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Towards a Cloud Infrastructure for Energy Informatics

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Abstract
The development of cloud computing has achieved the goal of computing as a service, abstracting the resource "as a cloud". This service has extended to include not only computation but its associated storage and communication components as well. The smart grid hopes to integrate the dynamics of distributed generation and demand. If the computational requirements of these demands are as dynamic as the phenomena they seek to control, then the cloud computing model provides an appropriately flexible platform for smart grid computing. This paper evaluates the Cloud for Energy Informatics (CEI), a computational-control abstraction that provides flexible and efficient computational resources on-demand as defined by the smart grid. We focus on how the CEI addresses performance and efficiency measures of smart grid related computation such as latency, bandwidth, storage and compute cycles. We compare CEI with traditional approaches using simulation to quantify the resource savings, efficiency and reliability gains from switching to a CEI model.

Keywords: Cloud for Energy Informatics, Service-Oriented Network, Energy Efficiency Metrics, Classified-Power Capping, Optimal Energy Saving

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INTRODUCTION

Energy Informatics (EI) presents significant potential for many types of information analysis and energy optimization in smart home (Pedrasa et al., 2010) and smart grids (Lee et al., 2011). In order to share a high-level cloud infrastructure with other domains, a domain-specific cloud or network structure must first develop its virtual data structures. These structures can facilitate a secure data sharing hierarchy in the cloud as requests for access pass through certain authorization rules in order to reach a specified level. This aspect aids organizations' management of data and service-sharing within a particular group.

In order to overcome the challenges of migrating smart-grid computing to a cloud computing model (in turn motivating its application), structures need to be developed with which data latency, design and security may be evaluated. Additionally, the mechanisms or functions of the shared cloud must be rooted/related to the data to support interpretation and integration between smart-grid services.

The benefits of such structuring of the cloud have been demonstrated in previous work in which this concept of a "Cloud for Energy Informatics" (CEI) is evaluated within the context of efficient data centers as green computing. While many fields related to cloud computing systems have adopted energy saving technologies to manage load, these have not been rooted in a basic cloud structure that can be shared with other domains. We propose a cloud design and its evaluations with the goal of providing a core structure that helps relate domain-specific cloud structures and resource sharing models to energy systems.

We describe the development of a Cloud for Energy Informatics (CEI) with the goal of demonstrating the utility of such energy-system related clouds in a structured design. In our work, we discuss how the National Renewable Energy Laboratory (NREL) is exploring this approach in its energy system integration projects and encouraging generative software development and data sharing of its energy models. CEI may become a promising direction of the NREL's Energy Systems Integration (ESI) efforts to integrate electricity, smart grid, service sharing and data storage at all scales across the grid.

Other benefits of Cloud computing provided by the CEI model include parallel computing and distributed control (as opposed to centralized control). The challenges as well as the capability for efficiency would be built on top of the high performance data-center, network infrastructure and software control system with smart energy management. Primarily we explore and describe a method to utilize cloud computing technologies to facilitate knowledge sharing and data analysis in the energy informatics domain.

The remainder of the paper is organized as follows: we will describe, in general, cloud computing as well as energy informatics design, explaining how the integration of the two will provide promising opportunities; First of all, we propose the overview idea of CEI ; Then, we provide an literature review of previous contributions and its link with CEI; In addition, we provide a motivating resource sharing design and case study demonstrating the value of clouds via efficiency metrics in the EI domain; To help our analysis, we provide the simulation results by comparing different power capping strategies; Finally, we describe conclusions and our future work at the end of the paper.

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MOTIVATION OF CLOUD FOR ENERGY INFORMATICS(CEI)

CEI aims at describing and formalizing the infrastructure and architecture a smart cloud that is beneficial to the actors in the EI domain: stakeholders, domain structures, applications, facilities, types of efficiency metrics, and the types of relationship analysis with smart grid. We discuss some of the functional and nonfunctional requirements of the cloud, its proposed structure, as well as the ways in which the cloud is beneficial to knowledge sharing for energy informatics and energy optimization. The goal of this project is to create a cloud design and theoretical basis for the EI domain and its investigations through energy related resource and data sharing.

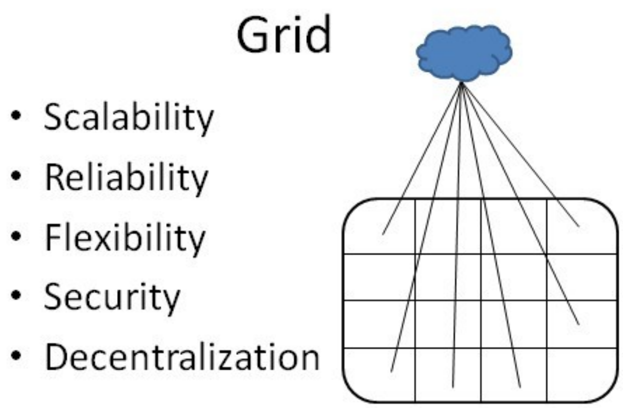

Figure 1: Grid Computing Benefits for Cloud

Cloud Computing and its Challenge

The idea of distributed computing motivated the research potential of grid computing. By design, grid computing has the benefits of scalability in time and space, reliability in data replication, flexibility in choice and security in its computing structure in a decentralized way. Figure 1 shows the benefits of grid computing. Previous work (Zheng et al., 2011) describes the evolution of the cloud computing models from distributed and grid models - shown in Figure 2.

As cloud computing evolved from grid computing, it has the benefits of grid computing along with a stronger potential for network sharing. While Figure 2 shows the evolution of cloud and its sharing characteristics with other computing methods, there are no clear energy characteristics

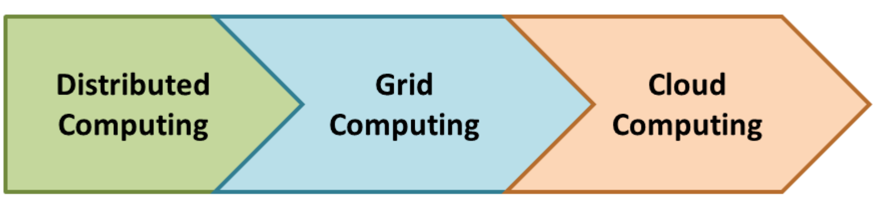

Figure 2: Evolution of Cloud Computing

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or standards defined to differentiate them simply because they are not just developed for energy domain. Rather, the focus here is more about using the cloud as a computing tool to reduce energy consumption and facilitate energy efficiency. Regarding to its potential as a tool, cloud has more power when it comes to network sharing and service control. The basic principle of cloud computing is to make the computing be assigned in a great number of distributed computers rather than a local computer or a remote server (Yamini, 2012). Cloud computing, due to its dynamic structure and real-time network properties, differs from current data centers in terms of its dynamic user locations and behaviors (Wu and Wang, 2010). As users may log into the server to access particular services, cloud computing thus handles resources in a elastic and scalable way. According to (Yogesh Simmhan and Prasanna, 2010), the greatest research challenges for the cloud are: streaming applications in the cloud, scheduling latency sensitive applications, and scalable data sharing and privacy preservation. To be more specific of the three challenges, although stream computing for video and audio streaming is well studied, currently we lack smart grid applications that can run across distributed consumer meters. The elasticity of cloud provides availability planning for all cloud resources, supporting the identification of computational resources needed for mission-critical and demand response applications.

The Relationship between Cloud and Energy

Cloud computing is highly relevant to energy-efficiency topics. This is because generally (due to virtualization overhead) cloud computing consumes more energy than a normal data center or personal PC. Energy related to data storage on the cloud is more complicated to understand as it is integrated into the costs of the cloud's inter-node network communication. To support green computing, existing techniques develop energy-aware load scheduling using algorithms and software that manage energy consumption associated with data processing and communication.

Also, the cloud can be used as the platform for these energy algorithms and software. It can serve as the center of energy applications when it controls information sharing and high-performance computing across domains. Figure 3 helps understand cloud's function regarding to its potential applications to energy informatics. Does cloud have to consume more energy than a normal data center? It is not always true as the energy consumption highly depends on the cloud size and service instances running on the cloud. When you talk about a data center, you're talking about one physical location with a certain amount of energy consumption, but cloud computing is usually physically distributed geographically which would make its energy consumption harder to characterize. In order to provide the energy-saving potential for large power-consuming loads in a broad scale, we study cloud energy model in terms of its virtual capability and distributed energy characteristics.

The Ultimate Objective of Energy Informatics

According USC's Center For Energy Informatics, Energy Informatics is:

> "... the application of information technology to integrate and optimize assets in the energy domain including energy sources, generation and distribution infrastructure, billing and monitoring systems, and consumers. "

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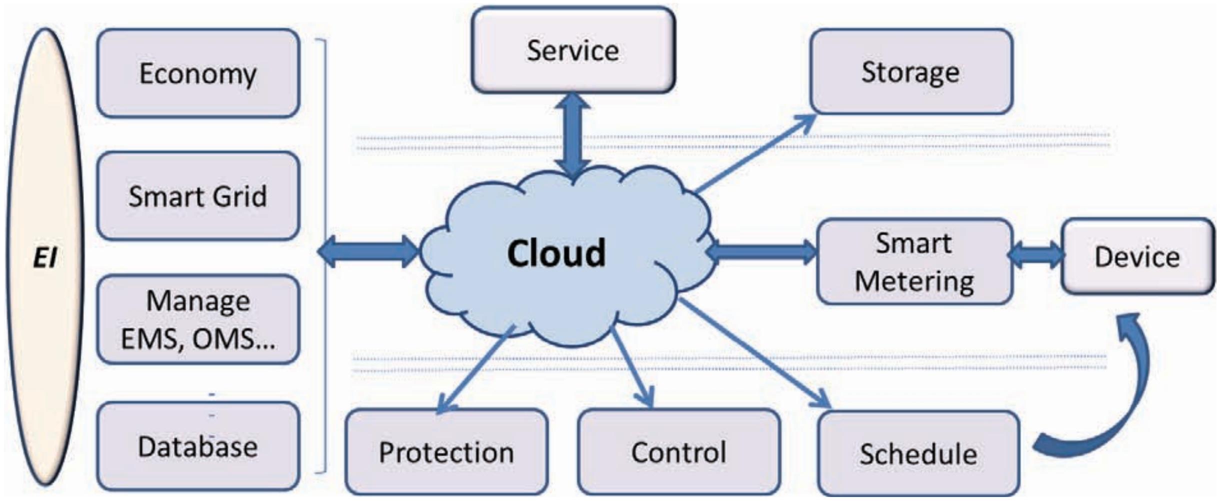

Figure 3: Cloud Relation to Application Areas

> "... the rapid rollout of smart grids makes information collection, integration, management, analysis and control of energy assets of vital importance. This area of research is referred to as Energy Informatics, as it applies traditional and novel information technology practices to solve complex problems in the energy domain using scalable cyber-infrastructure." Energy informatics can provide information regarding to smart power marketing, smart grid planning, system management software (e.g. Energy Management Software (EMS)) of energy and database.

Benefits of Cloud for Energy Informatics (CEI)

In this paper, we talk of EI as mainly about the smart grid, partly because of our awareness that cloud can be applied to build a function-control center like a super smart grid. Although there is a more expansive view of EI that could also be considered relative to cloud computing, there is no formal definition of Cloud for Energy Informatics. We therefore propose the idea of Cloud for Energy Informatics, aiming to build the link between cloud and Energy Infomratics and find out all mutual benefits between the two. Due to cloud computing's flexible computing abstraction and its functional role of linking resources, Energy Informatics can be better addressed by CEI. Cloud computing can work as a device control center using smart metering based on energy information or simply serves as a data hub. Additionally, for service sharing, cloud computing can have specific software developed and installed to support high performance computing in domain-specific and cross-domain applications. As shown in Figure 3, the potential functions for CEI in the smart grid include protection, distributed control, reliable data storage, and optimal scheduling for power resources, etc.

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LITERATURE REVIEW

Cloud Computing and Smart Grid

Recently, the cloud computing techniques have been increasingly applied to the energy domain in areas such as the smart grid. Recent research reveals that a lot of interest exists toward clouds and smart grid design. For example, Zheng et al. (2011) designs an intelligent cloud of power, as seen in Figure 4. It defines four functional layers, given clear relations to domain-specific functions. For example, the basic storage layer includes physical data storage device along with storage virtualization and monitoring, while the basic layer addresses the issues of distributed computing, P2P data management and data security.

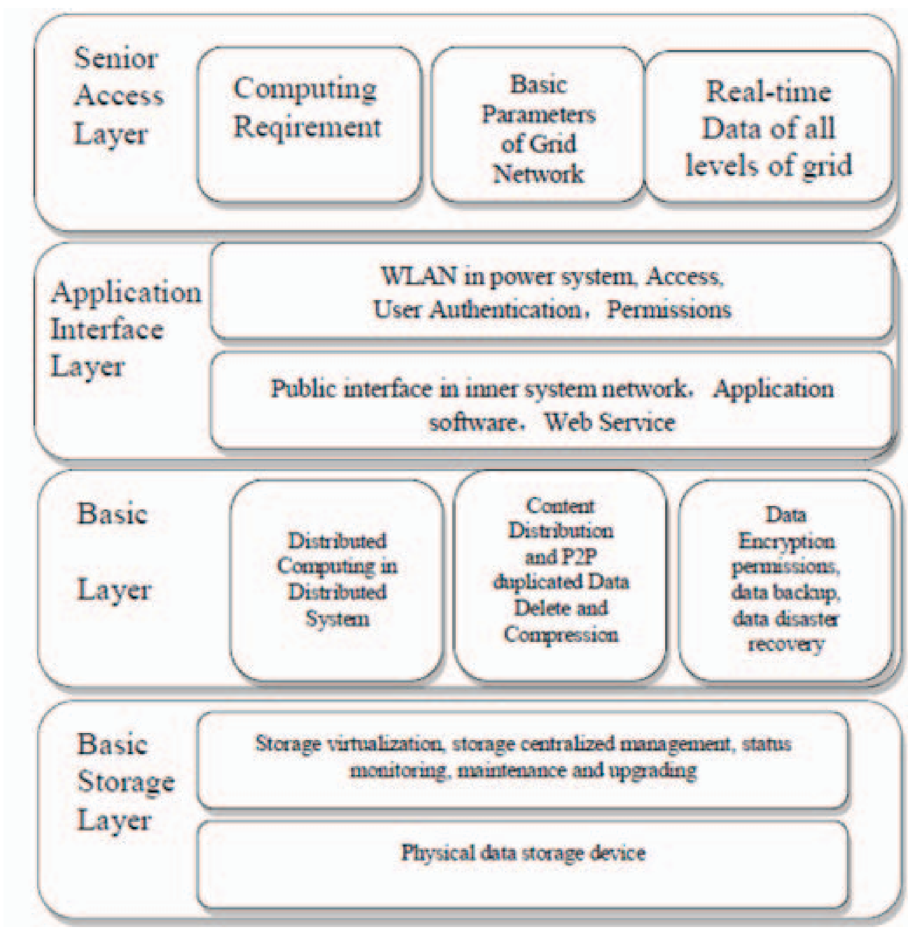

Figure 4: Structural and Hierarchical Model of the Intelligent Cloud of Power (Zheng et al., 2011)

Rusitschka et al. (2010) presents a model for smart grid data management based on specific characteristics of cloud computing. More specifically, it deals with distributed data management for real-time data gathering, parallel processing for real-time information retrieval and ubiquitous access. Lai et al. (2011) tries to establish electronic community building model based on the concept and features of cloud computing and, proposes the realization model of the community cloud architecture.

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Cloud for Energy Informatics

According to the work presented in Yamini (2012), the energy crisis brings rise to green computing, and, as cloud computing has the benefits of grid computing, distributed computing and parallel computing, the energy-efficient use of computing power with green algorithms and mechanisms is enabled. Information for energy systems analysis based on cloud computing needs its own system architecture to handle. Wang and Lv (2011) presents a four-layer system architecture (application softwaree layer, interface layer, platform layer, and physical layer) to deal with multi-source information services both at home and aboard based on cloud computing. Although clouds and grids are designed with massive computing capability, they have excessive energy dissipation in power and cooling as large-scale distributed computing systems (LDSs). Facing this problem, Hussin et al. (2011) addresses scheduling with different priorities for energy efficiency by exploiting resource heterogeneity. Dutta et al. (2012) presents the implementation of an efficient Quality of Service (QoS) based smart-scheduler along with Backfill strategy based light weight Virtual Machine Scheduler for dispatching job. To select ideal host for VM creation, they derive scheduling heuristic using queuing model with non-preemptive priority in the paper, assuming cloud-users jobs come to the server following Poisson distribution while the process time to each job by the server has a general distribution. Gomez et al. (2009) presents the energy-aware design and reporting capabilities in the management system of an Infrastructure as a Service (IaaS) platform in order to assist energy-efficient infrastructure architectures and provide its users and providers with service-level energy chargeback information. Abdelsalam et al. (2009) analyze mathematical relationship of these SLAs and the optimized server number and ideal running frequency of servers (with power relation: $P = A + BF_n^3$, where A and B are system constants and F_n is the normalized running frequency). Zhang and Fu (2011) present power profiling results on a cloud tested , combining both hardware and software power archives and collecting the power and energy usage data with varying server/cloud configurations to quantify their relation.

APPLICATION OF CEI

To apply cloud to EI, we need to overcome the challenges of cloud regarding to information and request handling in its service and management. In this section we will focus on specific design problem of the cloud regarding to energy management and service sharing.

Case Study and Model Design

For service-oriented cloud such as smart home cloud, layered architecture is provided (Gu et al., 2011). Intelligent cloud has multiple layers of service (Zheng et al., 2011). Infrastructure as a Service (IaaS) at the base, Platform as a Service (PaaS) in the middle ware, as well as Software as a Service (SaaS) defined on the top layer. In our paper, we focus on SaaS for our cloud service design.

Speed Challenge and Service-Oriented Network Design

In (Wu et al., 2011), cloud distribution tree is proposed for green computing and managing network service activity with algorithm similar to P2P logic to rank users according to their service

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ID and availability in a hierarchy. Figure 5 shows its designed structure base for cloud energy management.

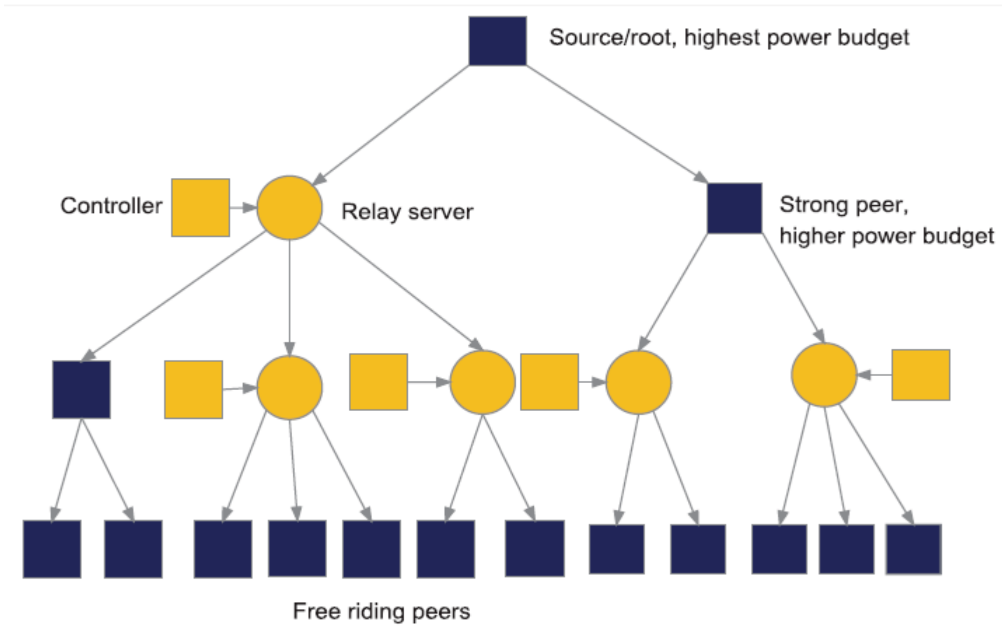

Figure 5: The Distribution Tree of Cloud. Rectangles are peers while circles are relay servers (Wu et al., 2011)

In this paper, we keep the design of logic tree distribution for cloud and further divide service according to their priority and requirement level. The relation of service with cloud is shown in Figure 6. The reason why we divide service level is because not all services are preferred by users to run in the cloud. People argue that they want the computing capability of their own personal computer. This is definitely true and does not conflict cloud computing to provide powerful high performance computing capability service. However, to be more efficient and give more freedom of choice regarding the services, we propose to divide service level so that they can be handled differently in the cloud. For example, for expensive software to purchase such as Matlab and its simulink toolbox, the cloud can provide shared service with higher level for users while for other software services that users have more economic access and freedom of choice like c programming software and Java eclipse, it may have lower access level compared to the expensive and secured data access. Therefore the idea of service cloud level is to classify service according to the property and requirement rank in the cloud, so that service itself has a hierarchy in the cloud tree and can be taken care by different kind of cloud center (e.g. main cloud or sub-cloud in different level). Each cloud can have its own controller, the same as the controller shown by rectangular in Figure 5. On the other hand, this higher level cloud called main cloud could then be shared by domain-specific sub-cloud, thus enabling those sub-cloud domains to share analysis tools and programs that utilize the concepts and relationships from the main cloud.

A difference between our paper and Wu et al. (2011) is that, in previous design, the relationship

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of peer nodes is described in one service tree. Peer nodes represent cloud users who request for the same cloud service and get served in a network. Here in Figure 6 different services and their relations are considered in several clouds and the peer node in the tree is replaced by leveled service requested by each user.

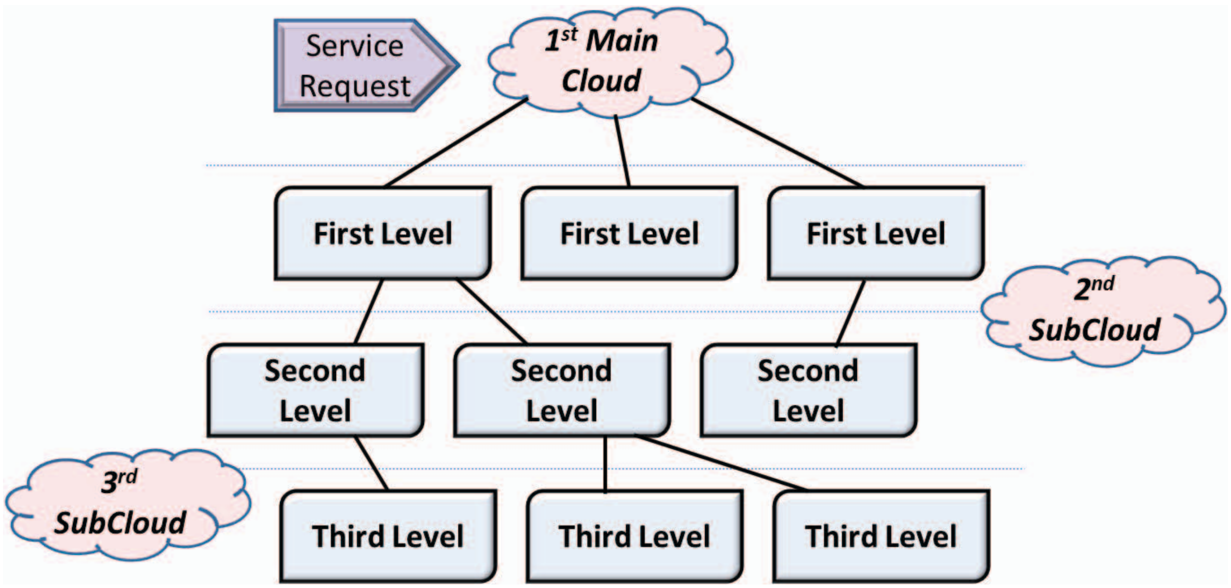

Figure 6: Service-Oriented Network of Cloud

Resource Saving

As not all users are using the same service at the same time, by resource sharing using a cloud, the idle service share of a user A can be used by another user B.

Single Software Case

Assume there are N users at the time t, and each of them have to use a service software. Take Matlab for example, normally users have to purchase and install N times on their machine without the cloud.
In comparison, by applying cloud link to provide all users the software, we can have the following situations:
When a user is using this software, the service probability of the software is 1; when not using, the service probability of using that software is 0. As users are not using Matlab all the time, so the average service probability of one user using the software at a certain time period $[t_a, t_b]$ is $\bar{p}_{a,b}$ and,

$$\bar{p}_{a,b} = \sum_{i=a}^{b} p_i t_i / \sum_{i=a}^{b} t_i < 1 \tag{1}$$

p_i is the service probability of one user using a software at time period t_i, $\sum_{i=a}^{b} t_i$ represents the

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total time of working periods. Based on this, now we consider N users using the cloud software. Instead of installing N pieces of the same software on each individual machine, we only need to provide a number of N_{use} $(N_{\text{use}} = p * N)$ available pieces of software access for the cloud. As average service probability $\bar{p} < 1$ which means most of time the probability of individual using a software at time t is less than 1, therefore $N_{\text{use}} = \bar{p} * N < N$. Therefore, the portion of the software usage we can save by the cloud is

$$N_{\text{save}} = N * (1 - \bar{p}) \tag{2}$$

If we consider different average probabilities of N users using the same software, which is p_i, then the total available pieces of software need is $N_{\text{use}} = \sum_{i=1}^{N} p_i$. As $p_i < 1$, therefore, $\sum_{i=1}^{N} p_i < \sum_{i=1}^{N} 1$, thus we still have $N_{\text{use}} < N$. In this case, the portion of the software usage we can save by the cloud is

$$N_{\text{save}} = \sum_{i=1}^{N} (1 - p_i) \tag{3}$$

For the case of multi-threading instead of N pieces of software, we characterize energy consumption for each particular service, considering both time and power. If a service utilizes more than one thread or core, that may decrease the time to run the service, but will also increase the amount of power used by the service.

Multiple Software Case

Considering N users using multiple software at time t, the expected usage of the total software needed at a certain time t is:

$$E\left(Ns\right) = \sum_{j=1}^{N} \left(p_j * Ns_j\right). \tag{4}$$

Let j represents the j th user, then p_j is the probability of j th user using cloud software at time t and, Ns_j is the number of different software needed by the j th user. Energy saving in the time period from time t_1 to t_2 to execute the service is:

$$E\left(Ns\right) = \sum_{j=1}^{N} (1 - p_j) * P * (t_2 - t_1) \tag{5}$$

In general, let $p_j = pr$, then we have

$$E\left(Ns\right) = N * (1 - pr) * P * (t_2 - t_1) \tag{6}$$

P is the general power consumption related to the cloud to run Ns software services. Therefore cloud can save resources by sharing its idle services to others on demand.

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Efficiency Metrics

Data Efficiency

The efficiency usually depicts the useful amount of power cost compared to the whole usage of power in total. According to Forrester, servers would use around 30% of their peak power consumption while sitting idle 70% of the time, although data centers are always built to suit peak load (Singh and Vara, 2009). For the long term, the Green Grid (Christian Belady et al., 2007) works on to define data center productivity (DCP) metrics, they define productivity as:

$$DatacenterProductivity = UsefulWork/TotalFacilityPower \tag{7}$$

According to (Singh and Vara, 2009), the Green Grid (Christian Belady et al., 2007) defines two useful metrics to evaluate data center efficiency: Power Usage Effectiveness (PUE) and Data Center Infrastructure Effectiveness $(DCiE)$.

$$PUE = (TotalPower)\,/\,(ITEquipmentPower) \tag{8}$$

$$DciE = (ITEquipmentPower)\,/\,(TotalPower) * 100 \tag{9}$$

(8) measures the amount of power that goes directly to computing compared to ancillary services, (9) calculates PUE reciprocal and indicates the percentage of actual power delivered to the servers compared to that delivered to the facility.

Time Efficiency

As energy is not only related to power: $Energy = Power \times Time$, therefore for a service-oriented cloud, the time spent for a particular service load is also important for the overall energy consumption and is helpful for understanding how a certain service request would cost energy in the cloud. In other words, we consider time constraints for service in our design as services tend to have time attributes with information query involved. Therefore we apply the metrics defined in (Jiang, 2012), and select the attribute to be time and redefine it as the flowing time efficiency metrics of cloud:

$$T_e = \sum_{i=1}^{N} p_i T_i \tag{10}$$

$$T_e = \sum_{i=a}^{b} p_i T_i \Big/ \sum_{i=a}^{b} p_i \tag{11}$$

(10) is the mean of all service time attributes associated with a class T query, here we see the query as a service request in the cloud. T_i is the time constraint of a particular service i and, p_i is the weight being the probability associated with each possible value T_i. (11) gives the mean value of the time attributes associated with a weighted query of all possible time values within the selection interval $[T_a, T_b]$.

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Optimal Energy Saving

Optimal energy saving of service considers service task conditions: service time constraints, price range, power range and peak difference. Sometimes metrics such as normalized running frequency $(P - P_{\text{min}}) \,/\, (P_{\text{max}} - P_{\text{min}})$ and power changing rate may also be helpful to measure cloud power status. The cloud power is balanced when $P_D = P_G - P_L$. Here P_D is the power demand or need of cloud service load, and P_G is the power generated for load. P_L is the power loss of a cloud, which includes the power spent on data communication and transmission loss in network. If we can allocate the power allocation of cloud to match its power service demand, then we can have maximized power saving by classifying service cloud attributes.

Simulation and Result Analysis

For the purposes of our study, we focus mainly on cloud services with respect to SaaS. In order to quantify our analysis, we simulate several potential cloud services and their power data. Here we follow the same simulation method in our previous work(Wu et al., 2011) , which includes a detailed explanation of the simulation method and comparison techniques. We do not fully describe them in this paper due to a different focus on CEI.

In general, we simulate the dynamic arrival of up to 300 users per day with even distribution, of which any users can randomly chose whatever available services to use. This shows the maximal number of users for the cloud network is N= 300, and the network will accommodate those users according to their software choices available in the cloud. The total network simulation uses the same arrival rate for user requests. Table 1 shows the simulation of energy consumption of SaaS service in a cloud. We simulate various number of users and the type of services they use in the cloud, which will affect the overall workload. Here we assume users all consume certain amounts of service power at a time.

For simulation parameters, we compare the power consumption of different techniques between two cases: cloud servers without useful load and cloud servers with useful load. Here, useful load refers to the actual service load requested and served in the cloud. This agrees with the idea of efficiency metrics, such as DCP (Data Center Productivity) we mentioned previously. For simplicity of the calculation, we ignore the Cooling Load Factor (CLF) and only consider Power Load Factor (PLF) (Christian Belady et al., 2007). We aim to show the idle switching benefits for cloud servers. According to the data efficiency concept presented in this paper, we consider useful work percentage and, we compare the outcome of different power allocation techniques using power planning and control in the cloud. This refers to power budgeting techniques in the cloud for power allocation (Wu et al., 2011). For efficiency calculation, we assume the total power cost equals the service load power cost and set power usage efficiency to be 100 $\%$ (all power spent on useful workload) for the biggest saving technique. The power costs and saving rates between techniques are also compared, by selecting the technique with the maximum power consumption and setting its rate to be 100$\%$. The focus is to show how efficiency differs by applying different power planning and control techniques in the cloud. In addition, we compare the power usage efficiency, power cost rate and saving rate between listed techniques.

The outcome of this comparison can be seen in Table 2. Based on the results, we prove that Classified Power Capping (Wu et al., 2011) outperforms the other techniques. Kmininal is the number of server nodes in the cloud network. We start from Kminimal=1 to Kminimal=15 and, we

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Day	Total Users	Emails	Games	Web Services	Day	Total Users	Emails	Games	Web Services
1	294	79	61	154	16	232	70	69	93
2	171	95	49	27	17	18	10	7	1
3	92	64	26	2	18	80	38	13	29
4	73	29	38	6	19	61	58	3	0
5	287	141	6	140	20	142	7	114	21
6	51	26	12	13	21	86	67	8	11
7	159	93	44	22	22	267	122	29	116
8	277	260	1	16	23	200	100	20	80
9	108	28	39	41	24	233	193	5	35
10	71	19	20	32	25	64	13	29	22
11	138	132	4	2	26	138	80	9	49
12	226	85	117	24	27	183	96	39	48
13	237	33	28	176	28	128	106	7	15
14	25	22	2	1	29	259	4	34	221
15	164	55	26	83	30	272	202	3	67

Table 1: Cloud Service Simulation of Energy Consumption

	Technique 1: Uniform Power Capping without Idle Scaling	Technique 2: Uniform Power Capping with Idle Scaling	Technique 3: Classified Power Capping with Idle Scaling
$K_{minimal}$=1, Single Network Node Power (watts)	1450	500	500
Monthly Total Power in Unloaded Case(watts)	43500	15000	15000
Power Cost Rate	100%	34.5%	34.5%
Power Saving Rate	0%	65.5%	65.5%
Power Usage Efficiency	65.5%	100%	100%
$K_{minimal}$=15, Entire Network Power (watts)	21750	7500	7500
Monthly Total Power in Unloaded Case(watts)	652500	225000	225000
Power Cost Rate	100%	36%	36%
Power Saving Rate	0%	64%	64%
Power Usage Efficiency	64%	100%	100%
End-of-month Total Power(watts) with Load	652500	452050	394650
Power Cost Rate	100%	60 %	69%
Power Saving Rate	0%	40 %	31%
Power Usage Efficiency	60%	60/69=86%	100%
Saving \ Residual Efficiency	0%	31/40=77.5%	100%

Table 2: Cloud Service Simulation of Energy Efficiency by Different Planning Techniques

calculate related power, assuming the total loaded power consumption equals the maximum power in the cloud. By using different planning techniques in the cloud, the actual power demand for a particular service at any given time can be allocated to match the scheduled power allocation of the underlying server hardware.

Based on the simulation and efficiency comparison, we know the total energy of a cloud is sensitive to the number of users, the virtual power consumption of a particular type of service, and the time cost of each service. On the other hand, we can see that Classified Power Capping consistently is better than the other techniques by having the minimum power cost rate, maximum power saving rate, and maximum efficiency. In fact, the idea of Classified Power Capping in the cloud belongs to smart power management techniques, including scheduling and control. The purpose is to reduce total power consumption as close as useful load demand in the cloud, so that we can maximize efficiency in the cloud. Therefore, we work on to match the total power consumption of the cloud to be close to the actual power spent on useful loads, targeting at maximized power savings and increased efficiencies. This gives a promising future of the Cloud for Energy Informatics on smart grid.

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Conclusion and Future Work

In this paper, we explored the data sharing and analysis capabilities of cloud computing in Energy Informatics. Cloud computing allows for energy data systems to integrate at the virtual level, enabling scheduling, data storage, analysis tools and service control to facilitate the optimization of energy saving and cost minimization.

Generic cloud computing and smart grid design facilitate high-level data integration capabilities and their relationships in a standard way. This enables cloud-based infrastructures to be optimized according to energy efficiency, usage and reliability by different domain-specific cloud services. While many fields related to energy systems have adopted power-saving techniques to develop multiple services and cross-field optimization, the challenges involved in energy efficient cloud, cloud-based infrastructure and cloud applications have not been completely solved.

Here, we presented the idea of a Cloud for Energy Informatics (CEI), a cloud-based structure targeted at facilitating domain-specific research in Energy Informatics and providing a network service structure that deals with energy systems and cloud efficiency. CEI takes advantage of the energy saving techniques for load scheduling and power budgeting already developed in the virtual data domain in the cloud server.

This paper also described the development of cloud computing, demonstrating the potential for an energy-system-related cloud given a shared network hierarchy and a service-oriented design. Additionally, we provided a case study demonstrating how cloud computing can improve efficiency in its own data processing systems and related models. By linking multiple databases and real-time data from a network, the cloud can facilitate multi-level analysis and integration of the data contained in those models.

In all, the paper has several contributions. First of all, we summarized and analyzed the contributing parts of previous work regarding cloud research related to Energy Informatics and described the potential developing zones of cloud computing. In addition, we examined and retained the peer-to-peer (P2P) network algorithm (Wu et al., 2011), extending the distribution tree in the cloud network design by dividing the cloud into service-oriented levels. Based on this, the efficiency metrics for data access in the cloud were evaluated with respect to service efficiency and time efficiency metrics with constraints proposed. Simulation results demonstrate the promising aspects of cloud for energy informatics with respect to energy saving and efficiency.

Future Work

Distributed computing and high performance computing facility can finalize the reliable cloud infrastructure that can be the basis for smart grid applications and intelligent control. We will continue our efforts in developing and extending CEI in order to have optimized energy saving and maximized energy efficiency. In addition, we will further explore and test service-oriented applications of cloud in the EI domain.

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REFERENCES

Abdelsalam, H., Maly, K., Mukkamala, R., Zubair, M., and Kaminsky, D. (2009). Analysis of energy efficiency in clouds. In *Future Computing, Service Computation, Cognitive, Adaptive, Content, Patterns, 2009. COMPUTATIONWORLD '09. Computation World:*, pages 416 –421.

Christian Belady, A. R., Pfleuger, J., and Cader, T. (2007). The green grid data center power efficiency metrics: Pue and dcie. *The Green Grid. Whitepaper.[online].*

Dutta, K., Guin, R., Banerjee, S., Chakrabarti, S., and Biswas, U. (2012). A smart job scheduling system for cloud computing service providers and users: Modeling and simulation. In *Recent Advances in Information Technology (RAIT), 2012 1st International Conference on*, pages 346 –351.

Gomez, M., Perales, D., and Torres, E. (2009). An energy-aware design and reporting tool for on-demand service infrastructures. In *Grid Computing, 2009 10th IEEE/ACM International Conference on*, pages 209 –216.

Gu, H., Diao, Y., Liu, W., and Zhang, X. (2011). The design of smart home platform based on cloud computing. In *Electronic and Mechanical Engineering and Information Technology (EMEIT), 2011 International Conference on*, volume 8, pages 3919 –3922.

Hussin, M., Lee, Y. C., and Zomaya, A. (2011). Priority-based scheduling for large-scale distribute systems with energy awareness. In *Dependable, Autonomic and Secure Computing (DASC), 2011 IEEE Ninth International Conference on*, pages 503 –509.

Jiang, Z. (2012). A decision-theoretic framework for numerical attribute value reconciliation. *Knowledge and Data Engineering, IEEE Transactions on*, 24(7):1153–1169.

Lai, H., Xin, W., and Ding, Y. (2011). Research on building of electronic community based on cloud computing. In *Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), 2011 2nd International Conference on*, pages 6744 –6747.

Lee, J., Park, G.-L., Kwak, H.-Y., and Jeon, H. (2011). Design of an energy consumption scheduler based on genetic algorithms in the smart grid.

Pedrasa, M. A. A., Spooner, T. D., and MacGill, I. F. (2010). Coordinated scheduling of residential distributed energy resources to optimize smart home energy services. *Smart Grid, IEEE Transactions on*, 1(2):134–143.

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Rusitschka, S., Eger, K., and Gerdes, C. (2010). Smart grid data cloud: A model for utilizing cloud computing in the smart grid domain. In *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*, pages 483 –488.

Singh, T. and Vara, P. (2009). Smart metering the clouds. In *Enabling Technologies: Infrastructures for Collaborative Enterprises, 2009. WETICE '09. 18th IEEE International Workshops on*, pages 66 –71.

Wang, W. and Lv, T. (2011). Research on multi-source information service system architecture based on cloud computing. In *Electronic and Mechanical Engineering and Information Technology (EMEIT), 2011 International Conference on*, volume 9, pages 4776 –4778.

Wu, Z. and Wang, J. (2010). Power control by distribution tree with classified power capping in cloud computing. In *Green Computing and Communications (GreenCom), 2010 IEEE/ACM Int'l Conference on Int'l Conference on Cyber, Physical and Social Computing (CPSCom)*, pages 319 –324.

Wu, Z., Zhang, J., Giles, C., and Wang, J. (2011). Classified power capping with distribution trees in cloud computing. In *Networking, Architecture and Storage (NAS), 2011 6th IEEE International Conference on*, pages 319 –328.

Yamini, R. (2012). Power management in cloud computing using green algorithm. In *Advances in Engineering, Science and Management (ICAESM), 2012 International Conference on*, pages 128 –133.

Yogesh Simmhan, Mike Giakkoupis, B. C. and Prasanna, V. (2010). On using cloud platforms in a software architecture for smart energy grids.

Zhang, Z. and Fu, S. (2011). Characterizing power and energy usage in cloud computing systems. In *Cloud Computing Technology and Science (CloudCom), 2011 IEEE Third International Conference on*, pages 146 –153.

Zheng, L., Chen, S., Hu, Y., and He, J. (2011). Applications of cloud computing in the smart grid. In *Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), 2011 2nd International Conference on*, pages 203 –206.

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