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Optimized flexibility management enacting Data Centres participation in Smart Demand Response programs

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HIGHLIGHTS

- Scheduling and optimizing Data Centres operation.
- Data Centre participation in Smart Demand Response programs.
- Data Centre flexible energy resources.
- Electronic marketplace for trading energy flexibility and ancillary services.

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ABSTRACT

In this paper we address the problem of Data Centres (DCs) integration into the Smart Grid scenario by proposing a technique for scheduling and optimizing their operation allowing them to participate in Smart Demand Response programs. The technique is leveraging on DCs available flexible energy resources, on mechanisms for eliciting this latent flexibility and on an innovative electronic marketplace designed for trading energy flexibility and ancillary services. This will enact DCs to shape their energy demand to buy additional energy when prices are low and sell energy surplus when prices are high. At the same time DCs will be able to provide increased energy demand due to a large un-forecasted renewable energy production in their local grid, shed or shift energy demand over time to avoid a coincidental peak load, provide fast ramping power by turning on their backup fossil fuelled generators and injecting the energy surplus in the grid and finally provide reactive power regulation by changing their power factor. Numerical simulations results considering traces of an operational DC indicate the great potential of the proposed technique for supporting DCs participation in Smart Demand Response programs.

1. Introduction

The Data Centre (DC) services business is blooming but, as it is usually the case, this is only one side of the story: the growing demand of their services increases their demand on energy resources, which directly translates to higher operational costs, not to mention the detrimental impact to the environment and, as such, to the society as a whole. Besides the significant economic and environmental impact, the annual increasing energy demand of DCs poses the severe risk of supply shortage and instability in the electricity network. This may cause exponentially increasing side effects. On one hand to the local economy, which may suffer accidental black-outs, and on the other hand to the normal operation of the DC, as it is expected to provide continuous operation and guaranteed availability (i.e. 99.995% for Tier 4 DC). All these factors are putting DC business in a risky position and creating higher pressure on the DC administrators on cutting down the energy demand and implicitly the associated bills.

The recent advances in digital technologies and renewable energy production have incubated the Smart Grid concept. It allows for bidirectional communication between utilities and their customers, as well as sensing along the distribution lines, while it integrates both traditional brown and green energy sources such as

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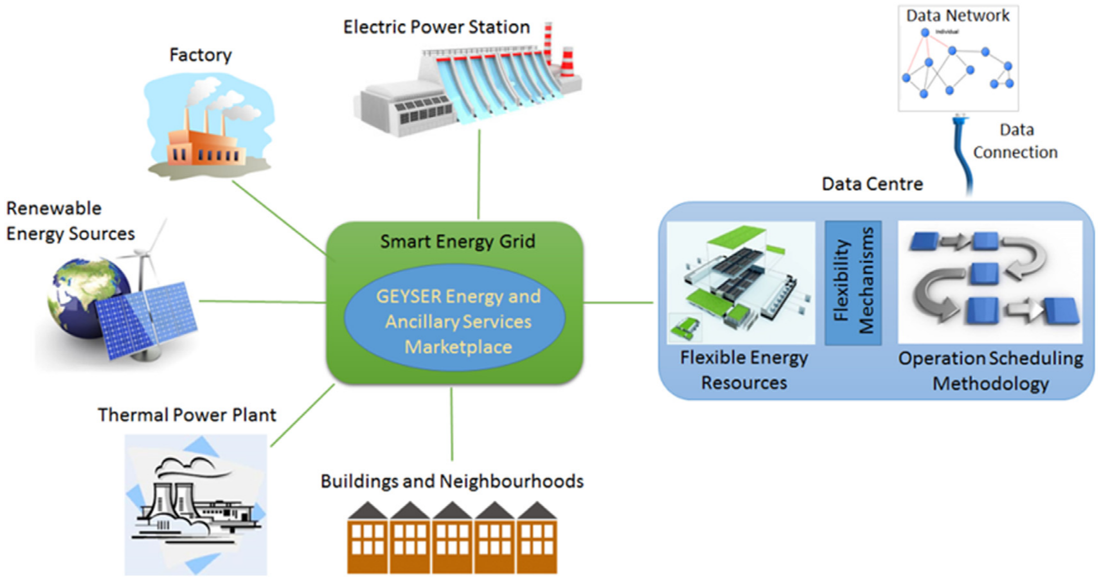

Fig. 1. DCs at the intersection of smart energy and data networks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

photovoltaic panels, wind turbines, geo-thermal power plants, etc. However, the integration of Renewable Energy Sources (RES) into the grid has added a level of uncertainty due to the intermittent and unpredictable nature of green energy generation. Variations in energy production, either surplus or deficit, may threaten the security of supply, leading to energy components overload and culminating with power outage or service disruptions. The problem is exacerbated by the lack of capabilities for energy storage, thus forcing the energy producers to shed their generation to match their customers' energy demand by deploying fast-reacting power reserves to maintain grid balance. To this end, utility companies have defined Smart Demand Response (DR) programs providing possibility for consumers to play a significant role in the operation of the electricity grid by shaping their energy demand to meet various grid level goals and obtaining in exchange financial benefits. Typically, at the beginning of a billing period, a regulation signal is sent to every customer specifying the desired energy profile for each of them. If a customer accepts the signal, it is required to schedule its operation for meeting the desired profile.

Utility companies must trade with commercial players to a far greater extent than nowadays in order to use flexibility products as a more cost-effective and reactive alternative to grid reinforcements. Accordingly, in our vision DCs are expected to be transformed into such flexible energy players providing different levels and types of flexibility to the interested stakeholders such as Distribution System Operator (DSO) or District Heating Operator, with a view to become adjustable and adaptive energy consumers able to participate in DR programs. Nevertheless, currently there are limited active links between, DCs on one hand or, in general, ICT networks and smart grid operators on the other hand. Practically, no energy or information exchange exists among them. Exacerbating this situation, DCs are operated in an uncoordinated way and their energy efficiency has been so far addressed in an isolated way. DCs have large, yet mostly unexploited, potential regarding their energy demand flexibility. Through this potential they can contribute to efforts for managing more efficiently energy at local grid level, while enabling optimized operation of the electricity grid.

2. DCs as technological hubs integrated in the smart grid

To address such energy integration concerns, within the FP7 GEYSER European R&D project [1], we have proposed the innovative approach of considering DCs as conceptual and technological hubs at the crossroad of energy (electricity, thermal, or a combination of the two) and data networks enacting the exploitation of their latent flexibility for achieving synergies and integration with other grid energy resources (see Fig. 1). In the context of the smart grid the DCs may act as *energy prosumers*, being both energy providers, exploiting on-site green or brown energy resources, and consumers with significant energy needs. We have defined *mechanisms for eliciting DC internal latent energy flexibility* by considering non-electrical cooling devices such as thermal storage, IT workload temporal and spatial migration through data networks, and dynamic usage of electrical storage devices or diesel generators.

The DCs active participation in exploiting the smart grid resources (when and where they become available), as well as their larger flexibility for the optimal management of energy networks is enacted through the *GEYSER Marketplace* concept. The marketplace is available in two variants: (i) an Energy Marketplace allowing the DCs to participate as active energy players buying and selling energy and (ii) an Ancillary Services Marketplace allowing DCs to trade with the DSO their capability to alter their energy profile and respond to ancillary services requests. Leveraging on proposed flexibility mechanisms, a *technique for scheduling and optimizing DC's flexible energy resources operation* is defined allowing DCs to adjust their energy demand profile to meet various smart grid level objectives and accordingly to achieve a major holistic smart city-level efficiency of urban energy networks.

As a result of the innovative GEYSER approach, the DCs are able to schedule and optimize their resources operation and as a consequence, to adjust their energy consumption aiming to buy energy from the Energy Marketplace when the prices are low (due to increased generation) and sell extra energy when prices are high, thus decreasing their operational costs. Also DCs have the technological capabilities for scheduling their operation to potentially respond to ancillary services requests by: (i) shaping their energy demand to provide additional load following reserve for large un-forecasted wind ramps, (ii) shedding or shifting energy demand over time to avoid a coincidental peak load in the grid, (iii) feeding in the smart energy grid the energy (either power or heat) produced by turning on their backup fossil fuelled generators (despite quite inefficient and highly pollutant, gaining, however, a net financial reward by the energy provider, who will avoid to turn on fossil-fuelled standby power generation plants) and finally (iv) changing their power factor for providing active reactive power regulation.

The rest of the paper is structured as follows: Section 3 highlights relevant related work, Section 4 describes the operation of the GEYSER marketplace, Section 5 presents the proposed scheduling technique and energy flexibility mechanisms, Section 6 presents numerical simulation-based experiments and results, while Section 7 concludes the paper and presents future work.

3. Related work

Recent studies have shown that DCs are great candidates for participating in DR programs due to the following reasons [2]: (i) are large energy consumers or producers if they have on-site renewable energy production facilities, (ii) are highly automated and may respond fast to DR signals and (iii) are composed by various types of hardware and software flexible energy resources so they poses a large amount of unexploited energy flexibility. One of the most comprehensive studies describing the potential of different DC's hardware components and strategies for providing smart demand response was released by Lawrence Berkeley National Laboratories [3]. The strategies are referring to: shutting down IT equipment, load shifting or queuing IT jobs, temperature set point adjustment, load migration and IT equipment load reduction. Even though the results were promising the DCs being able to adjust the demand profile with 10%–12% the approach fail to take into consideration the correlations and combination among strategies to obtain a stronger response as well as new types of flexible energy resources such as non-electrical cooling or batteries. Also even if the report shows that it is feasible for a DC to respond to DR signals, no operation scheduling and optimization algorithm is presented.

We have classified the techniques for scheduling and optimizing DCs operation to participate in DR programs according to the flexible energy resource they are based in: (i) techniques exploiting IT servers' flexibility through workload migration and consolidation, (ii) techniques exploiting electrical batteries' flexibility and (iii) techniques exploiting cooling systems' intensity flexibility and heat removal strategies.

Time and spatial load balancing and consolidation techniques are usually used for voluntary reduction of DC's energy demand [4]. Authors of [5] evaluate the DCs that offer ancillary services in form of voluntarily load reduction using an analytical profit maximization framework and propose an optimization technique based on profit maximization strategy. The authors propose a mathematical model that includes: DC's internet service revenue, the cost of electricity and the compensation DC may receive by offering ancillary services. Furthermore, it takes into consideration the servers' power consumption, DCs Power Usage Effectiveness (PUE), workload statistics and Service Level Agreements (SLAs). This approach interferes with the workload behaviour, resulting in performance degradation. Also, it does not consider any other form of energy flexibility mechanisms, such as, electrical storage devices, non-electrical cooling devices, etc. In [6] the authors present a solution for minimizing the electrical bill in a smart grid that employs both day ahead dynamic pricing and regulation signals. At the beginning of a billing period (several minutes to one day), the market participants (DCs) receive a regulation signal which specifies the trend of energy consumption during that period. During the billing period, DSO updates the initial trend, by sending regulation signals. A two level controller is implemented, which performs resource allocation and schedules task dispatch, achieving optimality in minimizing the overall cost. A more complex approach is presented in [7]. It takes advantage of two DC flexibility mechanisms: workload shifting and local generation (local diesel generators and local renewable energy). Using these mechanisms, algorithms are developed in order to avoid the coincidental peak and reduce the energy costs. The approach is based on the prediction of coincident peak occurrence from historical data to optimize the workload allocation and local generation and to minimize the expected cost. The authors of [8] present a dynamic pricing system for a federation of DCs and use a distributed constraint optimization solver to negotiate a mutually optimal price. Workload relocation between DCs is used to meet the energy need at various DCs from different geographic locations. This technique is limited by several factors, such as DCs capacity, workload security and SLAs, as well as extra energy needed for data transportation.

Lately with the advent *of batteries technologies* and due to the fact that they do not pose any workload degradation overhead they are starting to be considered as important resources for helping DCs to participate in demand response. One of the first approaches of using batteries as a flexible energy resource within the DC is presented in [9]. The authors propose the exploitation of batteries as an energy buffer with three functionalities: shave power peaks, store energy when it is cheap and increase the DC energy consumption when requested. In [10] a technique is proposed for balancing and keeping the DCs' peak power under a given threshold (due to electricity pricing) and at the same time allowing DCs to respond to the regulation control signals that may request an increase in power consumption. A detailed energy storage scheme is presented in [11] in which Uninterrupted Power Supply (UPS) units are used as energy storage devices. Based on the existence of delay-tolerant workload, it tries to reduce the time average electricity costs using Lyapunov optimization. The control algorithm decides at each moment of time how much energy to draw from the grid, how much to save into the energy storage and how much to draw from the storage such that the time average cost of these operations is minimized.

Even though efforts have been made to reduce the *cooling system energy* consumption it is still responsible for as much as 40% of the energy consumption in a DC thus it is *important resource for energy flexibility* [12]. In [13] a strategy of optimizing the energy consumption of the cooling system, by evaluating the time-varying power prices is presented. The system checks the prices in the hour-ahead market, and precools the air masses. In this way, later, when the power prices increase, the thermal masses can absorb heat for a given period of time. The electrical cooling system of a DC is detailed in [14], where a hybrid cooling system composed of traditional CRAC cooling, free air cooling and liquid cooling is presented. The authors propose a power optimization scheme that combines the different cooling techniques and dynamically adjust the cooling source to minimize the overall power consumption. Furthermore, the heuristic is extended to handle a network of DCs by dynamically dispatching the incoming requests among the DCs with various cooling systems. New approaches which consider the DCs as energy producers and target the reuse of the heat generated by the DC for heating nearby residential or commercial buildings are presented in [15]. Under certain conditions, the extra energy from DCs renewable sources may be fed back to the grid. The authors propose a solution that aims to integrate the DCs with smart grids. To show the results the authors use a grid simulation integrated with a DC operation simulation in which the DC observes the grid and adapts its internal state to meet grid's conditions.

Our approach takes the existing state of the art one step further paving the way for the next generation energy sustainable DC which is able to schedule and optimize its overall energy consumption considering all installed hardware components offering energy flexibility in a holistic and integrated manner. We have defined new flexibility mechanisms for the DC internal

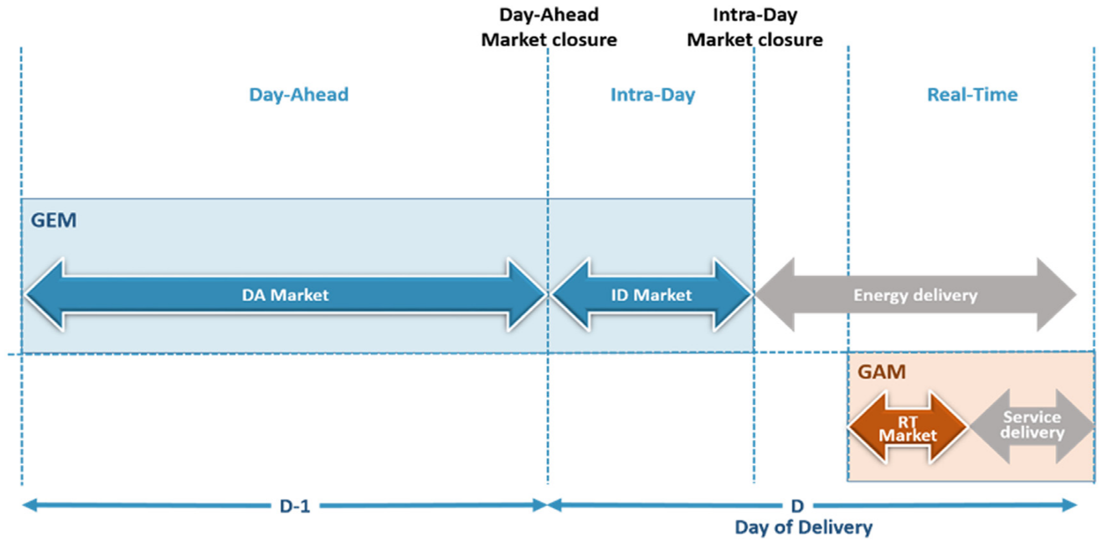

Fig. 2. GEYSER marketplace variants/timeframes.

flexible energy resources as well as an innovative marketplace for allowing the DC to trade its flexibility. The defined operation scheduling and optimization technique considers all flexibility mechanism in a holistic manner allowing DC to adapt its operation and energy demand profile to decrease the operational coasts and to meet different goals provided by the DSO.

4. GEYSER marketplace

GEYSER introduces an electronic marketplace (Fig. 2), where actors can trade their flexibility and compete with each other, based on relative prices for energy (in the GEYSER Energy Marketplace or GEM) or ancillary services types (in the GEYSER Ancillary Services Marketplace or GAM).

The trading of flexibility services enabled by the GEYSER marketplace will allow the energy suppliers to optimize their portfolios, the DSO to manage system imbalances at an efficient cost, avoiding expensive network reinforcement and the providers of flexibility (DCs) to benefit through direct payments or savings on energy purchases.

GEYSER Energy Marketplace (GEM) is responsible for arranging and managing energy trades with the general aim of scheduling generation and consumption units. GEM is not a purely financial market, where just prices and volumes are determined, but it is a real physical market, where physical injection and withdrawal programmes are defined. Moreover, it allows to consume energy where it is produced, preventing energy shifts away from the production sites with the ensuing problems. GEM is based on a power pool model, one of the main types of market organization adopted worldwide, such as in the Italian Power Exchange [16]. GEM consists of two submarkets:

- *GEM Day-Ahead (DA)* (*D-1* timeframe in Fig. 2, which is one day before the delivery), where producers and consumers may sell/buy energy for the next day;
- *GEM Intra-Day (ID)* (*D* timeframe in Fig. 2, which coincides with the day of delivery), where producers and consumers may adjust the injection/withdrawal programmes determined in the DA Market.

GEM is organized in a set of market sessions. In each session, supply offers/demand bids are received within a given time interval. Offers and bids consist mainly of pairs of values, representing the quantity and unit price of energy (MWh, €/MWh). Supply offers represent the willingness of a producer to sell a quantity of energy not higher than the one stated and at a unit price not lower than the one stated. Demand bids represent the willingness of a consumer to purchase a quantity of energy not higher than the one stated and at a unit price not higher than the one stated. The market resolution process adopted in GEYSER, described in the following, will ensure to buyers a cheaper energy price than the one in the national market.

When a market session is open, participants may submit bids and offers, both manually and automatically. Bids and offers need to pass successfully the validity checks, ensuring that market session rules are not violated. Once the session is ended, the market clearing process starts (Fig. 3): all valid supply offers are put in increasing price order on an aggregate supply curve and all valid demand bids are put in decreasing price order on an aggregate demand curve. The intersection of the two curves determines the clearing price, at which all accepted bids and offers are remunerated, and the overall quantity of energy traded in the session; consequently, accepted bids/offers programmes are identified. The acceptance of an offer/bid implies the market participant's commitment to inject/withdraw the quantity of energy specified in the offer/bid, or, in case of partial acceptance of the offer/bid, the corresponding share, in a prefixed time frame.

GEYSER Ancillary Services Marketplace (GAM) is responsible for arranging and managing the ancillary services procured by the DSO from market participants for a secure and reliable operation of the electrical grid. It is a near real-time system where the DSO procures the resources needed to operate, monitor and control the power system (relief of congestions, creation of energy reserve and real-time balancing). The DSO acts as a central counterparty in this market: it is the unique buyer with respect to the offers placed in the market by the potential service providers. GAM is a market where players provide their availability to offer specific services and is organized in a set of market sessions per ancillary service to be provided. The structure and duration of such sessions should ensure that DCs (providers on this market) have enough time to prepare in order to deliver the service traded in that session, which may vary between ∼10 and ∼20 min. The participation in GAM implies posting offers, both manually and automatically, and declaring the availability to provide the ancillary service. Similarly to GEM, the offers need to successfully pass the validity checks, ensuring that market session rules are not violated. At the end of the session, within a predefined period ("clearing period"), the DSO will select the offers that best cover its needs, based on current distribution requirements and smart grid status. The remuneration of the provided ancillary services will take place after their delivery.

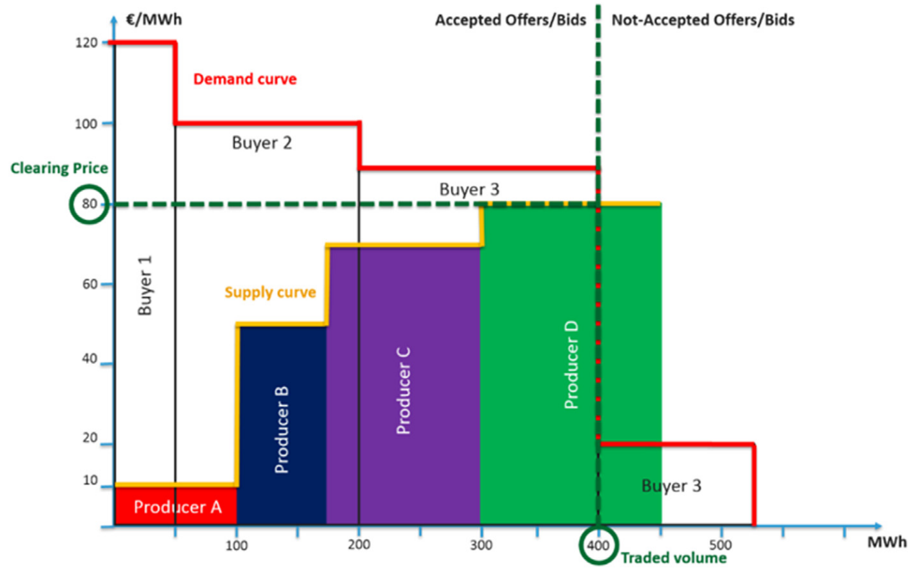

Fig. 3. Market clearing process example.

5. Scheduling and optimization technique

The defined technique is based on optimizing the operation of DC's components (both IT and facility) to shift their potential flexible energy in time with the overall goal of adapting the DC's energy demand profile for participating in DR programs. The DC energy baseline needs to be adapted in a given optimization window $[T_0, T]$ by optimally shifting flexible energy to match as close as possible a demand-response signal during a service response interval $[T_s, T_E]$ (a power consumption curve from the DSO), while altering as little as possible the DC energy baseline before $[T_0, T_s]$ and after the service period $[T_E, T]$ (see Fig. 4).

5.1. Optimization problem definition

We have approached the optimization technique by discrete modelling the DC as a system and defining the power demand of each DC's component and of the entire DC at timestamp t as a function of previous power demand states at timestamps $t-1, t-2, \ldots, t-k$, where $k < t$. At each timestamp t the optimal operation of the DC's components needs to be determined together with the amount of aggregated power to be shifted in time such that the DC adapted energy consumption curve matches the DR signal curve provided as goal.

The optimization decision making in this case involves non-linear system dynamics that affect the quality of the action plan. We solve these problems by mapping the optimization problem to a Nonlinear Programming (NLP) problem [17] aiming to find at each timestamp t the optimal combination of DC components power values $Combination\ [P_1, \ldots, P_i]$ and associated optimization actions to obtain an adapted DC power demand profile which matches the DSO request. Thus we formulate the optimization problem as:

$$\begin{cases} minimize & f_{objective}(P_{DC}^{Adapted}) \\ subject\ to & c\left(P_{DC}^{Adapted}\right) < 0 \\ & P_{DC}^{Adapted} = Combination\ [P_1, \ldots, P_i] \\ & P_i \in R,\ \forall i \in DCFlexibleRes \end{cases} \tag{1}$$

where $P_{DC}^{Adapted}$ represents the adapted DC power demand value for timestamp t determined as a combination of instant power consumption values (P_i) of each flexible components of the DC.

The objective function is defined as follows:

$$\begin{aligned} & f_{objective}\left(P_{DC}^{Adapted}\right) \\ & = \frac{1}{TE-TS} * \sum_{t=TS}^{TE}\left[P_{DC}^{Adapted}(t) - P_{signal}(t)\right]^2 \\ & + \frac{1}{TS-1} * \sum_{t=0}^{TS-1}\left[P_{DC}^{Adapted}(t) - P_{DC}^{Baseline}(t)\right]^2 \\ & * (TS-t-1) \\ & + \frac{1}{T-(TE+1)} * \sum_{t=TE+1}^{T}\left[P_{DC}^{Adapted}(t) - P_{DC}^{Baseline}(t)\right]^2 \\ & * [t-(TE+1)]. \end{aligned} \tag{2}$$

The objective function aims at shedding the adapted DC power profile to match a DR signal for the response interval $[TS, TE]$ while minimizing the adjustments of the DC power baseline on the rest of the optimization time window: $[1, TS)$ before and $(TE, T]$ after DC's response interval. Thus, the function aims to minimize the DC power profile $P_{DC}^{Adapted}(t)$, and the reference values requested by the DSO, P_{signal}, for each timestamp t during the demand response period $[TS, TE]$, as well as the normalized Euclidean distance between $P_{DC}^{Adapted}(t)$ and the DC power baseline $P_{DC}^{Baseline}(t)$ estimated based on the workload the DC has to execute for the rest of the optimization window $[1, TS) \cup (TE, T]$. Furthermore, in order to minimize the DC power profile variations from the initial baseline, the differences outside the demand response interval $[TS, TE]$ are weighted by a factor which increases with the distance from the interval. As a result, changes in the DC power consumption, compared to the initial baseline, are imposed within or close to the DR period, to the extent possible. It can be easily shown that the objective function is a twice continuously differentiable function being a weight sum of well-known functions of $(X-a)^2$ type.

The global constraint $c\left(P_{DC}^{Adapted}(t)\right) < 0$ which needs to be met at each timestamp is defined as:

$$\begin{aligned} c\left(P_{DC}^{Adapted}(t)\right) & = P_{DC}^{Adapted}(t) - P_{signal}(t) \\ & \leq 0, \quad \forall t \in [TS, TE] \end{aligned} \tag{3}$$

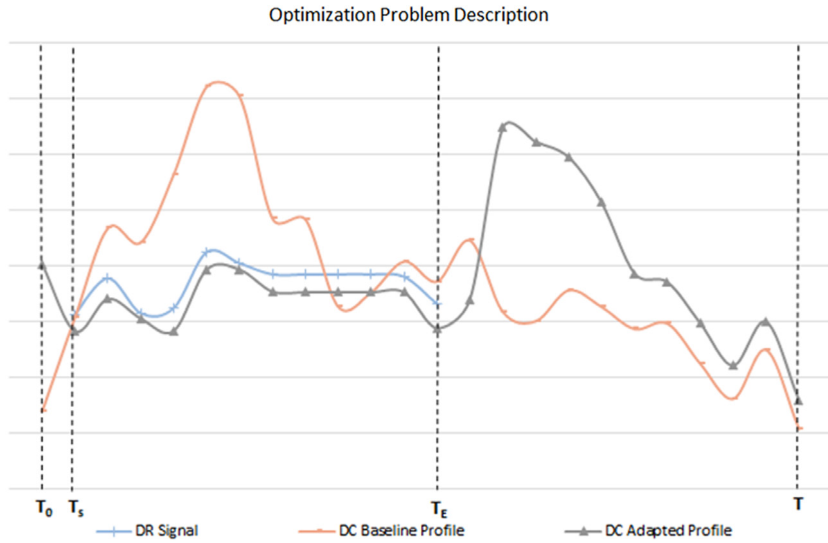

Fig. 4. DC energy demand optimization problem overview.

meaning that at each point during the service period the power consumption values of the DC will not exceed the reference values provided by the DR signal avoiding thus any penalties for not providing the requested service.

Analysing energy consumption of the hardware and software components typically installed in a DC, we have identified the main flexible energy resources as: (i) IT Servers and associated workload, (ii) electrical cooling system together with Thermal Storage Tanks (TES) [18] and (iii) Electrical Storage Device (ESD) (i.e. batteries):

$$DCFlexibleRes = \{Workload, Cooling\&TES, ESD\}. \quad (4)$$

Considering all flexible resources, the total DC power demand at each timestamp t can be aggregated from its main components as:

$$P_{DC}^{Adapted}(t) = P_{Workload}^{Adapted}(t) + P_{Cooling}^{Adapted}(t) + P_{ESD}^{Adapted}(t) \quad (5)$$

while the DC energy consumption shifted for the entire time window can be computed as:

$$\int_{T_0}^{T} P_{DC}^{Adapted}(t)\,dt - \int_{T_0}^{T} P_{DC}^{Baseline}(t)\,dt. \quad (6)$$

5.2. Power flexibility estimation

We have defined power flexibility mechanisms for IT Servers and associated workload, electrical cooling system (including TES) and ESD.

The *function for estimating the servers and associated workload flexible power demand* at each timestamp t is leveraging on time-shifting the delay-tolerant workload. We differentiate between real-time workload, which has stringent requirements on real-time execution, and delay-tolerant workload, which can be executed anytime until a given deadline. The DC power demand is reduced at timestamp t with the amount of power needed to execute the delay-tolerant load that is shifted at timestamp $t + u$, $u \in [1, T - t]$ while the DC power demand at timestamp $t + u$ is increased with the amount of power needed to execute the delay-tolerant load shifted from timestamp t.

The decision on the optimal timestamp and amount of delay-tolerant workload to be shifted is based on our estimation model for the power consumption of the DC's IT servers in a given workload configuration. We define the workload power shifting matrix $S = (s_{ij})_{T\times T}$, where s_{ij} represents the percentage of power consumed by the delay-tolerant workload scheduled at timestamp i, $(i = 1, 2, \ldots, T)$, and shifted for execution at timestamp j, $(j = 1, 2, \ldots, T)$, and T represents the maximum dimension of the optimization window $[T_0, T]$:

$$S = \begin{pmatrix} S_{11} & \cdots & S_{1T} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & S_{TT} \end{pmatrix}. \quad (7)$$

Due to the fact that the execution of a delay-tolerant workload cannot be scheduled before its arrival timestamp, S is an upper triangular matrix. A matrix row $(s_{ij})_{j\in 1,\ldots,T}$ represents the total power consumption of the delay-tolerant workload at timestamp i, split in percentages and shifted per execution timestamps j until the given execution deadline. As a consequence, the sum of the elements of every row is equal to 1. Accordingly, a matrix column $(s_{ij})_{i\in 1,\ldots,T}$ represents the total delay-tolerant workload scheduled for execution at timestamp j. The total power value of a column j yields the estimated amount of power required for executing the baseline delay-tolerant workload planed for execution at timestamp j (i.e. $i = j$ in relation 8) summed with the additional delay-tolerant workload shifted from other timestamps (i.e. $i < j$):

$$P_{Workload\text{-}DT}^{Adapted}(t) = \sum_{i=1}^{j=t} (s_{ij}) * P_{Workload\text{-}DT}^{Baseline}(i). \quad (8)$$

The power demand for executing the total DC workload at timestamp t is calculated as a sum of the power required for the execution of the baseline real-time workload (i.e. strong SLA levels with no possibility for adaptation), $P_{Workload\text{-}RT}^{Baseline}(t)$, and the delay-tolerant workload at t, using the following relation:

$$P_{Workload}^{Adapted}(t) = P_{Workload\text{-}DT}^{Adapted} + P_{Workload\text{-}RT}^{Baseline}(t). \quad (9)$$

The maximum and minimum limits for the adapted power workload values used in combinatorial optimization process are the following:

$$P_{Workload\text{-}RT}^{Baseline}(t) < P_{Workload}^{Adapted}(t) < Servers\ Total\ Power. \quad (10)$$

The *power consumption flexibility of the cooling system* is leveraging on the usage of non-electrical cooling systems such as the TES to precool the DC and compensating the electrical one. When charging the TES its coolant (i.e. water based thermal tanks)

Table 1
DC hardware components characteristics.

Component	Hardware characteristics simulated
Electrical cooling system	Cooling capacity = 4000 kWh, minimum cooling load = 200 kWh, maximum cooling load = 2000 kWh, COP = 3.5
IT computing resources	11,000 servers with: maximum power consumption (P_MAX) = 325 W, RAM = 8 GB, CPU frequency = 2.4 GHz, HDD = 1 TB
ESD	$\rho_{ESD} = 0.2$, $\delta_{ESD} = 0.2$, $\varphi_{ESD} = 0.995$ maximum charge and discharge energy = 1000 kWh, Max Capacity = 1000 kWh
TES	$\rho_{TES} = 0.1$, $\delta_{TES} = 0.01$, $\varphi_{TES} = 0.999$, maximum charge and discharge energy = 1000 kWh, maximum capacity = 3000 kWh

Table 2
Services that may be provided by DC.

Marketplace	DR service name	Description	Response time	Response length
Energy marketplace	Trade energy flexibility	Buy or sell energy driven by convenient energy prices	<2 h	24 h for day-ahead, 4 h for intra-day
Ancillary services marketplace	Regulation	Increase demand for large un-forecasted renewable energy production in grid	<20 min	1 h
	Scheduling (Energy)	Shed or shift energy consumption over time to match a requested profile	<20 min	>1 h
	Reserve (Capacity)	Provide fast ramping power	<10 min	>30 min
	Reactive Power Control	Response to random unscheduled deviations in scheduled net load	<1 min	15 min

is overcooled by using the electrical cooling at higher capacity resulting in an increased power demand. When TES is discharged the heat builds up and the DC cooled down by leveraging on using the precooled coolant while the electrical cooling is used at low intensity. The DC power demand at timestamp t is decreased by the amount of power compensated by energy discharged from TES (as consequence of lowering the intensity and demand of the electrical cooling system), while the DC power demand at timestamp $t+u$, $u \in [1, T-t]$ is increased by the amount of power needed to charge energy in TES (as a consequence of increasing the intensity of the electrical cooling system to overcool the TES). Thus the adapted power demand of the DC cooling system is calculated as a difference between the baseline power demand of the electrical cooling system and the power compensated by charging/discarding the TES:

$$P^{Adapted}_{Cooling}(t) = P^{Baseline}_{Cooling}(t) - \left[(1-\delta_{TES}) * P^{D}_{TES}(t) - (1+\rho_{TES}) * P^{C}_{TES}(t)\right]. \tag{11}$$

If the TES is charged then $P^C_{TES}(t) > 0$ and $P^D_{TES}(t) = 0$ and the adapted power demand of the cooling system is increased, otherwise if TES is discharged the $P^D_{TES}(t) > 0$ and $P^C_{TES}(t) = 0$ and the adapted power demand is decreased. The charging and discharging actions cannot happen simultaneously. In relation 11 the following TES device characteristics have been considered: charge loss factor during operation (ρ_{TES}) and discharge loss factor during operation (δ_{TES}). $1+\rho_{TES}$ represents a factor with the value above 1, that gives the amount of power effectively charged in TES (due to power losses more power is actually used to charge TES). Similarly, $1-\delta_{TES}$ is a sub unitary factor which gives the effective amount of power which is discharged from TES (due to power losses less power is actually fed to the system when discharging from TES).

The range of power flexibility that can be offered by charging or discharging TES, is estimated based on the amount of energy stored in a TES at timestamp t, $E_{TES}(t)$ and in the previous timestamp $t-1$ while considering the time discharge factor at idle state TES characteristic (φ_{TES}) as shown in relation (12):

$$\left|(1-\delta_{TES}) * \int_{i=t-1}^{t} P^{D}_{TES}(i)\, di - (1+\rho_{TES}) * \int_{i=t-1}^{t} P^{C}_{TES}(i)\, di\right| \le \varphi_{TES} * |E_{TES}(t) - E_{TES}(t-1)|. \tag{12}$$

To define maximum and minimum limits for the adapted power cooling values used in combinatorial optimization process we adopt the approximation defined in [19], according to which the total electrical energy consumed by the DC servers for workload execution is transformed into heat, which must be compensated by the DC cooling system. Thus the adapted power of the cooling system need to be sufficient to remove the extra heat build-up in the DC to maintain predefined safe temperature safe points. The minimum limit is determined using the DC cooling power formula from [13] as:

$$\frac{HeatRemoved}{COP} \le P^{Adapted}_{Cooling}(t) \tag{13}$$

where the COP is the Coefficient of Performance, depending on the output temperature of the cooling system.

The *flexibility mechanism for the electrical storage device (ESD)* is based on reducing the DC power demand at timestamp t by the amount of power discharged from batteries and increasing the DC power demand at timestamp $t+u$, $u \in [1, T-t]$ by the amount of power charged in batteries. A DC is equipped with batteries that store energy to cover its energy consumption needs for a short period of time in case of emergencies. State of the art batteries have a higher charge–discharge life-cycle that allows them to be used more frequently, offering a certain level of flexibility for the DC power demand. Similarly to TES, we need also to estimate the amount of power discharged from batteries when they are used to power the DC ($P^D_{ESD}(t)$), as well as the amount of power charged in batteries from the DC available surplus ($P^C_{ESD}(t)$). These values depend on the battery State of Charge value [20] in percentage (ESD_{SOC}) at timestamp t which is estimated using relation (14):

$$ESD_{SOC}(t+1) = \varphi_{ESD} * ESD_{SOC}(t) + \frac{\int_{i=t}^{t+1} P^{C}_{ESD}(i)\, di - \int_{i=t}^{t+1} P^{D}_{ESD}(i)\, di}{E^{MAX}_{ESD}} \tag{14}$$

where E^{MAX}_{ESD} is the maximum energy capacity of the battery, $20\% < ESD_{SOC} \le 100\%$ and charge loss factor during operation (ρ_{ESD}) and discharge loss factor during operation (δ_{ESD}) are specific to device characteristics similar with the ones from TES. The lower bound is selected considering the safe operation and limits of protecting equipment as specified in [21].

The amount of flexible power demand provided by the ESD in a specific timestamp is estimated as:

$$P^{Adapted}_{ESD}(t) = (1-\delta_{ESD}) * P^{D}_{ESD}(t) - (1+\rho_{ESD}) * P^{C}_{ESD}(t). \tag{15}$$

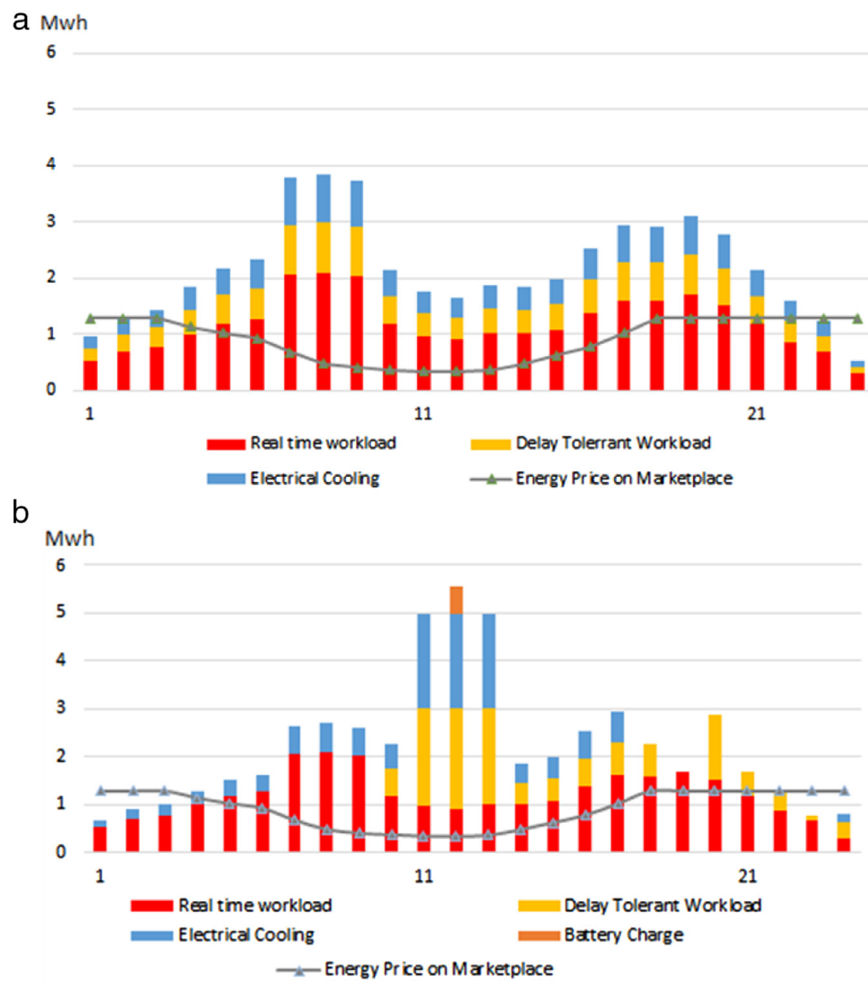

Fig. 5. DC as independent energy player: (a) DC baseline energy profile, (b) DC energy profile adjusted considering the convenient energy prices. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.3. Computational complexity

The optimization problem is a NLP problem being solved as a combinatorial problem in which the optimal combination of flexibility variables that minimize the optimization function (distance between power demand and objective curves) is determined while fulfilling all the constraints defined by the safe operation of each DC component. This is an NP-complete combinational problem [22,23].

This combinatorial problem is solved using heuristics such as simulated annealing or Hill-climbing which represents the search space as a graph whose vertices are possible combinations of power demand values (i.e. $P_{DC}^{Adapted} = Combination\ [P_1, \ldots, P_i]$) and whose edges are candidate moves (i.e. actions). The optimization technique searches the domain of flexible energy components of the DC leveraging on techniques such as range bounding (e.g., interval analysis and convex analysis) and range reduction (e.g., linear programming and constraint propagation). While searching the space, at each iteration a gradient that gives the rate of improvement of the objective function from relation (1) is computed for small changes of the power demand of DC flexible components. The power demand values that offer the greatest improvement of the objective are selected at each step. When the improvement becomes smaller than a threshold or the solution is constant over several iterations, the combination of power demand values for flexibility components is returned and associated optimization action plan is generated. The time complexity of our optimization approach is given by the time required for searching in the search space [22] thus proportional with the maximum number of optimization variables considered in combinations which is:

$$6 * T + T^2 \tag{16}$$

where, 6 is the number of possible power shifting actions considered (charge/discharge TES and ESD, shift do not shift delay tolerant workload) and T the dimension of the optimization time window.

6. Simulation results

The proposed technique has been tested through extensive numerical simulation-based experiments, with a view to subsequently apply and validate the approach in the coming months in real pilot DCs of the GEYSER project. To this end, a simulation environment has been developed, in which the hardware systems characteristics and operation (see Table 1) of an operational DC are modelled. The workload energy demand was taken from the IT power consumption traces of the DC [24] considering normalized samples acquired every five minutes.

The data source for the energy prices considered in marketplace is [25]. The technique is used to schedule the operation of the simulated DC to shape its energy demand profile to provide Table 2 services.

The services are distinguished by their following requirements: (i) GEYSER marketplace variant for trading services (ii) how

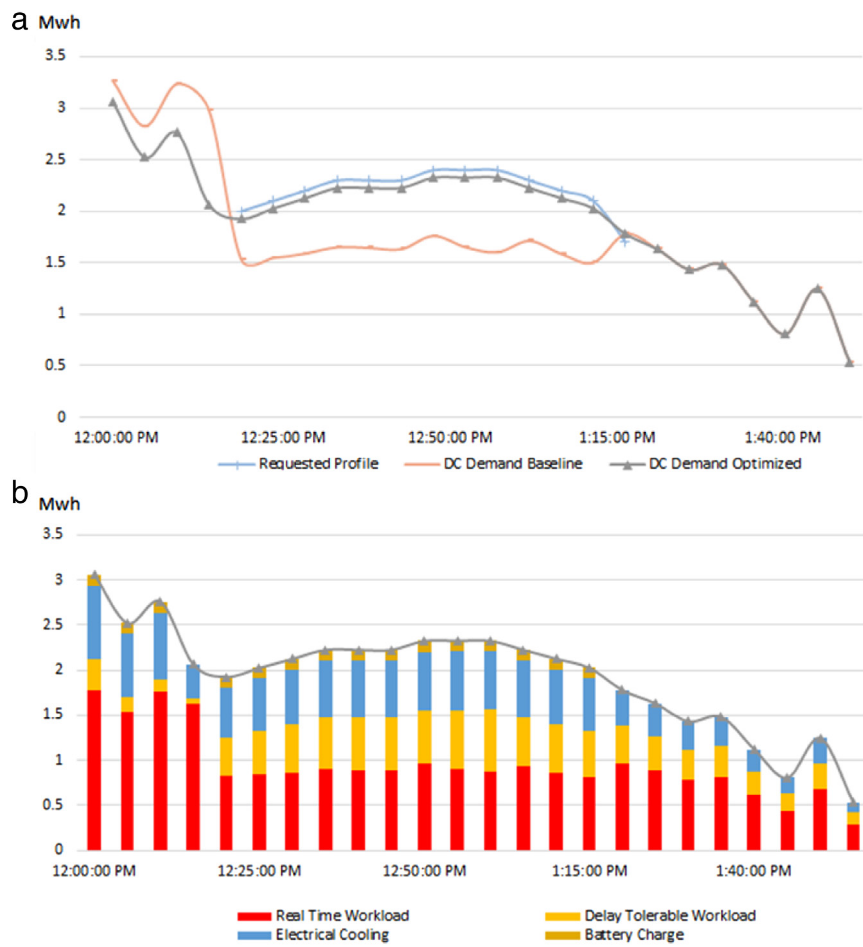

Fig. 6. DC providing regulation service: (a) DC original energy profile and regulation service request, (b) DC response and optimized energy consumption profile. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

fast the DC must respond in case it can fulfil the requested service (response time) and (iii) the minimum length of the DC response. The hardware resources on which the DC is leveraging for generating the requested output were selected considering factors such as the modelled hardware devices inertia in providing flexibility. For solving the minimization problems, Lindo Software [26] for nonlinear programming was used.

6.1. DC trading energy flexibility

In this scenario the DC will act as an independent energy player on the GEYSER Energy Marketplace aiming at minimizing its energy costs by scheduling its day-ahead and intra-day operation to be able to buy energy in timeslots with low price (surplus of energy generation in local grid) and sell energy in timeslots with high energy price (deficit of energy generation in local grid). The objective function (1) will be minimized allowing the DC to schedule its day-ahead energy consumption units driven by forecasted energy generation values for next day.

Our technique exploits the DCs latent energy flexibility determined using above flexibility mechanisms to schedule and optimize the DCs operation allowing them to trade energy flexibility. To trade *energy flexibility* our technique enacts a DC to schedule and optimize its operation in such a way that its energy profile is shifted from timeslot intervals when the energy prices in the marketplace are high to the timeslot intervals when energy prices are low (due to an increased RES availability in local grid).

Fig. 5(a) presents the DC's energy demand profile without the proposed optimization technique, highlighting the major elements which generate this demand. As shown, the DC's energy profile is not compatible with the situation shaped by the local marketplace considering the energy price as driving factor. Using the proposed technique, the DC will be enacted with the following operation scheduling possibilities. First it will increase its energy demand at noon where there is the surplus of energy generation and low energy price in the marketplace, by executing additional load and adapting the computational workload scheduling to anticipate as much as possible the work and/or make use of thermal storage for pre-cooling. Second it will reduce its energy demand in the morning and afternoon through workload shifting (time migration, considering cost for data transmission) and surplus of heating provisioning to alleviate cooling requirements. In this situation the DC will consume to the largest possible extent the available energy generated from the local grid.

Fig. 5(b) presents the DC's energy profile as a result of using the defined DC power flexibility mechanisms and operation scheduling technique. It can be noticed that execution of delay-tolerant workload, initially scheduled between timeslots 1–9 and 15–21, is now shifted to timeslots between 11 and 13, thus matching the low energy price in the marketplace. Also during the timeslots with low energy prices actions to overcool the thermal storage systems are executed; in doing so the electrical cooling system energy demand will be increased (see blue column). After the generation peak (i.e. after timeslot 13) actions to cool down the DC using the cold stored in the thermal storage are executed; thus the electrical cooling system demand is reduced, contributing to the decrease of energy consumption.

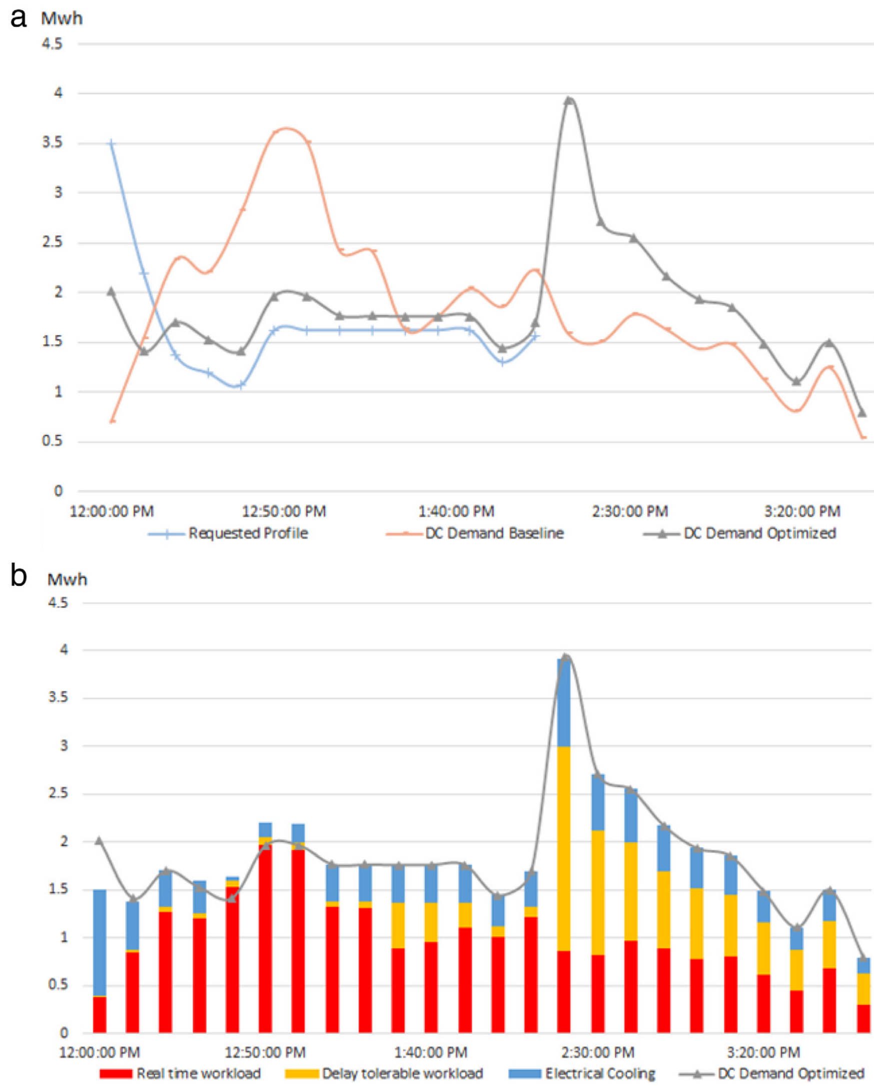

Fig. 7. DC providing scheduling service: (a) DC baseline profile and service request, (b) DC adjusted energy profile as a response to service request. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

6.2. DC providing regulation ancillary service

In this scenario we assume that there is large un-forecasted renewable energy generation peak (near real time) in the local energy grid which may threaten the grid stability. Consequently, the DSO publishes on the Ancillary Services Marketplace at 12 pm a regulation service asking for an increased energy consumption between 12:25 pm and 1:15 pm, to regulate the consumption according to the energy generation surplus. Fig. 6(a) presents the DC energy demand baseline in the orange line and the DSO requested energy profile in the blue line. To respond, the DC schedules and optimizes its demand using the available flexibility mechanisms, to consume more energy in the requested period, as revealed from Fig. 6(b).

By applying the proposed technique, the DC energy demand profile is adapted to the regulation ancillary service signal request. Consequently, it can be seen that most of the delay-tolerant workload arrived within the interval 12–12:25 pm has been delayed to be executed in the interval 12:25–1:15 pm thus more energy will be consumed. Also, the electrical cooling system is more extensively used in this interval to overcool the TES system, allowing for its later exploitation in cooling, instead of activating the electrical cooling system, reducing the energy consumption. As a result, the DC energy demand is increased by 34% from original baseline on the service response length.

6.3. DC providing scheduling ancillary service

In this scenario, an energy consumption peak is predicted in the local energy grid. To avoid it the DSO publishes scheduling service at 12 pm on the Ancillary Service Marketplace requesting the DC to shed or shift energy consumption over time to decrease its energy demand between 12:30 pm and 2 pm. Fig. 7(a) presents the DC energy demand baseline in the orange line, the profile requested by the DSO in the blue line and the DC response and adjusted energy profile in the grey line. Following our technique, the DC is able to schedule is operation to reduce the energy consumption over the service response period by 32% in order to meet the request (Fig. 7(b)).

Most of the delay-tolerant workload from the service response period is delayed after 2:30 pm. The electrical cooling device usage is decreased by 20% during the response period, leveraging on the TES device which was prior overcooled. It has to be noted that no batteries charging actions are taken during this period. As a result, the total amount of flexible energy shifted to provide the requested services is about 8.43 MWh.

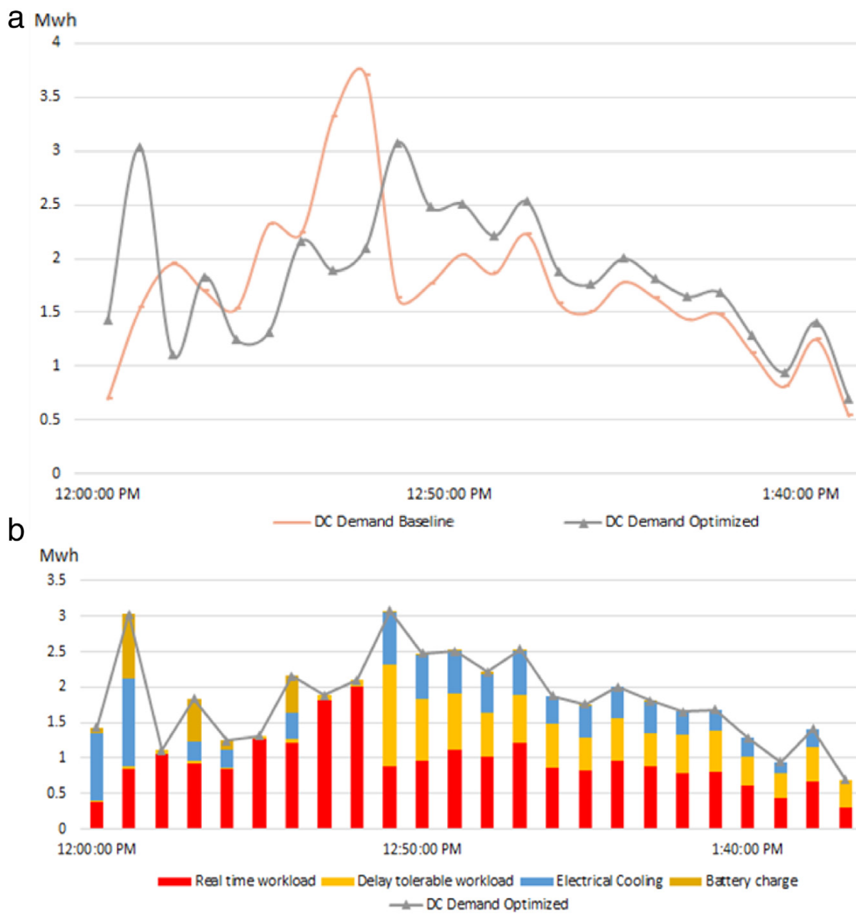

Fig. 8. DC providing reserve service: (a) DC baseline energy profile and (b) DC adjusted energy profile. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

6.4. DC providing reserve ancillary service

In this scenario, due to un-forecasted energy consumption peak in the local grid the DSO publishes at 12 pm a reserve service on the Ancillary Services Marketplace requesting for generating and injecting energy in the grid. The DC will provide fast ramping power starting from 12:10 pm with a response length of 30 min until 12:40 pm using its diesel generators (Fig. 8(a)). To increase the amount of energy fed to the grid, our technique is used for shifting, to the largest extent possible, the energy demand away from the time interval when the service is expected by using the electrical cooling system at minimum levels, compensating on non-electrical cooling and shifting the execution of delay-tolerant workload. Also, batteries discharging is planned to feed extra power to the grid.

Fig. 8(b) presents the DC response and adjusted energy profile, while Fig. 9 presents the energy generated and fed to the grid. During the reserve service duration, the proposed DC manages to shift about 4.15 MWh of flexible energy, resulting in a temporary decrease in energy consumption by 15%. Also, the amount of the energy fed to the grid is 8.79 MWh, 52% of which is the energy produced by the diesel generator, while the rest 4.15 MWh is the energy saved as a result of demand profile optimization.

6.5. DC providing active reactive power control

In this scenario a voltage drop threaten the local grid stability thus the DSO sends an active-reactive power regulation signal to the DC requesting to increase its reactive power in order to increase the voltage in the grid.

The reactive power can be used to compensate the voltage drops, but must be provided closer to the loads than real power needs (this is because reactive power tend to travel badly through the grid). The signal is issued by the DSO at 12.34 pm and the DC must respond very fast (almost in real time) by decreasing its power factor and provide the service between 12.35 and 12.55 (see Fig. 10(a)). To do so it leverage on the usage of the electrical cooling device at higher intensity levels, decreasing the temperature set point and pre-cool the DC during the response period (Fig. 10(b)). As a result of intensive usage of cooling device compressor increased reactive power is discharged.

7. Conclusion

In this paper, a technique for scheduling and optimizing the DCs operation aiming at enacting them to participate in Smart Demand Response programs is proposed. The technique is leveraging on flexibility mechanisms defined for DC hardware components such as load time shifting, alternative usage of non-electrical cooling devices (e.g. thermal storage), charging/discharging the electrical storage devices, etc. An innovative electronic marketplace has been designed to allow DCs to become active energy players in their local grid by trading their energy flexibility based on relative prices for energy or types of ancillary services. Simulation results validate the technique potential to shape and modify the DC baseline energy profile to meet energy network levels goals and provide various types of energy and balancing services. Our future work includes the validation of the approach in four operational DCs of the GEYSER project (Engineering and ASM Terni DCs in Italy, Alticom DC in the Netherlands and RWTH Aachen DC in Germany).

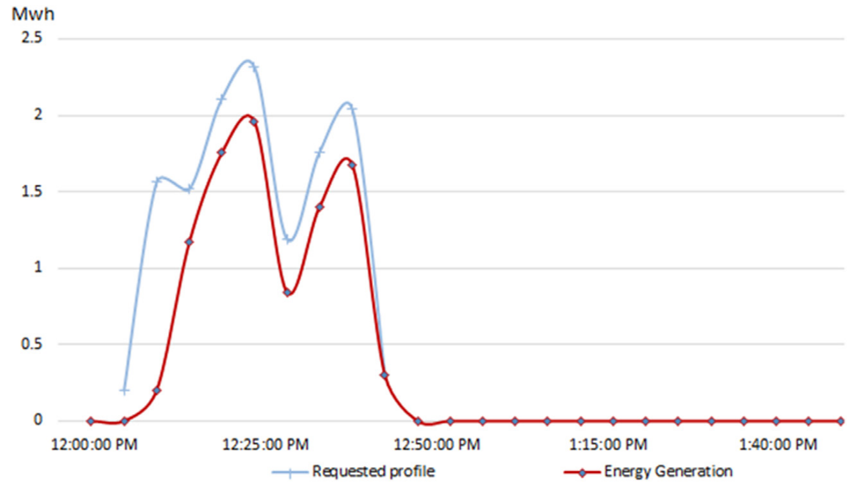

Fig. 9. DC generated energy fed to the grid.

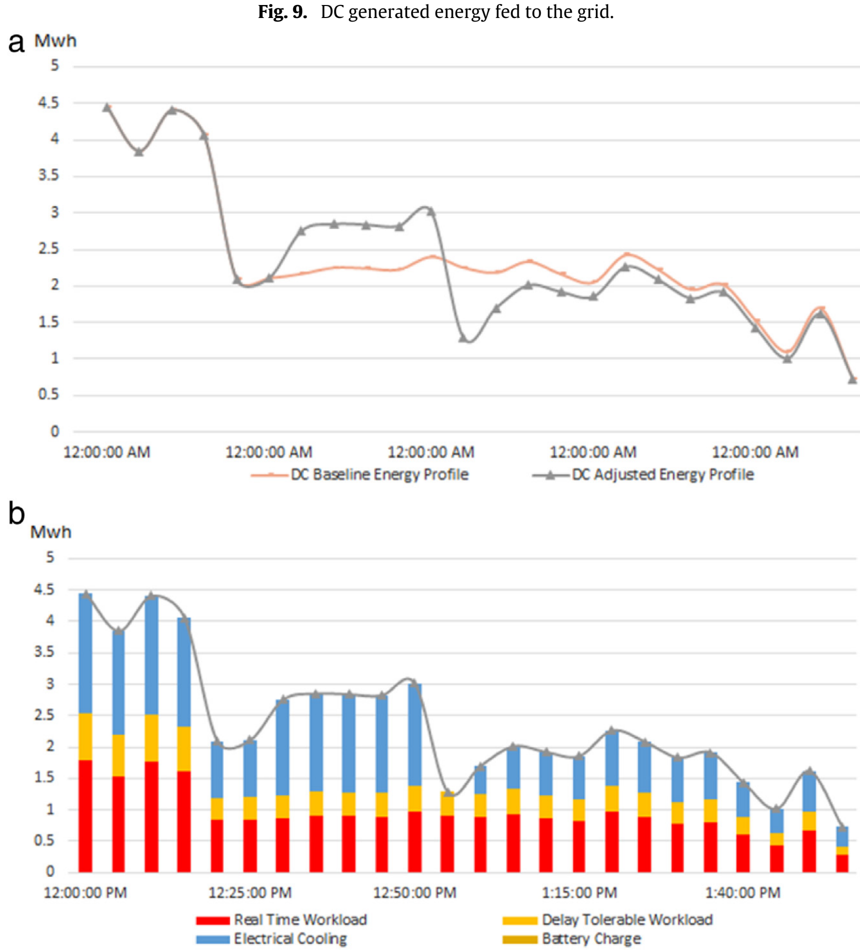

Fig. 10. DC providing active reactive power control: (a) DC baseline energy profile and (b) DC adjusted energy profile as a result of pre-cooling the DC during response. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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