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Objective: Analysis on Demand Response Concepts under Uncertainty for Demand Side Flexibility Employment within City Districts

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Purpose of the STSM:

The electrical energy grid currently changes significantly from a demand-side driven to a supply-side driven system due to an increasing amount of distributed energy resources. A promising approach for the integration of distributed energy resources, such as photovoltaic systems or wind turbines within the low and medium voltage network can be an efficient and robust demand side response management. The demand side flexibility is used to shift the energy consumption of flexible devices into times of, e.g. renewable energy supply for optimal balancing demand and supply. Flexibility on the demand side is achieved by the coordination of the operation of e.g. electro-thermal heating units or electric-vehicles. For the deployment of demand side flexibility through the operation of energy units on the demand side, the uncertainty, e.g. within the electrical or thermal energy demand or introduced through weather uncertainty, is in many cases not considered within the optimization problem.

This STSM should identify the most important sources for uncertainty for the deployment of demand side flexibility and the challenges for the optimization method by taking uncertainty into account. Requirements to address such challenges should be discussed and lead to a decision on a suitable optimization method, such as robust or stochastic optimization. Further, a mathematical model that enables demand response under uncertainty within a city district will be the main outcome at the end of the STSM.

Further, the STSM should bring the research areas, currently performed at the E.ON Energy Research Center of RWTH Aachen University in contact with some leading experts in optimization under uncertainty and also identify future options for collaboration.

Description of the work carried out during the STSM:

The STSM started with a presentation on the recent work carried out so far on Demand Response Management (under uncertainty) at RWTH Aachen University in order to identify suitable directions of research for this one-month research exchange and to identify the problem to be tackled.

The work started with a comprehensive literature review identifying suitable applications both for robust and stochastic optimization. Due to the fact, that before the STSM started some expertise within the cardinality constrained method for robust optimization, introduced in [1] could have been gained, we put the focus early on the usage and applicability of stochastic optimization. Many recent journals could be identified focusing on stochastic optimization for the unit commitment problem, such as [2] and [3]. However, also work related to demand side management under consideration of stochastic optimization was analyzed, such as [4] and [6]

We also agreed very early on a suitable architecture where the optimization problem for demand side management is integrated in. This architecture is derived from the official work of the SG3 Task Force for the European Commission [5] . An aggregation service provider, i.e. aggregator acts as supplier for its customers (prosumers). Both are connected via a flexibility purchase contract which enables the aggregator to steer certain loads on the demand side in order to provide certain services, such as portfolio balancing, to certain actors, such as a balance responsible party or the distribution system operator.

The aggregator´s objective is to minimize its overall day-ahead and imbalance electricity costs while still maintaining the beforehand contracted supply for its customers. The aggregator needs to make a decision on the import and export of electrical power on the day-ahead market in order to cover the total electrical demand of its customers. However, the aggregator will be faced by several uncertainties which might lead to deviations from the planned import and export and thus result in power imbalances, i.e. additional costs to the aggregator. Figure 1 describes the schematic of the architecture where the optimization problem is applied to.

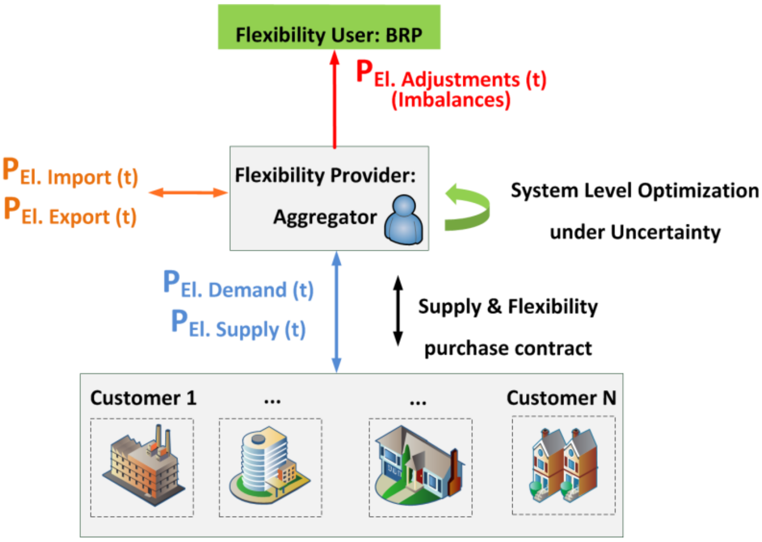

Fig. 1. Schematic of the Architecture according to [5]

Thus, the work carried on identifying the most relevant sources of uncertainty for that specific demand side management problem. Note that the identified uncertainties are in general also highly relevant for other energy related optimization problems. Relevant uncertainties identified were:

- Weather data information, such as outdoor temperature or global solar irradiation which would lead an increasing or decreasing electrical and in particular thermal energy demand
- Electrical consumption and/or domestic hot-water consumption
- Occupancy in the building which would also influence the electrical and thermal demand
- Imbalance prices

In certain research articles, also uncertainty in the building structure, such as kind of wall insulation etc. which would influence the thermal demand is considered as relevant. Within the work carried out in this STSM, we assume to have perfect information about the dwelling though.

In discussion with the host institution and in particular considering their expertise in stochastic optimization, we agreed in the next step that the above mentioned problem taking uncertainty into account should be addressed by looking into a two-stage stochastic optimization problem instead of focusing into rather conservative robust optimization.

Thus, the objective was formulated in order that the aggregator minimizes its total expected day-ahead and imbalance electrical costs. In other words, the aggregator makes its first decision in the first, i.e. day-ahead, stage and possible recourse decisions in the intra-day/real time second stage. The relevant uncertainties are considered through introducing different kinds of scenarios.

In order to evaluate the solution of the stochastic program, we discussed certain key performance indicators / metrics for evaluation and their positive and negative expressiveness. As for example introduced in [7], we put focus on the expected value of perfect information (EVPI) and the value of stochastic solution (VSS).

Therefore, we also implemented the feature to calculate the wait-and-see (WS) solution, which assumes all uncertainties and the corresponding decisions and objective values to be known. Through comparing WS solution with the here-and-now solution of the stochastic recourse problem (RP), we can make clear quantification of the EVPI. If we map this to our specific problem introduced above, the EVPI would be the amount of money the aggregator would be ready to pay to obtain the perfect information. In other words, this also could mean that the aggregator would pay a part of the EVPI value in order to obtain better e.g. weather forecast. Further, calculating the expected result of using the expected value (EEV) is adapted for calculating the VSS. For the aggregator this would be the cost for ignoring the uncertainty in choosing a decision or in other words, the gain for considering the stochastic solution. [7]

Description of the main results obtained

We implemented a first version of this optimization problem and tested it in Python using the object-oriented interface of the GUROBI solver. We considered an aggregator, acting as supplier being connected to one larger industrial customer. Note, that this was only for test purposes, but there is the option to connect a fleet of customers to the aggregator as well. The customer is equipped with photovoltaic (PV) units producing electrical energy and an electrical battery storage unit controlled by the aggregator. Uncertainty is considered in the PV power generation (coefficients in the restriction matrix A are involved), in the electrical power demand (coefficients in the vector b are involved) and in the imbalance prices (coefficients of the cost vector c are involved). For exemplification we assumed for each of the uncertain parameters three scenarios, i.e. 1) +20% 2) +-0% and 3) -20%, all with equal probability resulting in 27 scenarios being considered. The recourse problem allowed to handle the uncertainty through either import or exporting additional power on the imbalance market or through the introduction of the battery storage. The flexibility of the battery storage system is used to make recourse decisions without importing additional, rather expensive, imbalance power by charging- or discharging the battery storage.

Further, we always ran the optimization also for the additional case of no-battery storage installed in order to identify the effect of the battery storage to support catering uncertainty and in particular to quantify the cost reduction through flexibility. The data for the scenarios were taken from existing research data of the E.ON Energy Research Center, used for a typical summer period day and applied for exemplification of the two-stage recourse problem. This data is currently under an NDA, but the implementation offers the opportunity to change input data easily.

Table 1: Results for the optimization problem including EVPI and VSS

Metric	Costs in € for no-battery being installed	Costs in € for 864kWh battery being installed	Costs in € for 2000 kWh battery being installed
EEV	309.57	275.221	273.004
RP	302.433	258.526	251.662
WS	250.296	219.941	215.97
EV	246.81	217.673	214.803
EVPI	52.138	38.585	35.692
VSS	7.137	16.694	21.3417

The results in general show that the flexibility given by a battery installation can increase self-consumption and allows arbitrage across time periods due to differences in import and export prices, as for example also stated in [8]. The battery installation reduces the total cost for the aggregator for one day, considering the RP solution, by around 11% of the 864kWh and by around 12% for a 2000kWh storage. We also see that in particular for a case, where a battery is installed, the cost for ignoring uncertainty (VSS) are higher than without battery. This refers to the fact, that the VSS can be treated as the positive gain the aggregator gets from considering the stochastic solution. i.e. flexibility provided by the battery storage to handle uncertain PV generation and electrical demand.

We further see, that with an increasing storage size, i.e. 2000kWh, the accounting for uncertainty becomes less critical according to EVPI. The increasing storage size reduces the amount of money the aggregator would spend for getting the perfect information. This is obvious since the flexibility provided by the battery storage helps to handle the uncertainty in real-time and perfect information is less desired.

Furthermore, we also did some further tests within our calculations through changing the uncertainty within each scenario. In particular, we could show that both EVPI and VSS vanish, in case the objective value of the EV is similar to the objective value of the EEV, which is clear since both are bounded by the same quantity, i.e. EEV minus EV [7]. In other words, the expectations become true and there is no uncertainty anymore.

Outlook

Although this one month STSM was a great opportunity to get an introduction into stochastic optimization and in applying it to related energy management problems, there is some follow-up necessary. In particular, we need to answer the question how to approach and quantify the uncertainty of relevant variables and parameters in an appropriate way. This especially includes the generation of suitable scenarios out of e.g. weather forecasts and also certain scenario reduction methods in order to find the most important scenarios for a specific problem.

Future collaboration with the host institution and foreseen publications:

The STSM could identify certain relevant use cases and uncertainties to be considered for dynamic demand response management and we could get a good understanding of the basics of (multi-) two-stage stochastic optimization. However, areas of future research will include aspects of scenario generation and reduction which could be applied then to the model above and result in a possible publication.

References

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