Flexibility Management of Data Centers to Provide Energy Services in the Smart Grid

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ABSTRACT

In this paper, we address the problem of Data Centers (DCs) energy efficiency considering their integration into the electrical and thermal grids by emphasizing the role of the DC Digital Twin model in DC flexibility management. Due to their high digitization and controllable energy systems, the DCs can act as flexible assets, being able to dynamically adapt their energy profiles and valuable energy services. We present a flexibility management solution that is using a Digital Twin model of DC systems to determine action plans for shifting energy load. DC monitored data is acquired by integration with existing DC infrastructure management (DCIM) while energy predictions are computed for DC energy demand, energy flexibility, and heat generation. The flexibility optimization plans for DC operation are determined and enforced after DC manager validation via DCIM integration. Five energy services are identified as suitable to be provided by the DC with the help of described flexibility management solution: energy trading for increasing profit, grid congestion management by decreasing DC energy demand, scheduling by increasing DC energy demand to consume as much as possible the renewable available in the local grid, power factor compensation and sell heat on demand.

CCS CONCEPTS

• Information systems → Information systems applications → Enterprise information systems → Data centers; • Hardware → Power and energy →Energy distribution → Smart grid;

KEYWORDS

Data Centers, Energy Services, Energy Flexibility Management, Smart Grid, Heat Reuse.

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1 Introduction

In the last two decades, the Data Center (DC) industry had encountered massive development due to large-scale virtualization, massive software services development, and the advent of cloud platforms. The DCs are responsible for 1.4% of the global energy consumption [1] and 2% of carbon emissions [2]. Research has focused to reduce the DC energy footprint, aiming to develop energy-efficient or green DCs. One of the first research directions targeted to gradually optimize IT resource energy consumption using various techniques, such as server consolidation [3], Dynamic Voltage Frequency Scaling (DVFS) [4], or dynamic server allocation over a time window [5].

At the same time, both research and industry noticed that besides the energy demand of the IT resources, the cooling system is a major energy consumer in the DC, being responsible for as low as 10% of the overall energy demand for highly efficient systems, up to more than 60% for legacy systems [6]. Thus, research effort had channeled to enable the DC energy efficiency by cooling system optimization. Initial approaches aimed to decrease the cooling system energy demand by lowering the server outlet temperature by intelligent workload placement [7]. The complex thermodynamic processes within the server room are usually modeled using Computational Fluid Dynamics (CFD) simulations, to predict temperature distribution for specific server loads with less than 1-degree Celsius error [8]. Due to the high computational complexity of the CFD simulations, researchers focused to develop simpler models, that even if less accurate, allowing closer to real-time computations. Thus, initial approaches relied on mathematical models derived from thermodynamics laws [9], while more recent approaches rely on machine learning models for temperature distribution forecasting [10]. Furthermore, as chip density increased, and cooling systems started encountering difficulties for efficient heat dissipation making the DCs start adopting liquid cooling. New technologies, such as deep learning, are accelerating this adoption due to the high demand of processor power and energy [11].

Finally, the last few years saw a global embracement of renewable energy sources and their widely spread and integration in the energy grid. The Smart Energy Grid concept has emerged implementing a new paradigm to match and balance the energy consumption to the energy production as opposed to traditional grids where energy production was planned and controlled following the energy demand [12]. This new grid control paradigm needs to leverage and exploit potential flexibility assets. Due to its high digitization and many controllable sub-systems, the DC is such a flexible asset, being able to dynamically adapt its energy demand to match the requests from the Distributed System Operator (DSO) and contribute to the Smart Grid resilience and sustainability. The key for enabling a DC to become a part of this heterogeneous energy ecosystem is an intelligent flexibility management and optimization software able to accurately model the complex DC sub-systems, predict and simulate their behavior and compute optimization actions to shift flexible energy. The plans are then enforced by actuators to enable the DC to seamlessly integrate with the Smart Grid while meeting the Service Level Agreements of the DC client workload.

At the same time, the DC can exploit not only the electrical energy flexibility but also other variants such as thermal energy flexibility. In this case, the aim is to shift the DC thermal flexibility of the cooling system to DC heat reuse, viewing the DC as a thermal power plant that can supply heat on demand to nearby offices or households [13-17]. Thus, thermal models and workload scheduling techniques are developed for enabling the DC to produce and deliver heat in the local heat grid at the request of the Heating Operator.

Thus, in this paper, we address the above identified problems of DC optimal integration with the local electrical and thermal grids. We analyze the modeling of energy flexibility of several subsystems found in a DC and propose a flexibility management solution for shifting the energy load to provide energy services in the smart grid. Examples of the most suitable energy services to be provided by the DC are presented and discussed from the perspective of how the energy flexibility needs to be shifted.

The rest of this paper is structured as follows. Section 2 describes the DC sources of flexibility and flexibility management solution, Section 3 presents the energy services the DC may provide to the electrical and thermal grids, while Section 4 concludes the paper.

2 DC flexibility management

The DC is a complex and heterogeneous environment composed of multiple subsystems that can be grouped in four categories (see Figure 1): i) IT Resources such as servers, network equipment, and storage systems, ii) Cooling System Resources such as chillers, radiators, pipes filled with coolant, compressors, iii) Heat Reuse System Resources such as water tanks and heat pumps used to raise the heat quality; and iv) Energy Distribution Resources such as power lines, power supplies, inverters, rectifiers, batteries, etc.

The DC uses electrical energy from the Smart Grid as a fuel to run the IT equipment and auxiliary equipment, such as the cooling system. It is processing client workload and is generating heat which may be exploited as a service to be sold.

The energy transfer processes inside the DC are mathematically modeled (for more details please check [18], [19]) and a Digital Twin (DT) replica is constructed. The DT of the DC is used to analyze in conjunction with monitored data the energy flexibility behavior of individual systems and to decide on the action to shift flexibility to provide energy services. Considering the four categories, the DT model of a Dc is composed of a set of discrete heterogeneous models, encompassing linear or nonlinear equations and black box models based on machine learning, working together to assess and shift the energy load while meeting workload SLA constraints.

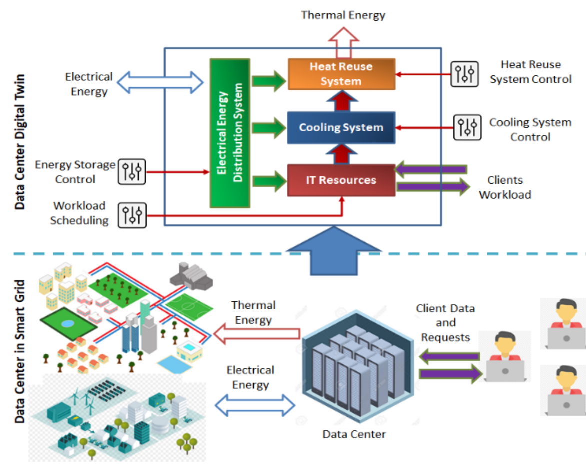

Figure 1: DC conceptual model

The **IT Resource** models aim to correlate the workload submitted by DC clients, characterized by resource requirements and SLA constraints, with the electrical energy consumption of the servers. This conversion is performed by correlating server resource usage due to task scheduling with server power demand. The flexibility control can be realized through a workload scheduling matrix that defines the mapping of each task on the servers and the time interval of running each task.

The **Cooling System Resources** models aim to estimate the temperature distribution and the heat map within the server room. The energy consumed by the IT resources for workload execution is transformed into thermal energy that leads to temperature increases in the server room. Cooling system models should estimate the temperature increases and potential hotspot formation in the server room. Also, they are used to compute the coolant temperature and flow to transport the heat and maintain a steady operating temperature. Mostly studied models are based on CFD simulations, gray-box parametric equations, or machine learning.

The Heat Reuse System Resources models aim to represent the process of harvesting the residual heat extracted by the condenser of the cooling system and raising its quality by increasing the temperature using a second refrigerant cycle. A set of coolant tanks can be used to store cold and hot coolant at both ends of the heat pump to increase the system inertia [13]. The behavior of these components can be described by a set of Partially Differentiable Equations (PDEs) discretized over a time window, leading to linear models. The heat reuse system flexibility control manages the coolant flow through the secondary refrigerant cycle and the buffer tanks.

The Electrical Energy Distribution Resources models the behavior of distribution components using equations derived from physics, discretized and represented as series dependent on time. The electrical energy distribution flexibility control consists of the quantity of energy charged or discharged from the battery system.

To successfully integrate the DC with the Smart Grid, by providing electrical and thermal services a **DC Flexibility Management** solution (see Figure 2) is proposed to work on top of the existing Data Center Infrastructure Management System (DCIM). It is organized according to the MAPE-K architecture [20] for adaptive systems considering monitored data.

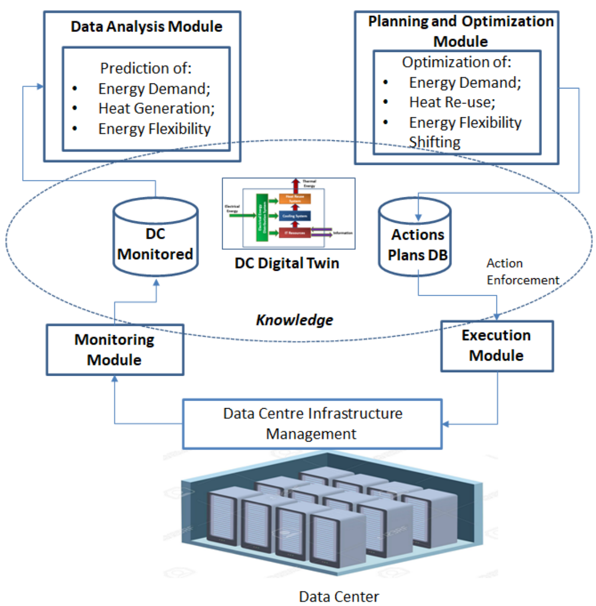

Figure 2: DC flexibility management solution

The *Monitoring Module is* composed of a set of APIs for integrating with existing DCIM that may already be deployed in the DC. It gets monitored data and feeds it into a NoSQL Database to be stored as tuples containing device IDs, monitored timestamps, and values.

The *Data Analysis Module* is responsible to forecast the DC electrical and thermal energy profiles to be then used in the data-driven simulation processing that are using the DC DT model. The forecasting window is defined in strict relation to the energy services' expected delivery interval.

Based on historical traces of DC monitored data the following energy flavors are predicted:

- Electrical energy demand - the DC energy consumption prediction over the optimization time window.
- Electrical flexibility - how much the DC can increase or decrease its energy demand in the given window. The values are used as constraints in the DC flexibility optimization processes.
- Heat flexibility - the DC heat generation for a given energy consumption.
- Baseline energy – the DC heat and electrical energy profiles in absence of services and optimization.

The *Planning and Optimization Module* aims to determine the optimization action plan and associated control variables for shifting the DC energy flexibility to provide various energy services (see Section 3). Each optimization component solves a mathematical optimization problem defined by an objective function having as arguments the control variables of the DC DT subsystems and a set of constraints expressed either as equalities or inequalities modeling the interaction of the subsystems. Due to the complex representations of the DC DT model, the resulting optimization problem is NP-hard. Depending on the cooling system model, it can contain equations defined as black-boxes and machine learning thus the traditional gradient-based solvers cannot be applied. Thus, heuristics are employed to solve the mathematical optimization problem in a combinatorial manner by encoding the candidate solutions as chromosomes and/or genes of individuals and performing multiple searches through a population of individuals to avoid local optimality plateau. The solution of the optimization problem is represented as a set of values of the DC subsystem control variables which encode a set of load shifting actions.

The *Execution Module* takes up the flexibility shifting actions and upon DC Manager validation enforce their execution by leveraging on the existing DCIM support and integration.

The *Knowledge Module* contains the DC DT as a connection between the monitored data and the corresponding action plans for enforcing energy flexibility. The DC DT contains the models, represented either as equations or machine learning models for various processes monitored and controlled by the DC flexibility management solution.

3 DC services for grid integration

Using the described flexibility management solution, the DCs will be able to potentially provide the energy services from Table 1.

Table 1: Energy services that may be provided by DCs [21]

Commodity	DC Services	Description	Interested Stakeholders
Electrical Energy	Energy Trading	Sell the energy generated or stored on-site	Energy Aggregators, other prosumers
		Buy energy when prices are low	
	Congestion Management	Shift flexible energy to decrease energy demand and avoid congestion point	Flexibility Aggregators, DSO
	Scheduling	Increase energy demand to match high availability of	

		RES in the local grid	
	Reactive Power Compensation	Modify the DC Power Factor to compensate voltage fluctuation in the Smart Grid	DSO
Thermal Energy	Sell heat	Inject generated heat in the heat grid	District Heating Operator

3.1 Energy trading

The energy trading services are aiming to increase the profit or minimize the energy costs of a DC by trading energy on an electrical energy market. A DC may exploit its latent electrical energy flexibility aiming to buy energy when the prices are low in the electricity marketplace and to sell energy when the prices are high. To buy electrical energy the DC will shift its energy flexibility to the time intervals when the energy price is low and as result, it will increase its overall demand (see Figure 3). To sell electrical energy the DC will decrease its energy demand by shifting the flexible energy outside the time interval in which the prices are high allowing it to sell its surplus of energy generation.

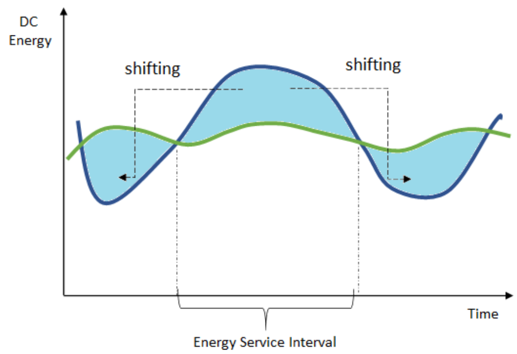

Figure 3: Flexibility shifting (with blue) for energy trading service: DC energy baseline with blue and DC adapted energy profile with green.

3.2 Congestion management

The congestion management services are referring to the reduction of energy consumption in a congestion area where the total consumption exceeds the contracted value. To offer congestion management services a DC shifts its flexible energy away from the service interval to reduce its energy demand profile. It must manage its operation so that a specific amount of flexible energy is shifted in time (see Figure 4). The Smart Grid energy planning is facilitated by following energy consumption profiles, especially in cases of medium-sized or big consumers like the DCs.

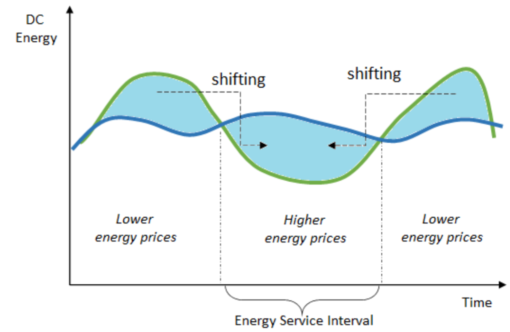

Figure 4: DC Flexibility shifting (with blue) for congestion management: DC energy baseline with blue and DC adapted energy profile with green.

3.3 Scheduling - maximize the usage of renewable

The DC is part of a microgrid within a Smart Grid, composed of a set of active energy prosumers, that can consume and inject energy into the grid. Renewable energy sources are dispersed within the microgrid, and the goal is to schedule the energy consumption so that it consumes all the renewable energy produced due to weather conditions. However, unpredicted weather conditions can lead to renewable production peaks that can overload the grid if they are not consumed at once. To handle this dangerous situation, a large energy consumer is needed to increase its energy demand.

The DC is a perfect candidate to solve this situation due to its large energy footprint and the high level of control and digitization. In case of an unpredicted renewable energy production peak within the local microgrid, the DSO sends a request to the DC indicating the additional quantity of energy to be consumed. The DC Flexibility Management solution analyses the DC energy consumption pattern and computes the set of control variables to shift energy flexibility and increase the DC energy demand (see Figure 5).

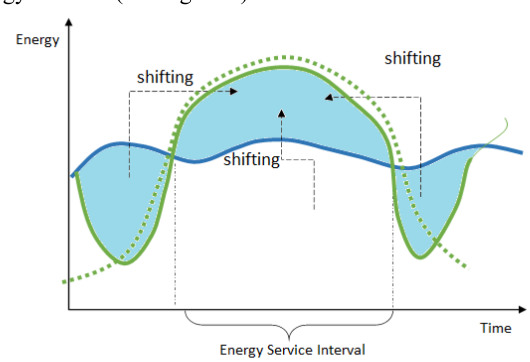

Figure 5: Flexibility shifting (with blue) for energy scheduling service: DC energy baseline with blue, DC adapted energy profile with green, renewable production in the local grid with dashed green.

Using the flexibility of DC subsystems such as delay tolerant workload scheduling for execution in the demand interval, increasing the cooling system usage by precooling mechanisms, which extract excess heat from the server room making it operate at a lower temperature at the cost of increasing the cooling system energy consumption, and finally by charging batteries to store excess energy from the grid.

As result, the DC can increase its energy demand for the energy service interval to shave renewable peaks that can unbalance the microgrid. Thus, the energy consumption is matched to the production and the microgrid can act as an independent energy island without external balancing and control as for traditional grids.

3.4 Reactive power compensation

The Smart Grid maintains a constant frequency and voltage by carefully balancing the active and the reactive power. Reactive power is supplied to the grid by capacitive (leading) power factor equipment and is consumed by inductive (lagging) loads. The amount of reactive power consumed or injected by an energy prosumer is described by its power factor, which is a unitless number between 0 and 1. In the grid, leading reactive power cancels lagging reactive power, decreasing the overall reactive power, making the grid more efficient as it gets closer to 1.

However, in case of a sudden failure of an energy generator, even if another generator is powered up to replace it, if the power factor of the two generators differs, an imbalance of reactive power appears in the grid that needs to be corrected by an energy prosumer that can dynamically adapt its power factor, either making it capacitive to inject reactive power or making it inductive to consume the excess reactive power.

The DC can act as a power factor compensation asset because it is composed of two large energy subsystems: the IT resources that are featuring capacitive loads [22] and the cooling system that is featuring inductive loads. By toggling the energy consumption of the server through smart workload scheduling and the cooling system load by precooling and post-cooling mechanism, the DC can adjust its PF. As result, the DC can either consume excess reactive power from the grid or inject reactive power to the grid.

To achieve this, the DC Flexibility Management solution computes an action plan that increases the energy demand of IT resources. As the IT resources are composed mainly of servers that are capacitive loads, they inject reactive power. However, the DC cooling system is an inductive load, that consumes reactive power. Thus, the flexibility management solution will determine a set of post-cooling actions aiming to decrease the cooling system load for a short period, if the server room temperature does not increase over the maximum operating threshold. The decrease of the cooling load leads to a decrease in the reactive power consumption, that together with the increase of the reactive power generation of the IT resources adjust the DC power factor. In this way, the DC will act as a capacitive load asset that injects reactive power into the grid.

When the grid encounters an increase in the reactive power, the DC will become an inductive load asset consuming reactive power. To achieve this, the DC flexibility management solution will generate an action plan that dynamically schedules workload to decrease the power demand of the servers and in consequence their reactive power supply. At the same time, it will increase the cooling system power demand by performing a precooling of the server room. The cooling system is operated at a higher rate, its power demand is increased and in consequence reactive power is consumed. Thus, due to the low reactive power generation of the capacitive loads and high reactive power consumption of the inductive loads, the DC becomes a reactive power-consuming asset contributing to the maintenance of a constant power factor in the local grid.

3.5 Sell heat to nearby grids

The DC can be integrated with the District Heating Network and provides heat on demand. The DC heat generation is correlated with its electrical energy consumption for executing the workload. The heat extracted from the server room by the cooling system may be passed through a heat pump, which uses a second refrigerant cycle to raise the heat quality by increasing the coolant temperature from $30-35\,℃$ up to $70-80℃$, suitable for domestic use. This heat generated by the DC is considered a reference baseline heat by the district heating operator. However, for some periods the heat demand in the local grid may vary, and the DC may adapt its heat generation to the heat demand by using its internal thermal flexibility mechanisms. These mechanisms are classified according to the duration and magnitude of the flexibility provided in Table 2.

Table 2. DC Thermal Flexibility Mechanisms

DC Thermal Flexibility	**Response Duration**	**Response Magnitude**
Server room precooling	Small (less than 30 minutes)	High (ranging from <10% up to 150%)
Server room post-cooling	Small (less than 30 minutes)	High (ranging from <10% up to 150%)
Dynamic usage of thermal storage	Medium (a few hours)	Medium (+/- 30%)
Workload scheduling	Long (up to a day)	Small (depends on the percentage of delay-tolerant workload)

In case of an increased heat demand request, the DC can make use of its short-term thermal flexibility mechanisms, such as the server room precooling or post-cooling techniques. Using these techniques and based on action plans computed the DC flexibility management solution, the cooling system can be completely turned off for a small period, up to 20-25 minutes, depending on the server room configuration. During this time, the heat accumulates in the server room, and heat with higher quality is delivered by the DC to the district heating network. To restore the temperature in the server room, the cooling system has to operate at a higher rate, before the response period in case of precooling or after the response period in case of post-cooling, leading to a valley of heat generation for up to 1-2 hours outside the response interval. In this case, the DC heat generation drops to less than 10% of baseline values.

In case of a request to increased heat demand for a few hours, the DC can make use of a set of thermal storage tanks, that are buffers of coolant capable of cooling the DC without using the electrical cooling system. The DC-generated heat quality can decrease to less than 10%, while the cooling system is turned off and the DC is cooled by the stored coolant. But it can increase to more than 130% during the service interval when the cooling system operates at a higher capacity to restore the coolant from the thermal storage tanks.

Finally, in case of a heat demand that differs from the DC heat baseline generation for a longer period, up to one day, the DC flexibility management solution can compute an optimal delay-tolerant workload scheduling so that the DC heat generation due to direct server heat harvesting matches closely the heat request. Thus, the DC can adapt its 24-hour heat generation with +/-10% concerning the heat baseline generation. Furthermore, the DC flexibility management solution can combine the three thermal flexibility techniques, short-term, medium-term, and long-term techniques, to manage high flexibility and match as close as possible the heat demand.

4 Conclusions

In this paper, we analyze the DC source of flexibility and models for the main energy resources. We present the architecture of a flexibility management solution that allows the computation of load shifting plans for the optimal integration of DC in the local electrical and thermal grids. The flexibility management solution is based on the MAPE-K architecture, where the knowledge component is driven by the DC DT model, monitored data, and decided action plans. The monitoring models acquire DC data by integration with existing DCIM, the analysis module computes predictions for DC parameters based on monitored data. The planning component computes the flexibility optimization plan for DC operation while the execution module enforces the execution of the actions via DCIM integration.

Finally, we have identified five energy services that may be provided by the DC with the help of described flexibility management solution: energy trading for increasing profit, congestion management, scheduling for consuming as much as possible the renewable available in the local grid, power factor compensation and sell heat on demand.

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