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Electricity Network Constraint Management using Individualised Demand Aware Price Policies

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Abstract

Electric Distribution Network constraint management is employed by Distribution System Operators in order to keep inside desired safety bounds the aggregated power demand at each network substation. In our context, such aggregated power demand is due to residential users requiring electricity to the substation they are connected to. This enables saving in substation maintenance and energy peak production, as users typically tend to use little energy for most of the day, except for demand peaks, especially during evenings. The main workhorse to obtain such a goal is Demand Side Management, that is, trying to change the users demand in order to meet aggregated demand safety bounds.

In this short paper, we introduce the problem and briefly review our recent approach to perform Demand Side Management for Electric Distribution Network constraint management, based on a network state estimator and a Model Predictive Control scheme. We also show experimental results on large scenarios using a real Electric Distribution Network in Denmark.

1 Introduction

An Electric Distribution Network (EDN) is composed of electrical *substations*, each servicing a number of residential users. The typical users behaviour, as for electricity power demand, is to use little energy for most of the day, and then request much electricity during the evening (*demand peak*). This increases costs for Distribution System Operators (DSOs) managing the EDN, as it results in peak power plant usage [37] and substation ageing [51]. In order to counteract such a problem, DSOs have to: i) detect, for each substation, the desired safety power bounds for the aggregated power demand, resulting from summing up the electricity power requested by all residential users connected to the same substation; and ii) enforce such bounds. This activity is typical referred to as *network constraint management*.

The main tool DSOs use in order to minimise the aggregated power demand outside substation desired bounds is Demand Side Management (DSM). Namely, DSOs try to modify the users power demand by employing either i) Direct Load Control (DLC), i.e., directly acting on users appliances (see, e.g., [39, 44, 20]) or ii) Autonomous Demand Response (DR), i.e., trying to economically incentivise users to shift their demands (see Section 5 for a discussion of the literature). Namely, in the DR setting, each residential user receives a Time of Use (ToU) (i.e., prices may change at different hours of the day) and/or Inclining Block Rate (IBR) (i.e., the per-kWh prices depend on the power demand itself) price policy. Such price policy must be computed so as users aggregated demand is within substation desired bounds, provided that most of the users follow their price policy. In order to follow the price policy, residential users have to avoid energy consumption in hours where the price is high, and instead shift loads in hours with low price. Finally, as for desired power bounds on substations, they are typically set up manually by domain experts.

Unfortunately, this simple scheme has to face the *peak rebound* effect: as all users have the same price policy, they tend to shift their demand in the same way, thus creating a new peak in the hours with low tariff [16, 40, 56]. Furthermore, manually determining substation bounds is expensive and time consuming.

In this short paper, we introduce the problem and review our recently proposed approach [26, 14] for the automatic computation of both desired bounds for substations (EDN Virtual Tomography, or EVT, service) and of *demand-aware individualised price policies* for users (Demand Aware Price Policy, or DAPP, service). Our approach is based on statistical methods such as Weighted Least Squares (WLS) [49] for the EVT service and on the Model Predictive Control (MPC) methodology [43] relying on the GLPK Mixed Integer Linear Programming (MILP) solver (gnu.org/software/glpk) for DAPP.

2 Problem requirements

An EDN is composed of several substations, where each substation serves a set of residential houses. We suppose to be able, using the measurements taken from the home electricity mains (Advanced Metering Infrastructure, AMI), to know each house power demand, with periodicity at least one hour. Our objective is to reduce costs for the DSO, by limiting the demand drawn at some or all substations of the EDN at times of peak demand. In fact, this reduces costs of buying energy from the market at times of peak electricity price, and reduces overloading of network components during times of peak demand (thus reducing substations aging), or during periods when the system is weakened due to line/transformer maintenance or other outages [51, 37].

This must be done avoiding the *peak rebound* effect. A study carried out by a Danish DSO [46] in 2013 showed an example of such an effect. In this study, residential users of a Danish city were given a ToU price policy, so as to test if the residential demand may be changed (actually, *shifted*) using only economic incentives. Thus, such price policy gave electricity *for free* during nights (from 8PM to 6AM), with a low price p during most part of the day (from 6AM to 5PM) and with an high price (more than $5p$) during evening (from 5PM to 8PM, which was the usual electricity peak). As a result, the peak was simply shifted: instead of occurring from 6PM to 7PM, it was from 8PM to 9PM, especially during Winter months. These effects are undesirable, since DSOs objectives are to smooth the load profile, increase the load factor (i.e., the ratio of average to maximum load), and reduce demand peaks.

3 Network constraint management through intelligent services

Our proposed architecture comprises the following two computational services [14, 26] (see Figure 1).

The EVT service uses available measurements of houses power demand (collected from Supervisory Control And Data Acquisition, SCADA, and smart metering/AMI systems/electricity mains) and the knowledge of the EDN topology to estimate, in real-time, the EDN state, using the WLS methodology [49]. Furthermore, EVT also carries out network analysis ahead of time, as described in [13, 11]. The results of the state estimation and network analysis carried out by EVT is used to set operational constraints on the EDN, by limiting the aggregated demand drawn at some or all substations within the EDN, especially at times of peak demand.

The DAPP service takes as input both the output from EVT (i.e., the bounds on substations aggregated demand) and again the power demand from houses of the EDN. Then, for each substation s in the EDN, computes (by using a MILP solver and the MPC methodology) a set of *individualised* ToU and IBR price policies. Such price policies are sent to users through the energy retailer (which may be the

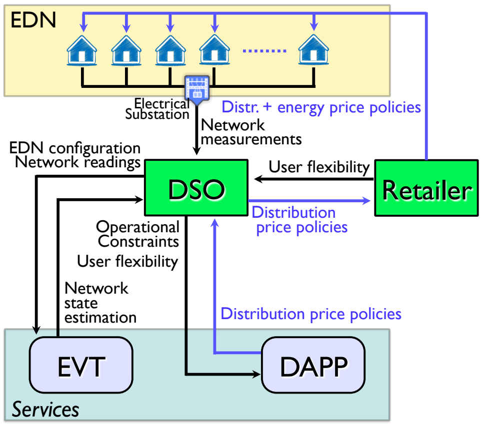

Figure 1: Our overall architecture.

Load Factor	Base Case	Global Case	Indiv. Case
Winter Peak	0.7116	0.6176	0.8124
Summer Min	0.5927	0.5280	0.7038
Overall	0.3471	0.3084	0.4415

Figure 2: Resulting Aggregated Load Factors

DSO itself). Namely, the following holds. i) Each price policy defines a *low tariff area* and an *high tariff area*, using the IBR methodology: if the power demand of the target house is within given power bounds, then a low price of energy is applied; otherwise the high price is used. Thus, users are economically incentivised to stay within the given power bounds. ii) Each price policy also follows the ToU scheme, i.e., the bounds for low and high tariff area may change every hour. This allows not to compress the overall demand, which would cause the DSO to lose money: a peak centred in a time slot is distributed on the adjacent time slots. iii) The price policies are individualised, i.e., different houses will get possibly different price policies. This avoids the peak rebound effect, as different houses are incentivised to shift their demand to different time slots. iv) In order to have price policies which may be actually followed by each user, we take into account each user *flexibility*, i.e., the capability of each house to shift its demand. This also allows to design DAPP so as to output not-discriminatory policies: all residential users have the same opportunities to always pay the low tariff.

4 Experimental results

We experimented our approach by using a case study from the European Commission project "SmartHG" (smarthg.di.uniroma1.it) [29]. Such case study consists of a suburban/rural 10kV EDN with a weakly-meshed structure, including 46 substations, each with 30 houses connected on average. We initially run EVT to determine power bounds on aggregated power demand of all 46 substations in the EDN. Then, we consider 3 different scenarios: the *base case* (data as actually recorded from house mains), the *global case* (all houses are given the same "global" price policy) and the *individualised case* (all houses get the individualised price policies output by DAPP).

As a result, the global price policy results in a rebound demand peak similar to that recorded in the Danish study [46] described in Section 2. Instead, in the individual price policy case, the demand peaks are much reduced due to the effect of the DAPP algorithm. This significantly improves the *load factor*, i.e., the ratio of average to maximum load. Figure 2 shows our results (the higher the load factor, the better).

This simulated increase in load factors due to the application of individualised price policies would have clear benefits for the DSO. This would reduce the amount of energy to be purchased from the wholesale market during expensive peak hours, and the flatter load profiles would result in less instances where network is overloaded, potentially reducing network maintenance and upgrade costs and allowing deferral of network investments. In fact, the global price policy results in heavier line loading values, whereas the individualised price policy results in reduced line loading. Namely, the number of overloads drops from 18 (global case) to 2 (individualised case), whilst it was 3 in the base case.

5 Related work

DSM for EDNs is a well-studied topic on smart grids. It consists of two main methodologies: DLC and DR. However, since here we focus on residential demand and DLC is mainly used to directly actuate large industrial loads [44, 39] (though [20] shows a possible application to residential users), here we discuss DR [53, 45, 12, 1, 26, 6, 7]. As discussed above, the main drawback to DR schemas using global price policies, i.e., in which all residential users get the same policy, is the peak rebound effect [16, 40, 56]. An alternative strategy is to expose residential users to wholesale market prices (real-time pricing). However, this causes demand to be shifted to hours with low electricity price, which can lead to a higher peak electricity price and peak-to-average ratio during the low price time [56]. There is a significant challenge in ensuring that such real-time prices do not cause physical or market instabilities [55], and it has been shown that multiple, uncoordinated responses to frequently changing prices can cause increased volatility, and potentially grid instability [17, 42].

Another problem is given by the fact that users may not follow (or too loosely follow) their price policy. Several approaches have been proposed to overcome such drawback [19], such as the "aggregator" [38] and "virtual power plant" concepts [41]. An alternative way is to compute the probability of failing in keeping the aggregated demand within substation safety constraints, given a reasonable probability of user deviations from their price policies, and show that such failure probability is low enough [36, 26], using statistical and model checking based techniques [31, 8, 28, 25].

Finally, from a computational point of view, our approach (in particular, the DAPP service) is based on several mature methodologies, such as MPC [43] as well as Artificial Intelligence and model checking using (possibly mixed linear) constraint solving [10, 23, 24, 22, 35], which we successfully exploited in very different areas, e.g., vulnerability of large networks to attacks [34] and *in silico* medicine, where we performed simulation-based (e.g., [21]) synthesis and safety/efficacy assessment of pharmacological treatments [47, 33, 27, 50], in an area (assisted reproduction) with low average success rates and many factors not under full control [15].

6 Conclusions

In this short paper we introduced the problem of computing and enforcing constraints on an EDN. Such constraints are expressed as bounds on the aggregated power demand resulting at each EDN substation. For such a problem, we surveyed our recent approach [14, 26] which, using two interoperating computational services, first computes safety power bounds for each network substation and then outputs a set of individualised (i.e., each user gets a different price policy) ToU and IBR price policies for each house in the EDN, so as to enforce the power bounds at each substation. Our experimental results, using real-world scenarios taken from a Danish area, show that our approach is able to improve the EDN load factor, while avoiding the peak rebound effect caused by global price policies (i.e., all users get the same price policy).

As future work, we plan to design a third service, to be run at users premises, that automatically follows a given price policy, thus relieving the residential users from such a task. This may be done either by automatically planning usage of smart appliances (see, e.g., [3], also in a centralised way [54, 2]) of by automatically driving home batteries (see, e.g., [4, 18], also in a centralised way [52, 48]). A second area of further research is to use model checking techniques to formally prove that our approach is correct [30, 32, 9].

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