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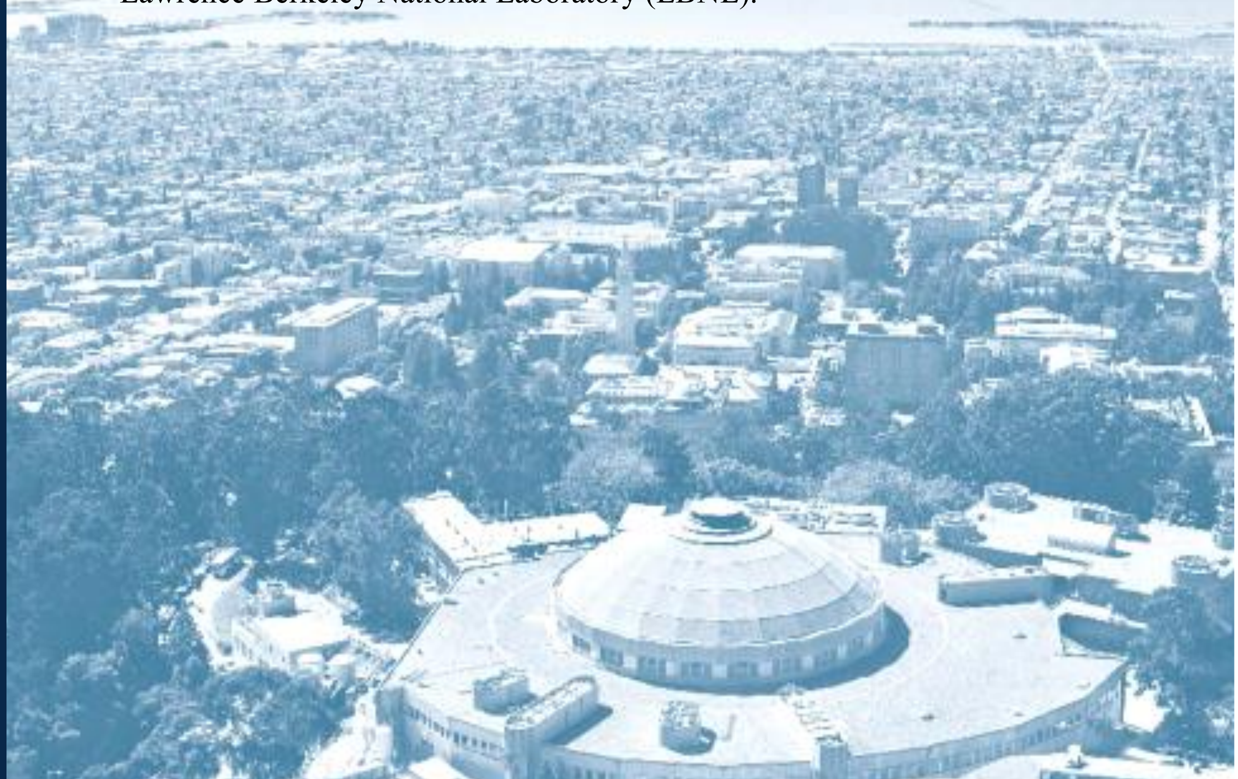

Disclaimer

Assessment of grid-friendly collective optimization framework for distributed energy resources

Alessandro Pensini, *Member, IEEE,* Matthew Robinson, *Student member, IEEE,* Nicholas Heine, *Student member, IEEE,* Michael Stadler, *Member, IEEE,* Andrea Mammoli, *Member, IEEE*

***Abstract*—Distributed energy resources have the potential to provide services to facilities and buildings at lower cost and environmental impact in comparison to traditional electric-grid-only services. The reduced cost could result from a combination of higher system efficiency and exploitation of electricity tariff structures. Traditionally, electricity tariffs are designed to encourage the use of 'off peak' power and discourage the use of 'on-peak' power, although recent developments in renewable energy resources and distributed generation systems (such as their increasing levels of penetration and their increased controllability) are resulting in pressures to adopt tariffs of increasing complexity. Independently of the tariff structure, more or less sophisticated methods exist that allow distributed energy resources to take advantage of such tariffs, ranging from simple pre-planned schedules to Software-as-a-Service schedule optimization tools. However, as the penetration of distributed energy resources increases, there is an increasing chance of a 'tragedy of the commons' mechanism taking place, where taking advantage of tariffs for local benefit can ultimately result in degradation of service and higher energy costs for all. In this work, we use a scheduling optimization tool, in combination with a power distribution system simulator, to investigate techniques that could mitigate the deleterious effect of 'selfish' optimization, so that the high-penetration use of distributed energy resources to reduce operating costs remains advantageous while the quality of service and overall energy cost to the community is not affected.**

***Index Terms*—microgrids, optimization, distribution feeder, distributed resources, power flow simulaiton.**

I. Introduction

DISTRIBUTED energy resources (DERs), including energy storage, are becoming increasingly important in todays' electric systems. This is the result of several technological, economic and regulatory pressures [9], including the retirement of coal plants, the development of attractive forms of energy storage, the declining cost of photovoltaic devices, and, most significantly, the ability to transfer and process information between systems.

One of the potential benefits of distributed energy systems is their ability to provide grid services, including congestion relief, frequency regulation, and voltage support [1]. A review paper that considers the transition from today's infrastructure to the 'Smart Grid' of the future [6] indicates a final topology where distribution microgrids are interconnected to a 'data exchange highway' and a 'power exchange highway'. During this transition, it will be necessary to implement a number of enabling components, including a system that manages the operation of distributed generation and loads at various timescales, ranging from day-ahead scheduling to real-time dispatch.

There is a growing body of work that describes control schemes for such microgrids. For example, Tsikalakis and Hatziargyorou [12] propose a three-tiered structure, composed of local controllers, a microgrid central controller, and a distribution management system. The local controllers track demands from the central controller, and adjust active and reactive power to support voltage and frequency. The central microgrid controller optimizes collective operation of the DERs using various market mechanisms, providing economic benefits to customers inside the microgrid. Finally, the distribution management system is an evolution of current products that also considers the added functionality of microgrids, including the ability to island from the grid. Service cost reductions of over 30% are observed.

A hierarchical control framework is also viewed as critical by Jiang and Dougal [8]. In the hierarchy presented, collections of heterogeneous resources form microgrids, that are viewed by agents higher in the hierarchy as single, dispatchable entities. Uncontrollable power sources, such as PV arrays, are coupled with storage or deferrable loads so that the collection of DERs is largely dispatchable. A multi-tiered control structure similar to that found in other works is proposed. Low-level controllers serve local purposed such as voltage regulation. 'Combo-Source' Inverter Controllers serve to maintain a set collective output power and voltage from several devices. Finally, a 'Microgrid Coordinating Controller' has the role of ensuring that service requirements within the microgrid are met, while also serving contractual requirements with the transmission system, in an optimal way. Proper control of a case-study system was demonstrated.

Various other studies explore similar concerns, with general agreement that coordinating the operation of multiple micro-grids or DERs following hierarchical principles is necessary [7], [13], [11], [14], [5].

A different perspective is taken by Ai *et al.* [2], who consider the effect of large-scale distributed generation (DG) on steady-state and transient stability of distribution system, in grid-tied and islanded mode. While DG has the ability to allow better stability, care needs to be taken in the placement of the DG, and in the control interface. A particularly important

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aspect is the effect of induction motors when the grid is in island mode. One of the conclusions is that traditional distribution grid designs are not adequate to meet loads in island mode, and simulation-assisted design of control infrastructure is desirable.

Voltage stability is also considered in a study by Arya *et al.* [3]. Test systems consisting of models of 6-bus and 30-bus distribution systems are considered. Buses for the location of DG are selected on the basis of incremental voltage sensitivities. For the optmization, a differential evolution algorithm is compared to a particle swarm method and a multi-membered non-recombinative evolution method. The results show that integration of DG is highly effective in reducing power loss and managing voltage, irrespective of the optimization used.

In the present work, we seek to combine the optimization of individual systems with a power flow simulation tool, to ensure that the collective action of multiple optimized distributed energy systems does not have deleterious system-wide effects. For example, a set of facilities with similar energy storage systems would produce identical optimized schedules, which in turn could result in a peak load due to coincident activation of energy storage, observed at the distribution feeder in the form of excessive load on the substation transformer, excessive voltage drops on certain branches of the feeder, or excessive power loss. Such system-wide effects are considered as an additional distribution-related cost, and are therefore used to modify the pricing schedule accordingly. The modified tariff is used for the purposes of scheduling only, and are not ultimately passed to the consumer.

II. Model system description

A. Loads

For this study, four facilities with DERs were considered that, unlike in the real case, in the present study are located (virtually) on the same distribution feeder (Studio14), whose characteristics are described later. These facilities are based on existing ones that are the object of ongoing investigations and were chosen to represent a diverse set of loads that are representative of systems that could become more common in the near future. These utility customers can benefit from week-ahead optimization, and are equipped with the hardware and control infrastructure that enables it.

A background feeder laod was derived from substation measurements and distributed along 18 different location on the feeder to simulate realistic operation. Furthermore, the feeder accommodates the load of the controlled customers. For each facility, a baseline electric load is established, that reflects the total electric load, including cooling, for an identical facility with no DERs. For this baseline, the thermal load is served directly by an electric chiller. This baseline is used to establish a feeder load that reflects conventional (i.e. non-DER) situations, so that the effect of heavy DERs presence can be observed.

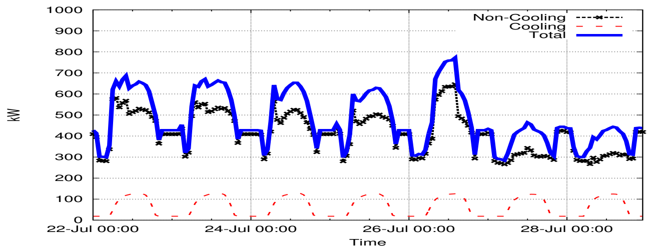
One Sun Plaza (OSP) is a two-building campus that provides general office space and server rooms for tenants. The total loads, also split into cooling only and electricity for non-cooling demands, are shown in Fig. 1a. OSP is cooled by a central plant that houses a 1514 m^3 thermal energy storage (TES) tank which is charged by two 1055 kW_t electric chillers. A 300 kW PV array, not present in the real facility, was added to the 'virtual' facility to add interest and complexity to the optimization problem. The Mechanical Engineering building at the University of New Mexico (UNM ME) is a four story facility that houses lecture rooms, laboratories, and offices. UNM ME cooling, non-cooling, and total loads are shown in Fig. 1b. UNM ME hosts a variety of energy resources that include: seven 50 m^3 cold water tanks, a 30 m^3 hot water tank, a solar array with a maximum thermal power of 170 kW_t, and a 70 kW_t single effect absorption chiller that is powered by solar hot water. Additionally, the building is connected to the campus district energy system by a 352 kW_t flat plate heat exchanger that acts as a virtual electrical chiller for the purposes of this study. Albuquerque Studios is a campus that hosts a number of large film production stages. It is cooled by a central plant equipped with twenty-four 6.81 m^3 ice tanks and two 1758 kW_t electric chillers. The typical baseline electric and thermal loads are shown in Fig. 1c. The Aperture Center (located at Mesa del Sol) is a newly constructed LEED-silver commercial building served by a microgrid. The total electric and cooling loads from a building of similar size and type were assumed (Fig. 1d). The microgrid that serves the Mesa del Sol building consists of an 80 kW_e fuel cell, a 240 kW_e natural gas generator, a 75.7 m^3 cold water tank, a 75.7 m^3 hot water tank, 160 kWh_e battery storage (advanced lead-acid), a 246 kW_t electric chiller, and a 70 kW_t absorption chiller.

The equipment at the host facilities is summarized in Table I. Performance characteristics of the distributed energy resources are listed in Table II. The efficiency of the charge is defined as the fraction of energy that is stored relative to how much is supplied to the storage. Efficiency of discharge is the amount of energy that reaches its end use relative to what is stored. Decay is the fraction of energy lost per hour in the storage device. The maximum charge rate is the percentage of the difference between total capacity and current energy in the storage that can be added per hour. The maximum discharge rate is defined as the percentage of the total capacity that can be removed per hour. The minimum state of charge is the lowest percentage of energy allowed in the storage device.

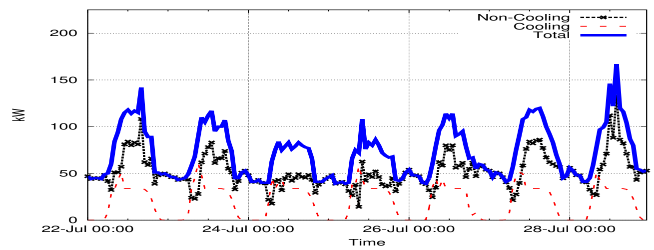
Each facility has a certain amount of flexibility in how to schedule the use of its distributed energy resources. Doing this at the lowest cost to the facility is a complex optimization problem, which can become an intractable task for the facility manager, even for systems with relatively low complexity. An efficient way to solve this problem is to apply the Distributed Energy Resource - Customer Adoption Model (DER-CAM), a cloud-based tool developed by Lawrence Berkeley National Laboratory. DER-CAM is mixed integer linear programming (MILP) scheduler for commercial scale energy systems that provides rolling seven-day schedules. DER-CAM can solve the optimization problem for the facility to minimize costs, CO_2 emissions, or a linear combination thereof [10].

B. Distribution system

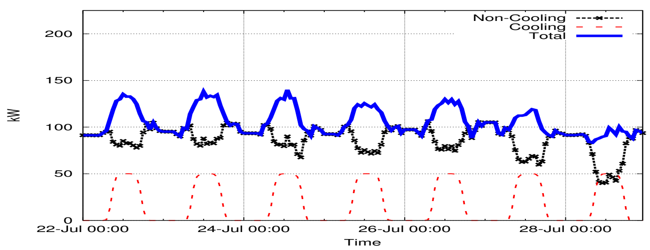
Studio14 is a sparsely populated radial distribution feeder serving residential, commercial, and industrial customers at



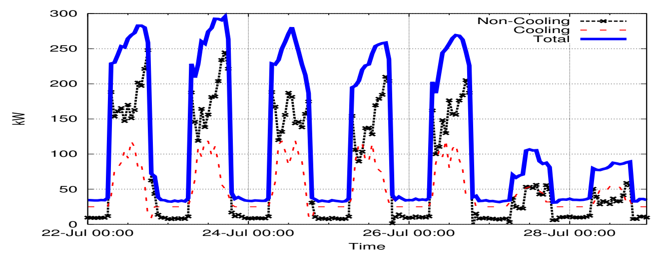
(a) One Sun Plaza



(b) UNM Mechanical Engineering



(c) Albuquerque Studios



(d) Aperture Center microgrid

Fig. 1. Electricity loads at various facilities. The total load is separated into electricity for cooling and electricity for non-cooling.

TABLE I
DISTRIBUTED ENERGY TECHNOLOGY AT THE FOUR HOST SITES.

Equipment	UNM ME	One Sun Plaza	ABQ Studios	Mesa del Sol
Battery	0	0	0	560 MJ$_e$ (160 kWh$_e$)
Hot Storage	1,836 MJ$_t$	0	0	7,657 MJ$_t$
Cold Storage	13,686 MJ$_t$	52,272 MJ$_t$	43,805 MJ$_t$	2,549 MJ$_t$
Absorption Chiller	70 kW$_t$	0	0	70 kW$_t$
PV	0	300 kW$_e$	0	50 kW$_e$
Solar Thermal	170 kW$_t$	0	0	0
Fuel Cell	0	0	0	80 kW$_e$
NG Generator	0	0	0	240 kW$_e$
Electric Chiller	352 kW$_t$	2,110 kW$_t$	3,516 kW$_t$	246 kW$_t$
COP	5.4	5.5	6.0	4.0

Note: subscript 'e' denotes electric, subscript 't' denotes thermal

TABLE II
CHARACTERISTIC PARAMETERS DESCRIBING THE PERFORMANCE OF THE STORAGE TECHNOLOGY AT THE HOST SITES.

	UNM ME			One Sun Plaza			ABQ Studios			Mesa del Sol		
	Cold Storage	Hot Storage	Electric Storage	Cold Storage	Hot Storage	Electric Storage	Cold Storage	Hot Storage	Electric Storage	Cold Storage	Hot Storage	Electric Storage
Charge Efficiency	0.99	0.95	N/A	0.99	N/A	N/A	0.99	N/A	N/A	0.9	0.9	0.99
Discharge Efficiency	0.99	0.95	N/A	0.99	N/A	N/A	0.99	N/A	N/A	0.9	0.9	0.75
Decay	0.01	0.01	N/A	0.01	N/A	N/A	0.01	N/A	N/A	0.01	0.02	0.004
Maximum Charge Rate	0.17	0.56	N/A	0.17	N/A	N/A	0.23	N/A	N/A	0.28	1.0	0.5
Maximum Discharge Rate	0.17	0.36	N/A	0.17	N/A	N/A	0.16	N/A	N/A	0.28	1.0	0.5
Minimum SOC	0.01	0.01	N/A	0.01	N/A	N/A	0.01	N/A	N/A	0.01	0.01	0.12

Mesa del sol, a growing master-planned community located in south-eastern Albuquerque. The feeder is over 12 km in length, operates at 12.47 kV and consists of 3437 busses and 4254 nodes. The feeder has a 530 amp rating, and is connected to a 3.55 MVA distribution substation. A model of the Studio 14 feeder was developed for OpenDSS, an open-source distribution system simulator developed by the Electric Power Research institute (EPRI) [4]. The model represents the current configuration of hardware and control settings as used by PNM. The feeder model was verified by comparing results from OpenDSS to the utilitys in house power flow simulation, Synergi.

III. METHODS

A. Simulation framework and inputs

The operation of the four large individually optimizing customers (described in § II-A) on a distribution feeder (described in § II-B) were simulated to determine the effects of DER optimization on power flow. The voltage profile at a critical node (located at the office complex, as shown in fig. 2) was monitored and chosen as the metric to determine power quality on the feeder. Clearly, this is not a definitive metric, but it is adequate to illustrate the general system behavior considered in this study. The simulations have a time horizon of one week with a time step of 15 minutes. To determine the optimal schedule for individual customers, the deterministic operations version of DER-CAM was used.

The basic inputs of the optimization are predicted electric and thermal loads, weather forecasts, available installed technology characteristics, and electricity tariff. Load and weather forecasts are required each time DER-CAM is called, while technology data and tariff structure are only provided once. Loads are met at any given time step either by utilizing utility electricity directly purchased from the grid or by local generation and storage. An optimized schedule is created that allows minimizing the utility cost incurred by the customer and meets all the restrictions dictated by technical constraints. During actual operation, customers adjust their utility consumption in real-time when current demand and on-site generation deviate from the forecasted values.

The feeder model contains the topology of the distribution network and technical specifications of the lines, transformers, and all other electrical equipment installed. The topology of the distribution feeder and the location of the loads are shown in Fig. 2.

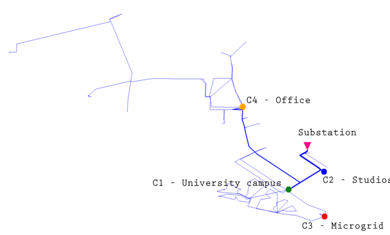


Fig. 2. Studio14 feeder model. The four controlled loads that follow optimized schedules calculated by DER-CAM are marked with colored dots (green=university blue=studios red=microgrid orange=office). The substation is indicated by the magenta triangle mark.

B. Optimization algorithm

As discussed previously, single large loads independently optimizing their loads may create significant voltage drops and reduce power quality, for example in the case that many large storage resourced are charged simultaneously. To mitigate this harmful (if unintended) collective behavior, a multi-stage approach was implemented, in which successive optimization runs are based on a dummy Real Time Price (RTP) signal instead of the Time Of Use (TOU) tariff that applies in the region. The multi-stage simulation framework is shown in Fig. 3.

The first RTP signal (RTP_1) is based on the TOU tariff (TOU) and adjusted by taking into account the first voltage profile produced by the feeder model (V_{TOU}), as shown in Equation 1.

$$\text{RTP}_1(t) = \begin{cases} \frac{\text{TOU}(t)}{[1 - V_{\text{ref}} + V_{\text{TOU}}(t)]^{\alpha}} & \text{if } V_{\text{TOU}}(t) < V_{\text{ref}}; \\ \text{TOU}(t) & \text{otherwise.} \end{cases} \quad (1)$$

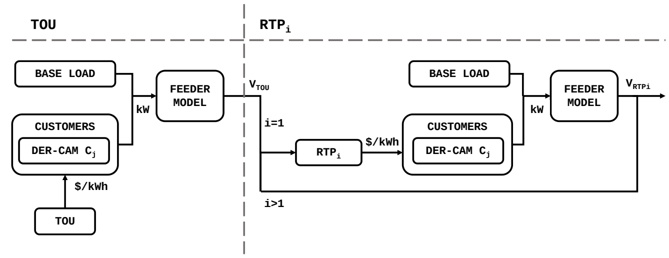


Fig. 3. Evaluation of RTP based on feeder power flow.

In successive iterations, for $i > 1$, the i^{th} RTP signal (RTP_i) is calculated based on the voltage profile from the previous stage, as shown in Equation 2.

$$\text{RTP}_i(t) = \begin{cases} \frac{\text{RTP}_{i-1}(t)}{[1 - V_{\text{ref}} + V_{i-1}(t)]^{\alpha}} & \text{if } V_{i-1}(t) < V_{\text{ref}}; \\ \text{RTP}_{i-1}(t) & \text{otherwise.} \end{cases} \quad (2)$$

The parameter V_{ref} was tuned to 0.960 p.u. and is used for determining whether the RTP must be changed from one iteration to the successive one. The RTP is not affected when the feeder model outputs voltage levels above V_{ref}. This has the effect of keeping the RTP profile as close as possible to the original TOU, the tariff that customers ultimately pay. As no grid-connected distributed generation was modeled, there was no need to take care of over-voltages during normal operation. Single customers achieve the best economic performance by following schedules based on TOU tariffs. Thus, RTP signals closer to TOU tariffs give smaller deviations from the optimal schedule for the single customers. The parameter $\alpha > 0$ is used to give the RTP signal in Equation 1 and Equation 2 a non-linear response with respect to voltage drops. If not explicitly stated otherwise, given results refer to simulations based on $\alpha = 4$, that was found to be a value that gives a good overall performance.

The resulting RTP signal profile still follows the typical on/off peak TOU tariff profile. However, fluctuations in the voltage level are mirrored into price signal deviation above the TOU profile. Specifically, the price signal slightly increase when the voltage drops below the reference value V_{ref}, while it does not deviate when $V(t) > V_{\text{ref}}$.

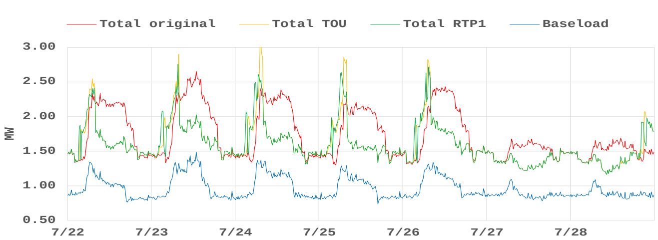
The iterative method based on RTP signals benefits from the knowledge of the entire feeder behavior and thus the contribution from all optimizing customers and background demand. The multi-stage approach presented here therefore leads to collective optimization, since a cost is associated with effect of collective behavior on power flow is considered. Nevertheless, the mathematical formulation of the optimization problem is for individual customers and remains simple, so that the solution to the problem remains scalable and fast. Significantly, implementation of the proposed method requires a centralized optimization service, which aggregates the TOU schedules from the optimizing customers, resolves the feeder model, and provides individual optimizations with the feeder-based RTP signal. As a consequence, the cloud-based model is ideally suited.

IV. Results and discussion

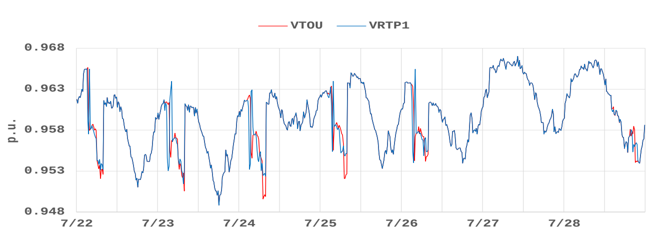
In this section the ability of the proposed method to reduce voltage drops induced by the optimizing schedules along the distribution network is discussed. The feeder operation of the independently vs collectively optimized approaches is compared and typical profiles are derived. Furthermore, voltage profiles are analyzed for increasing numbers of iterations in order to provide base knowledge for tuning purposes in future applications.

A. Performance assessment

The feeder load under different operation strategies is shown in Fig. 4 (a). The total non-optimized (no-DERs) feeder load (total original) has the typical consumption pattern of commercial and residential buildings, with peaks during the working hours and lower consumption rates during the night and weekend. A common practice for achieving smoother demand profiles is to introduce TOU tariffs structures that are defined for pushing customers to consume more during off-peak hours. When the four large loads are optimized , schedules take advantage of the low price during the off-peak periods (from 20:00 to 8:00 and during weekends and holidays) part of the on-peak (working days, from 8:00 to 20:00) demand is then shifted to hours when the cost of electricity is low. However, this strategy could be too successful, especially at the distribution scale and consumption peaks larger than the original case are created (total TOU).



(a) Load at critical node



(b) Voltage at critical node

Fig. 4. Simulation results, showing the advantages of distribution-level optimization on distribution system load and power quality.

As the optimization tool DER-CAM models storage losses, it tries to postpone the storage charging to the last hours of the off-peak period. This produces the high peaks that take place from 6:00 to 7:45, just before the beginning of the on-peak tariff period (referred to here as 'type A' events).

The effect of the two-stage optimization based on RTP (total RTP1) is clear when considering the early morning behavior. During 'type A' events, the load resulting from RTP shows smaller peaks than the corresponding TOU, and power consumption is shifted to a period several hours earlier. The downside of this strategy is higher storage losses, leading to higher energy use by the customers. However, thermal storage units are generally very well insulated and such losses account for a negligible percentage of the total utility cost. The difference in utility costs between TOU and RTP bills was calculated to be less than 0.05%. The load profile does not change significantly during the rest of the day from TOU to RTP, meaning that the collective approach corrects only critical events.

In order to assess the performance of the collective approach, the voltage profile at OSP was monitored and plotted for the TOU and RTP1 case in Fig. 4 (b). The TOU voltage profile shows large 'type A' voltage drops coincident with the high consumption peaks. The amplitude of 'type A' voltage deviations is decreased when customers perform the proposed two-stage RTP based optimization. The smoothing effect varies from day to day, depending on the particular operating condition of the feeder. The best performance is achieved on July 25^{th} and 26^{th}, when the voltage drop is reduced by 0.003 to 0.004 p.u. (for Studio14 the normal voltage range is +/- 0.05 p.u.). Smaller reduction of about 0.001 p.u. in voltage drops is achieved during the other working days of the week. In turn, the effect of this energy consumption shift creates new negative peaks occurring earlier than $TypeA$ ones, between 1:00 AM and 3:00 AM. Similarly to $TypeA$ events, balancing events that take place during this period of time will be referred as $TypeB$ events.

Fig. 4 (b) also shows large voltage drops occurring at around 18:00. These negative peaks are mostly caused by the effect of large background concurrent consumption (see Fig. 5) that cannot be controlled. The contribution of the optimized schedules is however minimized by the RTP operation. OSP facilities at 18:00 PM are more than 50% smaller than its daily peak consumption occurring at 7:00 AM but cannot be further reduced because of the limited storage capacity.

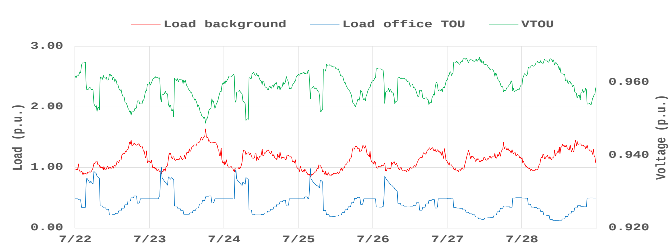


Fig. 5. Bacground and OPS normalized loads and voltage profile at OPS.

B. Increasing the number of iterations

Results presented in the previous section show that one single iteration of the proposed algorithm is able to reduce the amplitude of greedy optimization due voltage drops. In this section, the voltage profiles for successive iterations are compared. Fig. 6 shows the voltage profile measured at the office building on the July 25^{th}, from 0:00 to 10:00. The compensating mechanism between $typeA$ and $typeB$ events that was described in the previous section is amplified by the number of successive iterations. It can be observed that $typeA$ voltage drops are reduced with a second iteration (V_{RTP2}) but no further reduction is observed for successive ones. The balancing effect on $typeB$ voltage drops creation shows an interesting effect. The amplitude of $typeB$ created drops tends to increase with the number of iterations and starts to being affected by the real-time-price policy. In this way, $typeB$ drops begin to split (V_{RTP2}) and create new peaks, in a zig-zag fashion (V_{RTP3} and V_{RTP4}). As the minimum voltage level does not vary considerably (it actually slightly deteriorates) for an increasing number of iterations, it can be derived that for this particular study case the algorithm best performance is already achieved after the first iteration.

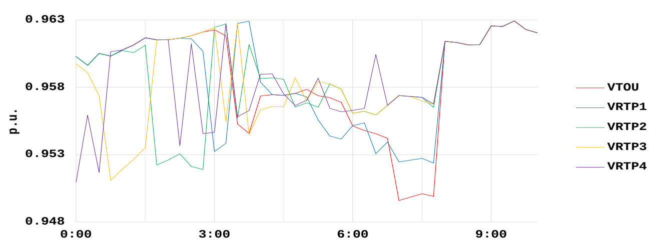


Fig. 6. Sensitivity analysis on the number of iterations.

V. Conclusions

Standalone optimized consumption schedules of large utility customers can induce significant voltage drops along distribution networks. A collective optimization method for reducing the amplitude of these negative voltage peaks was proposed. The method is iterative, and relies on a Real-Time-Price signal that is updated at each iteration and based on the feeder operating conditions. The DER-CAM optimization tool coupled with a feeder model based on the open source software OpenDSS were used.

Simulations show that the proposed method allows smoothening the large voltage drops caused by independent optimization whilst maintaining the same economic appeal. Preliminary results from cases with different load profiles and higher storage capacities indicate increasing performance when larger and more frequent optimization-induced voltage drops occur. The main implication from this study is that associating a cost to undesirable power flow effects allows more optimizing customers on the same feeder than standalone optimization without the need for costly hardware upgrade or the implementation on advanced utility market frameworks. This is highly relevant when large amounts of energy storage must be deployed especially for integrating large shares of renewable generation.

The proposed method is flexible, customizable, and fast. The distribution system operator could, in general, choose to monitor different locations for addressing the most congested areas, and could even provide different RTPs, based on local variables, to the schedule optimization for each individual facility. It is also possible to monitor other operating variables than the voltage profile, such as current for reducing grid congestion or power at the main transformer. DER-CAM can handle a large variety of DERs so that virtually any combination of assets can be simulated. Furthermore, the mathematical formulation in MILP was shown to be robust and fast even on common personal computers.

Being among the first of this type, this study opens the way to future work in several directions. Further development of the proposed method can focus on the possibility to create local dummy RTPs for different customers. Other improvements can be made based on RTP signal definition which is so far highly empirical, and on the persistence of memory from iteration to iteration. Finally, similar studies would be needed to assess different system configurations.

Acknowledgment

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