Stochastic programming model for scheduling demand response aggregators considering uncertain market prices and demands

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Abstract

This paper proposes a stochastic decision making model for a demand response (DR) aggregator as an interface between the market and customers in a competitive environment. The DR aggregator participates in day-ahead (DA) energy and balancing markets as well as offers selling price to the customers to maximize its expected profit, considering the reaction of customers to the rivals' offering prices. Moreover, the effect of load reduction due to implementing DR contracts on the decision making process of the DR aggregator is assessed. However, the main focus is on the operation of both shiftable and sheddable loads in price-based DR programs with detail. In order to investigate the behavior of different DR actions from the DR aggregator viewpoint, the restrictions imposed by the preferences of customers to the decisions made by the DR aggregators are modeled via a bi-level stochastic programming approach. The upper level represents the decisions made by the DR aggregator, while the lower level models the customers' behavior. To deal with various uncertainties, a risk-constrained scenario-based stochastic programming framework is presented where the DR aggregator's risk aversion is modeled using conditional value at risk (CVaR) method. Finally, a detailed illustrative case study based on the Nordic energy market data is provided and the effects of different DR actions and risk aversion factor on the profit of the aggregator are analyzed.

Keywords: Aggregator; bi-level stochastic programming; conditional value-at-risk (CVaR); demand response (DR); decision making model.

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20 **Nomenclature**

Sets and indices

$(\cdot)_{h,s}$	At time *h* and scenario S .
$(\cdot)_{h,\theta}$	At time *h* and scenario θ .
$r, r'(N_r)$	Indices (set) of aggregators.
θ (Θ)	Scenario index (set) of rival aggregators' prices.
$h(H)$	Index (set) of time periods.
s (S)	Scenario index (set) of market prices, demand loads.

Variables

$C_{r,r'}$	The fictitious cost that models the reluctance of customers and PEV owners to switch from aggregator r to aggregator r' (€).
E^{D}	The amount of energy supplied by the under-study aggregator (MWh).
$E^{pos}(E^{neg})$	Energy traded in positive (negative) balancing markets (MWh).
E^{DA}	Energy traded in day-ahead market (MWh).
χ_r	Percentage of customers that the rival DR aggregators supply.
χ_{r_0}	Percentage of customers that the under study DR aggregator supplies.
$\gamma_{r,r'}$	Percentage of customers shifted between the DR aggregators.
$\mu_{r,\theta}(\lambda_\theta)$	Lagrange multipliers.
$U^{X}_{r,\theta} / U^{\gamma}_{r,r',\theta}$	Binary variables.

Parameters

$Elas_{h,h}(Elas_{h,t})$	Self-elasticity (cross-elasticity) related to the demand of customers.
E^{T_D}	Total demand of customers (MWh).
$\widehat{E}^{T_D}_{h}$	Total expected demand of customers (MWh).
χ^{init}_{r}	The percentage of loads and PEVs demand supplied by each aggregator, initially.
β	Weighting factor for risk aversion.
π_s	Probability of scenario *s*.
$\phi^{pos}(\phi^{neg})$	Positive (negative) balancing market prices (€/MWh).
ϕ^{DA}	Price of day-ahead market (€/MWh).
ϕ_r (ϕ_{r_0})	Price signals offered by rival (under study) aggregator (€/MWh).
ρ_θ	Probability of scenario θ .

1. Introduction

Due to advancements in smart grid technologies especially in terms of two-directional communication infrastructures between load serving entities and end users, demand response (DR) is considered as a major method that can be taken in order to reduce consumer electrical energy usage when contingencies occur to disturb the balance of supply and demand. DR is introduced as a tariff or program to motivate the end-users in response to changes in the electricity price or to incentive payments which are designed to induce lower electricity consumption when system reliability is jeopardized or during high prices of the wholesale market [1]. In this regard, voluntary loads may reduce their hourly demands in response to electricity market prices. They may participate in load shifting (LS) options in order to shift their less critical loads to time periods with more moderate prices or in load curtailment (LC) options to curtail their loads without shifting it to other hours [2]. There have been large research works focused on load flexibility and DR. A DR strategy combining energy substitution and LS program is developed in [3] to handle the demand flexibility of smart buildings. The study in [4] has incorporated LC and LS programs in energy scheduling of the industrial virtual power plants to maximize profit.

In order to increase the presence of large volumes of consumers to wholesale electricity markets, DR aggregation is clarified as an effective solution. In this regard, DR aggregators participate in electricity markets as a mediator between the independent system operator and retail customers. DR aggregators work with retail customers to identify and offer appropriate DR programs that would allow customers to participate in the market clearing program. In a deregulated electricity market, aggregators purchase electricity by participating in power markets and sell it to their customers to maximize their profit. During the last years, decision-making problems for DR aggregators with the integration of DR programs were achieved increasing attention. In [5], a framework for optimizing the participation of DR aggregators only in day-ahead (DA) wholesale energy markets is proposed in which DR aggregators optimize their bids by considering specific DR contracts for local customers to elicit their load reduction. Authors in [6] presented an effective decision-making model for energy service providers and focused on the demand allocation in the distribution network as well as participation in the DA market. Authors in [7] provided a stochastic optimization to maximize the profit of the aggregator who aggregates a group of price-responsive loads and submits block-wise demand bids to DA and real-time markets without considering the preferences of customers. In [8], a bi-level optimization model for aggregator agent is presented to determine both the aggregator's minimum payments and the market clearing process, which assumes that the aggregators have a possible influence on the electricity market price; however, this work has not considered the DR aggregation. In [9], an energy management strategy for a load serving entity is provided to adjust the price-responsive loads and allow the group of customers to exchange energy at proper periods such that to maximize their utility function. In this reference, the energy management system is not a profit-seeking model as it is considered in this work. An optimization framework that jointly solves for the optimal participation of a DR aggregator in DA and real-time markets and the optimal scheduling of available DR resources is provided in [10] without focusing on the competition in the aggregator layer. Modeling of the interaction between the independent system operator and DR aggregators as well as the interaction between DR aggregators and customers for short-term scheduling is presented in [11], while competition among DR aggregators is ignored. Moreover, the danger of uncertainties to which the DR aggregator is subjected to is not lessened via a risk measurement tool. An optimization framework is presented in [12] for the participation of an energy aggregator in the DA market in the presence of demand flexibility, which manages energy and financial interactions between the market and distributed energy resources. In this study, the aggregator only participates in DA trading floor and as a result, cannot modify its offers before delivery time in order to reduce imbalance costs.

Although the mentioned above studies have contributed to submit a scheduling framework for an aggregator, risk measurement tools have not been considered in most of them. A bidding strategy model and a solution method for electric vehicle aggregator in smart demand-side management are investigated in [13] in which the conditional expectation of electricity purchase cost is minimized to optimally determine not only DA inflexible bids, but also real-time flexible adjustment bids including quantities and prices submitted by the aggregator. To cope with uncertainties, a risk-constrained stochastic programming problem is represented in [14] where the risk aversion behavior of the aggregator is captured by using the conditional value at risk (CVaR) measurement tool. A technique to obtain the best offering strategy for a hybrid power plant consisting of DR provider in the power market with considering CVaR to limit the risk of profit variability is proposed in [15]. Although, in both [14] and [15], the rivalry among the aggregators is neglected.

In the problem of decision making for a DR aggregator, the aggregated loads may have objectives in conflict with the objective of the aggregator. In fact, the aggregator should also tackle with uncertainties originated from the possibility of choosing other rival aggregators by the customers if the aggregator cannot propose a competitive selling price. Therefore, a bi-level model is required to address the profit-maximization of the aggregator as well as the preferences of the customers. In this regard, a bi-level problem is represented in [16] with the objective of profit- maximization of the aggregator and parking lot subject to the preferences of plug-in electric vehicles. In addition, the flexibility of parking lot is investigated through its integration with other sources such as DR. A bi-level model to derive bidding curves of a large consumer with supplying its required demand in DA pool under the uncertainties of offering curves of producers is investigated in [17]. A Stochastic optimization model is represented in [18] for optimal bidding strategies of EV aggregators in DA energy and ancillary services markets. Moreover, the game theoretic approach is developed for analyzing the competition among the EV aggregators, however, DR contracts are not investigated.

In most of the above works, the interaction between DR aggregators and end-users in a competitive market is paid little attention. A bottom-up model for DR aggregators in electricity markets is investigated in [19]. In this work, the customers' behavior in participating in the given DR program through a scenario-based participation factor is modeled without focusing on the competition among aggregators. In fact, the competitive environment provides new opportunities for consumers' behavior and different models of DR. A stochastic optimization model for optimal bidding strategies of aggregators in electricity markets is proposed in [20] in which game theoretic approach is used for assessing the competition among the aggregators; however, DR contracts are not investigated. A bi-level programming approach for decision-making of a power retailer in the medium-term horizon is presented in [21], although the DR model used in this study did not give customers characteristics and their load reduction preferences.

On the above premises, this paper presents a model for the interactions of DR aggregator with DA and balancing markets in a competitive environment. In this model, the effect of load reduction due to implementing DR contracts on the decision making process of the DR aggregator is investigated. Due to the preferences of customers which impose restrictions to the decisions of the DR aggregator, a bi-level stochastic programming is applied to the model. The objective of the upper-level is profit maximization of DR aggregator while the objective of the lower-level problem is cost minimization of customers. Then, the overall problem with conflict objectives is transformed into the equivalent single-level linear problem using Karush–Kuhn–Tucker (KKT) optimality conditions and duality theory. Since, the stochastic program for decision making of DR aggregator accounts for various resources of uncertainty, CVaR as a risk measure is embedded in the problem to control different levels of risk on profit volatility.

Overall, the main contributions of this paper are represented as follows:

- To develop a risk-constrained bi-level stochastic programming method for optimizing the participation of DR aggregator in the short-term electricity market by considering different DR actions for local customers to elicit load reduction,
- To model the effects of implementing DR programs on the decision making process of the under study DR aggregator with considering customers' response to the selling prices offered by rival DR aggregators in a competitive market,
- To evaluate the impact of different levels of DR participants and risk-averse attitudes on the profit volatility of the aggregator in the underlying optimization problem via sensitivity analysis.

The rest of the paper is arranged as follows: Section 2 explains the proposed decision-making strategy. Also, the stochastic risk-constrained bi-level decision-making problem is formulated section 3. The case studies together with simulation results are presented in section 4. Finally, section 5 draws the conclusions.

2. Proposed Decision-making Strategy

The framework of the proposed bi-level stochastic problem is illustrated in Fig. 1. In this figure, two optimization levels are shown. In the upper level, the aim of the aggregator is to maximize its expected profit. In this regard, the aggregator submits the hourly energy blocks to DA market several hours before the operating day. Then, during the operating day, depending on actual conditions of the loads, the aggregator may participate in the balancing market to compensate for the deviation from the DA scheduling. The uncertainty on market prices is taken into account using a set of scenarios.

As seen from Fig. 1, due to the competition among the aggregators, the under study aggregator as a decision maker investigates the price scenarios offered by rivals. Because of the incomplete information about the offering prices of rivals, the under study aggregator should estimate these prices through scenarios. Also, the aggregator requires to forecast the expected demand of customers. Once each aggregator offers a selling price, in the lower level the clients choose which aggregator to supply their electricity demand during the planning horizon. These decisions are made with perfect information regarding the selling price offered by the aggregators, whereas market prices and clients' demand are uncertain. This profit maximization problem considers that clients optimally react to the aggregators' prices. This reaction consists of determining the demand share supplied by each available aggregator (the under study aggregator and the rivals) so that the procurement cost of clients should be minimized. In this regard, in the lower level, the clients who may participate in DR programs prefer to minimize their payments by choosing the most competitive aggregator. Furthermore, the percentage of loads supplied by each aggregator would be obtained.

The DR portfolios containing financial and technical characteristics of hourly load reductions include LC, LS or both of them. Additionally, users find the opportunity to subscribe to a DR aggregator, which supplies their energy needs in a competitive environment. In the LC option, DR customers attempt to reduce their hourly electricity usage without shifting it to other hours. An LC option includes a price-quantity pair, which specifies how much it should reduce its hourly load. In addition, LC options contain an initiation cost for load reduction, which would cover customers' fixed costs for load curtailments. The constraints for customer for implementing LC options may include minimum/maximum daily time duration for LCs, maximum number of daily LCs, and daily time for initiating LC.

Moreover, in LS option, customers shift their reduced loads to other hours within a day. The shifting and supplying of the curtailed loads with the potential of shifting will be conducted in other hours of the day. In the proposed framework, once each DR aggregator offers a selling price, the customers select a proper DR aggregator to supply their electricity demand during the scheduling horizon. These decisions are made with perfect information about selling price offered by the DR aggregators, whereas DA and balancing prices and demands are uncertain.

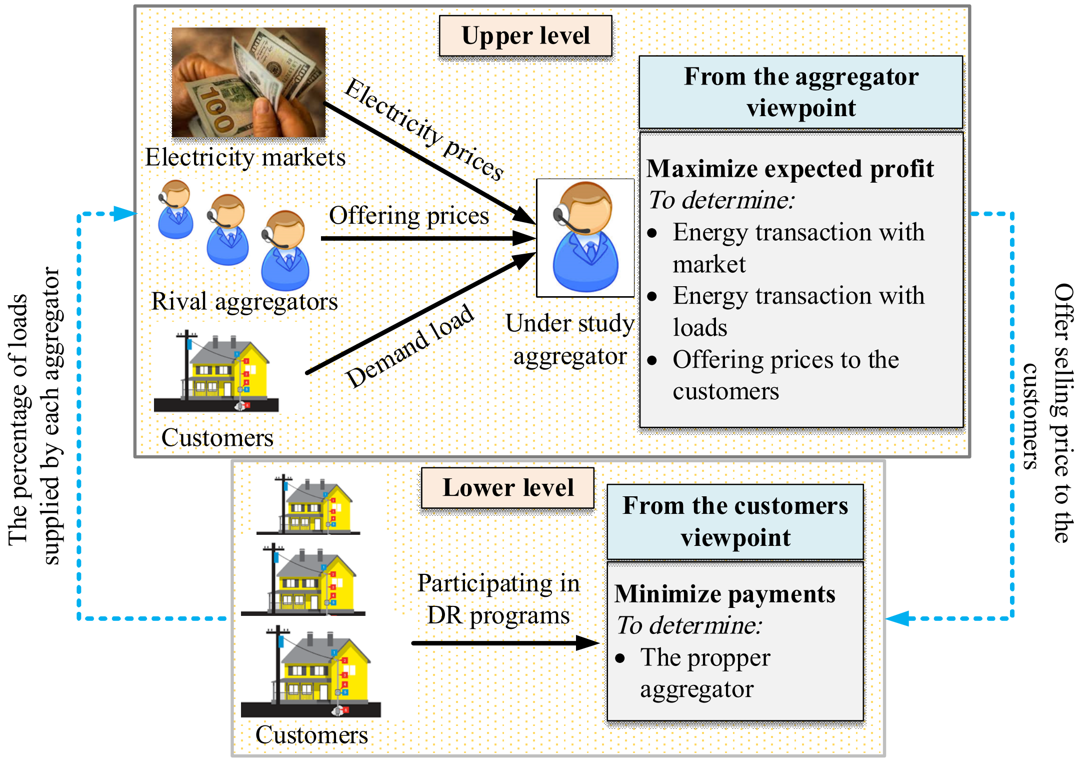


Fig. 1. The schematic of the proposed problem.

3. Mathematical formulation

A. Demand Response Modeling

The energy price is directly affected by demand and customers participate in DR programs and regulate their power consumption to minimize their electricity consumption costs. Therefore, to model the DR, the relation between energy price and demand in each time period should be modeled by using the price elasticity of demand [24]. To achieve maximum benefit, each customer may apply both LS and LC options and change its energy consumption from D_t^{int} to D_t in period *t*. Therefore, based on the model explained in [25], the energy consumed by the customers when participating in LC, LS and LCLS options are obtained by (1)-(3), respectively.

$$E_{h,s}^{D_D} = E_h^{D,\text{int}}.\left(\frac{\phi_{h,s}^{DA}}{\phi_h^{DA,\text{int}}} + \frac{1}{1+Elas_{t,h}^{-1}}\right)^{Elas_{t,h}} \tag{1}$$

$$E_{h,s}^{D_D} = E_h^{D,\text{int}}.\prod_{\substack{h=1\\h\neq t}}^{H}\left(\frac{\phi_{h,s}^{DA}}{\phi_h^{DA,\text{int}}} + \frac{1}{1+Elas_{t,h}^{-1}}\right)^{Elas_{t,h}} \tag{2}$$

$$E_{h,s}^{T_D} = D_t^{\text{int}} \exp \sum_{h\in T} Elas_{t,h} \ln\left[\frac{\phi_{h,s}^{DA}}{\phi_h^{D,\text{int}}} + \frac{1}{1+Elas_{t,h}^{-1}}\right] \tag{3}$$

where, $Elas_{t,h}$ is the elasticity of demand of responsive customers and $\phi_h^{D,\text{int}}$ is the average of $\phi_{h,s}^{DA}$.

B. Upper level modeling

The objective function of the upper level from the viewpoint of the under study DR aggregator is formulated as below.

$$Maximize \sum_{s=1}^{S} \pi_s \sum_{h \in H} \begin{bmatrix} -(E_{h,s}^{DA} \phi_{h,s}^{DA} + E_{h,s}^{pos} \phi_{h,s}^{pos}) \\ +(E_{h,s}^{D} \phi_{r_0,h} + E_{h,s}^{neg} \phi_{h,s}^{neg}) \end{bmatrix} \qquad (4)$$

This relation comprises of two terms including the costs for purchasing energy from DA and positive balancing markets and the revenues achieved from selling energy to the customers and the participation in the negative balancing market. The upper level problem is subject to the following constraints:

The energy balance for each scenario and at each time is explained in Constraint (5). Based on this equation, the DR aggregator supplies its requested demand from DA and balancing markets.

$$E_{h,s}^{DA} + E_{h,s}^{pos} - E_{h,s}^{neg} = E_{h,s}^{D} \qquad (5)$$

The energy supplied by the under study DR aggregator to supply the loads is estimated based on (6). This equation provides the expected value of demand purchased from the under study aggregator over all scenarios of prices offered by rival aggregators.

$$E_{h,s}^{D} = E_{h,s}^{T_D} \sum_{\theta \in \Theta} \rho_\theta \chi_{r_0,h,\theta} \qquad (6)$$

C. Incorporating Risk Management

The profit of the DR aggregator in the proposed stochastic optimization model is a random variable. In a risk-neutral formulation, the expected value of the profit is maximized while ignoring the other parameters influencing the distribution of the profit. Therefore, the achieved optimal expected profit may have high level of variability in which a high possibility of low profits or even negative ones (losses) exists. Therefore, CVaR as a risk management tool is added to the model to control the volatility of the profit of DR aggregator and to avoid undesirable profit scenarios due to various uncertainties [25]:

$$CVaR = Maximize(\xi - \frac{1}{1-\alpha} \sum_{s=1}^{S} \pi_s \eta_s) \qquad (7)$$

Subject to:

$$\begin{aligned} & -E_{h,s}^{DA} \phi_{h,s}^{DA} - E_{h,s}^{pos} \phi_{h,s}^{pos} + E_{h,s}^{D} \phi_{r_0,h} + E_{h,s}^{neg} \phi_{h,s}^{neg} \\ & + \eta_s - \xi \geq 0 \qquad : \eta_s \geq 0 \end{aligned} \qquad (8)$$

where, π_s is the probability of scenario s and η_s is an auxiliary non-negative variable equals to the difference between auxiliary variable ξ and the profit of DR aggregator when its profit is lower than ξ. With considering the objective function and the constraints of the upper level, the decision vector of this level is as $\left\{E_{h,s}^{DA}, E_{h,s}^{pos}, E_{h,s}^{neg}, E_{h,s}^{D}, \phi_{r_0,h}, \eta_s, \xi\right\}$

D. Lower level modeling

In order to model the motivation of customers to select the most competitive DR aggregator, customers' payments are considered to be minimized in the lower level problem. In fact, the DR aggregator should consider the benefit of customers in order to increase its market share in a competitive market.

$$\begin{aligned} &Minimize\ \widehat{E}_h^{T_D}[\phi_{r_0,h}\chi_{r_0,h,\theta} + \sum_{\substack{r\in N_r \\ r\neq 0}} \phi_{r,h,\theta}\chi_{r,h,\theta}] \\ &+ \sum_{r\in N_r}\sum_{\substack{r'\in N_r \\ r\neq r'}} \widehat{E}_h^{T_D} C_{r,r'}\gamma_{r,r',h,\theta} \end{aligned} \tag{9}$$

In the above equation, index r_0 denotes the under-study DR aggregator. The first line of this equation explains the payments of demand loads to the under-study and rival DR aggregators. The second line states the unwillingness of customers to change their DR aggregator to procure their energy. The lower level problem is subject to the following constraints.

Constraint (10) expresses the share of each DR aggregator to supply the required energy of demand loads. From this relation, it is seen that a percentage of the total load is supplied by each DR aggregator and also, another percentage is transferred between the DR aggregators. In other words, the demand supplied by each DR aggregator consists of the initial demand supplied by the DR aggregator plus the customers who transfer from other DR aggregator to this aggregator minus those clients who leave the aggregator and go to the rivals.

$$\begin{aligned} &E_{h,s}^{T_D}\chi_{r,h,\theta} = E_{h,s}^{T_D}\chi_{r,h,\theta}^{init} + E_{h,s}^{T_D}\sum_{\substack{r\in N_r \\ r'\neq r}}\gamma_{r',r,h,\theta} - E_{h,s}^{T_D}\sum_{\substack{r'\in N_r \\ r'\neq r}}\gamma_{r,r',h,\theta} \\ &: \lambda_\theta \end{aligned} \tag{10}$$

Constraint (11) denotes that all of the loads should be supplied by all of the DR aggregators.

$$E_{h,s}^{T_D}\chi_{r_0,h,\theta} + E_{h,s}^{T_D}\sum_{\substack{r\in N_r \\ r\neq r_0}}\chi_{r,h,\theta} = E_{h,s}^{T_D} : \mu_{r,\theta} \tag{11}$$

Equation (12) provides the total expected demand of customers:

$$\widehat{E}_h^{T_D} = \sum_{s\in S}\pi_s E_{h,s}^{T_D} \tag{12}$$

The decision vector for the lower level problem is given as: $\{\chi_{r,h,\theta}, \gamma_{r,r',h,\theta}\}$ for which the associated Lagrange multipliers are $\{\chi_{r,h,\theta}, \gamma_{r,r',h,\theta}\}$

E. Linear formulation of the equivalent Single-Level Problem

The obtained bi-level optimization framework is composed of the scheduling problem for the aggregator in the upper-level and the cost minimization of the clients in the lower-level. In order to incorporate the upper level and the lower level of the problem, the lower level is replaced with its Karush-Kuhn-Tucker (KKT) optimality conditions and the bilinear products are replaced with their equivalent linear expressions using duality theory. Therefore, the single level mixed-integer linear programming (MILP) problem is achieved with the objective function given in expression (13), in which the tradeoff between the expected profit of the aggregator and CVaR index is denoted by β as a weighting factor.

$$Maximize[\sum_{s=1}^{S}\pi_s \sum_{h\in H}\begin{bmatrix} -(E^{DA}_{h,s}\phi^{DA}_{h,s}+E^{pos}_{h,s}\phi^{pos}_{h,s}) \\ +(E^{D}_{h,s}\phi_{r_0,h}+E^{neg}_{h,s}\phi^{neg}_{h,s}) \end{bmatrix} + \beta(\xi - \frac{1}{1-\alpha}\sum_{s=1}^{S}\pi_s.\eta_s)] \tag{13}$$

With the constraints in (1), (5), (6), (8), (10)-(12) as well as the complementarity slackness conditions that are linearized by adding some binary variables based on the approach explained in [26] are given as follows:

$$\hat{E}_h^{T_D}\phi_{r_0,h} - \mu_{r_0,\theta} - \lambda_\theta \ge 0 \tag{14}$$
$$\hat{E}_h^{T_D}\phi_{r_0,h} - \mu_{r_0,\theta} - \lambda_\theta \le M_1 U^{\chi}_{r_0,\theta} \tag{15}$$
$$\hat{E}_h^{T_D}\phi_{r,h,\theta} - \mu_{r,\theta} - \lambda_\theta \ge 0 \tag{16}$$
$$\hat{E}_h^{T_D}\phi_{r,h,\theta} - \mu_{r,\theta} - \lambda_\theta \le M_1 U^{\chi}_{r,\theta} \tag{17}$$
$$\chi_{r,h,\theta} \le M_2[1-U^{X}_{r,\theta}] \tag{18}$$
$$\hat{E}_h^{T_D}C_{r,r'} + \mu_{r,\theta} - \mu_{r',\theta} \ge 0 \qquad r \ne r' \tag{19}$$
$$\hat{E}_h^{T_D}C_{r,r'} + \mu_{r,\theta} - \mu_{r',\theta} \le M_1 U^{\gamma}_{r,r',\theta} \qquad r \ne r' \tag{20}$$
$$\gamma_{r,r',h,\theta} \le M_2[1-U^{\gamma}_{r,r',\theta}] \qquad r \ne r' \tag{21}$$

where, $\mu_{r,\theta}$ and λ_θ are Lagrange multipliers, $U^{X}_{r,\theta}$ and $U^{\gamma}_{r,r',\theta}$ are binary variables and M_1 and M_2 are constants. Moreover, by using the strong duality theorem, the bilinear term of $E^{D}_{h,s}\phi_{r_0,h}$ is also replaced by its equivalent expression [27] as below:

$$E^{D}_{h,s}\phi_{r_0,h} = \frac{E^{T_D}_{h,s}}{\hat{E}^{T_D}_{h}}\sum_{\theta\in\Theta}\rho_\theta \begin{bmatrix} -\sum_{\substack{r\in N_r \\ r\ne 0}}\hat{E}_h^{T_D}\phi_{r,h,\theta}\chi_{r,h,\theta} \\ -\sum_{r\in N_r}\sum_{\substack{r'\in N_r \\ r'\ne r}}\hat{E}_h^{T_D}C_{r,r'}\gamma_{r,r',h,\theta} \\ +\sum_{r\in N_r}\chi^{init}_{r,h,\theta}\mu_{r,\theta} + \lambda_\theta \end{bmatrix} \tag{22}$$

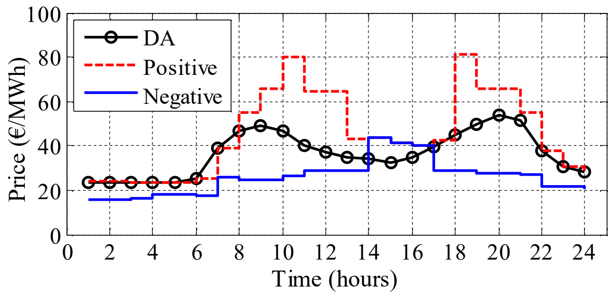
The linearization details of the problem are presented in Appendix.

4. Simulation and Numerical Results

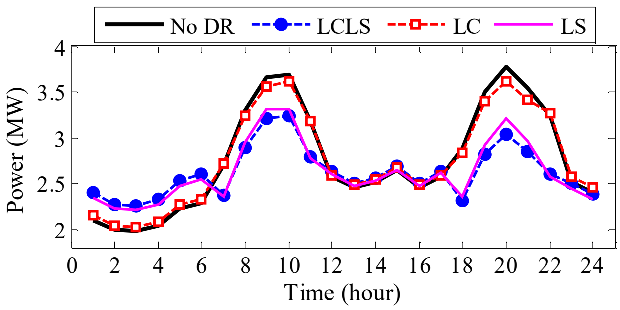
A. Case Study

The proposed decision making strategy is assessed in a realistic case based on the Nordic market. The scheduling period is considered one day with 24 equal time slots due to hourly market prices [28]. The forecasted values of DA and balancing markets as well as the total demand load which is correlated to DA market prices [23] in three cases are depicted in Fig. 2. Here, a dual-price balancing market is considered that the mechanism of imbalance prices has been extracted from [22]. MCS and RWM strategies are used to model the forecasting errors and reduction techniques [29] is implemented to select 45 scenarios. In this study, four DR aggregators are considered such that Agg_0 stands for the under study DR aggregator and Agg_1, Agg_2, and Agg_3 represent the rivals. The hourly prices offered by the rival DR aggregators are modeled by three randomly generated scenarios with different probabilities.

The initial hourly demands supplied by each DR aggregator denoted by $\chi_{r,h,\theta}^{init}$ are also generated randomly. The set of scenarios are applied to the proposed model to evaluate its effectiveness.



(a) Forecasted price profile of DA, up and down balancing market



(b) Total demand in cases: no DR, LCLS, LC, LS in DR=60%

Fig. 2. Forecasted values.

The optimization is carried out by CPLEX solver using GAMS software [30] on a PC with 4 GB of RAM and Intel Core i7 @ 2.60 GHz processor. With considering a *mip gap* of 0%, the computation time for the studied cases was between 3 and 6 minutes, with an average of 4 min and 42 seconds.

B. Numerical Results

The effect of different values of risk aversion factor (β) and DR participants on the expected profit of the under study DR aggregator in LCLS, LC and LS options are shown in Fig. 5. The implementation of LC causes a minor reduction as compared to Cases LCLS and LS. But, LS causes significant load reduction at peak hours and shift the load to off-peak periods. However, the implementation of both cases LC and LS provides a smooth equivalent load profile compared with the other two ones.

From Fig. 5, it is observed that with implementing DR programs and with increasing DR participants, the expected profit of the DR aggregator decreases. The reason is that the DR aggregator acts as an intermediary between wholesale and retail markets. On the wholesale, it competes against other demand-side participants for the low cost procurements of electricity and on the retail market, the DR aggregator competes against other DR aggregators for final customers, who offer similar services. On the other hand, by implementing DR programs, the total load reduction in the system, boils down the revenues of DR aggregator. In fact, the reductions in the revenues are due to the mitigation of total load that might be supplied by the under study aggregator. Therefore, DR utilization would reduce hourly peak loads and/or fill the valley periods which accordingly results in smoother load profiles. In LC case, where DR actions are mainly implemented based on sheddable loads, the customers' demand decreases in peak periods (when prices are high), but there is no change in off-peak or valley periods. Therefore, in this case, the total demand of customers' decreases and as the result, the amount of selling energy by DR aggregators decreases that gives less profit for them. On the other hand, in LS case, customers reduce their power demands during peak hours and shift a part of their consumption to other hours, especially to valley periods. In this case, DR aggregators sell more amount of their energy at low prices that decrease their profits. Furthermore, in LCLS case, with the participation of both sheddable and shiftable loads in DR programs, the customers' demand decreases in peak and shift a part of their demand from peak periods to off-peak or valley periods. The total required demand of customers and their participation in LCLS programs in different DR participants is illustrated in **Fig. 3**. In this case, the total demand of customers' decreases in peak periods and also more amount of energy is sold in off-peak hours with low prices. Also, the share of the under study aggregator in supplying loads is shown in **Fig. 4**. It is seen that by applying DR programs, the total required demand of loads reduces and as the result the share of the under study aggregator to supply the loads reduces which leads to lower profit for the aggregator.

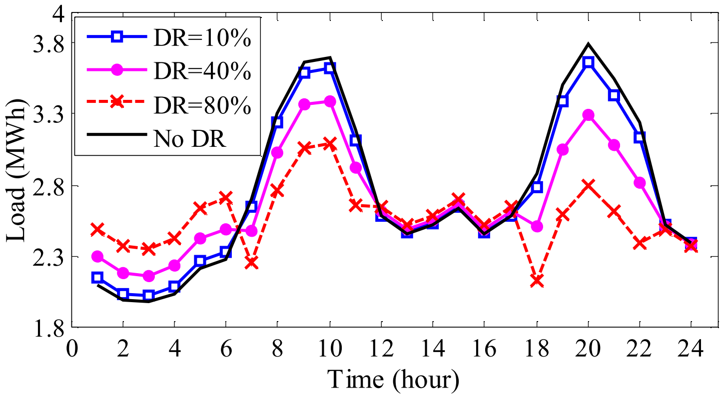


Fig. 3. Total demand in different DR participants

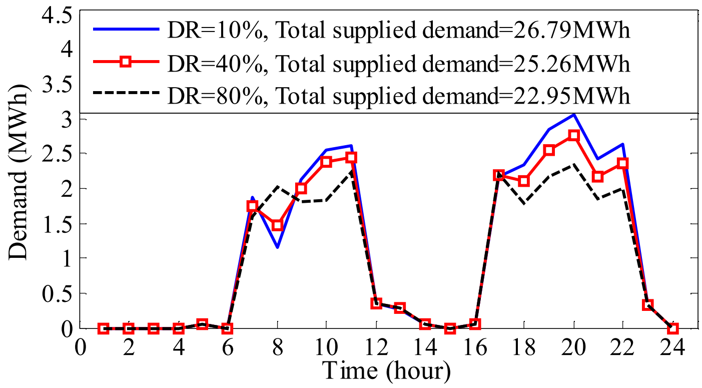
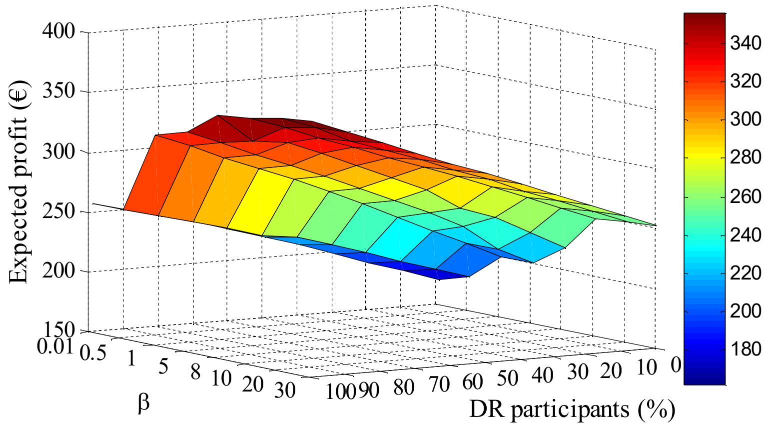


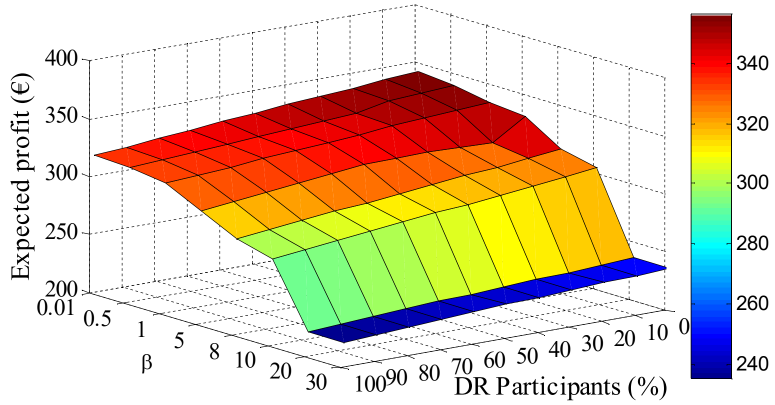
Fig. 4. Share of the under study DR aggregator to supply loads

Even though, by implementing DR, the loads at peak hours are optimally shifted to other hours at which the rivals might offer more proper selling prices which leads the under study aggregator to lose its customers. For example, in β=1 as a specific risk factor, the expected profit of DR aggregator in case no DR is 347.358€ which decreases to 327.134€ in case LC and to 262.213€ in case LS and to 240.507€ in case LCLS. With assessing the effect of loads' participation in LC and LS and both options on the decision making of DR aggregator, it is deduced that the profit losses in case LCLS is -30.76% which is more than the one in cases LC and LS which terminate to profit losses of -5.82% and -24.51%, respectively.

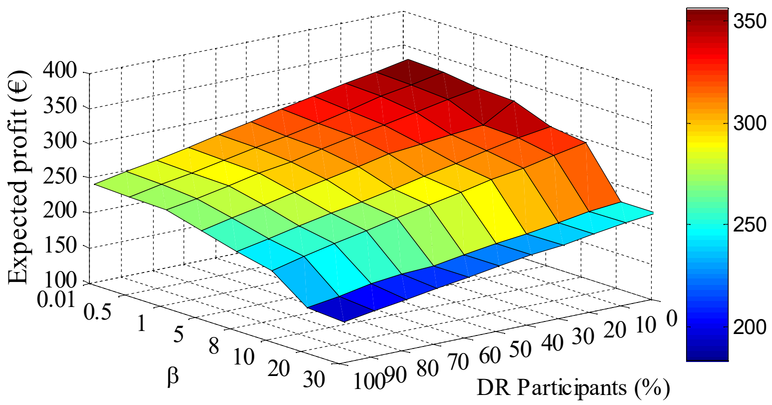
The reason is that the load reductions corresponding with LC option would not increase at other hours. And customers do not have substantial participation in LC options. However, most of the loads prefer LS option because they are willing to recover their reduced hourly load at another time period. It might lead them to choose another DR aggregator with a lower price at other periods which leads to low values of profit for the under study aggregator. Also, with implementing option LCLS, the DR aggregator encounters with the highest profit reduction due to implementing both load reductions and load recovering activities.



(a) LCLS case



(b) LC programs



(c) LS programs

Fig. 5. The expected profit versus DR participants and β in three Cases.

Also, it is seen in each DR participants, with increasing risk aversion factor, the expected profit of DR aggregator decreases. Therefore, in each DR participants, to obtain moderate mitigation in the expected profit, a desirable level of risk exposure should be chosen.

Fig. 6 depicts the prices offered by the rival and the under study DR aggregator in DR=60% and β=1 in LCLS option. As seen in Fig. 6, the aggregator offers lower prices in peak hours to attract the customers and middle prices in off-peak hours to obtain more benefit. However, it is desirable that the aggregator offers the selling prices as low as possible to be competitive in the market. Otherwise, the customers may leave it and switch to other aggregators.

Fig. 7 shows the selling prices by the under study DR aggregator in two β. As evident from Fig. 7, the prices offered by the under study aggregator increases in some hours as the risk parameter grows. This behavior results from a greater purchasing energy from expensive positive balancing market as a less volatile market. The increase in the selling price is also the result of reducing the profit volatility by decreasing the amount of customers' demand that is supplied.

In addition, it is worth pointing out that the aggregator does not increase the offered prices at all hours since it might lose its clients in the competitive market.

The share of all DR aggregators to supply the load in DR=0% for all values of β is shown in Fig. 8. It is seen that disregarding DR, the share of the under study aggregator to supply the load is highly dependent on the risk aversion factor. As observed, the share of the under study aggregator to supply the loads decreases as the risk aversion parameter grows. The reason is that as the aggregator behaves more risk-averse, as it was mentioned, it offers higher prices. Consequently, an increase in selling prices offered by the under study aggregator makes the prices offered by the rivals more attractive, which causes that the rival aggregators supply a great share of the customers. For example, the share of the under study aggregator in β=0.01 and 30MW is 29.9 and 19.5MW, respectively. It shows that 34.7% of customers lost it and went to rivals.

In the competitive market, the aggregators submit their competitive bids to the customers and try to attract them. With increasing DR participants, more customers are allowed to choose their DR aggregator and it is more probable that the under study aggregator lose its clients. Therefore, in such a competitive environment, each aggregator attempts to motivate the loads by submitting competitive bids to them.

Table 1 shows the share of each aggregator in supplying loads in two different DR participants and in all three DR contract with varying β. With increasing β from 0.01 to 30, due to offering higher prices by the under study aggregator, as expressed before, the share of the aggregator in DR=60% decreases from 25.7% to 16.5% which shows 35.7% decrement. Likewise, the share of the under study aggregator to supply the loads mitigates 34.6% and 35.6% for LC and LS options, respectively. Similarly, in DR=100% its share decreases 35.5%, 34.3% and 36.2% in contracts LCLS, LC and LS, respectively.

Moreover, with the application of shifting program in both LCLS and LS contracts that would normally shift the loads during peak hours to off-peak hours, the aggregator loses its clients. The reason is that as seen in Fig. 6, it offers low prices in peak hours and middle prices in off-peak hours. Therefore, with sifting the loads from peak to off-peak hours, the customers might choose rivals with lower selling prices. For example, in a specified β=1 and in DR=60%, the share of the aggregator is 24.3, 27.2 and 24.2MW in LCLS, LC and LS contracts, respectively. As seen, with the application of load shifting, the customers recover their reduced load from peak periods to the off-peak hours. In off-peak periods, as observed in Fig. 6, they encounter with lower prices offered by rivals. Therefore, in β=1 and in LS option, aggregators 1 and 2 motivated the customers to purchase their required energy.

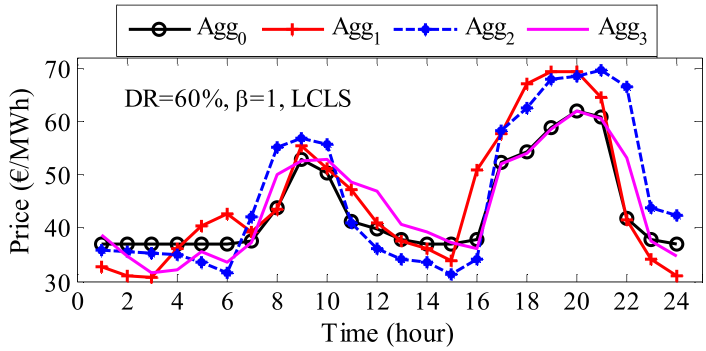


Fig. 6. The offering price by all aggregators in β=1.

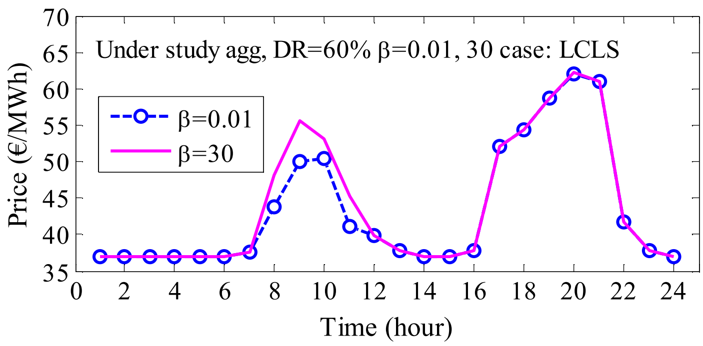


Fig. 7. Selling prices by the under study DR aggregator in two β.

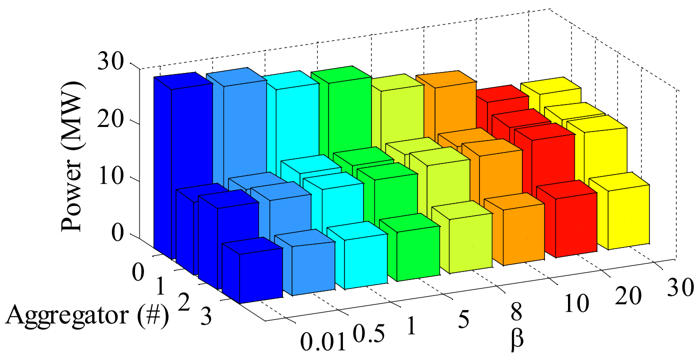


Fig. 8. The share of all DR aggregators to supply the load in DR=0% for all values of β.

Table 1. The share of all Aggregators to supply the loads (%).

LCLS								
β	Agg_0	Agg_1	Agg_2	Agg_3	Agg_0	Agg_1	Agg_2	Agg_3
	DR=60%				DR=100%			
0.01	25.7	13.2	15.1	8.4	22.5	13.8	15.5	8.3
0.5	25.3	13.6	15.0	8.4	22.2	13.8	15.9	8.3
1	24.3	14.2	15.4	8.4	21.9	13.8	16.2	8.3
5	22.1	15.5	16.1	8.5	19.7	15.6	16.5	8.4
8	20.7	15.5	16.9	9.2	16.6	16.2	17.9	9.4
10	19.6	16.1	17.2	9.5	16.6	16.2	17.9	9.4
20	16.7	17.4	18.1	10.1	14.8	17.2	18.2	9.9
30	16.5	17.5	18.2	10.1	14.5	17.3	18.4	9.9
LC								
β	DR=60%				DR=100%			
	Agg_0	Agg_1	Agg_2	Agg_3	Agg_0	Agg_1	Agg_2	Agg_3
0.01	29.4	13.1	14.5	8.6	29.1	13.2	14.7	8.6
0.5	28.2	14.2	14.5	8.6	28.3	13.9	14.7	8.6
1	27.2	14.8	14.9	8.6	27.3	14.6	15.1	8.6
5	25.4	15.7	15.8	8.7	25.1	15.8	16.1	8.7
8	23.7	15.7	16.6	9.4	23.5	15.8	16.8	9.4
10	22.9	16.1	16.9	9.7	22.6	16.2	17.1	9.7
20	19.2	17.9	18.1	10.4	19.1	17.9	18.2	10.4
30	19.2	17.9	18.1	10.4	19.1	17.9	18.2	10.4
LS								
β	DR=60%				DR=100%			
	Agg_0	Agg_1	Agg_2	Agg_3	Agg_0	Agg_1	Agg_2	Agg_3
0.01	26.1	13.1	14.8	8.4	23.7	13.1	15.2	8.3
0.5	25.1	14.1	14.8	8.4	23.1	13.6	15.2	8.3
1	24.2	14.5	15.2	8.4	22.2	14.2	15.5	8.3
5	22.6	15.4	15.8	8.5	20.5	15.3	16.1	8.4
8	21.1	15.4	16.6	9.3	19.1	15.3	16.8	9.1
10	20.2	15.8	16.9	9.5	18.1	15.8	17.1	9.4
20	16.8	17.4	18.1	10.1	15.3	17.1	17.9	9.9
30	16.8	17.4	18.1	10.1	15.1	17.1	18.1	9.9

An aggregator, as a mediator, signs contracts with both demand-side and supplier in the power markets with the objective to maximize its expected profit. However, the aggregator should tackle the uncertainties of market prices, loads and the possibility of choosing a different DR aggregator by the loads if it cannot offer competitive selling prices. Therefore, CVaR is used for managing the aggregator's financial risk. Fig. 9 shows the expected profit versus CVaR in all three DR contracts in three different DR participants (DR=0%, 60% and 100%). There are 8 points by modifying parameter β which models the tradeoff between the expected profit and the profit variability that is measured in terms of CVaR. The first point is obtained solving the problem with a near-zero β parameter as 0.01 and other values are chosen as 0.5, 1, 5 8, 10, 20 and 30. Also, it is observed that in each DR contract, with increasing DR participants, in risk neutral case, CVaR value reduces as the profit variability of the aggregator increases. It is because with increasing DR participants, the possibility that customers choose their supplier increases. Therefore, the level of uncertainty of the problem increases which results in decrement of CVaR value. Also, since the aggregator is risk neutral, undesirable outcomes in the worst scenarios might occur. Additionally, the negative value of CVaR indicates experiencing profit losses by the DR aggregator. But, with increasing both DR participants and in risk-averse case, approximately the same values of CVaR occur for all DR options in all contracts. Because, although with increasing DR participants the uncertainty characterization appearing in the problem increases, the aggregator applies risk management procedures to avoid implementing strategies which entail the possibility of low profits. Moreover, as can be seen from Fig. 9 in the revised paper, when β increases from 0.01 to 1, although the profit does not change so much, CVaR rises substantially. With further increase of β, the DR aggregator's expected profit will be significantly reduced and CVaR will be increased. Based on the risk aversion behavior of the DR aggregator, it can choose one of the points in the efficient frontier. Therefore, based on Fig. 9, lower amounts of β (e.g., β =1) is a proper choice for a non-conservative aggregator, because at this point, it can achieve high-risk aversion without substantial decrement of expected profit. However, for a conservative DR aggregator, it seems that the value of β =5 would be an appropriate selection. Because, in β more than 5, CVaR increases at the expense of high decrement of expected profit that is not suitable for an aggregator.

Fig. 10 illustrates the hourly energy procurement by DR aggregators through the scheduling horizon. In order to analyze the differences between considering the effect of risk-neutral (β=0.01) and risk-aversion (β=30) cases on the share of each DR aggregator, only LCLS option is considered to avoid wordiness. The analysis for the options LC and LS is the same way. It is observed that customers choose the most competitive aggregator to supply their demand.

It is seen that with increasing risk aversion parameter, the under study aggregator increases its offering prices because of its participation in positive balancing market as an expensive environment increases. In this regard, the clients choose the cheapest aggregator. For instance, in β=30, at 8:00, the under study aggregator offers a high price which leads to losing its clients. Therefore, the customers transfer to aggregator 1 which offers the lowest selling price. Consequently, it is reasonable that the aggregator chooses a specific risk aversion parameter in which it offers an appropriate price signal to stay in the game. This fact that lower prices attract more customers can be seen from comparing Fig. 6 and Fig. 10 (a) in which the hourly energy procurement by all DR aggregators is depicted. As can be observed, when the under study aggregator offers the cheapest price, i.e. at 7:00-11:00 and 17:00-22:00, most customers choose it to supply their loads. Likewise, at 1:00-3:00 and 23:00-24:00 that the offering price of Agg_1 is the lowest, it attracts more customers. Therefore, as shown in this figure, the customers try to choose the cheapest aggregator to minimize their energy procurement cost. It is assumed that the customers can transfer from one aggregator to other aggregators who offer the lowest selling price.

Fig. 11 depicts the offering price offered to the customers in different values of β. As seen, the offering price signal increases as β parameter grows. In fact, when the aggregator becomes more risk averse, it should supply the loads from a less volatile market which is usually more expensive. So, it offers higher prices to the customers to compensate for its own revenue. Also, the increase in the selling price is also a way of mitigating the profit volatility by decreasing the amount of demand that is supplied. Moreover, it is observed that the increase in the price does not occur during night peak hours, since the aggregator tends to keep its own clients and remain in the gain.

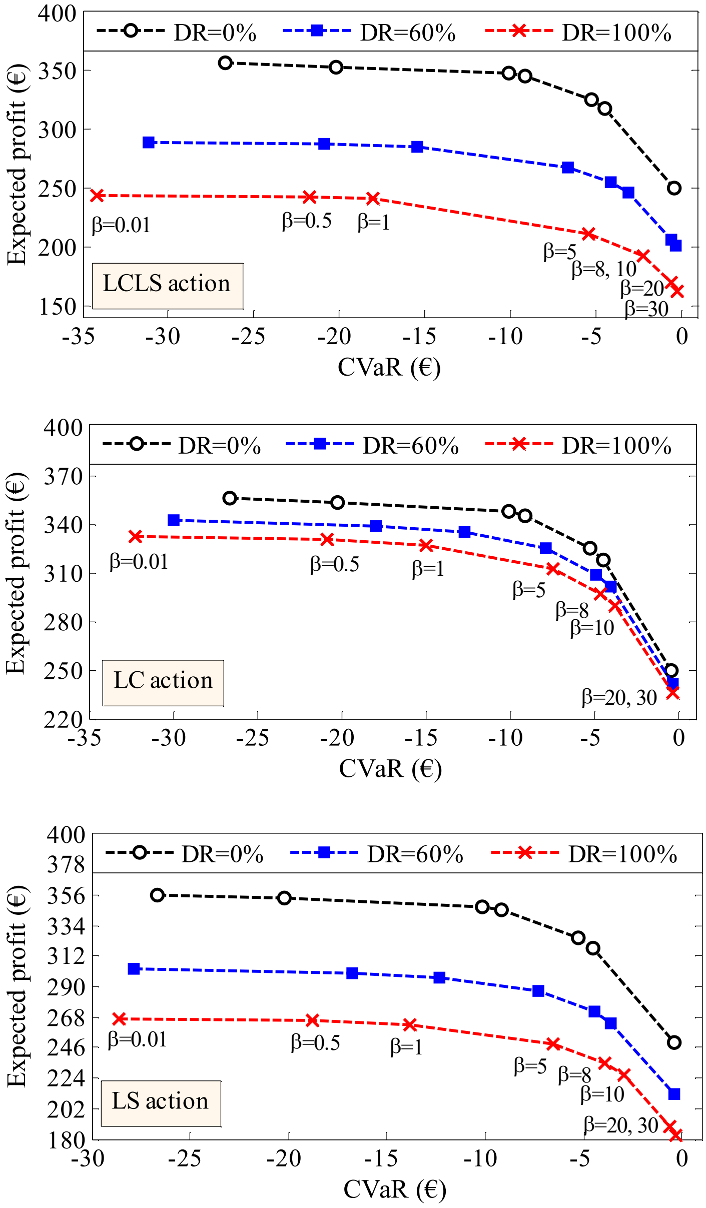
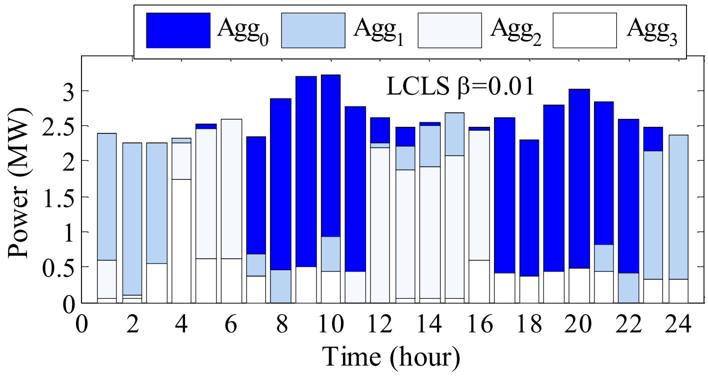
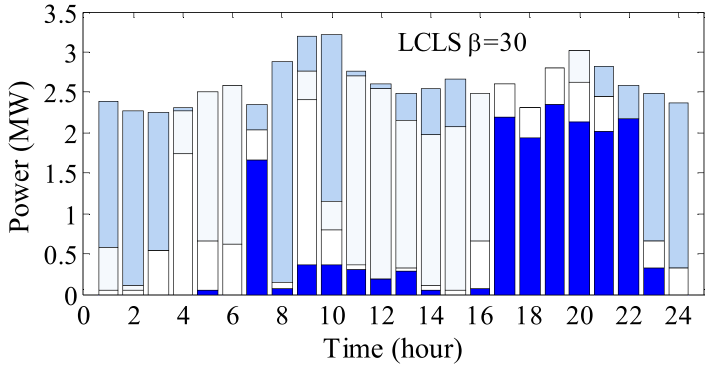


Fig. 9. the expected profit versus CVaR in all three DR contracts in three different DR participants (DR=0%, 60% and 100%).



(a) β=0.01



(b) β=30

Fig. 10. Share of all aggregators to supply loads.

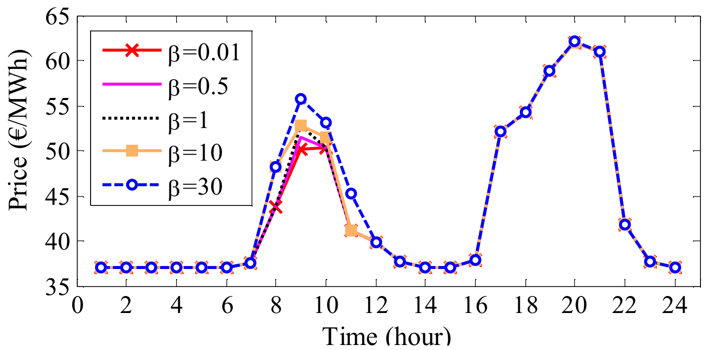


Fig. 11. Offering price by the DR aggregator in different values of β

To show the superiority and effectiveness of the proposed model, it is compared with two other existing methods presented in references [14]. In [14], an operation optimization model for a microgrid aggregator, which can procure energy from various sources including the pool market and local distributed energy resources to serve MG customers at a predefined retail rate and it also offers customers various contracts for adjusting their loads. In the case of the selling price determination, the competitive environment due to the existence of rival aggregators should be taken into account for an appropriate decision making modeling, while it is neglected in [14]. In order to investigate the effect of competition on the decision making of the aggregator, Fig. 12 illustrates the selling price offered by the aggregator. It is observed that when the competition among aggregators is not considered, the selling price by the aggregator is very high. In fact, in a dominated market structure, the customers are obligated to procure their required energy from only one DR aggregator. But, when the electricity market is evolved to a competitive trading floor, the customers are allowed to choose their own utility and as the result to reduce the net cost through such a competitive environment. Therefore, the aggregator, should offer its own offering prices in such a way to attract customers and as a result to remain in the game. In this regard, as shown in Fig. 12, the offering price in a competitive market, reduces in some hours to keep the customers, else, the aggregator might lose the clients under its jurisdiction. So, the competitive behavior of aggregators to offer optimal selling prices to the customers should be explicitly modeled as in our study.

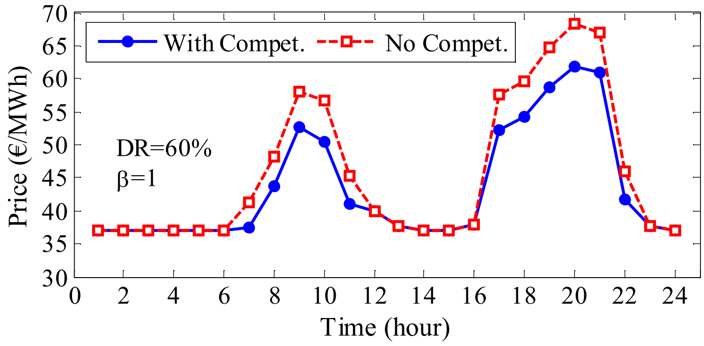


Fig. 12. The offering price signal by the under study aggregator with and without considering competition.

Table 2 provides the expected profit and CVaR values in cases with and without considering competition in all DR participants. As seen, when the competition is not considered, the expected profit of the DR aggregator in all DR participants is very higher than the cases with considering DR. In fact, without considering competition, the aggregator should supply all of the load and it is dominated that the customers procure their required energy from only one aggregator. But, in a competitive market, the clients have permission to choose their own aggregator such that to mitigate their payments. Therefore, the inevitable effect of the client' preferences yields in a better aggregator's performance and gives its exact profit. Also, with considering competition, from the lower and even negative values of CVaR, the possibility of negative profit in some scenarios is perceived. Also, in a competitive exchanging floor, the under study aggregator encounters with the uncertain nature of responsive loads who might choose the rivals and as the result, the danger to which the aggregator is exposed because of uncertainty augments. But, in a non-competitive market, the CVaR values are higher and positive which means that the aggregator is exposed with less uncertainties.

Table 2. The expected profit and CVaR values in cases with and without considering competition in all DR participants.

DR (%)	*No Competition*		*With Competition*	
	Expected profit (€)	*CVaR (€)*	*Expected profit (€)*	*CVaR (€)*
0	2796.6	59.616	355.765	-26.654
10	2822.006	60.379	326.117	-10.917
20	2788.359	61.143	314.981	-11.712
30	2754.713	61.908	303.612	-12.507
40	2721.066	62.672	292.119	-13.301
50	2687.419	63.436	280.576	-14.311
60	2653.772	64.201	268.994	-15.465
70	2619.83	64.67	257.37	-16.62
80	2584.013	63.264	245.928	-16.48
90	2548.197	61.858	234.415	-17.274
100	2452.532	60.452	243.631	-34.196

5. Conclusion

In this paper, a bi-level stochastic decision making framework was introduced in which the upper-level represents the DR aggregator profit maximization and the lower-level problem models the customers' behavior through their cost function. The bi-level problem was transformed into its equivalent single-level linear using mathematical techniques. The effect of different levels of DR participants in DR contracts, including LC, LS and both of them on the decision making of DR aggregator was also assessed. Moreover, due to the uncertainties associated with market prices, demand loads as well as the offering prices by rivals, risk assessment is carried out using CVaR. Several conclusions can be deduced by considering the results obtained from this study, as follows:

- Implementing DR programs boils down the revenues of DR aggregator due to load mitigation or shifting loads to hours with moderate prices offered by rivals;
- A DR aggregator offers moderate selling prices to keep its clients in the competitive market;
- In low levels of the risk factor, with increasing DR participants, the profit variability of the aggregator increases, but in high values of the risk factor, with increasing DR participants, the approximate profit variability occurs.

Appendix

After obtaining the upper level and lower level problem formulation independently, Lagrange function of lower level is obtained as below [31]:

$$
\begin{aligned}
L = {} & \widehat{E}_h^{D}[\phi_{r_0,h}\chi_{r_0,h,\theta} + \sum_{\substack{r\in N_r \\ r\neq 0}} \phi_{w,h,\theta}^{D}\chi_{r,h,\theta}^{D}] + \sum_{r\in N_r}\sum_{\substack{r'\in N_r \\ r\neq r'}} \widehat{E}_h^{T_D} C_{r,r'}\gamma_{r,r',h,\theta} \\
& + \lambda_\theta (E_{h,s}^{T_D}\chi_{r,h,\theta}^{init} + E_{h,s}^{T_D}\sum_{\substack{r\in N_r \\ r'\neq r}} \gamma_{r',r,h,\theta} - E_{h,s}^{T_D}\sum_{\substack{r'\in N_r \\ r'\neq r}} \gamma_{r,r',h,\theta}) \\
& + \mu_{r,\theta}(E_{h,s}^{T_D}\chi_{r_0,h,\theta} + E_{h,s}^{T_D}\sum_{\substack{r\in N_r \\ r\neq r_0}} \chi_{r,h,\theta}) \\
& + \sum_{r\in N_r} \eta\chi_{r,h,\theta}\cdot\chi_{r,h,\theta} + \sum_{r\in N_r}\sum_{\substack{r'\in N_r \\ r'\neq r}} \eta\gamma_{r,r',h,\theta}\cdot\gamma_{r,r',h,\theta}
\end{aligned} \tag{A-1}
$$

Then, the KKT optimality condition of the lower level problem is obtained by partial derivatives of the obtained Lagrange function. Then the lower level problem is incorporated to the upper level and therefore, the bi-level problem is converted to the equivalent single-level nonlinear optimization form. It should be noted that the bilinear products of continuous variables are replaced by their equivalent linear expressions using the linearization technique explained in [32]. Based on that technique, the multiplication of $g.x$ can be replaced with the linearized by introducing new binary variable u. Then, this expression can be linearized using a set of linear constraints as bellow:

$$x \le M.(1-u) \tag{A-2}$$
$$g \le M.u \tag{A-3}$$
$$u \in \{0,1\} \tag{A-4}$$

Where, M is sufficiently large constant. Therefore, the nonlinear complementary slackness conditions [21] can be equivalently expressed as a set of linear constraints as follows:

$$\hat{E}_h^{T_D}\phi_{r_0,h} - \mu_{r_0,\theta} - \lambda_\theta \ge 0 \tag{A-5}$$
$$\hat{E}_h^{T_D}\phi_{r_0,h} - \mu_{r_0,\theta} - \lambda_\theta \le M_1 U_{r_0,\theta}^{\chi} \tag{A-6}$$
$$\hat{E}_h^{T_D}\phi_{r,h,\theta} - \mu_{r,\theta} - \lambda_\theta \ge 0 \tag{A-7}$$
$$\hat{E}_h^{T_D}\phi_{r,h,\theta} - \mu_{r,\theta} - \lambda_\theta \le M_1 U_{r,\theta}^{\chi} \tag{A-8}$$
$$\chi_{r,h,\theta} \le M_2[1-U_{r,\theta}^{X}] \tag{A-9}$$
$$\hat{E}_h^{T_D} C_{r,r'} + \mu_{r,\theta} - \mu_{r',\theta} \ge 0 \qquad r \ne r' \tag{A-10}$$
$$\hat{E}_h^{T_D} C_{r,r'} + \mu_{r,\theta} - \mu_{r',\theta} \le M_1 U_{r,r',\theta}^{\gamma} \qquad r \ne r' \tag{A-11}$$
$$\gamma_{r,r',h,\theta} \le M_2[1-U_{r,r',\theta}^{\gamma}] \qquad r \ne r' \tag{A-12}$$

Where, $U_{r,\theta}^{X}$ and $U_{r,r',\theta}^{\gamma}$ are binary variables and M_1 and M_2 are constants.

Moreover, the bilinear term of $E_{h,s}^{D}\phi_{r_0,h}$ can be replaced by its linear expression using duality theory. Based on duality theory, the dual of each lower level problem for the variable $\phi_{r_0,h}$ is given as:

$$Maximize \sum_{r \in N_r} \left\lfloor \chi_{r,h,\theta}^{init}.\lambda_\theta + \mu_{r,\theta} \right\rfloor \tag{A-13}$$

Subject to:

$$\mu_{r_0,\theta} + \lambda_\theta \le \hat{E}_h^{T_D}\phi_{r_0,h} \tag{A-14}$$
$$\mu_{r,\theta} + \lambda_\theta \le \hat{E}_h^{T_D}\phi_{r,h,\theta} \tag{A-15}$$
$$\mu_{r,\theta} - \mu_{r',\theta} \le \hat{E}_h^{T_D} C_{r,r'} \quad r \ne r' \tag{A-16}$$

The strong duality theorem [33] states that $\{\chi_{r,h,\theta}^{D}, \gamma_{r,r',h,\theta}\}$ is an optimal solution to the lower level problem in (9)- (12) and $\{\lambda_\theta, \mu_{r,\theta}\}$ is an optimal solution to (A-13)-(A-14) if and only if:

$$\hat{E}_h^{T_D}[\phi_{r_0,h}\chi_{r_0,h,\theta} + \sum_{\substack{r \in N_r \\ r \ne 0}} \phi_{r,h,\theta}\chi_{r,h,\theta} + \sum_{r \in N_r} \sum_{\substack{r' \in N_r \\ r' \ne r}} C_{r,r'}\gamma_{r,r',h,\theta}] = \sum_{r \in N_r} \chi_{r,h,\theta}^{init}\mu_{r,\theta} + \lambda_\theta \tag{A-17}$$

Therefore, the bilinear term of $E_{h,s}^{D}\phi_{r_0,h}$ is replaced by its equivalent expression as below:

$$E_{h,s}^{D}\phi_{r_0,h} = \frac{E_{h,s}^{T_D}}{\hat{E}_{h}^{T_D}} \sum_{\theta \in \Theta} \rho_{\theta} \begin{bmatrix} -\sum\limits_{\substack{r \in N_r \\ r \neq 0}} \hat{E}_{h}^{T_D} \phi_{r,h,\theta} \chi_{r,h,\theta} \\ -\sum\limits_{r \in N_r} \sum\limits_{\substack{r' \in N_r \\ r' \neq r}} \hat{E}_{h}^{T_D} C_{r,r'} \gamma_{r,r',h,\theta} \\ +\sum\limits_{r \in N_r} \chi_{r,h,\theta}^{init} \mu_{r,\theta} + \lambda_{\theta} \end{bmatrix} \tag{A-18}$$

Acknowledgment

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