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

Fabio Lilliu, Torben Bach Pedersen, Laurynas Šikšnys, Bijay Neupane

Aalborg University

ACM e-Energy '23

June 23, 2023

Flexibility

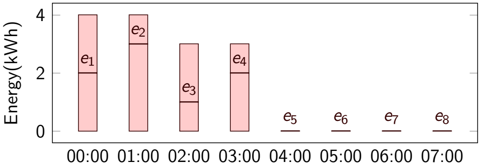
- Flexibility is the capability to change energy loads in time and amount.
- There are many mathematical models for representing flexibility from devices. The main desirable properties we identified for a flexibility representation are:
    - Representing multiple device types in a unified format.
    - Being scalable with respect to long time horizons and many loads.
    - Capturing most of the available flexibility.
    - Considering uncertainty over long time horizons.
- In the past, we created a model called FlexOffer (FO) that complies to the first three points. Our goal is to extend it in order to represent uncertainty.

State of art

- There are models that describe flexibility with accuracy (exact models); however, they may become unfeasible for optimization within long time horizons/many devices.
- FO is an approximate model, i.e., they represent flexibility for a device in a simple and device-independent format, but the representation may not be exact because of the format itself.
- The simplicity of FOs representation allows them to trade a slight amount of accuracy of flexibility representation in exchange for much faster optimization and aggregation.
- Flexibility models describe uncertainty for external variables (weather, user behavior), but not uncertainty of the approximation itself.
- In this presentation we will show FOs generated for a battery with capacity 14 kWh, charging/discharging power 5 kW, efficiency 90%, which will be our running example.

Contributions

Example of an FO: charging a battery. The bars indicate how much energy can be used at each time.

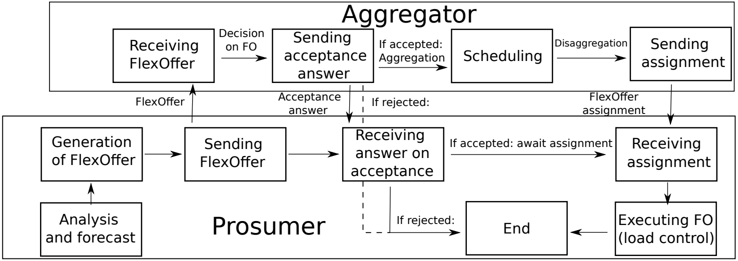


This work has the following contributions:

We will:

1. Expand FOs to represent uncertainty (Uncertain Flexoffers, UFOs).
2. Show how UFOs can be optimized and (dis)aggregated.
3. Show that UFOs retain more flexibility than other uncertain models, and scale much faster than exact models.

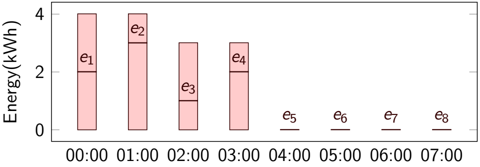
FlexOffers



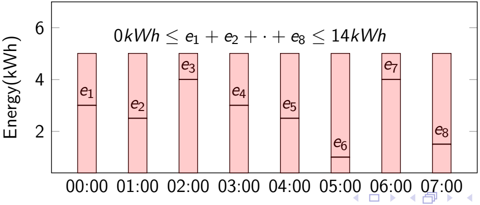
- FOs are defined as sets of constraints approximating flexibility for a certain device. In the figure we can see the life-cycle of an FO.
- The main actors are the prosumer, who issues and executes the FO via an automatic agent, and the aggregator, who processes it.

Types of FlexOffer

- **Standard FOs** (SFOs) have *slice constraints*: they determine the minimum and maximum amount of energy consumable at each time. They provide an accurate representation for flexiblity for wet devices.

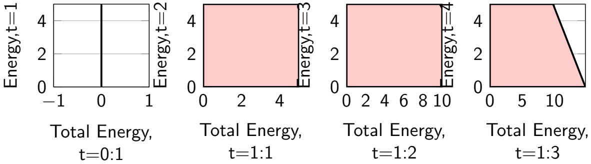


- **Total energy constraint FOs** (TECFOs) have slice constraints, plus a constraint on the total amount of energy consumed. They offer good flexibility approximations for charging batteries.



Types of FlexOffer

- **Dependency FlexOffers** (DFOs) have constraints describing how much energy can be used (y-axis), depending on how much has been consumed until that time (x-axis). They support batteries that operate freely.



- Flexibility can have *inner* and *outer* approximations. Inner approximations describe less flexibility than the actual amount, while outer approximations describe more.

Types of uncertainty

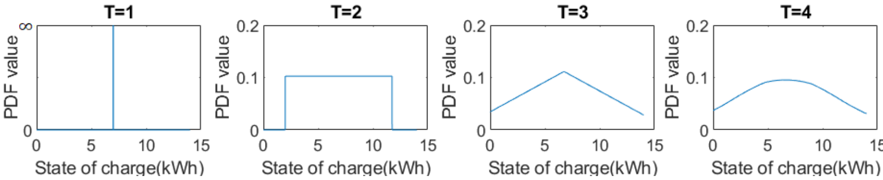
There are two main types of uncertainty.

- **Time uncertainty**: if/when the load will be available.
- **Amount uncertainty**: how much is the minimum/maximum consumable energy.

Device	Time	Amount
Wet device	✓	
Heat pump		✓
EV	✓	✓
Home battery		✓

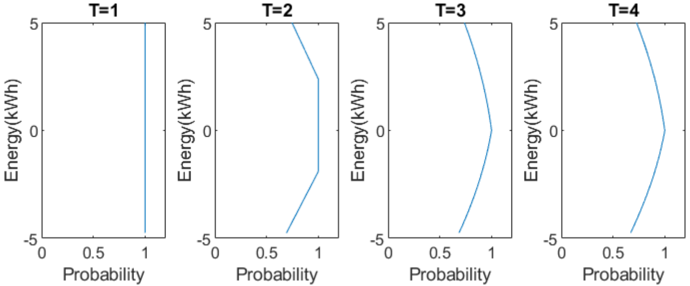
Uncertain FlexOffers

- The creation of UFOs happens in two main steps.
  1. Determine the probability of each state for the considered device, at each time.
  2. Determine the probability for each energy value to be available for consumption.
- Regarding the battery of our running example, the state of charge would have the following probability distributions:



Uncertain FlexOffers

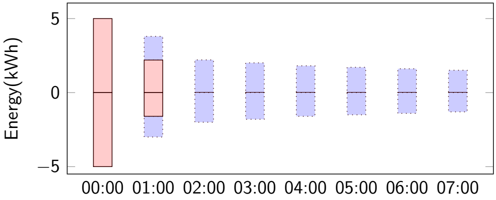
- From here, the following functions $f_1, \ldots, f_t$ are created: for each possible energy consumption value, they represent the probability for it to be available.



- We define the UFO as the tuple $g_1, \ldots, g_T$, where g_t is f_t multiplied by time uncertainty. Example: if $f_3(1) = 0.6$ and time uncertainty at $t = 3$ is 0.4, we have $g_3(1) = 0.24$.

UFO optimization

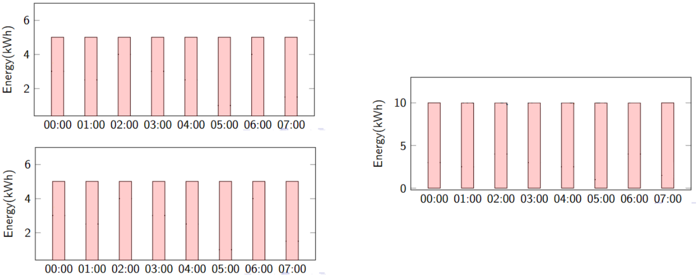
- FOs express constraints over energy values. Therefore, they can be used for solving optimization problems (e.g., cost minimization)
- UFOs can be used for optimization by choosing a threshold P_0, and generating an SFO by considering energy values whose probability is at least P_0.
- A two-step optimization can be done by optimizing for a DFO, and then performing a check for the probability of the energy variables of the schedule, eventually changing them to the nearest variables with probability at least P_0.



This is the battery SFO generated with $P_0 = 1$ (pink) and $P_0 = 0.8$ (blue).

UFO aggregation

- Aggregating N FOs means generating M FOs, with $M \ll N$, which represent their combined flexibility, with some losses. For example, the two FOs on the left can be aggregated to the one on the right.



- UFOs are aggregated by aggregating the SFOs generated by them with only the amount uncertainty, and rescaling them by time uncertainty.
- The idea is that the aggregator will bid the total expected value of the flexibility gathered from the devices.

Simulations - scenarios

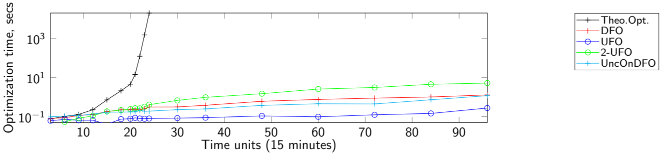
- We model flexibility for the next six time slices every time.
- The objective is profit maximization, and the idea for obtaining it is *buying low, selling high*.
- The baselines are theoretically optimal approaches (**Theo.Opt.**), and another uncertainty-aware approach that models uncertainty as a probability distribution on top of DFOs (**UOnDFOs**).
- The simulations have been run for batteries and EVs. In the aggregated case, we aggregated up to 6000 of each type of device.
- Data for spot and imbalance prices are from Nordpool, and refer to the day-ahead spot market in Denmark in the year 2018, January 1st to December 31st.

Results - Single device

Type	Pre-Imb	Imb.Pen.	Profit	% of TO
Theo.Opt.	14.27	0	14.27	100%
DFO	18.34	6.94	11.40	79.8%
2UFO-0.95	12.98	0.60	12.38	86.8%
UOnDFO-0.95	18.35	6.98	11.36	79.6%
2UFO-0.6	15.16	2.80	12.36	86.6%
UOnDFO-0.6	18.34	6.97	11.37	79.7%

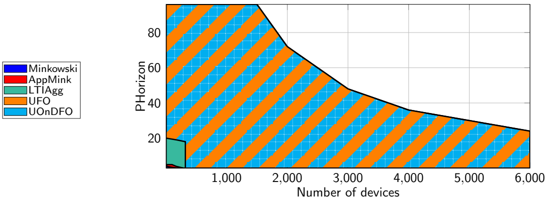
Type	Pre-Imb	Imb.Pen.	Cost	% of TO
Theo.Opt.	73.17	0	73.17	100%
DFO	63.31	55.01	118.32	61.8%
2UFO-0.95	53.05	39.41	92.46	79.1%
UOnDFO-0.95	51.87	46.50	98.37	74.4%
2UFO-0.6	52.83	30.77	83.60	87.5%
UOnDFO-0.6	60.80	39.72	100.52	72.8%

Figure: Result for batteries (left) and EVs (right) with high penalties, in euro.



- UFOs retain more flexibility than the uncertain baseline, especially when imbalance penalties are high.
- Optimization time increases exponentially for the theoretical optimum model, while for FOs it is 5s at most.

Results - Aggregation



- We compare UFOs against three baselines: **Minkowski** sum, an approximate Minkowski sum (**AppMink**), and a baseline that creates an exact model representing all the devices together (**LTIAgg**).
- DFOs (and therefore, UOnDFOs) and UFOs are feasible to aggregate, optimize and disaggregate for 1500 devices in 96 time slices, while other models fail to do so above 330 devices and 21 time slices.

Conclusions

- We created a device-independent, scalable and uncertainty-aware model by extending FOs to the UFOs model.
- We defined several ways for optimizing and aggregating UFOs.
- We showed that UFOs can retain more flexibility than other approximate uncertain models, while scaling much better than exact models for optimization and aggregation.
- Future work will focus on further improving accuracy on capturing flexibility.