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Poster: Uncertain FlexOffers, a scalable, uncertainty-aware model for energy flexibility

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ABSTRACT

The usage of Renewable Energy Sources in electricity grids is spreading more and more, and energy flexibility has a crucial role in it. Many models for flexibility have been proposed; in particular, FlexOffer (FO) is an approximate model with the following properties: i) it models flexibility from different device types in an unified format; ii) it is scalable with respect to optimization for long time horizons, and aggregation of many loads; iii) it captures most/all of the available flexibility. This work proposes an extension of that model, *uncertain FlexOffers* (UFOs), which has the same properties, plus iv) considers the uncertainty affecting flexibility over long time horizons. We show that UFOs are 5 orders of magnitude faster than exact models for optimization, can retain 88.3% of the total flexibility when imbalance penalties are high, and allow to aggregate up to 3000 loads and up to 96 time units in less than 30 minutes.

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1 RUNNING EXAMPLE

Within this work, we will consider as a running example the loads from a *Tesla Powerwall* battery. Its capacity is 14 kWh, its maximum charging and discharging power are both 5 kW, and its round-trip efficiency is 90%. We will consider time units of one hour. For describing the functioning of the battery, we use Coulomb counting [5]. There are two use cases that we are considering: in the first, the battery starts empty and can only be charged, in the second, the battery starts at half the maximum charge and can be either charged or discharged at each time unit. We refer to these as the *charging* and *switching* cases, respectively.

2 FLEXOFFERS

An FO is an object representing flexibility: it is a set of constraints on the values of the consumable energy for the following time units. Figure 1 shows the life-cycle of an FO. Two main parties are involved: the prosumer, who generates and executes the FO, and the aggregator, who processes and issues schedules for the FO. The tasks on the prosumer's side are performed automatically by an agent, which operates according to the prosumer's requirements. The prosumer agent forecasts flexibility for his/her devices, and generates FOs accordingly. Each FO is then sent to the aggregator, which will determine if the FO is useful for its needs; after that, it decides whether to accept the FO or not and informs the prosumer of the response. If the FO is not accepted, it is not executed and the cycle ends here; otherwise, the aggregator processes it, aggregates it with other FOs, and establishes a schedule for each FO. FO schedules are then sent back to the prosumer agent, which will then execute them by controlling the device. There are three main types of constraints that have been used to define FOs: Figure 2 shows them for the *charging* example. *Slice* (energy) *constraints* establish, for each time unit, the minimum and maximum amount of energy that can be consumed. A *standard FO* (SFO), shown in Figure 2(a), is an FO whose constraints are all slice constraints. The numbers e_t represent a possible value for energy consumption at each time t. A *total energy constraint* (TEC) specifies the lower and upper bounds for the energy that can be consumed over the considered time horizon. A *total energy constraint standard FO* (TEC-SFO). shown in Figure 2(b), is an FO with slice and total energy constraints.Finally, a

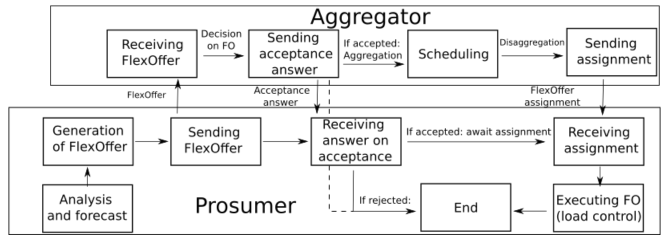

Figure 1: A schematic description of the FO life-cycle.

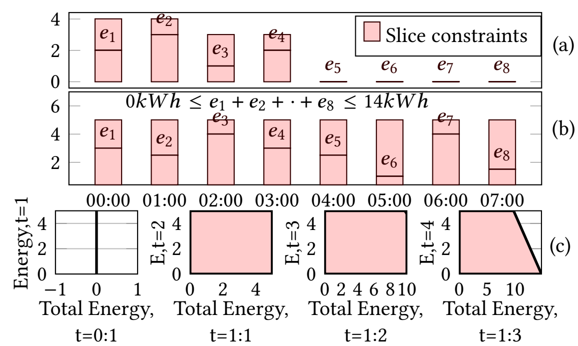

Figure 2: SFO (a), TEC-SFO (b) and DFO (c)

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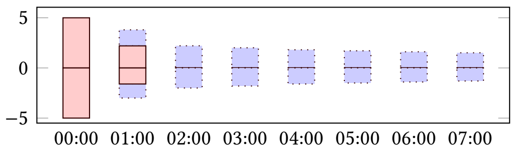

Figure 3: An uncertain FlexOffer ($P_0 = 1$ and $P_0 = 0.8$)

dependent energy constraint specifies at each time unit t a lower and an upper bound on the amount of consumable energy, depending on the total amount of energy that has been consumed before time unit t. An FO with these constraints is called a *dependency FO* (DFO). An example is shown in Figure 2(c): at each time unit, the x axis indicates the energy consumed before time t, and the y axis indicates the consumable energy based on the value on the x axis.

3 UNCERTAIN FLEXOFFERS

We will consider three types of uncertainty: **existence**, **time** and **amount uncertainty**. Suppose that a prosumer wants to recharge an electric vehicle (EV) overnight. Here, existence uncertainty refers to the probability of the user actually plugging in the EV for recharge for that night. At each time unit, time uncertainty refers to the probability for the EV to be plugged in for recharge at that time, and amount uncertainty refers to the amount of energy that can be given to/taken from the EV at that time.

An UFOs is created in two steps. First, uncertainty related to the device status is modeled at each time t; second, we calculate the probability for each energy value at each time to be feasible, taking into account all three types of uncertainty. We will then obtain some functions $\{f_1, \ldots, f_T\}$ describing those probabilities: those functions will define the UFO. UFOs can be visualized by choosing a probability threshold P_0. At each time t, the energy values having probability at least P_0 of being feasible can be described by intervals. Figure 3 shows what happens in the *switching* case: with $P_0 = 1$, the feasible energy values are described by the pink bar; however, if we choose $P_0 = 0.8$, the available flexibility is represented by the combined pink and blue bars. The figure shows that the choice of a value for P_0 generates a SFO: optimization and aggregation of UFOs are performed by choosing a value for P_0, and then optimizing and/or aggregating the resulting SFOs. Finally, it is possible to exploit correlation between probaibility functions: for example, if we know how much energy has been consumed by the battery B until time $t-1$, we can determine with much higher accuracy the probability for energy values to be feasible at time t. This leads to a two-step optimization, in which we first issue and optimize a DFO, and then change the schedule by choosing the closest possible energy value which probability of being feasible is higher than P_0.

4 PRELIMINARY RESULTS

In order to evaluate the performances of UFOs, we have run some experiments and measured the amount of provided flexibility. There are several metrics that can evaluate flexibility [6], but in a real case, one of the most important is economic revenue [3]. We simulated the battery B described in Section 1. The experiment simulates the functioning of the battery according to the case (*charging* or *switching*) chosen, issuing flexibility by generating a FO for the next T time units, and optimizing it for economic revenue maximization: if the schedule is unfeasible, imbalance penalties are paid. This process is then repeated again and again, until the simulation covers a total of 365 days. The baselines are an **Exact** approach based on a linear time invariant (LTI) model [2], and **DFOs**. We have run this experiment for $T = 4$: results showed that UFOs can capture all the available flexibility for the *charging* case, and up to 88.4% of it for the *switching* case when imbalance penalties are high, while DFOs can capture at most 77.4% of flexibility in this case. Regarding optimization time, the exact baseline takes more than 5.6 hours for $T = 24$ [3], making it infeasible in practice. In comparison, DFOs can be optimized in 0.329 seconds and two-step UFOs in 0.802 seconds.

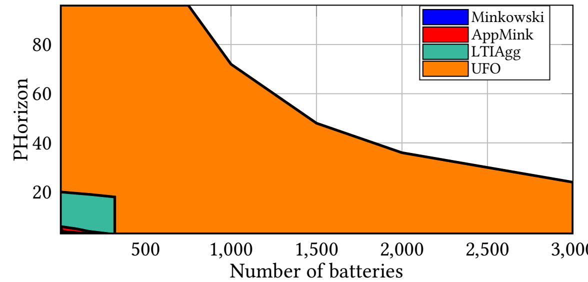

Figure 4: Results for aggregation

We have also performed experiments for measuring the effectiveness of UFOs aggregation. We compared it against four baselines: **DFOs**, **Minkovski**, an approach based on approximated Minkovski sum [1] (**AppMink**), and an exact baseline called LTI Aggregation [3] (**LTIAgg**). We measure the retained flexibility by economic revenue. The experiment generates flexibility according to the chosen model and, in succession, perform aggregation of NB batteries, optimization for profit, and disaggregation. Since bids for flexibility need to be done at most one hour before the deadline, in order to reduce errors [4], and flexibility has to be modeled before it can be aggregated, we consider 30 minutes as the time limit for considering an approach *feasible*. Figure 4 shows that it is possible to aggregate 3000 UFOs for $T = 24$, and 750 UFOs for $T = 96$. In comparison, **LTIAgg** fails for $T > 21$ or $NB = 330$, **Minkowski** and **AppMink** are infeasible for $T > 6$, and $NB = 290$. Regarding profit, UFOs retain more than 90% of the profits even for $T = 18$ and $NB = 60$.

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