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A bottom-up approach for demand response aggregators' participation in electricity markets

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ABSTRACT

This paper proposes a bottom-up model for demand response (DR) aggregators in electricity markets. This model enables a DR aggregator to consider the technical constraints of customers in developing an optimal trading strategy in the wholesale electricity market. In the bottom level, DR options, called load shifting, load curtailment and load recovery are comprehensively modelled in a stochastic programming approach. Each DR program is mathematically formulated in such a way that practically models the constraints of customers. Further, the proposed model considers the customers' behaviour in participating in the given DR program through a scenario-based participation factor. On the other hand, the upper level proposes trading the DR outcome in day-ahead and balancing markets with uncertain prices, as well as in forward contracts with a predefined price. The overall bottom-up problem is formulated as a stochastic profit maximization model for the DR aggregator, in which the risk is taken into account using the Conditional Value-at-Risk (CVaR) measure. The feasibility of the given strategy is assessed on a case of the Nordic market.

1. Introduction

1.1. Motivations and approach

The ever-growing significance of Demand Response (DR) programs has introduced a new player within electricity markets, known as a "DR aggregator". DR aggregators are allowed to participate in some electricity markets such as the US (through the Federal Energy Regulatory Commission (FERC) order [1]), while other markets such as the Australian National electricity Market (NEM) are working towards providing this permission [2,3]. This role indeed faces the DR aggregator with two key challenges in *the bottom-level of customers* and *the upper-level of the wholesale market*.

In the bottom level, the DR aggregator seeks for performing DR programs with the lowest costs, while accurately modelling the technical constraints of customers as well as their uncertain behaviour in responding to offered incentives. In the upper-level, the DR aggregator is challenged with determining optimal trading options in the wholesale market. These options range from the pool market whose prices are uncertain, to bilateral forward contracts, which are usually set in a fixed quantity and fixed price for a certain period.

Given the above challenges, this paper mathematically formulates a bottom-up risk-constraint profit maximization model for DR aggregators. The bottom-level approach proposes new models for DR programs, i.e. load shifting, load recovery and load curtailment programs, which consider customers-driven constraints. For each program, a linear cost model is developed by proposing a stepwise function. A stochastic cost function is proposed through which the uncertainty of customers' behaviour is modelled using a scenario-based participation factor. On the other hand, a new trading strategy is proposed in the upper level, which enables the DR aggregator to trade the obtained DR into three resources, known as day-ahead and balancing markets, as well as forward contracts. The overall problem is a stochastic programming approach through which the DR aggregator makes the optimal bottom and upper levels decisions according to its risk preference, which is modelled using the Conditional Value-at-Risk (CVaR) measure.

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Nomenclature

A. Indices

b	index for block of forward contracts ($b = 1, 2, \ldots, N_B$)
drp	index for DR program including $drp = \{lc, ls, lrc\}$
f	index for forward contracts ($f = 1, 2, \ldots, N_f$)
j	index for the level of the stepwise function ($j = 1, 2, \ldots, N_j$)
lc	index for the load curtailment program
lrc	index for the load recovery program
ls	index for the load shifting program
t	index for time ($t = 1, 2, \ldots, T$)
w	index for scenario ($w \in \pi(w)$)

B. Parameters

$D_{drp}^{\max}$	maximum valid duration for DR program drp
$D_{drp}^{\min}$	minimum duration that customers agree to provide DR program drp
$E_{drp}^{\max}(t)$	maximum energy available for DR program drp
$N_{drp}^{\max}(t)$	number of times that DR program drp can be called in a day
$P_{drp}^{\max}(t)$	maximum available hourly DR of DR program drp
$PF_{drp}(t, w)$	scenario-based participation factor for DR program drp
$roc_{drp}^{\max}(t)$	ramp rate of DR program drp
RCF	recovery factor for load recovery
$T_{drp}^{On}(t)$	valid time for DR program drp
$\lambda^{DA}(t, w)$	day-ahead price in scenario w and time t
$\lambda^{imb,pos}$	positive imbalance price in scenario w and time t
$\lambda^{imb,neg}$	negative imbalance price in scenario w and time t
$\lambda_{drp}(t)$	offered incentive (fee) in DR program drp. Note that incentive is offered in LS and LC, while fee is charged in LRC.
$\lambda_{f,b}(t)$	forward contract price for block b of contract f
β	confidence level, equal to 0.95
ρ	risk factor (Rho)
$\pi(w)$	probability of scenario w
$\eta(w)$	auxiliary variable for calculating CVaR
ξ	auxiliary variable for calculating CVaR

C. Variables

$I_{drp}(t)$	binary variable indicating if DR program drp is initiated at time t
$P_{f,b}(t)$	forward contract power for block b of contract f
$P_{drp}(t)$	DR power for DR program drp
$P^{DA}(t, w)$	day-ahead power in scenario w and time t
$P^{pos}(t, w)$	positive imbalance power in scenario w and time t
$P^{neg}(t, w)$	negative imbalance power in scenario w and time t
$S_{drp}(t)$	binary variable indicating if DR program drp stops at time t
$v_{drp,j}(t)$	binary variable indicating the level of the stepwise function
$U_{drp}(t)$	binary variable indicating if DR program drp is on (carried out) at time t
$\lambda_{drp}(t)$	incentive (fee) of DR program drp

1.2. Literature review and contributions

Many papers in the literature address DR studies such as modelling, challenges and DR participation in electricity markets. We summarize the most relevant investigations to our model as follows.

DR aggregators participations in several capacity (PJM, ISO-NE, Ontario) and energy-only markets (Singapore, ERCOT, Alberta) are reviewed in [3]. The study only considers various options such as demand bidding, capacity DR, and ancillary services DR in these markets, while no explanation on how these DR products are obtained from consumers is given. A similar study is carried out in [4], where the benefits and challenges of aggregated load participation in markets, particularly balancing markets, are provided for the German markets. Authors in [5] propose a DR model for large consumers through which a consumer carries out DR on CHP cogeneration to participate in the day-ahead market. Ref. [6] develops a new approach through which DR aggregators employs load reduction from thermostatically controlled loads to bid in the reserve market on a day-ahead basis. Paper [7] models a two-stage approach in which the DR aggregator schedules the thermal heating load based on the day-ahead prices, but carries out DR in the balancing market through encouraging consumers by bonus prices. DR trading approaches in electricity markets as well as bilateral contracts are proposed in [8–11], without modelling the bottom-level DR programs. A new model is proposed in [12] through which the DR aggregator sells the DR obtained from load shifting, load curtailment, onsite generation and storage in the energy market. The given model considers DR constraints for load shifting and load curtailment programs while disregarding the customers' uncertain behaviour as well as the risk preference of the aggregator. A trading strategy is modelled in [13], using a game-theoretic approach in which the DR aggregator is modelled as an influencer in the market, which curtails consumers load while minimizing their inconvenience. DR is also considered from the market operators' perspective [14–16], where it is mostly considered in a bulk volume disregarding the detailed constraints of customers.

Many researchers focus on modelling DR programs only, without considering DR participation in electricity markets. A comprehensive survey of DR programs is delivered in [17]. The survey provides DR classification based on several factors such as types, customers, communication, purposes and control strategies. Authors in [18] model customers' response to incentives according to their comfort as well as sensitivity factors such as time of load shifting and energy reduction level. Authors in [19,20] address incentive and price-based DR programs. The given model considers the elasticity as the only constraint of customers when performing DR. Residential DR programs and the required facilities in the UK are explained in [21], where direct load program commands are used to control three load groups, i.e. fridges and freezers, washers and dryers, and ovens. The given model does not consider the technical limitations of the load, whereas only their typical load profile is used in performing DR. Authors in [22] develop new incentive mechanisms for economic and emergency DR programs. For the economic DR, the way that customers respond to the reward is determined using a game theory approach. For emergency DR, however, the behaviour of customers, either price-taker or price predictor, is modelled in a fixed DR. A DR model is presented in [23], where consumers use a rolling window scheme to respond to real-time prices according to the previous hour price. DR models for various appliances are provided in several studies such as [24–28]. Ref. [24] studies real data for water heater and provides recommendations for utilities in performing DR on this type of the load. Authors in [25] provide physical models for appliances such as space heating/cooling, water heating and dryers. While control models for air conditioning are provided in [26,27], a DR model for electric heating systems is presented in [28]. An automated energy management framework is proposed in [29], which employs energy use behaviour of consumers to control their controllable loads. Appliances are modelled while considering their timing constraints, i.e. start and end control times, but ignoring constraints