Project Report Applied Mathematical Optimization

A Bilevel Demand Response Approach To Integrating Renewable Energy Into Electricity Markets

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The git repository can be found at the following link:

https://github.com/labedisa/AMO-Single-Project

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Nomenclature

DBK	set of demand response offers between consumer and aggregator.
DRK	set of demand response offers between ISO and aggregator
$g(NG)$	set of generator units
gen	generator unit
k	set of demand response offers
l	set of transmission lines
n	set of nodes
s	set of scenarios
t	set of hours
LC	load curtailment
LS	load shifting
C	cost
R	reserve
pf	transmission line capacity

$shed/spill$ superscript for load shedding/ wind spillage

Abstract

This paper presents a bilevel demand-response model for electricity markets from the perspective of a demand response aggregator. The bilevel model is formulated as an upper-level and a lower-level problem. The upper-level problem aims to minimize the total cost of operation, while the lower level is aimed at minimizing the total costs of operation. The results indicate that the proposed model can reduce load peaks by shifting a certain amount to off-peak hours.

1. Introduction

As global energy demands continue to rise and environmental concerns remain at the forefront, renewable energy sources such as solar, wind, and hydropower are becoming increasingly important. However, despite their many benefits, integrating these renewable sources into existing power grids can present challenges. One of the primary obstacles is the volatility of renewable energy sources, particularly in terms of peak load provision.

To address this challenge, researchers are exploring approaches such as the Bilevel Demand-Response model, which offers a solution for integrating renewable energy sources into power grids while minimizing costs for consumers. While current demand response programs typically cater to larger energy consumers, there is growing interest in extending these programs to smaller end-consumers.

The integration of renewable energy sources into the electricity market requires flexibility and innovative solutions. Demand response is one such solution, which can reduce overall system costs, decrease CO2 emissions, and mitigate price volatility resulting from renewable energy source fluctuations. By incentivizing consumers to use energy during periods of high renewable energy production, demand response programs can help manage the fluctuating supply and demand of energy within the grid.

Only small bus systems have been found in literature; however, it would be interesting to see if and how such a model would work in a more complex system. Furthermore, there seems to be no literature that examines how public welfare could be increased if certain constraints are removed (e.g. constraints on wind scheduling). This paper describes a model for demand response from the perspective of a DR aggregator. The study provides an overview of the existing literature and background information in Section 2, followed by a description of the model and data sources in Chapter 3. The results are presented and discussed in Chapter 4, while the limitations of the study are discussed in Chapter 5. Finally, Chapter 6 provides an outlook on possible avenues for further research in the field of demand response and renewable energy integration.

2. Background

In contrast to conventional generators, renewable energy sources have a significant difference: their output cannot be adjusted arbitrarily, as it depends on meteorological conditions. Additionally, their output can only be predicted up to a certain level. Therefore, a higher degree of flexibility is necessary for the integration of renewable energy into our power grids, both on the supply and demand side.

The evolution of our power grids towards a system where demand depends on supply requires operational and possibly legal changes. Various approaches in the literature exist to take advantage of the flexibility of consumers. One important approach is dynamic pricing, where an electricity price is offered from the demand side and the consumer must weigh potential savings against immediate consumption. Zugno et al. (2013) assume that consumers respond to dynamic price signals by shifting their consumption to periods of lower prices, thus minimizing their electricity costs. This concept of influencing consumer behavior through price signals can therefore play an important role in shifting consumption to off-peak hours.

Morales et al. (2014) list entities for which this type of demand response could be relevant: electricity retailers, power producers, distributed system operators (DSOs), transmission system operators (TSOs), power producers and aggregators. Electricity retailers serve as intermediaries between consumers and the wholesale electricity market, absorbing the risks of consumption variations from the predetermined schedule. By implementing dynamic pricing for demand response, retailers can effectively reduce their market risks and costs. Similarly, power producers are susceptible to market prices and face penalties for deviations from their production plans in real-time. However, by integrating price-responsive demand, they can enhance their market performance.

DSOs and TSOs share a common interest in ensuring the balance and reliability of the transmission grid. System costs can be reduced by choosing dynamic price signals, and the reliability of the power system can be increased by shifting consumption to periods of higher production. Typically, DSOs face more stringent capacity limitations due to their management of local distribution grids, which may incorporate smaller-scale generation units.

In the literature, an independent system operator (ISO) can be found as well, which uses the DR aggregator as an interface and enables customers to minimize their costs through smart or intelligent devices. Gkatzikis et al. (2013); Parvania et al. (2014) and Talari et al., (2019) examine DR models from the perspective of ISOs. In their research, the upper-level's goal is to minimize the total operation cost, representing the decisions of the ISO, while the lower-level problem represents the decisions of the DR aggregators, who aim to maximize their profit. This project aims to extend this model to a 24-bus system.

Zugno et al. (2013) present a three-stage model in which energy retailers influence consumption through price signals and demonstrate that there are economic incentives for consumers to increase their flexibility when real-time price programs are in place.

Furthermore, there is a subfield of literature that deals with the charging demand of electric vehicle (EV) owners. For example, Li & Li (2019)introduced an optimal scheduling approach that incorporates demand response of EVs and is successful in reducing load peaks.

3. Modeling and Solution Approach

3.1 Data Sources and Bus System

The proposed bilevel demand response model was applied using the modified IEEE 24-bus system, which includes four wind farms located at nodes 3, 5, 16, and 21. Although the system is based on the 1979 IEEE reliability subcommittee's developed reliability test system, it has been updated with the wind farms. This modified system is available on Ilias. The system shown in Fig. 1 includes 12 conventional generators and 4 wind farms. Each node is assumed to have a Demand

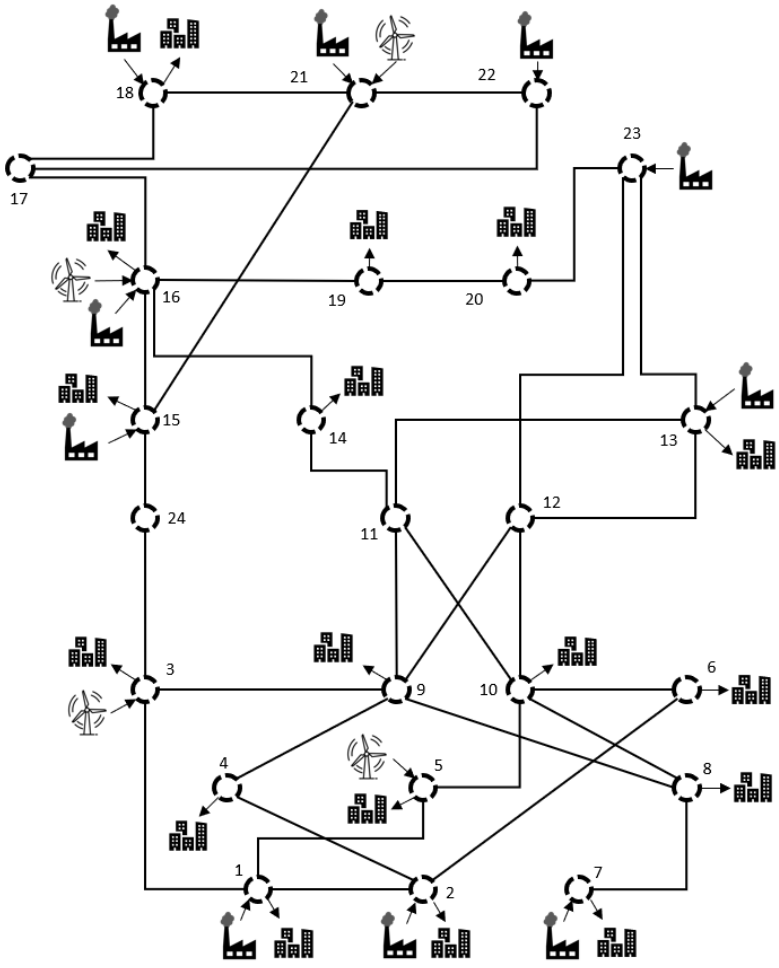

Figure 1: IEEE-24 Bus System

Response (DR) aggregator. The DR aggregator can be of various types, such as a microgrid operator or a community load aggregator of a for-profit organization.

Conventional generators						1	2	3	4	5	6	7	8	9	10	11	12
Location [node]						1	2	7	13	15	15	16	18	21	22	23	23
Production cost [$/MWh]						13.32	13.32	20.7	20.93	26.11	10.52	10.52	6.02	5.47	7	10.52	10.89
Upward reserve cost [$/MW]						1.68	1.68	3.30	4.07	1.89	5.48	5.48	4.98	5.53	8.00	3.45	5.11
Downward reserve cost [$/MW]						2.32	2.32	4.67	3.93	3.11	3.52	3.52	5.02	4.97	6.00	2.52	2.89
Capacity [MW]						106.4	106.4	245	413.7	42	108.5	108.5	280	280	210	217	245
Maximum upward reserve provision capability [MW]						48	48	84	216	42	36	36	60	60	48	72	48
Maximum downward reserve provision capability [MW]						48	48	84	216	42	36	36	60	60	48	72	48
Wind farms														1	2	3	4
Location [node]														3	5	16	21
Installed capacity [MW]														500	500	300	300
Day-ahead forecast [MW]														120.54	115.52	53.34	38.16
Demands	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Location [node]	1	2	3	4	5	6	7	8	9	10	13	14	15	16	18	19	20
Consumption [MW]	84	75	139	58	55	106	97	132	135	150	205	150	245	77	258	141	100
Curtailment cost [$/MWh]	500	500	500	500	500	500	500	500	500	500	500	500	500	500	500	500	500
Transmission lines: From node	1	1	1	2	2	3	3	4	5	6	7	8	8	9	9	10	10
To node	2	3	5	4	6	9	24	9	10	10	8	9	10	11	12	11	12
Susceptance [per-unit]	0.0146	0.2253	0.0907	0.1356	0.205	0.1271	0.084	0.111	0.094	0.0642	0.0652	0.1762	0.1762	0.084	0.084	0.084	0.084
Capacity [MW]	175	175	350	175	175	175	400	175	350	175	350	175	175	400	400	400	400
Transmission lines: From node	11	11	12	12	13	14	15	15	15	16	16	17	17	18	19	20	21
To node	13	14	13	23	23	16	16	21	24	17	19	18	22	21	20	23	22
Susceptance [per-unit]	0.0488	0.0426	0.0488	0.0985	0.0884	0.0594	0.0172	0.0249	0.0529	0.0263	0.0234	0.0143	0.1069	0.0132	0.0203	0.0112	0.0692
Capacity [MW]	500	500	500	500	250	250	500	400	500	500	500	500	500	1000	1000	1000	500

Figure 2: Data for IEE-24 Bus System

Fig. 2 contains crucial information such as production costs, upward and downward reserve costs, generator capacity, reserve provision capability, and transmission line capacity and susceptance. These parameters were obtained from the IEEE 24-bus system. However, adjustments were made to the demand data since the bilevel demand response model requires knowledge of the demand at different time intervals when various demand response offers are made. To adapt the bus system

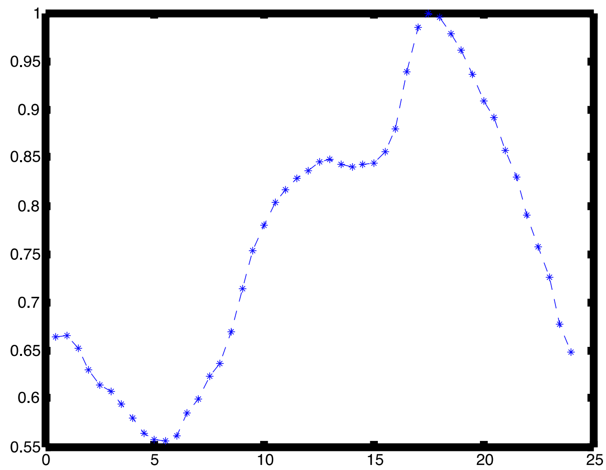

Figure 3: Load Profile

accordingly, a demand profile depicted in Fig. 3 was utilized.

The data source is provided in [1]. The consumption at each time interval 't' is calculated by multiplying the consumption specified in the bus system by the corresponding percentage value obtained from Fig. 2.

For wind data, the "Western Denmark" wind dataset provided by Energinet.dk, which is widely used in research projects, served as the basis.

3.2 Demand Response Framework

The structure of the bilevel demand response model is based on a framework developed by Parvania et al. (2014), as depicted in Fig. 4.

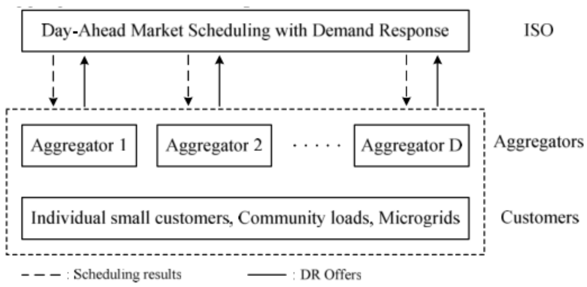

Figure 4: Structure of bilevel demand response model

The model operates through DR aggregators who submit DR offers to the ISO, which in turn utilizes these offers to clear the day-ahead market. The model is formulated as a bilevel problem with an upper-level and lower-level problem.

The lower-level problem focuses on maximizing the profits of the DR aggregators, wherein the decisions of the DR aggregators concerning the ISO and consumers are represented. On the other hand, the upper-level problem minimizes the total operation cost through a two-stage programming problem with an objective function and constraints. In this case, the decisions of the ISO with respect to operation cost and DR options are represented.

DR aggregators generate hourly DR offers in terms of customer load reduction options, which are comprised of load curtailment (LC) and load shifting (LS) blocks in this model. The LC option enables DR customers to reduce their electricity consumption for a given hour by implementing energy-efficient measures without altering the time of consumption. An LC proposal includes a combination of price and quantity, which specifies the compensation that the DR aggregator anticipates for reducing its hourly load.

In the LS option, customers shift reduced loads to other hours within a day.

Both of those contracts include a minimum and maximum quantity of LC or LS.

3.3 Bilevel Programming

The day-ahead market clearing model can be described using a bilevel model. The objective function of the model can be generalized in the following manner:

$$
\begin{aligned}
Min \sum_{t\epsilon T}^{T} (& \boxed{\sum_{g\epsilon G}^{G} (C_{tg}^{gen} \times P_{tg}^{gen} + C_{tg}^{up} \times R_{tg}^{up} + C_{tg}^{dn} \times R_{tg}^{dn} + SUC_{tg}^{gen})} \\
& + \boxed{\sum_{n\epsilon N}^{N} (DRC_{tn} + DRS_{tn})} + \pi_s (\boxed{\sum_{g\epsilon G} C_{g}^{gen} \times (C_{tgs}^{aup} - C_{tgs}^{adn})} \\
& + (\boxed{\sum_{n\epsilon N} C_{snt}^{ws} \times WSpill_{snt} + C^{ls} \times LShed_{snt})) \forall s\epsilon S}
\end{aligned}
$$

Based on Parvania et al. (2014) andTalari et al. (2019)

The formulas in the red boxes refer to the first stage of the program where the general costs of the generators including startup and shutdown costs are considered. Additionally, the costs of load curtailment and load shifting are considered.

The formulas in the green boxes refer to the second stage of the program and include the costs of load shedding, wind spillage, and the costs for up and down reserves.

The objective function is defined by load reduction offers, line constraints, and load reduction offers constraint. The constraints can be broadly divided into six groups: generator limits, transmission line limits, curtailment constraints between ISO and DR aggregator, shifting constraints between ISO and DR aggregator, curtailment constraints between DR aggregator and customer, and shifting constraints between DR aggregator and customer. Limits on wind scheduling were not set. In case the wind is stronger than predicted, the wind farms are allowed to take advantage of it.

Regarding the generator constraints, it can be said that the power generated by a generator at a given time, along with any upward regulation, should not exceed the generator's capacity times its availability. Additionally, the upward regulation should not exceed the generator's maximum upward reserve capacity, and the downward regulation should not exceed the generator's maximum downward reserve capacity. The equations of these constraints look like this:

$$P_{tg}^{gen} + R_{tg}^{up} \leq P_{g}^{cap} \times u_{tg}^{gen}, \forall t, \forall g$$

$$0 \leq R_{tg}^{up} \leq R_{g}^{maxup}, \forall t, \forall g$$

$$0 \leq R_{tg}^{dn} \leq R_{g}^{maxdn}, \forall t, \forall g$$

As for the equality constraints, the net power generation from all generators connected to a node, plus the scheduled curtailment of any DR resources, should be equal to the total demand at that node, plus any power flow into the node from transmission lines.

$$\sum_{g\epsilon G} p_{tg}^{gen} + W_{tn}^{sch} + \sum_{k\epsilon KD} (DRK_{tnk}^{LC} + DRK_{tnk}^{LS}) = LD_{tn} \sum_{l\epsilon NL} pf_{tl}, \forall t, \forall n$$

With regards to transmission line limits, the power flow through a transmission line at a given time should not exceed the line's capacity, nor should it be less than the negative of the line's capacity.

$$pf_t^{min} \leq \ pf_t \leq \ pf_t^{max}, \forall t, \forall l$$

The DR curtailment constraints between the ISO and the DR aggregator can be expressed as follows: The scheduled curtailment of a DR resource at a given time should not exceed the maximum curtailment allowed for that resource multiplied by its availability. Furthermore, the scheduled curtailment of a DR resource at a given time should not be less than the minimum curtailment allowed for that resource multiplied by its availability.

Regarding the DR shifting constraints between the ISO and the DR aggregator, the following constraints must be met: The scheduled shifting of a DR resource at a given time should not exceed the maximum shifting allowed for that resource multiplied by its availability. Additionally, the scheduled shifting of a DR resource at a given time should not be less than the minimum shifting allowed for that resource multiplied by its availability. Finally, the scheduled reverse shifting of a DR resource at a given time should not exceed the maximum reverse shifting allowed for that resource multiplied by its availability.

The curtailment and shifting constraints between the DR aggregator and customer can be described as follows: The scheduled curtailment or shifting of a DR resource at time t should be less than or equal to the maximum shifting allowed for that resource multiplied by its availability. The scheduled curtailment or shifting of a DR resource at time t should be greater than or equal to the minimum shifting allowed for that resource multiplied by its availability. It is important to note that load reduction (LR) and load shifting (LS) should not be taking place at the same time.

4. Results

In the following section, we will look the results. Firstly, we will compare the loads with and without DR, as depicted in Fig 5. The x-axis shows the timestamp t, the y-axis shows the load in MW. It can be observed that in both cases, the peak is reached at 18:00 hours.

The demand increases from 6:00 hours and decreases after 18:00 hours. The load profile with DR is between 11:00 hours and 21:00 hours below the original load profile. Outside of these hours, the load with DR is slightly above the original profile.

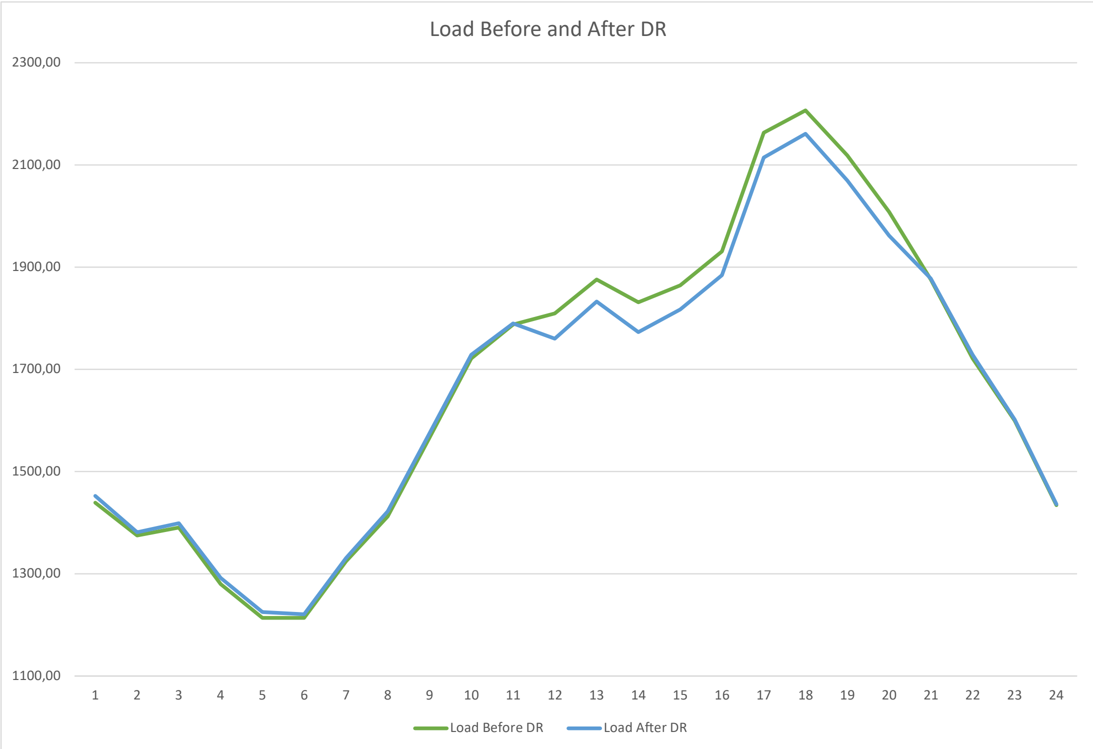

Figure 5: Load before and after DR

Fig. 6 graphically illustrates the deviation of the load in MW with DR from the original value at every timestamp t. We can observe that there is a negative deviation between the hours of 12:00 and 20:00, where the demand is the strongest.

Figure 6: Difference after DR

When examining the difference between the loads before and after DR, it can also be noted that it is overall negative. The negative difference between 12:00 and 20:00 is not fully compensated for during the periods of lower demand.

The load peak is reached at 18:00 hours. After DR, the load is reduced by less than 50 MW, which is 2.27% of the peak demand of 2207 MW. It is important to note that the reduction during the load peak is particularly relevant, as it is crucial to ensure energy supply and maintain the stability of the network.

5. Discussion

In the following section the results will be interpreted. The peak is reached at 18:00 hours in both cases, while demand increases from 6:00 hours and decreases after 18:00 hours. The load profile with DR is below the original load profile between 11:00 hours and 21:00 hours, and slightly above the original profile outside of these hours.

Figure X shows the negative deviation of the load with DR from the original value between 12:00 and 20:00 hours, when demand is strongest. This implies that the DR mechanisms can be successfully utilized for load shaving.

When comparing the loads before and after DR, it is found that the difference is overall negative. The negative difference between 12:00 and 20:00 hours is not fully compensated for during periods of lower demand.

This suggests that not only load shifting is being utilized, but also load curtailment, where consumption is reduced without being shifted to other times.

Load peak is at 18:00 hours. After DR, load is reduced by 2.27% of peak demand (2207 MW). One possible explanation for this could be that the incentives for consumers were not sufficiently chosen to induce a higher reduction.

6. Limitations and Further Research

While the current model provides insights into the usability of bilevel demand response, there are certain limitations that need to be acknowledged, and areas for further research that require exploration. The modified IEEE 24-bus system serves as the basis for the model. The data provided in terms of the demand per node were adjusted using a demand profile (Figure X) to represent hourly demand, although actual hourly data would be more precise. The model could be extended to better represent real-world conditions by incorporating unit ramp-up and ramp-down constraints, as well as sources of uncertainty, such as system failure of generators. On the consumer side, there are various possibilities for expanding the model. Customers could be given the opportunity to choose between competing DR aggregators. Various utility functions could be used to simulate the customer's trade-off between electricity price and comfort. Various parameters can be defined to customize the DR offers. For instance, a comfort band could be established with lower and upper bounds. Additionally, different categories of energy consumers can be distinguished. For example, a customer might specify a tolerance for temperature changes while heating, or a time frame within which a particular activity (such as EV charging) should occur, allowing for flexibility within that window.

DR aggregator offers could be expanded to include energy storage options, as described in the literature on EV charging and vehicle-to-grid.

7. Conclusion

This paper presents a DR framework for electricity markets from an ISO point of view. DR aggregators behavior was modeled to maximize their profit, while the upper-level problem aims to minimize the total cost of operation. The results indicate that the proposed model can reduce load peaks by shifting a certain amount to off-peak hours.

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