An Ancillary Services Model for Data Centers and Power Systems

Sahibzada Muhammad Ali, *Student Member, IEEE*, Muhammad Jawad, *Student Member, IEEE*, M. Usman S. Khan, *Member, IEEE*, Kashif Bilal, Jacob Glower, Scott C. Smith, *Senior Member, IEEE*, Samee U. Khan, *Senior Member, IEEE*, Keqin Li, *Fellow, IEEE*, and Albert Y. Zomaya, *Fellow, IEEE*

Abstract—Enormous energy consumption of data centers has a major impact on power systems by significantly increasing the electrical load. Due to the increase in electrical load, power systems are facing demand and supply miss-management problems. Therefore, power systems require efficient and intelligent ancillary services to maintain robustness, reliability, and stability. Data centers can provide the computational capabilities to manage power systems; however, data centers consume a tremendous amount of energy, and energy price accounts for a significant portion of their operational cost. Power system jobs will make this situation even more critical for data centers. In our work, we seek an Ancillary Services Model (ASM) to service data centers and power systems. In ASM, we find an optimal job scheduling technique for executing power systems' jobs on data centers in terms of low power consumption, reduced makespan, and fewer preempted jobs. The power systems' jobs include Optimal Power Flow (OPF) calculation, transmission line importance index, and bus importance index. Moreover, a Service Level Agreement (SLA) between data centers and power systems is shown to provide mutual benefits.

Index Terms—Energy-efficient computing, load flow, data center, optimization, smart grid

1 Introduction

Energy crises pose some of the key problems faced by the world today. Power hungry data centers make the problem even worse for power systems. For example, Google's data centers consume more than 260 MWh of power per month, which is more than the power consumed by the entire Salt Lake City [1]. The growing usage of World Wide Web and cloud computing services increases the power consumption and operating costs of data centers [2]. The increase in power consumption of data centers has a significant influence on the operation of the power system [2]. The computational services provided by the data center for stable and reliable operation of the power system are known as *ancillary services* [2]. The key ancillary services required by the power system are: (a) optimal power flow on all Transmission Lines (TLs), (b) voltage stability, power loss reduction, and (c) identification of endangered TLs and buses. In conventional power system, the lack of fast and intelligent control results in contingencies in some power system sections. The resultant contingencies lead to Transmission Line Failures (TLFs), un-optimized power flow, degradation in Quality of Service (QoS), electrical equipment failure, and complete blackouts [3]. The parallel computing capability of data center can meet the computational requirements of intensive power system jobs for steady-state operation in a manageable time.

The power system's revenue is highly dependent on reliability and steady state performance [4]. Unreliable power systems that lack in QoS result in revenue loss. Moreover, the economic factors of power systems, such as demand-supply management, operational cost, and salaries of the utility crew get disturbed. Furthermore, degradation in QoS will prevent the electrical network from further expansion. Therefore, this problem is significantly different from normal cloud computing jobs, because power system jobs need to be computed very fast to prevent the power system from failing or degrading its operation. To accomplish power system jobs, other cloud computing jobs can be preempted. However, preempting other cloud computing jobs could result in a decrease of revenue for the data center [5].

This paper develops an Ancillary Services Model (ASM) and Service Level Agreement (SLA) that maximize data center revenue while ensuring that the power system maintains in stable operation. The problem is a research optimization problem and our model yields a symbiotic and inevitable relationship between the power system and the data center, which is unlike any other relationship between the data center and its jobs (e.g., the power system needs its jobs completed in a timely manner to maintain stability, while the

- *M. Jawad, S.M. Ali, M.U.S. Khan, and K. Bilal are with the COMSATS Institute of Information and Technology, Islamabad 45550, Pakistan. E-mail: {engrhallianali, Ushahid, kashifbilal}@ciit.net.pk, mjawad@ciitlahore.edu.pk.*
- *J. Glower and S.C. Smith are with the North Dakota State University, Fargo, ND 58108 USA. E-mail: {jacob.glower, scott.smith.1}@ndsu.edu.*
- *S.U. Khan is with the Department of Electrical & Computer Engineering, Mississippi State University, Starkville, MS 39762 USA. E-mail: skhan@ece.msstate.edu.*
- *K. Li is with the State University of New York, New Paltz, NY 12561-2443 USA. E-mail: lik@newpaltz.edu.*
- *A.Y. Zomaya is with the University of Sydney, Sydney, NSW 2006, Australia. E-mail: albert.zomaya@sydney.edu.au.*

Manuscript received 4 Jan. 2016; revised 12 Mar. 2017; accepted 30 Apr. 2017. Date of publication 3 May 2017; date of current version 3 Dec. 2020.
(Corresponding author: Muhammad Jawad)
Recommended for acceptance by S. Murugesan.
Digital Object Identifier no. 10.1109/TCC.2017.2700838

data center needs the power system to be stable for its own continuous reliable power). Therefore, a mutually beneficial ASM is developed in this paper that achieves this while maximizing profit for both the power system and data center. The experimental results show that the research contribution is more versatile and covers a broader area in the field of smart power systems using the ASM compared to prior works.

Contribution Synopsis. The proposed ASM for data centers and power systems consists of the following:

- We evaluated Longest Time First (LJF), Shortest Job First (SJF), and Shortest Remaining Job First (SRTF) to determine that SRTF is the best job scheduling technique in terms of average queue time and data center workload makespan, while SJF performs better in terms of data center workload preemption and power system job preemption. Our evaluation is based on power consumption, makespan, number of preempted jobs, queue time, and resource utilization. Details are provided in Section 7.
- We proposed three main ancillary services for stable operation of the power system, namely: **(a)** Optimal Power Flow (OPF), **(b)** Transmission Line Importance Index, and **(c)** Bus Importance Index. We performed our experiments on standard IEEE bus systems, and observed the convergence condition for the OPF solution. We compare different optimization algorithms for OPF calculation based on convergence time and Transmission Line Losses (TLLs). Moreover, we identified endangered TLs and Buses, when two or more TLs are out. See Sections 3.2 and 7 for details.
- We defined a SLA for priority execution of ancillary services on data centers. The SLA elaborates the revenue generation and penalty on the data center, if the ancillary services are delayed. The SLA is tested for variable load of the data center, variable energy price, and variable job lengths given by the power system during a month's time. The details are presented in Sections 4 and 7.
- The proposed ASM is based on the optimal job scheduling technique for data centers, ancillary services for the power system, and SLA. The ASM reduces the revenue loss of the power system during contingencies with minimum effect on the data center.

The remainder of the paper is structured as follows: Section 2 discusses the related work. The system model is described in Section 3. Section 4 presents the SLA between data center and power system. Section 5 describes the revenue modeling of the data center. Section 6 presents the simulation settings of the system model. The results and discussions are presented in Section 7 that validate the ASM. Section 8 concludes the paper with a summary and proposal for future enhancements of the current work.

2 Related Work

Over the past decade, intensive research has been published on power management issues in data centers for revenue maximization [2], [6], [7], [8], [9], and [10]. Alternatively, the power system research community is mainly addressing issues of demand and supply management and voltage stability by providing OPF solution [11]. However, interaction between data centers and power systems has recently attracted the attention of research community to address the issues of load balancing in power systems and power management in data centers for revenue maximization [12], [13]. Moreover, none of the earlier works have focused on usability of data centers' computational capability for maintaining stability in power systems.

In [2], the authors described a cost minimization method for data centers that incorporated cloud computing workload and electricity price differences. In [6], the authors discussed the aforesaid problem for renewable energy. The concept of deregulated electricity price for data centers was discussed in [7]. The stochastic model for workload distribution on servers of the data center for cost reduction was elaborated in [8]. The work in [9] discussed that major cause of energy inefficiency in data centers is the wastage of idle power when ICT resources such as servers and data storage run at low utilization. In [10], the authors discussed the energy management issues in data center networks from the perspective of data center architecture connectivity analysis. In all aforesaid models, the cost saving criterion was only related to geographical load conditions that was not an optimal approach, as climatic conditions are not the only controlling parameter. Moreover, the revenue of the data centers was only discussed in the perspective of workload, and optimal electricity prices.

Due to inadequate expansion in generation and transmission, power systems are operating under stressed conditions. In [11], the authors presented a voltage stability constraints based OPF approach that improved voltage stability and minimized power system losses during emergency conditions. The data centers are one of the major power consumers for the power systems that can cause stability and reliability issues in power systems.

In [12], the authors addressed the problem of power load balancing in smart grids by taking advantage of data centers' load distribution capability. The authors in [13] proposed a model for a data center to offer ancillary services to the smart grid. The data center is a dynamic load for any smart grid and the data center will offer load distribution as an ancillary service to the smart grid. In response, the smart grid will offer a lower electricity price to the data center.

To the best of our knowledge, no such mechanism is known to the authors for a data center to provide ancillary services to power systems, such as fast OPF solution to reduce Transmission Line Losses (TLLs) and identify endangered TLs and buses for maintaining stability and reliability. Moreover, none of the earlier works addressed the issues and effects on data centers while providing ancillary services to power systems. Furthermore, the SLA between data centers and power systems had not discussed in any previous studies. Consequently, our work provides a thorough treatment of the aforementioned problem, with a complete theoretical derivation and simulation validation.

3 System Model

In this section, we define a system model named ASM and notations for both data center and power system. We use these notations and system model to define a SLA and revenue model. The high-level architecture of the system model is shown in Fig. 1. The data center has $\mathfrak{M}_{max}$ servers that compute internet services and cloud workload. In return, the data center demands a service cost from customers.

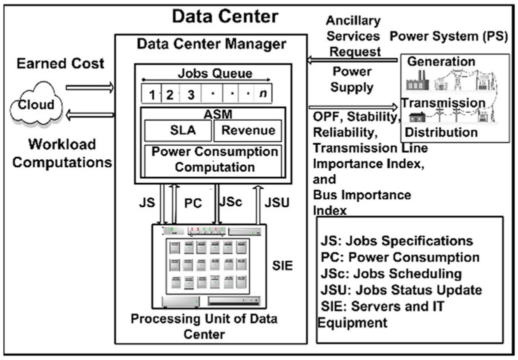


Fig. 1. System architecture.

Moreover, the data center spends a large portion of its revenue on purchasing reliable and stable power from the power system. Alternatively, the power system revenue is highly dependent on demand-supply stability. The power system requires fast computing workstations for ancillary services to maintain reliability. Therefore, we are proposing a system model in which the power system will use the data center for its reliability assurance and in return provides service cost and monetary incentive to maintain the revenue of the data center. The flow of the proposed ASM is depicted in Fig. 1, where the arrow directions represent the flow of the data. Moreover, we divide our system model into two major parts: **(a)** data center module, and **(b)** ancillary services for the power system.

3.1 Data Center Module

The module provides an appropriate job technique that handles the power system jobs with minimal effect on the data center. The effect is calculated in terms of power consumption, makespan, number of job/task preemptions, and job queue time. The estimated revenue of the data center is highly dependent on electricity unit price and power consumption. Therefore, the discussion on electricity price and workload based power consumption is essential.

3.1.1 Electricity Price

The electricity price model depends on the regulated or deregulated power market of the region [14]. In a regulated market, the electricity price remains uniform throughout the day. Conversely, in deregulated markets, the electricity price changes during the day depending on changes in the wholesale electricity market. The non-uniform pricing tariffs include time of use pricing, day ahead pricing, and real-time pricing. In the real world, the varying order of magnitude between demand and supply, and average pricing of electricity units make real-time pricing the most complex pricing tariff [14]. We used real-time pricing tariffs in the data center.

3.1.2 Power Consumption

The total power consumption of the data center is the sum of power consumption by computer servers, cooling plants, and lighting facilities, as given below [13].

$$\mathcal{P} = \mathfrak{M}[\mathcal{P}_I + (PUE - 1)\mathcal{P}_P + (\mathcal{P}_P - \mathcal{P}_I)\mathfrak{U}]. \quad (1)$$

In Eqn. (1), $\mathcal{P}_I$ denotes the power consumption of an idle server, and $\mathcal{P}_P$ is the average peak power when a server is busy handling requests. The term $\mathfrak{M} \leq \mathfrak{M}_{max}$ denotes the number of "on" servers, $\mathfrak{U}$ denotes CPU utilization in servers, and PUE is the power usage effectiveness of the servers [13]. The power consumption of data center varies throughout the day depending on workload. The detailed description of workload, power consumption, CPU utilization in servers, job scheduling techniques, queue time analysis, job preemption mechanism, and revenue calculation are discussed in Sections 6 and 7.

3.2 Ancillary Services for the Power System

In our proposed model, the power system is modeled as a set of buses interconnected by TLs to form a network topology. The total number of buses defines the size of the power system. The loads and generators are connected to the buses that consume and inject power into the transmission network, respectively. The total load of the power system is the sum of background load (commercial and residential) and data center power load. The above network topology is suitable to solve for steady-state voltages and power flows [15]. The three main ancillary services provided by the data center to the power system include the following: Optimal Power Flow Analysis, TL Importance Index, and Bus Importance Index.

3.2.1 Optimal Power Flow Analysis

The primary objective in a balanced power system is to minimize generation cost. There are two main constraints in power balancing: **(a)** equality constraints (generation-load balance) and **(b)** inequality constraints (upper and lower limits on the output of generating units). In a power system, the generating units and loads are not connected to the same bus. Therefore, the economic dispatch will result in voltage instability within the power system. Moreover, an optimal solution is required that results in acceptable power flows on all transmission lines. The OPF is among the key parameters of power system that provides an optimal solution for the above mentioned problem, and has a cogent relationship with cascading failures [16].

In the OPF, the equality constraint is to balance complex power at each bus using power flow equations. The inequality constraints consist of TL flows and voltage limitations of control variables, including active power of generators, voltage of generating units, position of phase shifters, status of reactors and switched capacitors, and disconnected loads. State variables are used to describe the system response due to the change in control variables. Voltage magnitude is defined at each bus except generator buses. Similarly, the voltage angle is defined for each bus except the slack bus. The main parameters for OPF calculation are the known system characteristics, system topology, and network parameters (generation limits and generation cost function) [18]. The objective function is to minimize power generation cost, as stated in Eqn. (2) [15]:

$$\min_{u} \sum_{i=1}^{N} Co_i(P_i), \quad (2)$$

where Co_i is the cost of bus i, P_i is the active power of bus i, N is the total number of buses, and u is the vector of control variables. The other objective functions are: **(a)** minimizing following, and

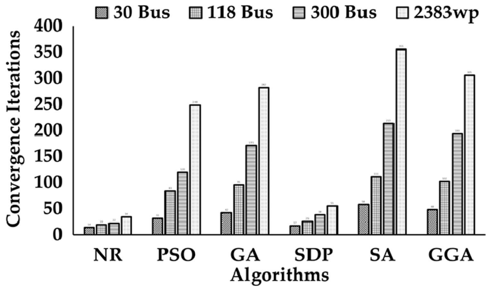


Fig. 2. Convergence of algorithms for the tolerance between power injection and power consumption.

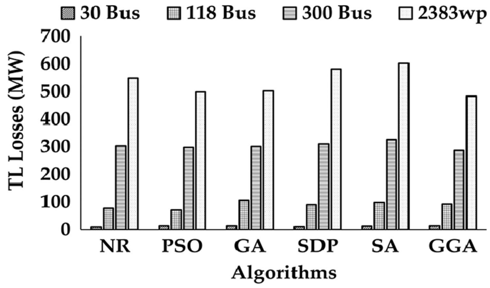


Fig. 3. Power loss comparison on TLs.

$$\min_{u} \sum_{i=1}^{N_u} Co_i \left| u_i - u_i^0 \right|, \tag{3}$$

(b) minimizing the TLLs using objective function O [15].

$$O = \sum_{i=(k,j)} \left(G_k(V_i^2 + V_j^2 - 2V_iV_j\cos\delta_{ij}) \forall k \in N_b\right). \tag{4}$$

In Eqn. (4), V_i is the voltage of bus i and V_j of bus j, G_k is the conductance of TL k, N_b is the number of TLs in the network, and δ_{ij} is the voltage angle difference between bus i and bus j. The power flow equations used for equality constraints are given below [15]:

$$\begin{gathered} P_k^G - P_k^L = \sum_{i=1}^{N} V_k V_i [G_{ki}\cos(\theta_k - \theta_i) + B_{ki}\sin(\theta_k - \theta_i)], \\ Q_k^G - Q_k^L = \sum_{i=1}^{N} V_k V_i [G_{ki}\sin(\theta_k - \theta_i) + B_{ki}\cos(\theta_k - \theta_i)], \\ Compact\ Expression : G\ (x, u, y) = 0, \end{gathered} \tag{5}$$

where P_k^G is the active power of the generator, P_k^L is the active power of the load, Q_k^G is the reactive power of the generator, Q_k^L is the reactive power of the load, G_{ki} is the mutual conductance, B_{ki} is the mutual susceptance, and θ_k is the phasor angle. The state variables vector and parameter vectors are denoted by x and y, respectively. For inequality constraints, the limits on the control variables must be imposed as: $\underline{u} \leq u \leq \bar{u}$, the operating limits on power flows are $|P_{ij}| \leq \overline{P_{ij}}$, the operating limits on voltages are $\underline{V_j} \leq V_j \leq \overline{V_j}$, and the compact expression of inequality constraints is written as $H(x, u, y) \geq 0$ [15]. The OPF problem is complex due to the non-linear behavior of all the components of the power system. Eqn. (5) is a set of non-linear expressions that need to converge as $G(x, u, y) \cong 0$ [16]. We employed different optimization algorithms, such as Newton-Raphson (NR) [15], Particle Swarm Optimization (PSO) [16], Genetic Algorithm (GA) [17], Semi-Definite Programming (SDP) [19], Simulated Annealing (SA) [20], and Genitor Genetic Algorithm (GGA) [17] to solve the OPF, where the tolerance of the power injection and consumption mismatch is 10^{-6} [15]. If the tolerance is below or equal to 10^{-6}, the OPF solution is considered to be converged. The OPF convergence iterations results for standard IEEE bus systems are shown in Fig. 2. The detailed description of IEEE bus systems used in the study is presented in Table 1. The IEEE bus systems are the replica of real-world power systems; therefore, the standard bus systems have technical importance. All the aforementioned algorithms are iterative methods that locally or globally converges [18]. The convergence time comparison of the IEEE bus systems is also shown in Table 1. The comparison results of the algorithms with respect to TLLs are shown in Fig. 3. Theoretically, the cost function value indicated in Eqn. (5) should converge to the optimum solution. How close is enough? This question is problem dependent and most difficult to measure in practice [18]. However, decades of practice show that all aforementioned algorithms converge for most OPF problems. Therefore, the theory has practical importance and our results in Section 7 support the theory.

3.2.2 Transmission Line Importance Index

We develop and evaluate the TL importance index ($TLII_i$) for fault detection and cascading failure avoidance in the power system, as shown in Eqn. (6).

$$TLII_i = \frac{PF_i}{PF_{max}}, \tag{6}$$

where PF_i is the power flow on ith TL and PF_{max} is the maximum power flow the ith TL can sustain. When a TL failure occurs, the AC power flow on some other TLs will increase and cause voltage instability. The TL importance index identifies those TLs whose failure can lead to a complete or partial

TABLE 1
IEEE Bus Systems Specifications and Algorithms Convergence Times

IEEE Bus Systems	No. of TLs	No. of Generator Buses	No. of Load Buses	Generation Capacity (MW)	Total Load (MW)	Each Bus Average Load (MW)	Average Convergence Time (seconds) Comparison for OPF calculation on a Single Processor					
							NR	PSO	GA	SDP	SA	GGA
30	41	6	20	191.6	189.2	9.46	5.88	27.6	49	4.89	28.2	54.25
118	186	54	99	4,374.9	4,242	42.84	72.06	191.9	295.4	10.1	292.6	310.4
300	411	69	201	23,935.4	23,525.8	119.07	162.2	382.7	489.9	23.9	543.9	501.6
Polish 2383wp	2,896	327	1,826	25,281	2,458.4	13.84	480.2	830	1,027.2	529	1,200.2	927.2

blackout. If the AC power flow (PF_i) on any TL increases above a certain threshold, then an outage will occur on the TL. The threshold depends on the maximum AC power flow (PF_{max}) a TL can sustain. Therefore, power system operators can take preventive measures before the occurrence of a failure.

The judgment criteria for detecting whether a TL outage can cause system failure depends on two factors: **(a)** the convergence of OPF solver and **(b)** power loss constraints on TLs. If the algorithms explained in Section 3.2.1 provide a converged OPF solution but unacceptable power loss on TLs, then the system will still be considered as un-converged. Therefore, both conditions are necessary and sufficient for an acceptable optimized OPF solution.

3.2.3 Bus Importance Index

The bus importance index is another important measure for the power system that depends on the concept of centrality [21]. The most common and famous method is Eigenvector centrality that assigns the centrality value β to all of the isolated buses within a network [21]. Mathematically, the Eigenvector centrality of a network is defined as:

$$C_i = \alpha \sum_j A_{ij} \frac{C_j}{k_j^{out}} + \beta, \tag{7}$$

where α is a damping factor that can have value $0 < \alpha < 1$, A_{ij} is the entry of the adjacency matrix, C_j in the centrality of bus j that is directly connected to bus i, k_j^{out} is the out degree of bus j, and $\boldsymbol{\beta}$ is the constant centrality value assigned to the isolated bus. The out degree describes how many buses are taking power from bus j. If there are buses in the power system that have an out degree equal to zero, then the first term in Eqn. (7) will be undefined. To avoid such condition, k_i^{out} is set to 1 for all such buses. The matrix notation of Eqn. (7) is represented as:

$$C = \alpha A D^{-1} C + \beta 1, \tag{8}$$

where '1' is the vector (1, 1, 1, ...) and D is the diagonal matrix with elements $D_{ii} = \max(k_j^{out}, 1)$.

The power system operation depends on the calculation of OPF, whose solution defines whether the system is operating normally or the TLLs exceed the threshold. During an emergency, when outages occur on multiple TLs, the power system needs an optimized OPF solution. Moreover, the system requires identification of TLs that can cause a cascade outage and endanger buses due to over-voltage. The TL importance index identifies such TLs that are in danger of failure due to excess power flow. The bus importance index identifies power system buses that have excess voltage, which can trip relays on these buses.

4 Service Level Agreement

The core of the ASM is to define a SLA between the data center and the power system with minimum loss at both ends. The nature of the workload in data centers is stochastic and the execution time of each job varies [22]. Therefore, the following calculations are necessary for defining the SLA:

- How much revenue loss is acceptable for the data center to prioritize execution of power system jobs?
- How much uptime can the data center provide to the power system in a month's time?

In our proposed model, ancillary services for the power system are the highest priority jobs. The ancillary services provide optimize control settings for maximum capacity utilization and operational cost minimization. Without proper and in-time ancillary services, the power faces the problem of load unbalancing or complete blackout in the worst case that will indirectly affect the power supply of the data center. Therefore, the power system jobs must be treated as priority jobs on the data centers.

If the data center is operating at its peak, then the scheduler must preempt other cloud computing jobs to execute an ancillary service request. There is no such mechanism known to the authors to determine how much delay a power system can withstand before power transmission gets perturbed. Excess delay in ancillary services also indirectly affects the data center's power supply. Moreover, if ancillary services are delayed, then how much extra will power cost the data center? Furthermore, when a data center delays cloud computing jobs more than a certain time, data center revenue will be drastically affected. For example, if the Amazon Elastic Compute Cloud (EC2) delays a job by up to 1 percent of the total agreed upon execution time, then Amazon pays a penalty (named service credit by amazon) of 10 percent of the agreed upon cost for the job. Moreover, if the delay is more than 1 percent of the agreed upon time, then the penalty is increased to 30 percent of the agreed amount [23]. The mathematical expression of SLA penalty is defined as:

$$P_{SLA} = \begin{cases} delay \leq 1\%, \ 10\% \ of \ agreed \ amonut. \\ delay > 1\%, \ 30\% \ of \ agreed \ amount. \end{cases} \tag{9}$$

We define a SLA that minimally affects the cost of the data center and maintains reliability of the power system. According to the SLA, the increased power consumption cost of the data center due to the execution of ancillary services will be paid by the power system. Moreover, a threshold will decide the number of cloud computing jobs that a data center can delay without penalty. We calculate this threshold in Section 7.

5 Revenue Modeling

The revenue model depends on the job preemption of the data center that is calculated by Eqn. (1) for any instant in time, where $\mathfrak{M}$ is the number of "on" servers in the data center. The revenue ($\Re$) of the data center is calculated as:

$$\Re = \sum_{i=1}^{T_J} (1 - q_i(\mu_i)) \left[1 + \frac{\mathfrak{F}_i}{\mathcal{L}_i}\right] - q_i(\mu_i) \left[1 + \frac{\mathfrak{F}_i}{\mathcal{L}_i}\right]. \tag{10}$$

The job service rate μ_i is defined as:

$$\mu_i = k\mathfrak{M}_i. \tag{11}$$

Let $\mathcal{T}$ be the time taken by a data center server to finish a job. In Eqn. (11), the variable k represents jobs per second ($^1/_\mathcal{T}$). In Eqn. (10), $q_i(\mu_i)$ is the probability of job failure, and T_J is the total number of jobs in the month. The data center's loss for preempting a cloud computing job and executing the ith power system job is represented by $\mathcal{L}_i$. The data center will demand $\mathcal{L}_i$ dollars from the power system to

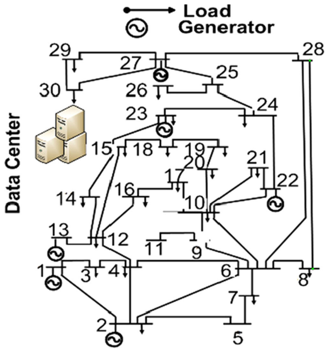


Fig. 4. Network topology of the IEEE 30 bus system for reliability testing, where the data center is acting as a load.

minimize revenue loss. Moreover, $\mathfrak{F}_i$ is the monetary incentive that the data center can demand from the power system. In Eqn. (10), the term $(1 - q_i(\mu_i))[1 + \frac{\mathfrak{F}_i}{\mathcal{L}_i}]$ denotes the total revenue earned by the data center for completing the computational jobs of the power system in sufficient time. The term $q_i(\mu_i)[1 + \frac{\mathfrak{F}_i}{\mathcal{L}_i}]$ is the penalty that the data center will pay for delaying power system jobs. Eqn. (10) minimizes the revenue loss of the data center and provides incentives to prioritize power system jobs.

6 Simulation Settings

We consider IEEE 30 bus, IEEE 118 bus, IEEE 300 bus, and Polish 2383wp bus systems for the power system reliability tests [24]. The IEEE bus systems are the replica of real world power systems, for example IEEE 30 bus system is well known as 10-machine New-England Power System [24]. As the size of the power system increases, job lengths associated with the workload increase accordingly. The detailed descriptions of the IEEE bus systems are given in Table 1. To understand the network topology of IEEE bus systems, the IEEE 30 bus system is shown in Fig. 4. The data center is powered from bus number 30 in the IEEE 30 bus system. Our exemplary data center consumes on average 1.885 MW of power operating at peak-load during a day with 1,056 servers running. A typical data center server has $\mathcal{P}_P = 213$ watts and $\mathcal{P}_I = 100$ watts, as shown in Table 2 [22].

TL outages are taken as an emergency condition for the power system, requiring ancillary services from the data center. TL outages are modeled as a "two state Markov" model on each TL. A Markov state of the power system is defined by a condition where every TL is in a given state of its own. All possible states of the TLs make up the state space. The TL state (Up/Down) is a continuous random variable. In our study, the distributions for up and down states of the TLs are taken as exponential. The exponential distribution has the following probability distribution defined as:

$$F(x) = 1 - e^{-\rho x} = z. \tag{12}$$

In Eqn. (12), the mean of random variable X is denoted by ρ^{-1}. We set the exponential function given in Eqn. (12) equal to a uniform random decimal number, z, with values between 0 and 1. Equation (12) is then rewritten as:

$$x = -\frac{\ln(1-z)}{\rho}. \tag{13}$$

The occurrence time of TL failures and their maintenance time duration is determined by Eqn. (13). Moreover, in the real-world the nature of the load is random and precise load forecasting is challenging. Therefore, the background load distribution on power system buses is also modeled as a random variable with normal distribution [15]. For example, the mean value of active power on all load buses in the IEEE 30 bus system is 9.46 MW (nominal), as shown in Table 1.

We use a real-world data center workload, collected from Computational Research of State University of New York at Buffalo to validate the ASM [5]. The workload is a collection of a 30 days' time span taken during February 20, 2009 to March 22, 2009. In the data center workload, all jobs are categorized on job length and job size. The jobs are further classified into three types: **(a)** short (less than 1 hour), **(b)** long (greater than 1 hour), and **(c)** very long (greater than 10 hours). The very long jobs (around 20 percent of overall jobs) are delay tolerant and their deadlines generally are not rigid [5]. The complete data center specification is given in Table 3. The workload exceeds 100 percent on 7 days during a month's time (105 hours total), as shown in Fig. 5. Therefore, data center resources are inadequate to complete all jobs during these times, and these over utilization hours cannot be ignored. Moreover, the unit electricity price

TABLE 2
Peak Power Consumption of a Typical Server

Component	Peak Power (W)	Count	Total Power (W)
CPU	40	2	80
Memory	9	4	36
Disk	12	1	12
Motherboard	25	1	25
PCI Slots	25	2	50
Fan	10	1	10
Total System Power			213

TABLE 3
Data Center Specification

Time Duration	20 February 2009–22 March 2009
Total data center jobs executed	22,385
Total distinct servers	1,056
Processor name	1,056 Dell PowerEdge SC1425
Processor speed	3.0 GHz or 3.2 GHz
Peak performance	13 TFlop/second

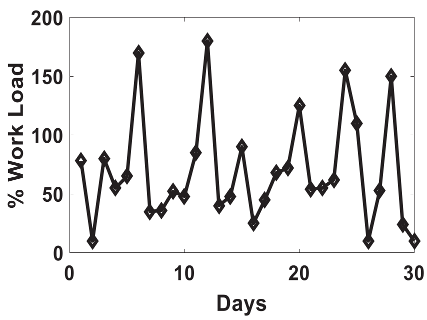


Fig. 5. Total data center load per day over a month duration.

TABLE 4
Power System Job Types and Details

Power System Jobs Type	Range for Execution Time (minutes)	Number of CPUs Utilized
Emergency	1-5	100-500
Reactive	1-10	50-300
Periodic	1-10	1-100

offered to the data center is taken from the New York Independent System Operator (NYISO) for the same period, February 20, 2009 to March 22, 2009 [14].

For clarity, ancillary services for the power system that will execute on data centers are called "power system jobs". Moreover, we represent all other cloud computing jobs as the "data center workload". We model three categories of power system jobs in our simulations along with the data center workload. The highest priority jobs are emergency jobs that arrive when a failure occurs in the power system. The data center will allocate the maximum required resources for the completion of these jobs in least amount of time. The second highest priority jobs are called reactive jobs, which occur when there is a sudden large drift in the load. The data center will allocate a large number of resources to complete reactive jobs in a reasonable time with minimum effect on the data center workload. All the remaining power system jobs required for normal operation are called periodic jobs, which will execute periodically on the data center. These periodic jobs also require significant resources, but delay is acceptable. A detailed description of power system jobs is given in Table 4.

We include "five" emergency jobs, 30 reactive jobs, and 2,930 periodic jobs in our dataset. Emergency power system scenarios rarely occur in a month's time. Therefore, we only include "five" emergency jobs in our simulations scenario. Reactive jobs occur more often than emergency jobs. Therefore, we include one job per day at a random time in the workload. Regular jobs required for stable power system operation are executed periodically every 15 minutes. We cannot dedicate some data center servers solely for the power system jobs because need based allocation is less costly compared to dedicated allocation. For example, the periodic jobs are coming after every 30 mins and the jobs are taking a maximum of ten minutes to execute, if we dedicate 100 CPUs for periodic jobs than the CPUs will run idle for approx. 20 minutes and will consume 100×100 W $= 10$ KW of idle power for every 20 mins in every half hour timespan.

The power system jobs can vary from a few minutes to a couple of hours, depending on the number of TL outages and network size. In Table 1, the Polish 2383wp system which is the replica of the PTN for the capital of Poland is taking minimum of 529 seconds (8.8 mins) to provide a converge solution that itself is a large amount of time. However, most practical power systems in the world have hundreds/thousands of buses and transmission lines. The convergence time of the OPF is sufficiently large compared to standard IEEE bus systems. Therefore, we presented a reasonable processing time and number of CPU requirement in Table 4. Moreover, the OPF is not the only ancillary service that is required by the power system. A few other known ancillary services are sensitivity analysis, short and long terms generation and transmission expansion predictions, short-term operational simulations, and power market analysis, prediction, and bidding. All of the aforementioned services are computationally extensive and categorized into periodic, reactive, and emergency jobs. For testing and validation of the ASM, the power system job timing (e.g., OPF convergence time) varies from one minute to twenty minutes [25]. End user power consumption is always variable over time, and this phenomenon is also considered in the simulations.

Substantial research in the field of parallel and distributed computing has introduced several jobs scheduling algorithms, categorized as two main types: **(a)** time-sharing and **(b)** space-sharing. Space-sharing algorithms allocate resources to a single job until the job executes completely. In contrast, time-sharing algorithms divide time on a processor into several slots and assign the slots to every unique job. In our work, due to the priority of power system jobs, we choose most popular space-sharing scheduling algorithms for the data center. Our purpose is to check the power system jobs load on the data centers in terms of fast processing of ancillary services. The three space-sharing job scheduling techniques used are: **(a)** Longest Job First (LJF), **(b)** Shortest Job First (SJF), and **(c)** Shortest Remaining Time First (SRTF). The LJF space-sharing scheduling algorithm allocates resources to the longest job first. LJF is known to maximize server utilization. Similar to LJF, SJF periodically sorts incoming jobs and executes the shortest job first. SJF tends to minimize turn-around time. SRTF is the preemptive form of SJF. In SRTF, the job with the smallest remaining time will be executed first till completion unless a new job is added that requires less execution time than the remaining time of the current job.

The above job scheduling algorithms are used to execute power system jobs along with the data center workload. The priority of all power system jobs is set to be higher than the data center workload, such that inclusion of power system jobs can delay the data center workload. In our simulation settings, the job delaying criteria for all scheduling techniques is to preempt the very long job(s) that also have the longest remaining time. Moreover, the very long jobs have on average 20 hours of total execution time and 1 percent delay in execution is 12 minutes. The selected SLA penalty (Eqn. (9)) is well suited for the preemption of very long job(s) because the execution of ancillary service takes less time than the afforded delay time of very long job(s). Therefore, the SLA is not violated for most job preemptions and minimally affects data center revenue. Furthermore, whenever there are two or more jobs with the same time remaining and one of these jobs must be preempted, the first job in the queue will be selected first for preemption. The reason for comparing job scheduling techniques is to find an optimal job scheduling technique that has the minimum effect on number of preempted jobs, makespan, and average queue time. Moreover, an optimal job scheduling technique will also reduce idle power consumption and improve data center resource utilization. Conversely, a scheduling technique that results in a large number of preempted jobs and long duration of jobs in queues will adversely affect the SLA. Similarly, a scheduling technique that creates a large makespan for the data center workload will result in increased power consumption. In the ASM, the monetary cost to execute a job is based on the "on-demand pricing criteria" of Amazon [23]. For example, a job utilizing 8

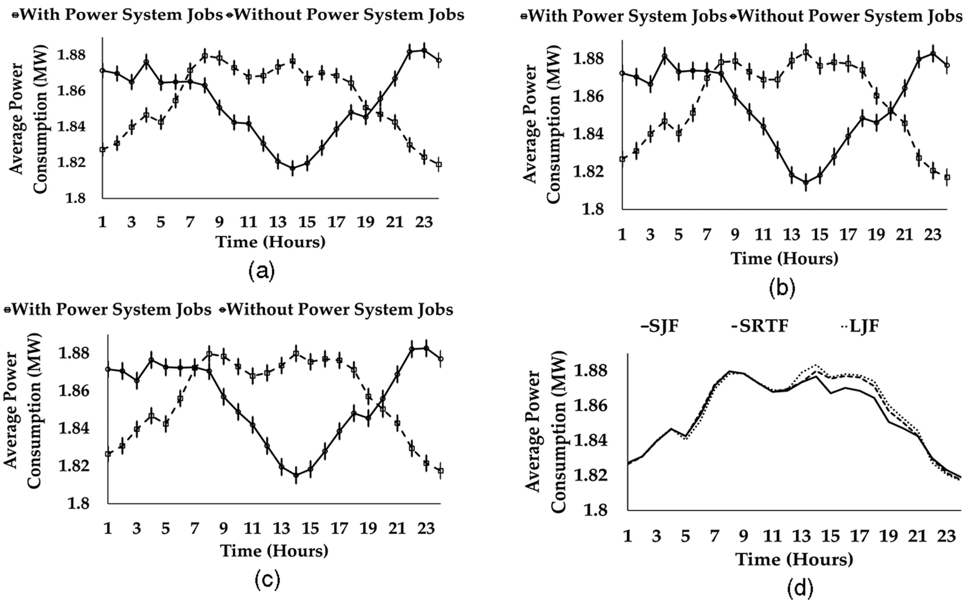


Fig. 6. Power consumption comparison of data center under: (a) SJF, (b) LJF, and (c) SRTF job scheduling techniques. (d) Power consumption comparison of data center for all three job scheduling techniques when power system jobs are included.

CPUs will bear a cost of \$0.840/hour [23]. Moreover, the job preemption penalty is also the same as the service credit rate of Amazon EC2 [23].

7 Results and Discussion

We have carried out simulations of our proposed ASM on a server SYS-7047GR-TRF system. The data center provides in-time OPF solutions and identification of endangered TLs and buses for establishing a robust power system. However, because of power system jobs, power consumption of the data center increases. This increase in power consumption has various reasons that are described later in the section.

The ASM is simulated for the period of one month using three job scheduling techniques, as stated in Section 6. Figs. 6a, 6b, and 6c show the average power consumption of the data center averaged over 20 runs for a 24-hour period, under the influence of the LJF, SJF, and SRTF job scheduling technique, respectively. The aforesaid figures elaborate that the power consumption of the data center increases after the inclusion of power system jobs. However, we can observe from the figures that in the beginning and end hours of the day, the average power with the added power system jobs is less than the average power without power system jobs, which is counter intuitive. Since Fig. 6 reports the average power consumption graphs over a month's time, and the inclusion of power system jobs increases the makespan of the overall workload of the data center, the total hours of work increases, which reduces the average power consumption with power system jobs in the beginning and end hours of the day, but still yields a net overall increase in average power consumption per day of 0.05527, 0.05754, and 0.06342 percent, using SRTF, SJF, and LJF, respectively. Fig. 6d shows this power consumption comparison graphically for all three job scheduling techniques. The graph trend shows that most of the time power consumption remains the same; however, during the peak load period (starting from late afternoon till midnight), SRTF performs better than LJF and SJF. To calculate the obvious increase in power consumption cost, a real-world electricity unit price is used, as shown in Fig. 7 [14].

7.1 Impact of the ASM on the Data Center

This section describes the impact of executing power system jobs on the data center. The influence is observed on the number of preempted jobs, makespan of the jobs, average queue time, and resource utilization. Job preemption involves the purging of the data center work load in favor of power system jobs. Fig. 8 shows the number of preempted tasks in one month's time. A job in the data center workload can have more than one task depending on the number of CPUs utilized by the job. In the data center, task preemption affects job execution time, which may result in a monetary

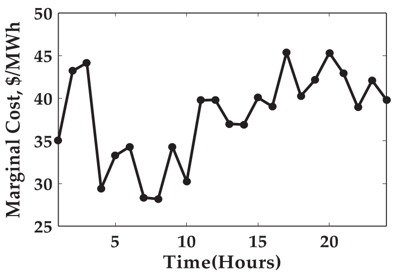


Fig. 7. Real-time electricity unit pricing offered by the power system to the data center during a 24-hour period.

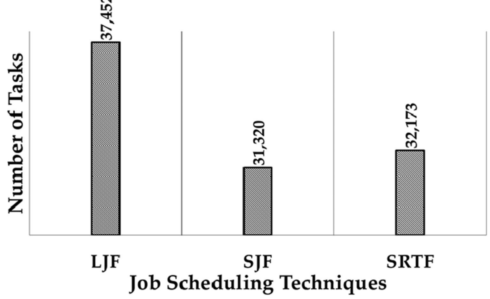


Fig. 8. Preempted tasks in data center workload in one month's time due to the inclusion of power system jobs.

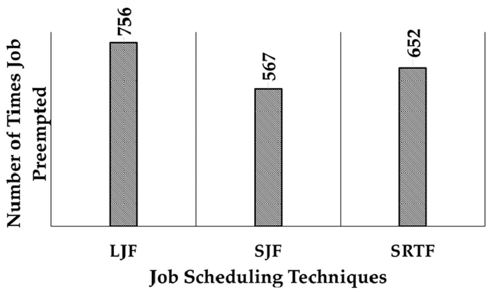


Fig. 9. Comparison of data center workload job preempted the most times.

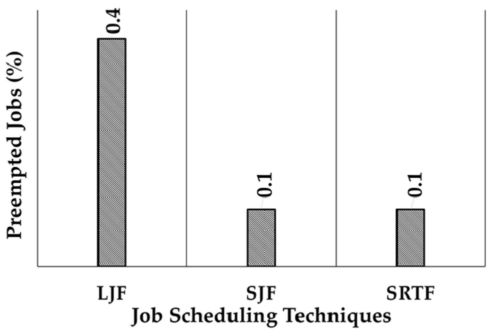


Fig. 10. Comparison for preempted power system jobs.

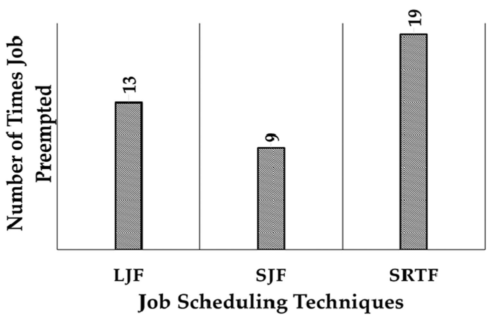


Fig. 11. Comparison of longest running periodic power system job preempted the most number of times.

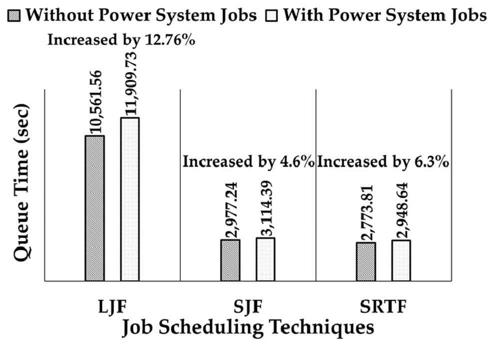


Fig. 12. Comparison of data center workload average queue time over the period of one month.

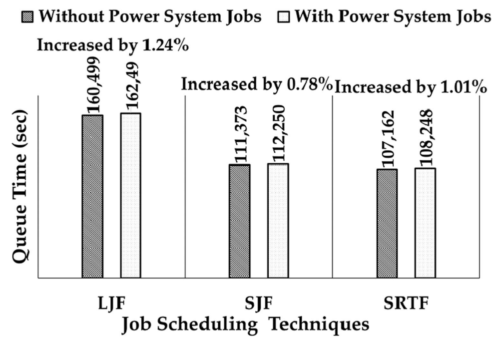


Fig. 13. Comparison of data center workload job with longest queue time.

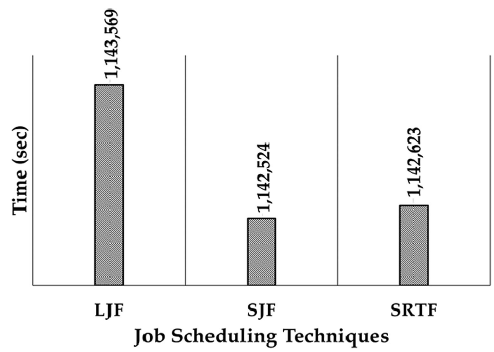


Fig. 14. Comparison of makespan for power system jobs during a month's time.

penalty, per the SLA defined in Eq. (9). The more preempted tasks, the more the data center will be penalized for delaying jobs. In Fig. 8, we observe that SJF preempts fewer tasks compared to SRTF and LJF. We also observe the job that was preempted the most number of times, as shown in Fig. 9. Moreover, the job that is preempted the most times is also the longest running job in our data center workload. Furthermore, when the SJF job scheduling technique is used, this job is preempted fewer times compared to SRTF and LJF.

Although, the priority of power system jobs is higher than the data center workload, the job preemption effect of the different scheduling algorithms is still noticeable on the power system jobs, as shown in Fig. 10, which illustrates that SJF and SRTF preempt fewer power system jobs compared to LJF over a month's time. SJF and SRTF preempt less than 0.1 percent of power system jobs; whereas LJF preempts four times the number of power system jobs, 0.4 percent. As shown in Fig. 11, we also identify the effect of preemption on the longest running periodic job of the power system, illustrating that SRTF results in more preemptions compared to SJF and LJF.

Job queue time is another important metric that directly affects data center performance. The longer the queue time, the longer overall execution time for jobs will be; and data center power consumption is directly related to job execution time. Fig. 12 shows that average queue time using SJF, SRTF, and LJF increases by 4.6, 3.6, and 12.76 percent, respectively, after adding power system jobs. This percentage increase in queue time is directly proportional to the increase in number of preempted tasks of the data center. The longest queue time in the data center workload also increases proportionally after the inclusion of power system jobs, as shown in Fig. 13. In our case, the job with the longest queue time is also the longest running job in the data center workload.

The workload makespan demonstrates the total running time of jobs on the data center. A job scheduling technique with a longer makespan results in increased power consumption. The makespan of LJF for power system jobs is approximately 17.4 minutes longer than for SJF and 15.6 minutes longer than SRTF, as shown in Fig. 14. As illustrated in Fig. 15, a similar effect is observed for the overall data center makespan, which increases by 2.37, 0.5, and 0.53 percent using LJF,

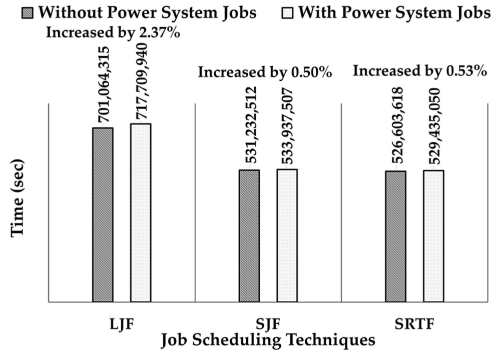


Fig. 15. Comparison of makespan for data center's workload during a month's time.

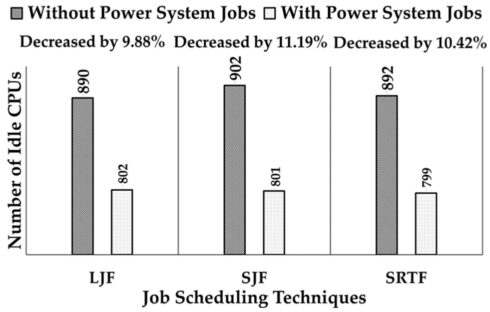


Fig. 16. Comparison of average idle CPUs in data center.

SJF, and SRTF respectively, after adding power system jobs. As shown in Figs. 8 and 12, SJF preempts fewer jobs and the percentage increase in average queue time for the jobs is smallest compared to the other two job scheduling techniques. However, SRTF has minimum average queue time among all three job scheduling techniques.

The power consumption of the data center is also affected by idle running resources. We observed the effect of resource utilization in the data center, as shown in Fig. 16. The waste of idle running resources was reduced most by using SJF; however, SRTF results in the least number of idle CPUs. SRTF results in the least makespan and queue time, which allows jobs to complete earlier. Therefore, more resources will be available for execution of power system jobs within the allotted time.

Given the current simulation parameters for data center workload and number of power system jobs, we assess that SJF is the best job scheduling technique among all three, when we consider number of power system job preemptions, preempted tasks in the data center workload, and makespan of power system jobs. However, SRTF performs best in terms of queue time and makespan of data center workload, and average idle resources of the data center. Therefore, using SJF and SRTF, the data center can safely agree on a SLA (as defined in Eqn. (9)) with the power system for computationally intensive ancillary services with minimum impact on the rest of the data center workload. We conclude that there is a trade-off between the two job scheduling techniques (SJF and SRTF). If we choose SJF, we have less preemptions of power system jobs. However, we must compromise on average queue time and makespan of data center workload.

In our ASM, the power system provides incentives to the data center to nullify the negative impact on data center revenue due to prioritizing power system jobs. These incentives include a lower electricity unit price during the execution period of power system jobs. Moreover, as illustrated in Fig. 10, SJF and SRTF preempted the fewest power system jobs during the entire month, which is the minimum job preemption possible for executing power system jobs. Therefore, we define this percentage as our threshold. If the data center preempts more jobs than this threshold, then the data center will sustain a penalty cost.

7.2 Impact of the ASM on the Power System

The stability and reliability of the power system depends on a balanced power flow solution. Once TL failures occur, the main requirement is to balance the generation and load. As described in Section 3.2, there are two types of loads present in IEEE bus systems: **(a)** background load and **(b)** data center load. The background load is the conventional load of the power system, for example residential load, commercial load, and industrial load. In the real-world, the background load varies depending on consumer requirements and the daily load curve. Therefore, inequality constraints are applied to the random background loads. The bound on the inequality constraint is adjusted, such that the sum of the background load power (active and reactive) does not exceed the total generation of the IEEE bus system minus the peak power consumption of the data center. Second, standard deviation of the background load on any given load bus is set at 10 KW with mean value of the loads for all tested IEEE bus systems provided in Table 1.

The cost/objective function for the OPF solution is active power loss on all TLs. The power loss in the system is calculated with real power miss-match between the sending and receiving bus of each TL. TL outages are randomly generated. Whenever an outage occurs, the power system jobs become emergency jobs. Moreover, when there is a drastic change in load, the jobs generated are called reactive jobs. For normal steady-state operation, the power system requires periodic checks on load and generation. These jobs are called periodic jobs. The data center will calculate the OPF solution to balance the power system for all three cases. If the OPF fails to converge, then this situation is known as a blackout or system failure. Moreover, if the OPF converges but TLLs exceed 5 percent of the generated power, then the system is still considered to be in a failure state. The OPF converges in all algorithms for most situations; however, Fig. 17 illustrates the OPF convergence iterations for the Polish 2383wp bus system with 17 TLs out, which does not

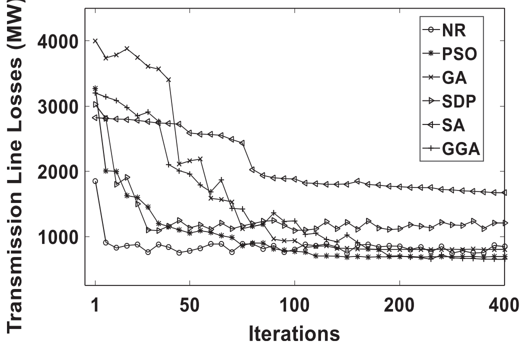
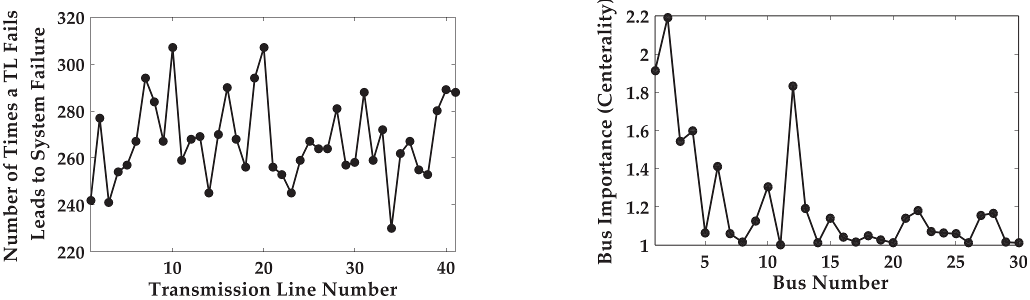


Fig. 17. TLL convergence using the OPF algorithm for the Polish 2383wp bus system when 17 TLs are out.



(a) Transmission Line Importance Index (b) Bus Importance Index

Fig. 18. IEEE 30 bus system status during emergency, when an outage occurs on *N-k* transmission lines.

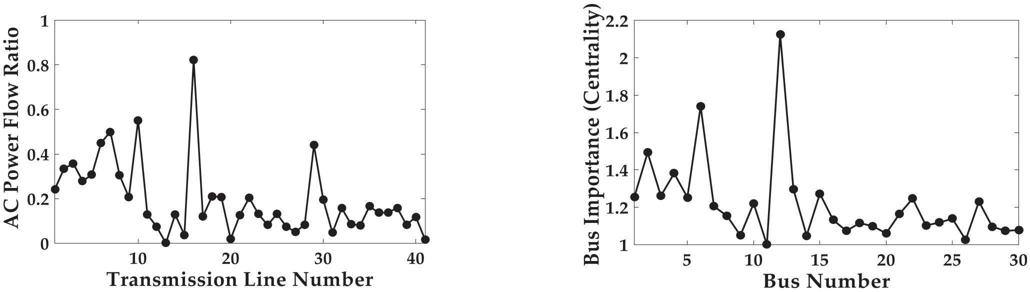
converge for any algorithm if more than 17 TLs are out. The least TLLs achieved for this case is 650.23 MW for GGA, which is less than 5 percent of the total generated power from Table 1, making this an acceptable loss. During contingencies, the TL importance index is also calculated. For the clarity of the readers, the results for the IEEE 30 bus system are presented in Fig. 18a.

The IEEE 30 bus system presents a more elaborative picture of TL outages. With increased power system network size, such as the Polish 2383wp bus system, the influence of TL outages on the system is not well visualized graphically. Fig. 18a shows that TL 10 and TL 20 are the most endangered TLs in the IEEE 30 bus system because the AC power flow ratio of these TLs are higher than the threshold. Therefore, the overall system has more chance of failure if an outage occurs on these TLs. Furthermore, Fig. 18b shows the centrality based bus importance index. Buses with higher centralities are more prone to cause TL failures because these buses are associated with those TLs that have high AC power flow, and load power on these buses is more than for other buses. This concept is similar to the node centrality concept in networks [21]. In Fig. 18b, we observe that Bus 1, Bus 2, Bus 3, Bus 4, and Bus 12 are the most critical buses in the IEEE 30 bus system. The data center provides an optimized OPF solution to reduce AC power flow on endangered TLs. The OPF solution also reduces overloading on these buses. Fig. 19a shows the optimized AC power flow ratio of all TLs after running the OPF algorithm. The AC power flow on TLs 10 and 20 has been reduced, such that the remaining TLs are no longer in danger. Fig. 19b illustrates the reduction in the bus importance index compared to Fig. 18b. The decrease in centrality values of the endangered buses is observed. However, Fig. 19b shows the increase in centrality values of Bus 6 and Bus 12. From Fig. 4, we can observe from the one-line diagram of the IEEE 30 bus system that bus 6 is the most central and critical bus in the network. Therefore, the centrality value of Bus 6 will remain high. Moreover, Bus 12 is directly connected to Bus 13 that is directly linked with a 37 MW generator. Bus 12 is the only connection between the 37 MW generator and the entire network, such that when the transmission line between Bus 12 and Bus 13 is out, the network suddenly faces a power drop of 37MW. Therefore, Bus 12 is the second most critical bus in the system; and after the OPF solution it remains critical. The aforementioned analysis and discussion plays a pivotal role for maintaining stability, robustness, steady-state operation, and reliability of the power system.

7.3 Data Center Revenue

Section 7.1 describes the results of the data center's revenue loss for providing ancillary services to the power system on a priority basis. In the ASM, the data center is compensated for this loss by the power system. Therefore, the data center will be motivated to prioritize execution of the power system's jobs. According to Eqn. (10), the power system will not only provide the cost, $\mathcal{L}_i$, for the ancillary services to the data center, but will also provide incentive, $\mathfrak{F}_i$, to maintain a minimum profit level for the data center. If the data center provides ancillary services to the power system without any delay, then the SLA (Eqn. (9)) will mutually benefit both the data center and power system.

However, a problem arises when the data center is unable to complete ancillary services in time. Fig. 20 depicts the data center revenue curve, as illustrated in Eqn. (10). In Fig. 20, 100 percent revenue means that the incentives, $\mathfrak{F}_i$, provided by the power system, all become the profit of the data center. Moreover, 0 percent revenue means that the data center revenue loss for delaying its workload is recovered, but no extra profit is earned. Furthermore, the graph



(a) AC power flow on Transmission Lines (b) Bus Importance Index

Fig. 19. IEEE 30 bus system status after OPF solution provided by the data center.

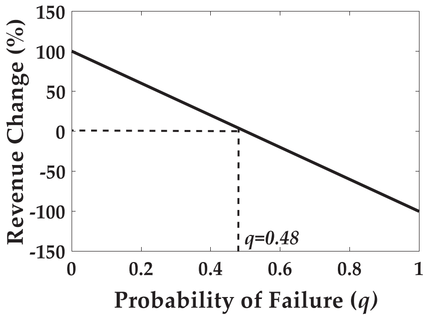


Fig. 20. Data center revenue curve due to the implementation of the proposed service level agreement.

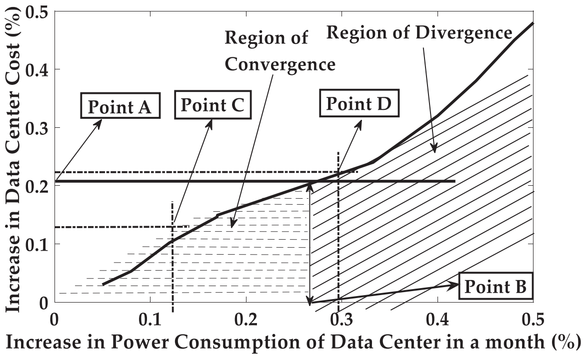


Fig. 21. Revenue convergence region for the data center. Point A depicts the percentage cost saved by OPF to reduce TLLs for the case of 17 TLs out. Point B depicts the maximum increase in power consumption of the data center to not lose revenue. Point C depicts the increase in cost due to SJF and SRTF. Point D depicts the increase in cost due to LJF.

below 0 percent depicts when the data center incurs a net loss in revenue by delaying cloud computing jobs to execute power system jobs. Fig. 20 also illustrates the minimum failure rate ($q_i = 0.48$) for a power system job that is bearable for the data center. In Fig. 10, the LJF preempts 0.4 percent of power system jobs during a month's time that means eleven power system jobs are preempted. However, SJF and SRTF only preempt two power system jobs per month. Moreover, from Fig. 15, we can observe that the makespan of data center workload is only increased by 0.5 percent that is less than 1 percent defined in the SLA (Eqn. (9)). Therefore, if two or more power system jobs are delayed more than 48 percent as per minimum rate of failure, the data center will lose revenue.

7.4 ASM Convergence

To understand the concept of ASM convergence, a specific case of the Polish 2383wp bus system is considered. The parameters of the system have certain limitations, as listed in. Table 5. We arbitrarily selected 17 out of the 2896 TLs of the Polish 2383wp bus system to incur an outage for a period of ten minutes. The TLLs are increased to 656.2 MW. The OPF algorithm reduces the power loss to 652.69 MW and saves 3.517 MW of power. In response, the incentives provided to the data center will be equivalent to the power saved by reducing TLLs.

TABLE 5
Input Parameter Constraints for Model Convergence at Peak-Load Hour (Only for Polish 2383wp Bus System and the Case When 17 TLs Incur an Outage for Ten Minutes)

System Model	Parameters Description	Convergence Constraints
Power System	Maximum number of TL outage that the power system can sustain	17
	Tolerance between power injection and power consumption	10^{-6}
	Background Load Limit	13.84 MW $\pm$ 10 kW
	Max. Background Load (BL)	$0 < \text{BL} \leq 2458.4$MW
	Maximum Power Loss (PL) savings resulting from the OPF data center calculation for the case of 17 TLs out	$\$0 < \text{PL} \leq \$3880$
Data Center	Maximum Incentives given to the data center ($\mathcal{L} + \mathfrak{F}$)	$\mathcal{L} + \mathfrak{F} \leq$ PL

Fig. 21 shows a nonlinear curve between percentage increase in data center power consumption and corresponding percentage increase in data center cost, when power system jobs are executed on the data center. The intersection points C represents the percentage increase in data center cost when SJF and SRTF job scheduling techniques are used, while point D represents the percentage increase in data center cost when LJF is used. The horizontal solid-line defines the threshold amount that the power system will offer to the data center for providing OPF solution and reduction in power losses, as mentioned above. Therefore, Point B represents the maximum increase in power consumption (0.29 percent) of the data center that will be compensated by the power system. If the increase in power consumption is more than this threshold, the data center will lose revenue. The discussion is only for the specific case of 17 TLs out in the Polish 2383wp bus system. The threshold defined by the horizontal solid-line is dependent on the power system network size and number of TLs out. In the Polish 2383wp bus system, if the number of TLs out is more than 17, then the OPF algorithm will not provide a converged solution. Therefore, we conclude that the region of convergence for data center revenue, for this case only, will have a threshold of approximately 0.29 percent increase in power consumption of the data center. The data center's revenue will decrease whenever its power consumption exceeds this threshold, as the power system will not be able to provide enough compensation to the data center.

8 Conclusion and Future Work

In this paper, we proposed an analytical model for a mutually beneficial relationship between a data center and its power system. The model ensures data center revenue maximization and power system stability and reliability enhancement. Our model includes several factors, such as Service Level Agreement (SLA), electricity price, data center revenue model, Optimal Power Flow (OPF) solution for the power system to reduce transmission line losses, and identification of endangered buses and transmission lines. The simulations using a real-world data center's workload and IEEE standard bus systems validate the performance of the Ancillary Services Model (ASM).

The proposed ASM will be further extended to multiple data centers attached to the power system. Demand response pricing scheme, such as time-of-use pricing will be incorporated to develop cost reduction models and power management algorithms for the data centers.

Acknowledgments

Samee U. Khan's work supported by (while serving at) the National Science Foundation. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the US National Science Foundation.

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Sahibzada M. Ali is an assistant professor with COMSATS Institute of Information Technology, Abbottabad, Pakistan. He is a student member of the IEEE.

Muhammad Jawad is an assistant professor with COMSATS Institute of Information Technology. Lahore, Pakistan. He is a student member of the IEEE.

M. Usman S. Khan is an assistant professor with COMSATS Institute of Information Technology, Abbottabad, Pakistan. He is a member of the IEEE.

Kashif Bilal is an assistant professor with COMSATS Institute of Information Technology, Abbottabad, Pakistan.

Jacob Glower is an associate professor in the Department of Electrical and Computer Engineering at North Dakota State University.

Scott C. Smith is a professor and Department Chair of Electrical and Computer Engineering at North Dakota State University, Fargo, North Dakota. His research interests include computer architecture, asynchronous logic, computer arithmetic, and VHDL. He is a senior member of the IEEE.

Samee U. Khan received the PhD degree from the University of Texas, in 2007. Currently, he is the Department head and the James W. Bagley chair of Electrical & Computer Engineering at the Mississippi State University (MSU). Before arriving at MSU, he was Cluster lead (2016-2020) for Computer Systems Research at National Science Foundation and the Walter B. Booth professor at North Dakota State University. His research interests include optimization, robustness, and security of computer systems. His work has appeared in more than 400 publications. He is associate editor-in-chief of the IEEE IT Pro, and an associate editor of *Journal of Parallel and Distributed Computing* and *ACM Computing Surveys*.

Keqin Li is a distinguished professor in the Department of Computer Science, School of Science and Engineering, State University of New York, New York. His research interests mainly include the areas of parallel and distributed computing, and computer networking. He is a fellow of the IEEE.

Albert Y. Zomaya is currently the chair professor of high performance computing with the School of Information Technologies, The University of Sydney, Sydney, Australia. He is a fellow of the Institution of Engineering and Technology and of the American Association for the Advancement of Science. He is a fellow of the IEEE.