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Research Article

ANALYSIS OF AN ENHANCED AND RELIABLE BALANCE MAINTENANCE COSTS AND DISTRIBUTED ENERGY IN CLOUD DATA CENTERS

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ABSTRACT:

The achievements of cloud computing services have led to large, managed and very expensive computing infrastructures. In particular, the operating costs of major infrastructure are dominated by power supply and various solutions must be introduced to reduce such operating costs and make the entire infrastructure sustainable. Typically, data center operators face three significant problems with the operation of their data centres: increased electricity bills, increasing carbon footprints and unexpected power outages.For this purpose the operation of micro grid data centers is a good choice because microgrid solutions can improve energy efficiency, sustainability and electrical services reliability. We consider EcoMultiCloud as an already proposed charging strategy for multi-objectif charging strategies in the literature and adapt it to the presence of renewable energy sources. The cost savings are therefore achieved during the load assignment process when virtual machines (VMs), by considering the energy costs variations and the presence of renewable energy production, are assigned to a data center of the considered infrastructure.For a specific infrastructure made up of four data centres, performance is analyzed. Results show that, while intermittent and highly variable, in geographical data centers renewable energy can be efficiently exploited by the implementation of an intelligent charge allocation strategy. The results also confirm that EcoMultiCloud is extremely flexible and appropriate for the scenario considered.

1. INTRODUCTION

The most common way of delivering modern software is cloud computing. The formal definition of cloud computing has been given as a broad-sized distributed computing paradigm based on economies of scale in [81] in order to supply external customers with an on-demand pool of abstract, virtualised, dynamically scalable, managed compputing power, storage, platforms and services. Basically, the Internet provides users with computing resources remotely.

In this paper, we present a new approach to the efficient use of the RES in a distributed data center scenario through adjustment and refinement of a literary workload management strategy, that is, EcoMultiCloud[2]. EcoMultiCloud includes a hierarchical architecture for geo-distributed data center management and a set of algorithms that drive virtual machine assignment and transition (VM) based on management's technical and business objectives. EcoMultiCloud consists of two layers: each location on the lower layer adopts its own strategy for internally distributing and consolidating workloads.In the top layer, the behavior of single sites is assessed and the workload distributed by a series of algorithms – shared by all sites. This architecture offers several advantages, which include I scalability because the major workload allotment problem has been decompiled into a smaller intradatacenter and the interdatacenter problem; (ii) autonomy for single data centres, as every data center can adopt its own algorithm for internal allocation;

Ata Centers (DCs) became an important component in the field of information technology and communication (ICT).From a historic point of view, it dates back to the first part of the nineteenth century when the concept of global brain [1] was defined by various prominent scientists,[2] with the aim of providing encyclopedic wisdom. In the meantime the incredible growth in the ICT sector has revolutionized the ability of DCs to be used for computing purposes completely, including the improvements in HardWare (HW) production and the almost infinite characteristics provided by SoftWare (SW).DCs are now widely distributed throughout the world to support several applications, including web browsing, streaming, video high definition, and cloud storage. It is not surprising that DCs generally use the cloud computing paradigm [3], [4], whereby virtualized applications (and all operating systems), which can even be located on various continents, are running on a number of distributed physical servers. Therefore, Cloud Data Center (CDC) management is a key aspect for the DC owner (which is referred as a content provider from here on).

2. RELATED WORK

2.1 Cloud Control

Cloud control often takes account of energy efficiency. We categorises cloud control approaches relevant to the work presented in this thesis into methods for: (1) scaling CPU frequencies in PMs hosting VMs, (2) initial VM placement, (3) subsequent dynamic VM reallocation using live migration and (4) the optimisation theory used to find the best allocation strategy.

2.1.1 CPU Frequency Scaling

In many studies, frequency scaling has been focused to reduce energy use by reducing the CPU frequency. The cloud planner assigns the incoming jobs to VMs based on the user SLAs. Each VM is assigned the minimum resource requirement and the low-compressor CPU frequencies of the PMs are decreased to minimize resource waste without affecting the performance of the work. In the proposed scheduler, the queued VMs are allocated with the PMs while at the same time reducing the running frequencies for a VM performance requirement, preferably for PMs with lower frequencies.

2.2 Energy Efficiency Legislation

Energy efficiency controls exist in data centers - metrics like power efficiency (PUE) [9] (CUE), water efficiency [8] and other have been fundamentally turned into industry standards by joint efforts of the policy makers and cloud providers behind the Green Grid consortium |7]. The energy efficiency control measures are the main focus of industry standards. The problem with these measurements however is that they focus only on the efficiency of infrastructure – transforming as much energy into IT equipment computing.But once the electricity reaches the IT equipment, every formal regulation of energy efficiency stops making it a black box approach. That's why we are trying to bring the internal operation of clouds - the resource scheduling - with energy efficiency control.

Overview

As discussed in the initial section, the majority of approaches proposed were to resolve the whole problem centrally and risk causing the three main problems; low scalability because of problem size, heterogeneity, the capacity to adapt poorly to changing conditions (e.g. changes in workload, electricity pricing, or carbon dioxide).In order to deal efficiently with such issues, we believe that part of the intelligence needs to be decentralized and decision-making points distributed while still taking advantage of central architecture and functioning in a single data center offered by virtualisation infrastructure. Naturally, this leads to a hierarchical infrastructure where individual data centers autonomously manage the local workload, communicate between them to route and migrate VMs. There was a proposal for a self-organize hierarchical architecture, but until now the management of one data center is restricted.A recent study has proposed a hierarchy of inter-DC and intra-DC application routing. The VM scheduling problem was broken down and solved in single data centers, and various targets, such as reducing electricity costs, carbon taxes and bandwidth costs, were able to be combined. Although the work certainly merits attention, it has only solved the routing problem and failed to take advantage of the dynamic migration of workload, nor does the approach seem readily extendable in that direction.

3. MODEL AND FORMULATION

As Fig. 1, we see a data center operator with geodistributed data centers that operate in a smart micro-grid environment (SMG) in different electric regions. There are two modes, i.e. isolated mode and grid connectivity mode, as for the operational condition of an SMG.

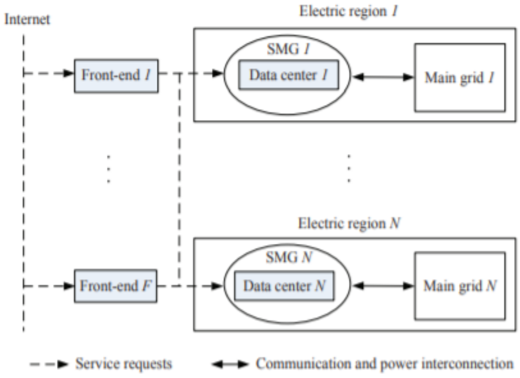
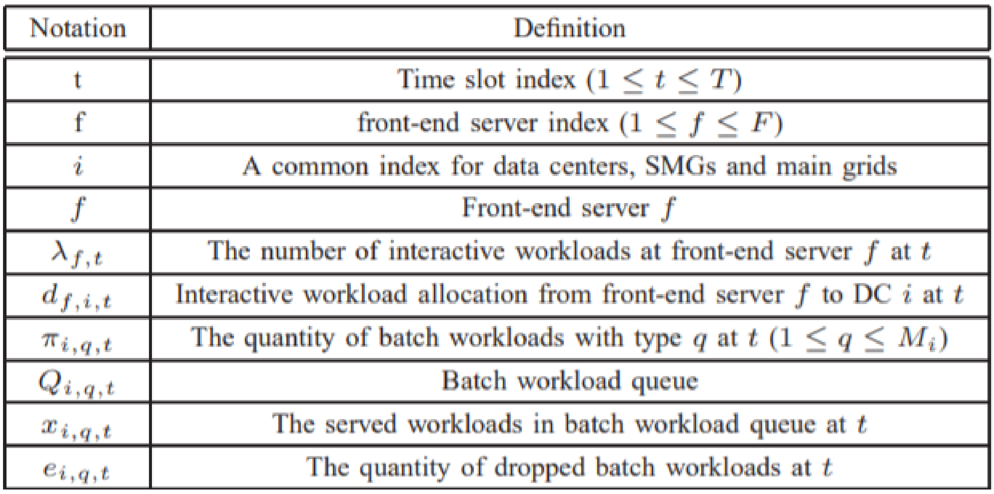


Fig. 1. System model

SMG's could supply loads with a variety of energy resources, such as energy storage devices, renewable generators, and backups, in island mode. A SMG can sell (buy) energy in grid-connected mode, by contrast, to (from) a main grid. A SMG includes four main components, i.e. a generation system, a charge system, an energy storage (ESS) system and an energy management system (EMS).In particular, a generation system consists of several renewable generators and a conventional generator (usually the backup) while the EMS schedules other components within the SMG for energy. As the aggregate load in the SMG, an interactive workload from front-end servers and the workloads in the data center must be completed by the data centre. In this paper, we take into account a time slot system and suppose that the length of each slot is one time. The most important notes are presented in table I for easy reading.

TABLE I NOTATIONS



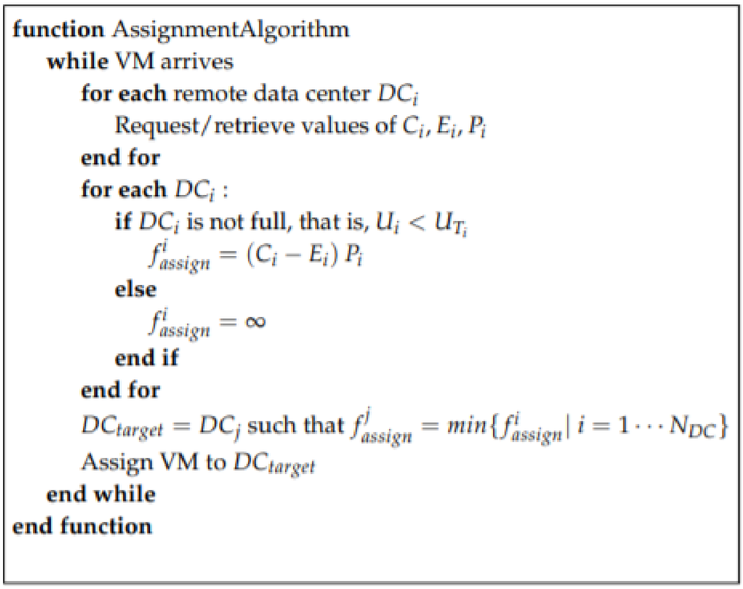
Notation	Definition
t	Time slot index ($1 \leq t \leq T$)
f	front-end server index ($1 \leq f \leq F$)
i	A common index for data centers, SMGs and main grids
f	Front-end server f
$\lambda_{f,t}$	The number of interactive workloads at front-end server f at t
$d_{f,i,t}$	Interactive workload allocation from front-end server f to DC i at t
$\pi_{i,q,t}$	The quantity of batch workloads with type q at t ($1 \leq q \leq M_i$)
$Q_{i,q,t}$	Batch workload queue
$x_{i,q,t}$	The served workloads in batch workload queue at t
$e_{i,q,t}$	The quantity of dropped batch workloads at t

Workload Assignment and Migration

As mentioned in the last section of the report, the DCM has a key role to play in analyzing and summing up details on the local data center which are then transmitted to distant DCMs for task assignment and re-distribution.

EcoMultiCloud is very flexible and can take several high-level information pieces into account. This information changes on the basis of general multi-site infrastructure objectives.

$$f^i_{assign} = \sum_{i=1}^{M} \alpha_i \frac{F_i}{F_{max}} \qquad \sum_{i=1}^{M} \alpha_i = 1$$



```
function AssignmentAlgorithm
    while VM arrives
        for each remote data center $DC_i$
            Request/retrieve values of $C_i, E_i, P_i$
        end for
        for each $DC_i$ :
            if $DC_i$ is not full, that is, $U_i < U_{T_i}$
                $f^i_{assign} = (C_i - E_i)\, P_i$
            else
                $f^i_{assign} = \infty$
            end if
        end for
        $DC_{target} = DC_j$ such that $f^j_{assign} = min\{f^i_{assign} \mid i = 1 \cdots N_{DC}\}$
        Assign VM to $DC_{target}$
    end while
end function
```

Figure 2. The EcoMultiCloud assignment algorithm, executed by the DCM of each data center.

$$f^i_{assign} = (C_i - E_i)\, P_i$$

Figure 2 shows the pseudo-code that a DCM uses in order to choose a target data center for a VM originating locally in the NDC system data centres. For all remote data centres, the DCM calls for the values of Ci, Ei and Pi; the exchange of data is very low, but it can be periodically refreshed in order to reduce the exchange of information when the flow of the VMs is large. The assign function is then calculated in (above) for every data center with some replacement capability, i.e. where a UTI threshold has not been exceeded by the use of the bottleneck resource.Finally, the DC with the lowest value is assigned the VM (above). The VM is assigned to a physical host by using the local algorithm for the assignment once assigned to the target DC.

4. RESULTS

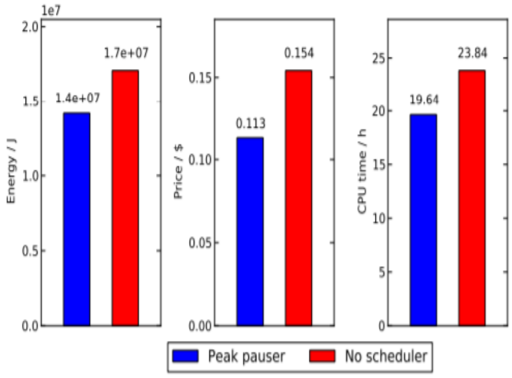


Figure 3: Synthetic data results

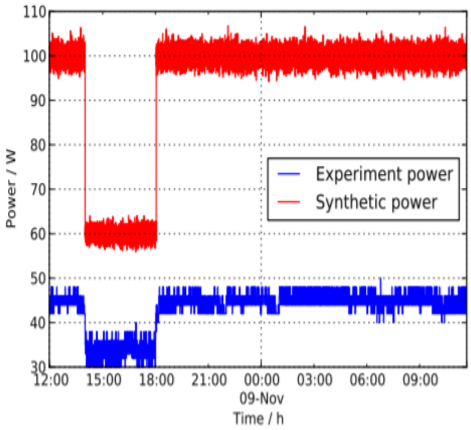
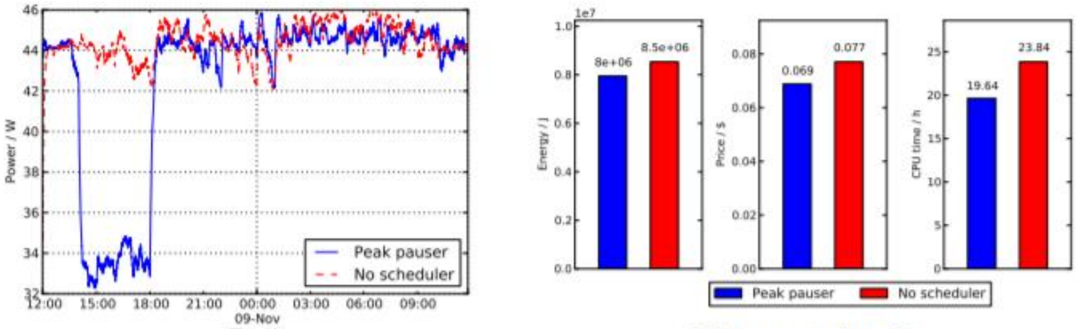


Figure 4: Power consumption in our experiment and a derived synthetic signal

According to a simple model of our empirically collected data, a synthetic time series was created to correspond to the parameters of production quality from[77]. We assumed that normally distributed oscillation around the peak (during VM performance) and idles (during a pause event). The signals of empirical and synthetic power can be seen in Fig. 4. During VM execution, power is concentrated at around 100 W of peak power and 60 W of idle power during the VM pause. For estimating savings under various energy elasticity parameters a synthetic signal was used.



(a) Dynamic behaviour

(b) Aggregated results

Figure 5: Empirical evaluation results

CONCLUSION

We focused on managing the costs of maintenance and the electricity consumption in a CDC together. After having demonstrated that changes to PS power conditions affect both failure cost management and energy consumption, we have formulated the OMEC problem with the aim of managing the above-mentioned costs jointly. Because of the NPHard problem of OMEC, we described the MECDC algorithm designed to wisely leverage the balance between various costs and to take their long-term impact into consideration.By reducing controllable availability, this mechanism reduces energy costs. If this type of service is offered only to ready users as green instances under special SLAs, no damage would be done from a user perspective. Furthermore, this is an ecofriendly approach, because the energy generation uses faster and less efficient methods to put pressure on the environment during peak demand.

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