reserved in the cloud is proposed. It characterizes the streaming command on the Internet. The MinES and MinCS algorithms that optimally find out both their reservation time and a number of reserved resources in the cloud based on a guess of future demand [5]. Li *et al*., [16] investigate more useful algorithms for predicting the ending times of game sessions by studying the problem of how to transmit the play requests to the cloud servers in a cloud gaming system. The dispatching approach of play requests may greatly involve the total service cost of the cloud gaming system is presented. The play request dispatching problem can be considered as an alternative to the dynamic bin-packing problem. Proposed scheme assigns play requests as per the predicted ending times of game sessions. The decrease in the resource waste is mainly considerable for match-based games.

Gaggero *et al*., [6] present the improvement of proper mechanisms to lower the impact of VM migrations on the SLA working toward the implementation of the prototype by depicting an approach of predictive control for energy-aware consolidation of VMs in a cloud computing infrastructure. Proposed approach tells about virtual machines which are properly migrated among physical machines to reduce the number of active units and it allows one to trade among power savings and violations of the service level agreement. Liu *et al*., [10] observe that the server overload problem in cloud storage systems which prevents providing the deadline guaranteed services. A new form of SLAs, which enables each tenant to specify a percentage of its requests it wishes to serve within a specified deadline is introduced. First, the several objectives in developing schemes to satisfy the SLAs are identified. A Parallel Deadline Guaranteed (PDG) scheme, which schedules data reallocation through load re-assignment and data replication using a tree-based bottom-up parallel process, is proposed. Two algorithms: i) a prioritized data reallocation algorithm which tells the request arrival rate variation, and ii) an adaptive request retransmission algorithm that deals with SLA requirement variation. Results dynamically move data request load from overloaded servers to under loaded servers to ensure the SLAs for tenants. Xu *et al*., [17] pay little attention to the incurred performance interference and cost on both source and destination servers during and after VM migration. To avoid potential violations of Service Level Agreement (SLA) demanded by cloud applications, iAware is a lightweight interference-aware VM live migration strategy. iAware is flexible enough to cooperate with existing VM scheduling or consolidation policies in a complementary manner, such that the load balancing or power saving can still be achieved without sacrificing performance is demonstrated. iAware can qualitatively estimate VM performance interference, and improve I/O and network throughput and execution durations.

Zaman *et al.*, [1] in order to generate higher profit, addressed the problem of dynamically provisioning VM instances in clouds while finding the allocation of VM with a combinatorial auction-based mechanism. A technique called CA-PROVISION to solve the problem and performed effective simulation experiments with real workloads to evaluate is designed. This mechanism assures the VMs dynamically and it does not require the evaluation of the workload characteristics, rather the current demand for VMs is captured. Dalvandi *et al.*, [18] investigate the routing problem and VM placement which allocates both network resources and server for the particular time duration to offer resource guarantees. A novel time-aware request model which tells tenants to identify an expected required time-duration in the count to their required server resources for their communication through Virtual Machines (VMs) and network bandwidth is proposed, in addition to this a switch migration and server-migration approaches which migrate the VMs between the powered-on servers. The usefulness of the proposed heuristics in requisites of power saving, migration, and acceptance ratio overhead using complete simulation results is demonstrated. Wolke *et al.*, [19] dealing with the problem of assigning VMs with volatile demands to physical servers in a static way such that energy costs are minimized. This has led to a new stream in the capacity planning literature. There is hardly any empirical evidence for the benefits of dynamic resource allocation so far. Private cloud environments with a stable set of business applications that need to be hosted as VMs on a set of servers is mainly focused. With typical workloads of transactional business applications dynamic resource allocation does not increase energy efficiency over the static allocation of VMs to servers and can even come at a cost is demonstrated.

Gook *et al.*, [20] in order to overcome the challenges of implementing dynamic pricing and energy consumption scheduling. The proposed reinforcement learning algorithms that allow each of the service provider and the customers to learn its strategy without a prior information about the micro grid. Reinforcement learning-based dynamic pricing algorithm can effectively work without a priori information about the system dynamics is showed and the proposed energy consumption scheduling algorithm further reduces the system cost thanks to the learning capability of each customer. Two improvements, Energy consumption-based Approximate State (EAS) definition and the adoption of virtual experience update in the conventional Q-learning algorithms are observed.

Belabed *et al.*, [21] investigate the impact of these novel features in DCN optimization by providing a comprehensive mathematical formulation and a repeated matching heuristic for its resolution. In particular, how virtual bridging and multipath forwarding impact common DCN optimization goals, Traffic Engineering (TE) and Energy Efficiency (EE), and assess their utility in the various cases of four different DCN topologies is investigated. How Traffic Engineering (TE) and Energy Efficiency (EE) goals in virtual machine placement can coexist with the emergence of virtual bridging and of multipath forwarding is demonstrated.

Ramezani *et al.*, [22] solves the mapping problem the VM migration process can affect the performance of applications unless it is supported by smart optimization methods. A multi-objective optimization model to address this issue is presented. The objectives are to minimize power consumption, maximize resource utilization (or minimize idle resources), and minimize VM transfer time. Fuzzy Particle Swarm Optimization (PSO), which improves the efficiency of conventional PSO by using fuzzy logic systems, is relied upon to solve the optimization problem. The proposed algorithm competes efficiently with other promising approaches to the problem. Hwang *et al.*, [4] analyzed that the virtual machine consolidation in a cloud computing environment is an approach of decreasing daily energy consumption of the system. The demands are treated as random variables with known standard deviations and means. These random variables may be associated with one another and there are multiple types of resources which can be performance bottlenecks. As a result, both resource type heterogeneity and correlations must be measured. The problem of virtual machine consolidation is thus calculated as bin packing stochastic multi-capacity problem.

Octavio *et al.*, [23] proposes distributed problem solving system for load management supported by VM live migration in data centers. Collaborative agents are capable within energy-aware consolidation protocol and a load balancing protocol to consolidate and balance heterogeneous loads while reducing energy consumption costs in a disseminated manner. A novel load balancing heuristic that transfers the VMs cause the largest resource usage imbalance from overloaded hosts to underutilized hosts whose resource usage imbalances is reduced the most by hosting the VMs. Movahed *et al.*, [24] addressed the problem of designing efficient mechanisms for Virtual Machine (VM) and dynamic VM provisioning and allocation in clouds by drawing truthful mechanisms. This problem is formulated as an integer program considering several types of resources for the auction-based model then greedy and optimal mechanisms are designed such that the cloud provider provisions VMs based on the requests of the winning users and determines their payments. Using real workload traces are done so as to investigate the performance and promising results in terms of revenue for the cloud provider are achieved.

Nguyen *et al*., [25] deals with the problem of best flow assignment for a virtual slice that allows improving energy efficiency and dealing with intermittent renewable power sources based on software defined paradigms in order to provide environmentally conscious services recommendation for cloud worker. Such dynamic processes involve optimized and flexible networking format to enable elastic virtual tenants across multiple physical nodes. Zotkiewicz *et al*., [26] presented a novel methodology named Minimum Dependencies Energy-efficient DAG scheduling (MinD+ED) that operates in data centers and dynamically schedules workflows consisting of interrelated tasks in an energy-efficient and communication aware fashion. The proposed scheduling strategy combines the advantages of state of the art workflow scheduling strategies with energy-aware independent task scheduling approaches. The process of scheduling consists of two phases. In the first phase, virtual deadlines of individual tasks are set in the central scheduler. These deadlines are determined using a novel strategy that favors tasks which are less dependent on other tasks [27].

Lama *et al.*, [8] came across complexity and increasing scale of virtualized server systems hosting multi-service multi-tier applications create considerable challenges to performance. APPLE ware, an autonomic middleware for power control and the joint performance of co-placed web applications in virtualized data centers is proposed and developed. It marks a distributed control structure that offers expectable energy efficiency and performance for large complex systems. Based on self-adaptive modeling, a machine learning to capture the time-varying relationship and complex between the allocation of resources and application performance to various application components, in the look of highly dynamic busty workloads is submitted [28].

III. PROBLEM DEFINITION

The problem of MinEC and MinCS algorithms consumes more energy and high network cost during virtual machine's allocation in data centers.

3.1 Objective

The main aim of this paper is to provide a proportional learning of the performance of energy efficiency of virtual machines in a cloud data center and thereby choosing the optimal scheduling algorithm. To achieve this, the successive tasks are performed: i) To study the various techniques by comparing the performance of various algorithms by considering metrics like energy consumption, CPU utilization, threshold limit and Processing cost. ii) To choose the renowned energy-efficient VM algorithm that accomplishes in minimizing the energy consumption, which will further fade away CPU utilization and carbon diffusion rate that is the dreadful need of cloud computing systems. Hence, Data virtualization is used for eschewing profound overload on the resources and intersects the traffic amidst data and servers. Files can be sent and received without much delay. This virtualization of data enables to reduce the total waiting time of the resources. Thus, Data virtualization helps to accomplish fair allocation of each computing resource in data centers.

3.2 Physical Server Energy Consumption

If a server is idle the energy consumption is $P_{idle}(P_{busy})$. If a server is running at a normalized speed, the use of physical server (u) CPU speed measured as u ε [0, 1] the server energy consumption calculated as

$$P(u) = P_{idle} + (P_{busy} - P_{idle}) \times u^{\varepsilon} \qquad (1)$$

Where ε is a constant that depends on the type of physical server. The P_{idle} is the real data is around $0.6{\times}P_{busy}$ and is seldom lower than $0.5{\times}P_{busy}$. The exponent ε can set to 1 without loss of generality from Google data centers [5].

IV. SYSTEM MODEL

The Fig. 1, shows the System model for Data Virtualizations. The error messages are developed to alert the user whenever anyone commits some mistakes and guides him in the right way so that invalid entries are not made. There are three main modules to design a system model.

1) Data Owner
2) Cloud Service Provider (CSP)
3) End User

Let us see deeply about this system module for design.

Data Owner: In this module data owner created by Cloud Service Provider (CSP), initially creates the virtual machines and allocates memory and threshold limit for all the created VMs respectively. Then the data owner is secondly responsible for browsing files from the database and uploading those file to cloud server, thereby due to the process respected virtual machines memory and threshold will be decreasing based on the file uploaded. User authentication procedures are maintained at the initial stages itself. A new user may be created by the administrator himself or a user can himself register as a new user but the task of assigning projects and validating a new user rests with the administrator only.

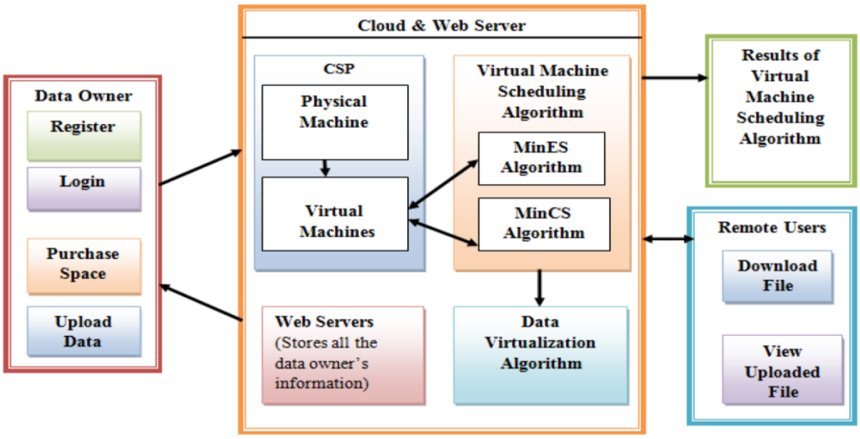

Fig. 1. The System model for Data Virtualizations.

Cloud Service Provider (CSP): The Cloud server is responsible on behalf of the file content provider for both allocating the appropriate amount of resources in the cloud and reserving the time over which the required resources are allocated. CSP creates a virtual machine for each resource requested by the user by giving VMs name, memory space and threshold limit. Cloud server will store all the data owner information and stores all the end users information and it also allows access to the information through IP network.

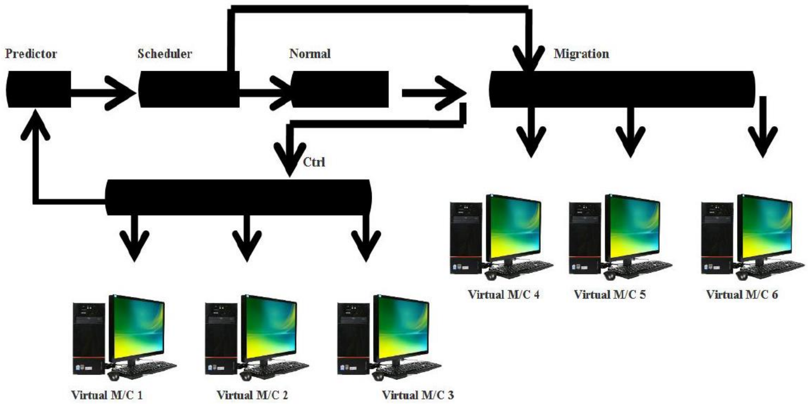

Fig. 2. The detailed design of Data Virtualization.

End User: In this, module end user can download the file content. Before downloading user has to register first, in this case, data owner will create an end user to access their files. Later user can login to the cloud and download the files. The user can also view the uploaded files and they can access the file. Every Authorized user can download the files according to their requirement.

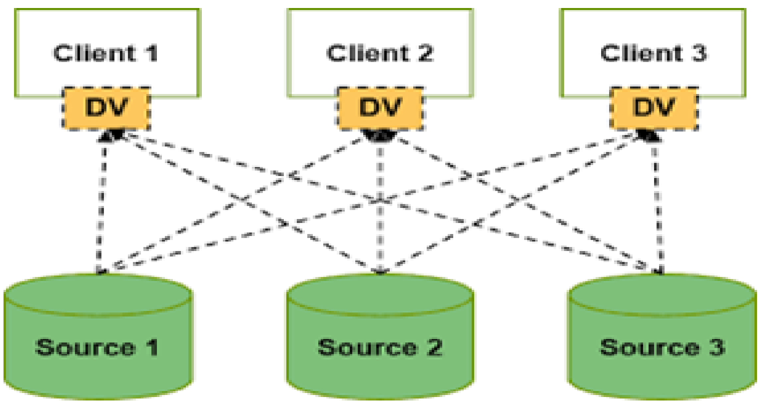

Fig. 3. The internal design of Data Virtualizations.

The detailed design of Data Virtualization (DV) as illustrated in Fig. 2. The authenticated users can allocate their virtual memory when they requested. The allocated memory is used by the users when they upload files. If the virtual memory is available or not predicted by the predictor then the memory available is scheduled and store into respective virtual memory. This process is called "virtual memory without migration". The user upload file size is more than the allocated memory then the file is moved to another virtual machine, this process is called "virtual memory with migration". Example, let us take virtual machine1 (M/C) having the memory size is 20GB, user 1 used 10GB for upload a file. The user 2 requests virtual memory of size 10GB, the machine 1 allocates but he upload a file of size 15GB, it is not available in machine1 only 10GB available, then predictor checks the virtual machine 4, if it is available to allocate and stores in it. This process is called virtual memory with migration. Otherwise, the memory allocated virtual machine1 (VM1). The internal connection of different sources, client's and data virtualizations as illustrated in Fig. 3.

V. ALGORITHM

5.1 Proposed Algorithm

The Dynamic Data Virtualization (DDV) is a process of pushing all the information which is there in the lower database level to the user upper level.

Algorithm 1: Dynamic Data Virtualization (DDV) of different virtual machines.

```
Input: {F'_i to F'_{i+1}}, {V_j to V_{j+1}}, {D_k to D_{k+1}}
Output: Vir{F'_i to F'_{i+1}}
BEGIN
Set: initialize {V_j to V_{j+1}}  ← { D_k to D_{k+1}}
while {V_j + V_{j+1}  == Running } do
        Pick Request R_q
        R_q ← { V_j to V_{j+1} ↔ F_i to F_{i+1} }
        F_i(D_k) =  dk = new F_i(D_k)
        dk(l) = {V_j to V_{j+1}}  ↔ F_i to F_{i+1}
        l = l+1
        Vir[dk(l)] ← object[F_i to F_{i+1}]
        low_level ← Vir[dk(l)]
        high_level ← object[F_i to F_{i+1}]
                for (m=0; m< high_level; m++) do
                        push ← object[m]
                        set user U_i ← Request R_i
                        U_i ← R_i ← object[m]
                        U_i = high_level {object[m]}
                        U_i = Access {Vir[F_i to F_{i+1}]
END
```

This leads to the lower consumption of energy by the virtual machines in the data centers which in turn reduces the CPU Utilization, number of requests can be sent, users are no longer need to wait for much time, energy saving in all possible scenarios, the system becomes feasible and network cost is reduced by the algorithm. The algorithm 1 describes the virtualization of data by the virtual machine in data centers. As an input will take number of files as F_i, number of virtual machines as V_i and Data centers as D_k.

The output will get Virtualized Files in the sense the files present in the lower database level is available in the higher user level.

VI. PERFORMANCE EVALUATION

The energy consumption, cost consumption, bandwidth consumption, weight consumption using DDV, MinES and MinCS algorithms are computed. We analyzed the performance of different algorithms. The energy consumption in VM's without Migration is illustrated in Table I.

Table I

Energy consumption in vm's without migration.

	DDV	MinCS	MinES	mPP
VM1	2.377	4.754	7.131	9.509
VM2	0.601	1.202	1.803	11.886
VM3	2.387	4.774	7.161	14.263

Table II

Energy consumption in vm's without migration.

	DDV	MinCS	MinES	mPP
VM1	2.377	4.754	7.131	9.509
VM2	0.601	1.202	1.803	11.886
VM3	0	0	0	0

Table III

Total cost consumption in vm's.

	DDV	MinCS +MinES
VM1	37.540	55.080
VM2	42.020	75.040
VM3	57.740	93.480

Table IV

Total weight consumption in vm's

	DDV	MinCS +MinES
VM1	63.580	77.160
VM2	52.140	94.280
VM3	78.593	92.186

The energy consumption is measured in Joule where as more energy of power is measured in kWh. In DDV algorithm the energy consumption is very less when compare to MinCS, MinES and mPP algorithms. The different VM's consumes different energy as shown in Table I. The Energy consumption in VM's with Migration is illustrated in Table II. The energy consumption is measured in kWh. In DDV algorithm the energy consumption is very less when compare to MinCS, MinES and mPP algorithms. The different VM's consumes different energy as shown in Table II. The Total cost consumption in VM's are allocated by the user as shown in Table III. The cost is measured in the dollar ($). In DDV algorithm the cost consumption is very less when compare to MinCS with MinES algorithms. Because of the dynamic virtualization of resources. The different VM's consumes different energy as shown in Table III. The total weight of the energy consumption in VM's as illustrated in Table IV. The total weight consumption for different VM's is less in DDV algorithm when compared to MinES with MinCS algorithms. The total bandwidth consumption for different VM's is shown in Table V. In DDV algorithm consumes less bandwidth when compare to MinES with MinCS algorithm. The energy consumption when uploading a file is as shown in Fig. 4. The user needs resources, initially, request resources then the resources available the VM's allocated if the requested memory is not available with checks for another memory if it's available then allocated otherwise the user will wait for until VM's are free.

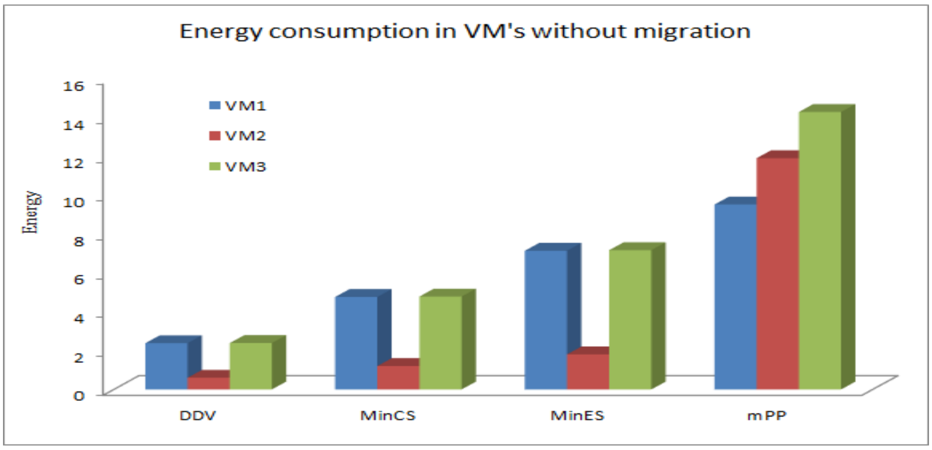

Fig. 4. The energy consumption without migration.

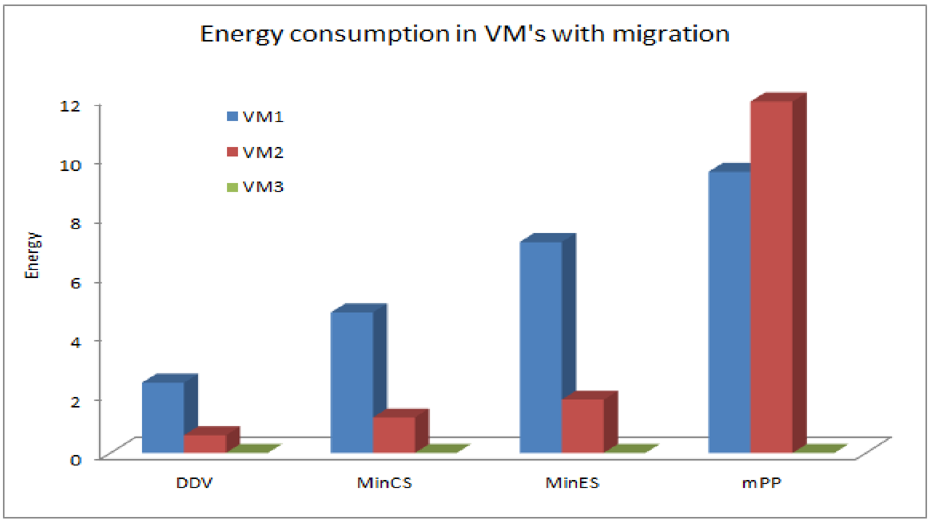

Fig. 5. The energy consumption with migration.

The user uploads a file the predictor checks his VM's allocated if it's free then store into their VM's and calculates the energy of the files. This is called energy without migration. The different energy consumption's for VM's using DDV, MinES, MinCS and mPP algorithm as shown in Table I. In DDV algorithm whenever user uploads a file VM's will be allocated and VM's available dynamically so the energy consumption is less when compared to MinES, MinCS and mPP algorithm because these algorithms statically allocated at initial time user request. The user didn't want VM's they are free by requesting using DDV algorithm. It's not possible in MinES, MinCS and mPP algorithm.

The energy consumption when uploading a file is as shown in Fig. 5. The user needs resources, initially request resources then the resources available the VM's allocated if the requested memory is not available with checks for another memory if it's available then allocated otherwise the user will wait for until VM's are free. The user upload a file the predictor checks his VM's the memory is not available of their file size, the file transfer to available VM's. The energy consumes more in the migration of a file. This is called energy with migration. In DDV algorithm whenever a user uploads a file VM's will be allocated and VM's available dynamically so the energy consumption is less when compared to MinES, MinCS and mPP algorithm because these algorithms statically allocated at initial time user request. The user didn't want VM's they are free by requesting using DDV algorithm. It's not possible in MinES, MinCS and mPP algorithm.

The cost consumption when uploading a file is as shown in Fig. 6. In DDV algorithm whenever a user uploads a file VM's will be allocated and VM's available dynamically so the cost consumption is less when compared to MinES, MinCS and mPP algorithm because these algorithms statically allocated at initial time user request. The user didn't want VM's they are free by requesting using DDV algorithm. It's not possible in MinES, MinCS and mPP algorithm.

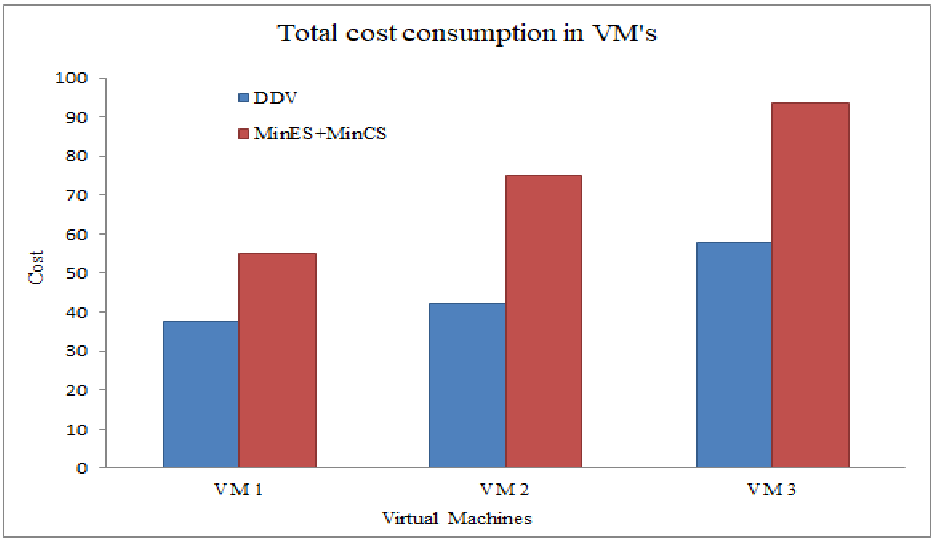

Fig. 6. The total Cost consumption in different virtual machine's.

The bandwidth consumption when uploading a file is as shown in Fig. 7. In DDV algorithm whenever user

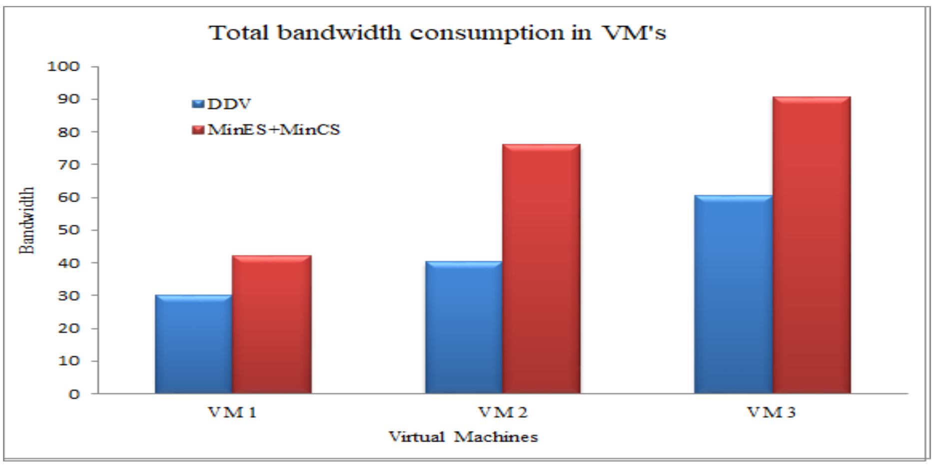

Fig. 7. The bandwidth consumption of the file.

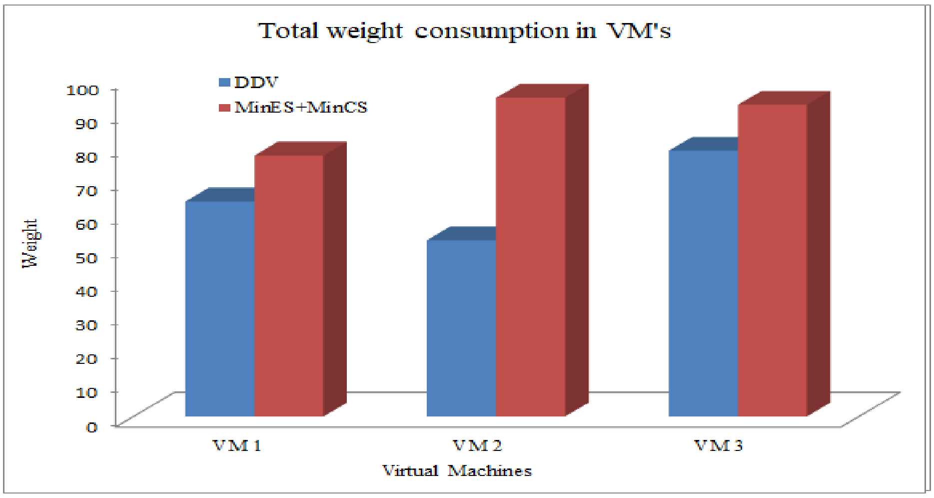

Fig. 8. The Total weight consumptions in virtual machines.

uploads a file VM's will be allocated and VM's available dynamically so the bandwidth consumption is less when compared to MinES, MinCS and mPP algorithm because these algorithms statically allocated at initial time user request. The user didn't wants VM's they are free by requesting using DDV algorithm. It's not possible in MinES, MinCS and mPP algorithm. The weight consumption when uploading a file is as shown in Fig. 8. In DDV algorithm whenever a user uploads a file VM's will be allocated and VM's available dynamically so the weight consumption is less when compared to MinES, MinCS and mPP algorithm because these algorithms statically allocated at initial time user request. The user didn't want VM's they are free by requesting using DDV algorithm. It's not possible in MinES, MinCS and mPP algorithm.

VII. CONCLUSIONS

In this paper, we initially defined the base vitality VM planning for server farms within the sight of data transfer capacity ensures as a number of programming issue and demonstrated its NP-hardness. To tackle the issue successfully, *MinES* and *MinCS* algorithms are used. Both algorithms are consume *more energy* and increases their *cost*. To overcome this drawback, we proposed a secure *Dynamic Data Virtualization (DDV)* algorithm. The virtual machines are allocated when request by the user's. The DDV algorithm reduces the *CPU utilization*, *energy consumption*, *cost* in data centers and network *bandwidth* by more number of requests can be sent to the server is demonstrated.

REFERENCES

[1]. S. Zaman and D. Grosu, "A combinatorial auction-based mechanism for dynamic VM provisioning and allocation in clouds," IEEE Transactions on Cloud Computing, vol. 1, no. 2, pp. 129–141, 2013.
[2]. Y. Song, Y. Sun, and W. Shi, "A two-tiered on-demand resource allocation mechanism for VM-based data centers," IEEE Transactions on Services Computing, vol. 6, no. 1, pp. 116–129, 2013.
[3]. J. Li, D. Li, Y. Ye, and X. Lu, "Efficient multi-tenant virtual machine allocation in cloud data centers," Tsinghua Science and Technology, vol. 20, no. 1, pp. 81–89, 2015.
[4]. M. Pedram et al., "Hierarchical, portfolio theory-based virtual machine consolidation in a compute cloud," IEEE Transactions on Services Computing, 2016.
[5]. X. Dai, J. M. Wang, and B. Bensaou, "Energy-efficient virtual machines scheduling in multi-tenant data centers," IEEE Transactions on Cloud Computing, vol. 4, no. 2, pp. 210–221, 2016.
[6]. M. Gaggero and L. Caviglione, "Predictive control for energy-aware consolidation in cloud datacenters," IEEE Transactions on Control Systems Technology, vol. 24, no. 2, pp. 461–474, 2016.
[7]. A. Alasaad, K. Shafiee, H. M. Behairy, and V. C. Leung, "Innovative schemes for resource allocation in the cloud for media streaming applications," IEEE Transactions on Parallel and Distributed Systems, vol. 26, no. 4, pp. 1021–1033, 2015.
[8]. P. Lama, Y. Guo, C. Jiang, and X. Zhou, "Autonomic performance and power control for co-located web applications in virtualized data centers," IEEE Transactions on Parallel and Distributed Systems, vol. 27, no. 5, pp. 1289–1302, 2016.
[9]. P. Muthi Reddy, S. H. Manjula, and K. R. Venugopal, "Secure data sharing in cloud computing: A comprehensive review," International Journal of Computer (IJC), vol. 25, no. 1, pp. 80–115, 2017.
[10]. G. Liu, H. Shen, and H. Wang, "Deadline guaranteed service for multitenant cloud storage," IEEE Transactions on Parallel and Distributed Systems, vol. 27, no. 10, pp. 2851–2865, 2016.
[11]. K. Parikh, N. Hawanna, H. PK, N. C. S. Iyengar et al., "Virtual machine allocation policy in cloud computing using cloudsim in java," International Journal of Grid and Distributed Computing, vol. 8, no. 1, pp. 145–158, 2015.
[12]. P. Muthi Reddy, S. H. Manjula, and K. R. Venugopal, "Sdspg: Secured data sharing with privacy as a group in cloud computing," International Journal of Current Advanced Research (IJCAR), ISSN: 2319-6505, vol. 7, no. 2, pp. 10036–10043, 2018. DOI: http://dx.doi.org/10.24327/ijcar.2018.10043.1683.
[13]. A. Beloglazov and R. Buyya, "Managing overloaded hosts for dynamic consolidation of virtual machines in cloud data centers under quality of service constraints," IEEE Transactions on Parallel and Distributed Systems, vol. 24, no. 7, pp. 1366–1379, 2013.
[14]. A. G. Kumbhare, Y. Simmhan, M. Frincu, and V. K. Prasanna, "Reactive resource provisioning heuristics for dynamic data flows on cloud infrastructure," IEEE Transactions on Cloud Computing, vol. 3, no. 2, pp. 105–118, 2015.

[15]. P. Muthi Reddy, R. Dasar, R. Tanuja, S. H. Manjula, and K. R. Venugopal, “COIRS: Cost optimized identity based ring signature with forward secrecy in cloud computing,” International Journal of Computer Science and Information Security (IJCSIS), vol. 16, no. 3, pp. 71–79, 2018.

[16]. Y. Li, X. Tang, and W. Cai, “Play request dispatching for efficient virtual machine usage in cloud gaming,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 25, no. 12, pp. 2052–2063, 2015.

[17]. F. Xu, F. Liu, L. Liu, H. Jin, B. Li, and B. Li, “iaware: Making live migration of virtual machines interference-aware in the cloud,” IEEE Transactions on Computers, vol. 63, no. 12, pp. 3012–3025, 2014.

[18]. A. Dalvandi, M. Gurusamy, and K. C. Chua, “Time-aware VM flow placement, routing, and migration for power efficiency in data centers,” IEEE Transactions on Network and Service Management, vol. 12, no. 3, pp. 349–362, 2015.

[19]. A. Wolke, M. Bichler, and T. Setzer, “Planning vs. dynamic control: Resource allocation in corporate clouds,” IEEE Transactions on Cloud Computing, vol. 4, no. 3, pp. 322–335, 2016.

[20]. B.-G. Kim, Y. Zhang, M. van der Schaar, and J.-W. Lee, “Dynamic pricing and energy consumption scheduling with reinforcement learning,” IEEE Transactions on Smart Grid, vol. 7, no. 5, pp. 2187–2198, 2016.

[21]. D. Belabed, S. Secci, G. Pujolle, and D. Medhi, “Striking a balance between traffic engineering and energy efficiency in virtual machine placement,” IEEE Transactions on Network and Service Management, vol. 12, no. 2, pp. 202–216, 2015.

[22]. F. Ramezani, M. Naderpour, and J. Lu, “A multi-objective optimization model for virtual machine mapping in cloud data centres,” in Fuzzy Systems (FUZZ-IEEE), IEEE International Conference on. IEEE, 2016, pp. 1259–1265.

[23]. J. O. Gutierrez-Garcia and A. Ramirez-Nafarrate, “Collaborative agents for distributed load management in cloud data centers using live migration of virtual machines,” IEEE transactions on services computing, vol. 8, no. 6, pp. 916–929, 2015.

[24]. M. M. Nejad, L. Mashayekhy, and D. Grosu, “Truthful greedy mechanisms for dynamic virtual machine provisioning and allocation in clouds,” IEEE transactions on parallel and distributed systems, vol. 26, no. 2, pp. 594–603, 2015.

[25]. K. K. Nguyen and M. Cheriet, “Environment-aware virtual slice provisioning in green cloud environment,” IEEE Transactions on services computing, vol. 8, no. 3, pp. 507–519, 2015.

[26]. M. ˙Zotkiewicz, M. Guzek, D. Kliazovich, and P. Bouvry, “Minimum dependencies energy-efficient scheduling in data centers,” IEEE Transactions on Parallel and Distributed Systems, vol. 27, no. 12, pp. 3561– 3574, 2016.

[27]. M. Pantazoglou, G. Tzortzakis, and A. Delis, “Decentralized and energy efficient workload management in enterprise clouds,” IEEE transactions on cloud computing, vol. 4, no. 2, pp. 196–209, 2016.

[28]. P. Muthi Reddy, S. H. Manjula, and K. R. Venugopal, “Time optimization for authentic and anonymous group sharing in cloud storage,” International Journal of Computer Engineering and Technology (IJCET), vol. 9, no. 2, pp. 16–31, 2018.

Muthi Reddy P “Energy-Cost Efficient of Secure Dynamic Data Virtualization in Multi-Tenant Data Centers” International Journal of Computational Engineering Research (IJCER), vol. 08, no. 09, 2018, pp. 28-38.