Towards Constraint-based Aggregation of Energy Flexibilities

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ABSTRACT

Flexibility of individual energy prosumers (producers and/or consumers) has drawn a lot of attention in recent years. Aggregation of such flexibilities provides prosumers with the opportunity to directly participate in the energy market and at the same time reduces the complexity of scheduling the energy units. However, aggregated flexibility should support normal grid operation. In this paper, we build on the flex-offer (FO) concept to model the inherent flexibility of a prosumer (e.g., a single flexible consumption device such as a washing machine). An FO captures flexibility in both time and amount dimensions.

1. INTRODUCTION

One of the main goals of the Smart Grid is the energy use increase from Renewable Energy Sources (RES). However, due to RES being characterized by volatile power production (e.g., wind power), Smart Grid takes advantage of the prosumers' inherent flexibility to match energy demand better with supply, termed Demand Response (DR), and thus enables an increased share of RES energy.

In our work, we model flexible demand/supply devices (referred to as *loads* for simplification) using the flex-offer (FO) concept [3]. A FO captures the flexibility of a prosumer in terms of energy and time requirements, as presented in the following example.

Example 1. The owner (consumer) of an electrical vehicle (EV) wants to charge his EV at 20:00 and have it charged by 7:00 the following day. The EV takes 3 hours to be charged and requires 15kWh. Thus, the EV can start its charging between 20:00 and 4:00.

Such flexible loads and, consequently, their corresponding FOs are connected to an electrical grid. However, the grid is characterized by power capacity limitations and the high power requirements of new devices, such as EVs, might lead to electrical grid congestions. Grid sensitive load locations (bottlenecks) are in different voltage elements. They could be in low (local distribution) and in high voltage elements (supra-regional distribution) [2]. For instance, a bottleneck might be a distribution transformer (0.4-1kV) with a maximum power value of few hundred kW. Such a transformer might serve from few (e.g., in North America) to several hundred households (e.g., in Europe).

The number of loads that are flexible is recently increased due to new technological achievements (e.g., vehicle-to-grid (V2G), heat pumps, and smart fridges). The existence of appropriate information and communication technology (ICT) infrastructure and the establishment of a flexibility market [1] will provide flexibility with the opportunity to be traded. However, the energy amount from an individual FO is too small to be traded in the market. Thus, it is essential to aggregate FOs in order to produce commodities that can be traded in the emerging energy flexibility markets. Furthermore, aggregation of FOs is essential to reduce the highly complex Unit Commitment (UC) problem [4]. According to the UC problem, FOs are scheduled, i.e., the operational time and amount is defined, based on an objective function. Consequently, aggregation of FOs, applied before scheduling, does not only provide prosumers with the opportunity to participate in the market, but also reduces the complexity of scheduling them and improves scheduling results.

Using traditional aggregation techniques [3], the FOs are aggregated resulting in aggregated FOs (AFOs). Each profile of an AFO is produced by summing up one or more profiles of the 4 FOs. Without considering constraints, loads might be placed at the same time since it may be more beneficial, e.g., from a financial point of view. However, this could lead to violations. For instance, we see that the power of the left AFO (first dark-shadowed slice in 2) exceeds the constraint imposed by the grid. After being aggregated, the AFOs are traded and scheduled, see 3. Scheduling transforms AFOs into *assignments* and forms the root power value. However, it is impossible to schedule the output of traditional aggregation and to respect the constraint. where the power value exceeds 300kW in the first time slot (red circle). Consequently, FO aggregation techniques that take into account grid constraints are required.

2. FO AGGREGATION

We demonstrate how aggregation is taking place through an example. We see in Figure 1a, two FOs (f_1 and f_2) that produce the aggregated FO (AFO) f_{12}^a. The two FO are aligned based on their earliest start time and their profiles are summed up. AFO f_{12}^a has t_{es} the minimum t_{es} among the FOs and $f_{12}^a\_tls$ equal to the sum of t_{es} and the minimum tf among the FOs. However, we see that such an aggrega-

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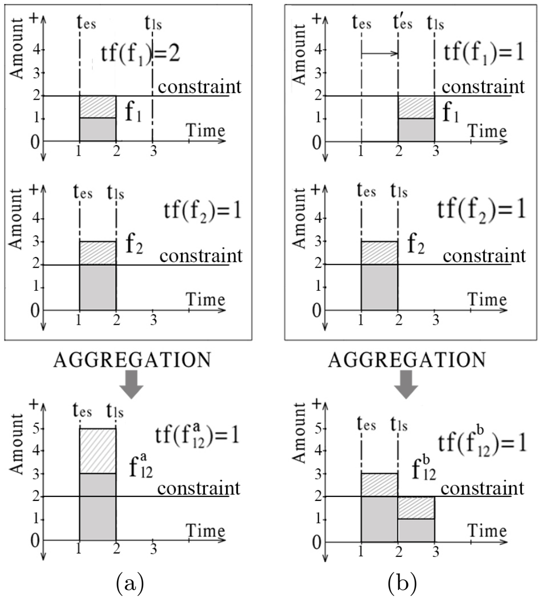


(a) (b)

Figure 1: Different alignment examples for aggregation.

tion produces an AFO that *does not* respect the constraint, i.e., there is at least a slice with minimum amount above the constraint. On the contrary, we see Figure 1b that when a different alignment of f_1 is used for aggregation, AFO f_{12}^b is produced and the constraint is respected.

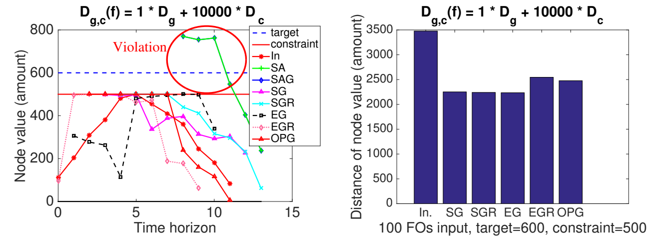
2.1 Heuristic constraint-based aggregation

In our aggregation techniques, we consider apart from the constraint, a target as well. We propose two greedy aggregation techniques that are based on binary aggregations. They both start aggregation by selecting the most distant FO f_{nom} from the constraint. Their goal is to produce AFOs that are closer to the target and the constraint but do not violate the constraint.

Definition 1. We define the *target_to_constraint distance of a FO* f to a target function g and a constraint function c, $D_{g,c}(f)$, as the minimum distance among all its assignments to g and c, i.e., $D_{g,c}(f) = \min_{as\_f \in L(f)} D_{g,c}(as\_f)$.

Example 2. For instance, given $\alpha = 1$, $\beta = 10$, $c(t) = 2$, and $g(t) = 3$, an assignment of f_{12}^a in Figure 1 with the minimum distance is: $as\_f_{12}^a = [1, 3]$ where $D_{g,c}(as\_f_{12}^a) = 1{\cdot}0{+}10{\cdot}1 = 10 = D_{g,c}(f_{12}^a)$. On the contrary, an assignment of f_{12}^b with the minimum distance is: $as\_f_{12}^b = \langle[1, 2], [1, 2]\rangle$ where $D_{g,c}(as\_f_{12}^b) = 1 \cdot (1 + 1) + 10 \cdot 0 = 2 = D_{g,c}(f_{12}^b)$.

Exhaustive Greedy (EG). Apart from f_{nom}, SG also selects a single FO f_{tmp} to examine whether it will aggregate them or not. Then, in each step, it examines all the potential aggregations between the two FOs, i.e, f_{nom} and f_{tmp}. If there is an AFO with smaller distance than f_{nom}, the algorithm continues aggregation with the aggregated one and removes f_{tmp} from the initial set SF. Otherwise, it considers f_{nom} as AFO, stores it in a different set (SA), and continues by selecting another f_{nom} from the remaining FOs in SF. The technique stops when the initial set is empty and returns set SA with the AFOs. The technique is similar to SG. However, EG explores a larger solution space than SG. In particular, during each step, it examines *all* the potential binary aggregations between f_{nom} and all the FOs in set SF and stores the AFO with the smallest distance. When the comparisons finish, it returns the AFO with the minimum distance (f_a) and the FO (f_{tmp}) that participated in the production of f_a.



(a) Node value (b) Final distance

Figure 2: Target>Constraint. Set of 100 FOs with identical flexibilities and similar profiles.

3. PRELIMINARY RESULTS

We use a dataset of 100 FOs representing a fleet of EVs plugged into a charging park of a workplace. The FOs are characterized by the same flexibility characteristics and similar amount profiles. Their earliest start time is 0 and their time flexibility is equal to 8. The number of the slices and the minimum amount requirements per slice follow a uniform distribution on the interval $[3, 6]$ and $[6, 9]$, respectively. Amount flexibility (af) values of the FOs follow a uniform distribution on the interval [0,3].

We examine a case where the business objective (target) contradicts the capacity limitation of the grid (constraint). In order to evaluate our techniques in terms of constraint respect, we apply a stochastic scheduling algorithm on the aggregation results [4]. Our propose technique(s) prioritize the constraint respect and lead to schedules that respect the constraint. We also use for comparison, the Start Alignment (SA) aggregation. We see in Figure 2 that SA violates the constraint where our proposed techniques respect it.

4. CONCLUSIONS

This paper is a first attempt to aggregate energy flexibilities taking into account power capacity constraints imposed by the electric grid. It focuses on the energy domain due to the prominent role of flexibility in the Smart Grid and the future energy market. We show that our proposed aggregation techniques can respect the constraint imposed by the grid where previous techniques lead to violations. In the future, we will investigate our techniques in more complex scenarios and examine an hierarchical approach.

5. REFERENCES

[1] L. Ferreira, L. Siksnys, P. Pedersen, P. Stluka, C. Chrysoulas, T. le Guilly, M. Albano, A. Skou, C. Teixeira, and T. Pedersen. Arrowhead compliant virtual market of energy. In *ETFA*, pages 1–8, 2014.

[2] F. Salah, J. P. Ilg, C. M. Flath, H. Basse, and C. van Dinther. Impact of electric vehicles on distribution substations: A swiss case study. *Applied Energy*, 137, 2015.

[3] L. Siksnys, E. Valsomatzis, K. Hose, and T. Pedersen. Aggregating and disaggregating flexibility objects. *TKDE*, 27, 2015.

[4] T. Tusar, E. Dovgan, and B. Filipic. Evolutionary scheduling of flexible offers for balancing electricity supply and demand. In *CEC*, 2012.