Minimizing Costs and Risks in Demand Response Optimization: Insights from Initial Experiments

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Abstract

This paper presents a method for changing the energy use of consumers participating in Demand Response (DR) programs, focusing on peak balancing to improve grid stability. Multiple objectives including costs and risks are considered, and a weighted sum is used to transform them into a single objective. This results in an optimization problem that can be optimally solved. To calculate the costs, the load consumption baseline needs to be established. Since this is challenging and can be exploited, we conduct initial experiments to test whether our method to adjust the baseline can be easily manipulated. We explore an original scenario and three of its variants to examine the effects of various parameters on the optimization outcome. Our results indicate that 1) an excessive emphasis on risk results in no energy change, 2) enforcing a net zero energy change minimizes energy use while still securing the rebate, and 3) without an adjustment period, the consumer is less inclined to increase the load just before the demand period. In future work, we will reformulate some objectives to avoid exploitation and better reflect the real-world needs of DR.

Keywords

multiobjective optimization, mixed-integer linear programming, demand response, baseline consumption, electrical grid

1 Introduction

Peaks in energy demand can strain the electrical grid, leading to inefficiencies and potential failures. A widely used strategy for balancing these peaks is Demand Response (DR), in which the Distribution System Operator (DSO) forecasts future peaks and requests from consumers to adjust their energy use to reduce them. In the peak time rebate DR program [2], consumers receive a rebate if they reduce their load in the demand period. On the other hand, if they commit to respond to the demand, but fail to do so, they can be penalized. It is therefore of utmost importance to accurately assess whether and how much a consumer reduced their load to meet the demand.

The load reduction of a consumer is computed as the difference between its baseline (the amount of energy the customer would have consumed without a demand request) and its actual use [2]. The importance of establishing a baseline and the various ways of calculating it are presented in [5]. Common methods for calculating baselines include simple historical data averages, exponential moving averages and short-term load forecasting techniques. However, baselines can be exploited, e.g., when consumers artificially increase consumption before an event to inflate their baseline and maximize the awarded rebate.

Through the SEEDS project[1], we are developing a methodology for providing energy flexibility services to prosumers – participants in energy markets capable of both producing and consuming energy – in order to enhance grid stability. Machine learning is used to predict the baseline energy usage of prosumers and their flexibility, while mixed-integer linear programming (MILP) is used to optimize the operation of prosumers within their flexibility. Our approach will be tested in the Slovenian pilot, in collaboration with Petrol d.d. and Elektro Celje d.d.

Our work integrates prosumer flexibility into DR optimization, focusing on minimizing costs and risks while limiting energy fluctuations. While the goal is to eventually use this approach on real-world data from the pilot, this paper reports on some initial experiments verifying whether the current problem formulation results in solutions with desired properties. In particular, we wish to test if our adjusted consumer baseline approach can be easily exploited.

Research on prosumer flexibility, optimization techniques, and demand response optimization includes a wide range of approaches [8]. In [3], Balázs et al. quantify residential prosumer flexibility using engineering models and real-world data. Their work provides valuable insight into prosumer behavior and energy management. Capone et al. [4] optimize district energy systems by balancing costs and carbon emissions with genetic algorithms and linear programming, showing significant emission reductions at a modest cost increase. Magalhães and Antunes [7] compare thermal load models in demand response strategies using MILP, finding that discrete control formulations improve computational efficiency. Thus, our methodology is in line with related work while the actual optimization problem (its variables, objectives and constraints) differs from existing ones as it is adapted to our specific use case.

This paper is further organized as follows. In Section 2, we provide a brief overview of the optimization problem, followed by its detailed definition in terms of its variables, constraints and objectives. The optimization approach is explained in Section 3, where we discuss the scalarization technique used to transform our multi-objective problem into a single-objective MILP form and the method used to solve it. The experiments and their results are given in Section 4. Finally, conclusions and further work ideas are described in Section 5.

2 Optimization Problem

The problem formulation in this work assumes a peak time rebate DR program in which the DSO and the consumer have a contract stipulating the following conditions: 1) the consumer can chose whether to respond to a demand request, 2) if the consumer

[1] https://project-seeds.eu/

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participates in DR, it receives a rebate proportional to the reduced load, 3) if the consumer participates in DR but does not reduce the load by at least 75 % of the required amount, it is penalized, 4) the load reduction is estimated using an adjusted consumer baseline, which takes into account the forecast consumer energy usage as well as its actual consumption before the demand period.

The optimization task is to set the energy consumption of all loads of a consumer participating in DR taking into account their flexibility so that consumer costs, risks and energy fluctuations are minimized. This ensures efficient grid operation while maintaining economic feasibility for the consumer.

To formally define our optimization problem, we first introduce its variables, followed by the constraints and the objective functions we aim to optimize. Finally, we provide an overview of the weighted sum approach, which serves as the scalarization technique to transform all objective values into a single one.

2.1 Variables

A solution is specified by the energy amounts $E_{c,i} \in \mathbb{R}$ for each consumer load $c \in C$ and time interval $i \in \{1, \ldots, n\}$. They correspond to the change of consumption from the forecast one. These are the only variables of this optimization problem.

From these energy amounts and the forecast timetable of energy usage, the resulting energy consumption E_i in time interval $i \in \{1, \ldots, n\}$ is computed as

$$E_i = E_i^{\mathrm{F}} + \sum_{c \in C} E_{c,i}.$$

2.2 Constraints

The energy amounts of a solution need to adhere to two kinds of constraints. The first type are the interval energy constraints:

$$E_{c,i}^{\min} \leq E_{c,i} \leq E_{c,i}^{\max},$$

for each consumer load $c \in C$ and time interval $i \in \{1, \ldots, n\}$. The second are the total energy constraints:

$$E_c^{T,\min} \leq \sum_{i=1}^{n} E_{c,i} \leq E_c^{T,\max},$$

for each consumer load $c \in C$.

2.3 Objective Functions

The three objectives to be minimized in this scenario are the costs, risks and energy fluctuations.

The first optimization objective f_1 consists of all costs associated with the solution and equals

$$f_1 = f^{\mathrm{E}} - f^{\mathrm{R}} + f^{\mathrm{P}},$$

where f^{E} represents the energy costs, f^{R} is the rebate for the recognized load reduction and f^{P} is the penalty that is charged in case the recognized load reduction does not meet the requirements.

The energy costs f^{E} equal the sum of energy costs over all time intervals $i \in \{1, \ldots, n\}$,

$$f^{\mathrm{E}} = \sum_{i=1}^{n} p_i E_i,$$

where p_i is the interval energy price.

The solution gains a rebate it the load is reduced in the demand period $\{t^{\mathrm{S}}, \ldots, t^{\mathrm{E}}\}$. Note that the recognized load reduction E_t^{R}, $t \in \{t^{\mathrm{S}}, \ldots, t^{\mathrm{E}}\}$, is computed from the adjusted timetable energy E_t^{A} instead of the forecast one E_t^{F}, where the adjustment is determined by the energy amounts in the adjustment period – the n^{A} intervals before the start of the demand period t^{S}. More formally, the adjusted timetable is computed as

$$E_t^{\mathrm{A}} = \begin{cases} E_t^{\mathrm{F}} - \dfrac{1}{n^{\mathrm{A}}} \displaystyle\sum_{j=t^{\mathrm{S}}-n^{\mathrm{A}}}^{t^{\mathrm{S}}-1} \left(E_j^{\mathrm{F}} - E_j\right), & \text{if } n^{\mathrm{A}} > 0; \\ E_t^{\mathrm{F}}, & \text{otherwise} \end{cases}$$

for all intervals $t \in \{t^{\mathrm{S}}, \ldots, t^{\mathrm{E}}\}$ in the demand period. Then, the recognized load reduction E_t^{R} at demand time interval $t \in \{t^{\mathrm{S}}, \ldots, t^{\mathrm{E}}\}$ is determined as

$$E_t^{\mathrm{R}} = E_t - E_t^{\mathrm{A}},$$

while the total recognized load reduction E^{R} is computed as

$$E^{\mathrm{R}} = \sum_{t=t^{\mathrm{S}}}^{t^{\mathrm{E}}} E_t^{\mathrm{R}}.$$

A rebate is awarded if E^{R} is negative (the consumption has been reduced). If the total recognized load reduction exceeds the total demanded energy reduction E^{T}, the rebate is capped, i.e.,

$$f^{\mathrm{R}} = \begin{cases} p^{\mathrm{B}} \min\left(\left|E^{\mathrm{R}}\right|, \left|E^{\mathrm{T}}\right|\right), & \text{if } E^{\mathrm{R}} < 0 \\ 0, & \text{otherwise} \end{cases}.$$

Finally, a penalty is added to the total costs if the demand has not been met, that is, the ratio between the recognized and demanded energy reduction, E^{D}, in any of the demand time intervals $t \in \{t^{\mathrm{S}}, \ldots, t^{\mathrm{E}}\}$ is lower than 75 %,

$$f^{\mathrm{P}} = \begin{cases} p^{\mathrm{P}} \left|E^{\mathrm{T}}\right|, & \text{if } \dfrac{E_t^{\mathrm{R}}}{E^{\mathrm{D}}} < 75\,\% \text{ for one or more } t \in \{t^{\mathrm{S}}, \ldots, t^{\mathrm{E}}\} \\ 0, & \text{otherwise} \end{cases}.$$

The second optimization objective f_2 represents risks. In order to penalize any changes to the timetable when the risks are high, the objective function is defined as

$$f_2 = \sum_{i=1}^{n} r_i \sum_{c \in C} \left|E_{c,i}\right|,$$

where r_i represents the risk at time interval i.

To penalize unnecessary energy fluctuations, the third objective f_3 averages the consecutive changes in energy amounts for all consumer loads, i.e.,

$$f_3 = \frac{1}{(n-1)|C|} \sum_{i=2}^{n} \sum_{c \in C} \left|E_{c,i} - E_{c,i-1}\right|.$$

2.4 Weighted Sum Approach

Since the optimal solutions to this problem appear to reside in the convex region of the objective space, we use a weighted sum approach to transform all objective values into a single one. The single objective function to be minimized thus equals

$$f = w_1 f_1 + w_2 f_2 + w_3 f_3$$

under the condition $w_1 + w_2 = 1$. The weight w_3 can be set independently of w_1 and w_2 and serves as a measure of limiting the energy fluctuations.

3 Optimization Approach

3.1 Setting Weights in the Weighted Sum

To obtain diverse solutions with the weighted sum approach, a good strategy for setting the weights is needed. While we plan to use a more sophisticated approach for this purpose in future work, these initial experiments were made by choosing equidistant values of w_1 from the interval $[0, 1]$ and defining w_2 as $1 - w_1$. In order to limit energy fluctuations, we set w_3 to 10^{-3}. Smaller weights proved insufficient in limiting the fluctuations while larger weights interfered with the first two objectives, which are more important than the third.

3.2 Linearization

Since all of the objective functions specified in Section 2.3 are either non-linear or contain non-linear parts, specific techniques are required to linearize these objectives and ensure the problem fits the MILP form. In particular, it is necessary to linearize the absolute value of a real variable, the product of a binary variable and a real variable, the minimum of two variables, along with other non-linear function conditions. We use standard approaches to achieve linearization for all these cases [9].

3.3 Tool and Solver

We use the OR-Tools Python library[2] to implement and solve the single-objective MILP problem. The library is a comprehensive tool for solving optimization problems, including linear programming, integer programming, and combinatorial optimization. Specifically, we use the SCIP (Solving Constraint Integer Programs) solver [1] integrated within OR-Tools[3] for solving MILP problem instances.

To solve a MILP problem using OR-Tools and the integrated SCIP solver, the following steps are performed: import the linear solver wrapper, declare the SCIP solver, define the variables with their respective bounds, set the constraints and the objective function and lastly, analyze and display the solution.

4 Experiments

We first conduct experiments using a basic scenario with a single consumer load. Then, we variate some parameters of this scenario to see how they affect the resulting solutions.

4.1 Experimental Setup

The basic scenario has the following parameters:

- Time is represented as 28 15-minute intervals.
- The demand period starts at $i = 13$ and ends at $i = 16$.
- The total required reduction E^{T} equals -8 kWh and the required reduction E^{D} at each interval equals -2 kWh.
- The adjustment period has a duration of four intervals.
- The load change needs to be within $[-3\,\mathrm{kWh}, 3\,\mathrm{kWh}]$ for each interval $i = 5, 6, \ldots, 24$ and is fixed to 0 kWh for the remaining intervals.
- The forecast timetable energy E_i^{F} is constant and equals 12 kWh for all time intervals.
- The total energy constraint is unbounded.
- The risk equals 0.50 for all time intervals.
- All prices are constant: $p_i = 0.25$ EUR, $p^{\mathrm{R}} = 0.50$ EUR and $p^{\mathrm{P}} = 1.00$ EUR.

[2] https://developers.google.com/optimization
[3] https://github.com/google/or-tools/blob/stable/ortools/linear_solver/samples/mip_var_array.py

The three scenario variants differ from the basic as follows. The first scenario variant has no demand. In the second and third scenario variant, the total energy change is set to 0 kWh ensuring the reduction in energy consumption in some intervals is matched with its increase in others. Additionally, the third scenario variant has no adjustment period, i.e, $n_{\mathrm{A}} = 0$.

4.2 Results and Discussion

We discuss here the results of our original scenario and its three variants. They are depicted also in plots in Figures 1 to 4, which show with a black line how the consumer load changes from its planned timetable. Consumer load flexibility at each time interval is shown in gray (there is no flexibility in the first four and last four intervals). The demand period is denoted in red and the adjustment period in blue. In most cases (unless the risk has a large weight), the consumer reduces the load in the demand period enough to meet the required demand and earn the entire available rebate while not incurring any penalty. The amount of this reduction and the energy change outside of this period differ for the various scenario variants.

4.2.1 *Original Scenario.*

When the risk has a large weight, the load does not change outside of the demand period (see the top plot in Figure 1). However, when the impact of risk is minimal (bottom plot in Figure 1), the load is reduced everywhere except during the adjustment period. This strategy artificially increases the perceived load reduction to maximize the rebate, as dictated by the rebate calculation formula.

4.2.2 *Scenario Variant #1: No Demand.*

If the optimization is called without a demand, the result depends on the weighting of the first two objectives. As long as the impact of risk is significant (top plot in Figure 2), the load does not change. Otherwise, the load is reduced to the maximum extent in each interval (bottom plot in Figure 2). This approach minimizes the function f_E, therefore reducing costs. This means that the consumer behavior can change when optimized even if no demand is present.

4.2.3 *Scenario Variant #2: Zero Total Energy Change.*

Due to the zero energy constraint, the consumer makes adjustments solely within the demand and adjustment periods (see Figure 3). During the adjustment period, the user offsets the consumption from the demand period, thereby achieving a maximal rebate. To adhere to the requirement of minimizing risks and fluctuations in other intervals, no additional changes are made, as such actions would increase the objective value.

4.2.4 *Scenario Variant #3: Zero Total Energy Change and No Adjustment Period.*

When the baseline is not adjusted, the load is increased in intervals outside of the demand period, regardless whether they occur before or after it. The specific intervals when this happens depend on the solver and are random as they lead to the same objective function value. An example of such a case in depicted in Figure 4.

The last two variants additionally confirm that the usage of the adjustment period enables exploitation – the entire rebate can be gained with a smaller load reduction in the demand period if the load is increased in the adjustment period.

5 Conclusions

This paper focuses on demand response optimization and the growing role of prosumers in energy systems. A standard MILP framework is used to set the consumer load energies within

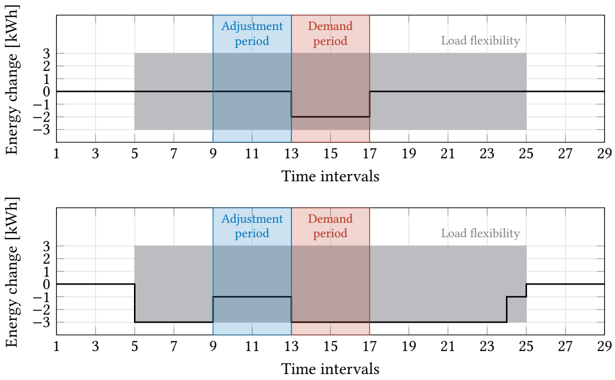

Figure 1: Results for the original scenario with $w_1 = 0.6$ and $w_2 = 0.4$ (top) and $w_1 = 0.8$ and $w_2 = 0.2$ (bottom).

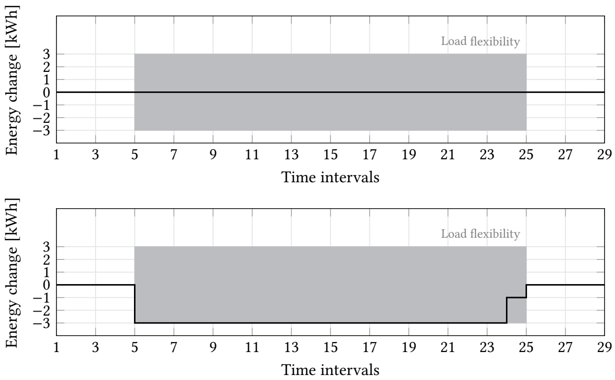

Figure 2: Results for the variant without demand with $w_1 = 0.5$ and $w_2 = 0.5$ (top) and $w_1 = 0.7$ and $w_2 = 0.3$ (bottom).

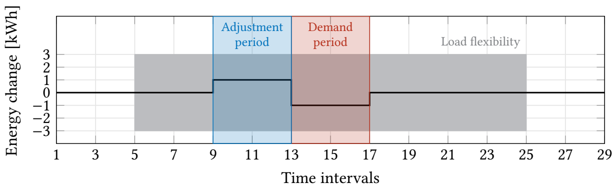

Figure 3: Results for the variant with zero total energy change with $w_1 = 0.6$ and $w_2 = 0.4$.

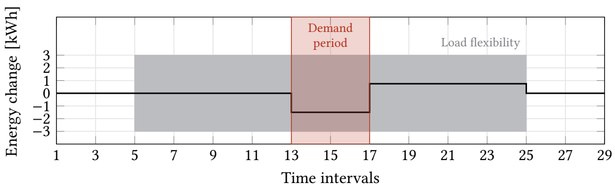

Figure 4: Results for the variant with zero total energy change and no adjustment period with $w_1 = 0.6$ and $w_2 = 0.4$.

their flexibility so that the costs, risks and energy fluctuations are all minimized. Since the objectives are scalarized with the weighted sum approach, correctly setting their weights is crucial for generating a set of diverse solutions representing various trade-offs between costs and risks.

By creating three scenario variants, we were able to explore the effect of some parameters on the optimization outcome. We observe that:

- Regardless of the variant, the optimal load schedule does not deviate from the forecast one if the importance of risk is too high, i.e., if the weight w_2 is too large. This critical value of w_2 depends on the scenario variant.
- If the consumer is obliged to a zero sum in load increase and reduction, the optimal solution uses the minimal necessary resources to earn a rebate while avoiding excessive energy changes.
- When the adjustment period is unspecified, the prosumer is less likely to increase the load just before the demand period.

Moving forward, we need to refine the objectives. The current method to assess the baseline consumption is susceptible to exploitation and should be amended. We could calculate the consumer baseline from similar consumers that do not participate in DR as suggested in [6]. We will also need to revise the penalty calculation to account for the imminent change of tariffs in the Slovenian energy market. We additionally plan to improve the calculation of risks to ensure more robust optimization and real-world applicability. Finally, we intend to develop a better strategy for setting the weights, targeting values with the most significant impact rather than evenly distributing them.

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