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Stochastic Risk-Constrained Decision-making Approach for a Retailer in a Competitive Environment with Flexible Demand Side Resources

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SUMMARY

This paper presents a risk-averse stochastic bi-level programming approach to solve decision-making of a retailer in a competitive market under uncertainties. The retailer decides the level of involvement in day-ahead (DA) and regulation markets by making an optimal bidding strategy with the goal of expected profit maximization. Uncertainties associated with DA prices, up/down regulation market prices, customers' demand and rival retailers' behaviors are tackled through a stochastic programming model. In the proposed model responsive loads and electric vehicles (EVs) track the real-time prices and choose the proper retailer to minimize their payments in the competitive trading floor. The obtained nonlinear stochastic model is transformed into an equivalent linear single-level program by replacing the lower-level problem with its Karush–Kuhn–Tucker optimality conditions and using duality theory. Finally, the proposed methodology is evaluated by applying to a realistic case study and the results demonstrate the effectiveness of the proposed framework.

***Index Terms*—Demand response (DR), conditional value at risk (CVaR), competitive market, electric vehicle (EV), stochastic bi-level program.**

1. INTRODUCTION

Retailers, as one of the main players of the electricity market, can purchase energy from different sources to supply their customers [1]-[3]. The objective of a retailer is to maximize its expected profit and to satisfy the electricity demands by optimal purchasing energy and offering proper prices to the end users. During the trading process, a retailer normally encounters different uncertainties in both market and demand side. Therefore, to avoid experiencing very low profits in some unfavorable scenarios, the retailer should consider a certain risk level in the decision-making problem. Moreover, the customers may be encouraged to manage their consumption patterns especially in in emergency conditions. In this regard, within a robust optimization approach, decision making problem of electricity retailers with considering the effect of DR programs on total procurement cost, is proposed in [4]. In [5], a stochastic dispatch model for responsive load is developed in order to investigate the effect of price-based DR programs in a microgrid environment.

In future smart grids, demand-side resources can play a more active role in decision-making problem of the retailer. New technologies such as electric vehicles (EVs), as flexible resources at the demand side, bring significant challenges to the retailer's decision-making process by their charging and discharging behavior [6]. When EV acts in vehicle-to-grid mode, it works as a source providing energy for the grid [7]. In this condition, a retailer can play a critical role as an intermediary between consumers and the system operators [8], by aggregating EVs for participation in energy market [6]. Moreover, a retailer as a demand response (DR) aggregator may act like brokers between DR resources and system operator in electricity markets. In some studies, authors have presented optimal algorithms for scheduling the flexible loads and investigated their impacts on the demand patterns or electricity cost [9] and [10]. But, they have not considered the retailers' procurement plan in details. Decision-making strategies for retailer participating in electricity markets have also been investigated in several research works. Some of these works address decision-making problem of EVs aggregator as a retailer to participate in energy market [11]-[15]. For example, a bi-level programming approach has been proposed in [10] based on the Stackelberg game model. In [12], a bidding strategy for EV aggregator has been proposed to minimize the expected electricity costs considering price volatility. Authors in [13] present a fuzzy information gap decision theory based framework for electricity retailers to determine the energy acquisition strategy. Additionally, the point estimate method is proposed to deal with the uncertainty of rivals' strategies. A theoretical model of the competition between DR aggregators for selling energy previously stored in an aggregation of storage devices given sufficient demand from other aggregators through an incomplete information game is proposed in [14]. The performance of a plug-in EV aggregator in electricity markets is proposed in [15] in which the aggregator maximizes the profit and optimizes EV owners' revenue by applying changes in tariffs to compete with other market players for retaining current customers and acquiring new owners. In [16], unlike the usual market operations, it has been assumed that the aggregator's bidding influences the market prices. In the same work, the effect of the aggregator's bidding strategy on the prices has been analyzed via a bi-level program.

Most of the reviewed literatures have not addressed the competition among players in the decision-making problem. Also, some of them have not considered the preferences of EV owners and their discharging process in the scheduling program of the aggregator. In some other research works, decision-making strategies for retailers with considering both EVs and other flexible demands have been studied in [17]-[19]. In [17] a bidding strategy for retailers with flexible demands has been presented to maximize its expected profit. In the same work, a stochastic programming has been used to manage the uncertainties of spot price, regulating price, customers' behaviors with considering price based-DR programs. Moreover, in [19] and [20] the same structures have been presented for bidding strategies of retailer for energy trading in day-ahead (DA) market. In [20] optimal scheduling problem of plug-in EV aggregators in electricity market considering different uncertainties is discussed.

Stochastic programming provides an adequate modeling framework in which decision-making problem of the retailer under uncertainties are properly formulated. Moreover, utilization of risk measurement tools within the stochastic optimization framework would allow effective risk management for a retailer [21]. On the other hand, some of the researchers have developed appropriate decision-making models in electricity markets by considering risk management tools to encounter the effects of undesired scenarios [22]-[24]. Conditional value at risk (CVaR), as a commonly used risk measurement tool, has been applied into the formulation of EV aggregators aiming to deal with their profit volatility [22]. Moreover, a stochastic optimization model for optimal bidding strategy of an EV aggregator has been proposed in [23], where CVaR has been used for managing financial risks caused by uncertainties. In the same manner, in [24], a risk-averse optimal bidding formulation has been proposed for the aggregator at the demand side based on CVaR method. The proposed approach ensures the robustness of the DA bidding strategy while considering the uncertainties associated with the renewable generation, real-time price, and loads demand. A risk-constrained profit maximization for microgrid aggregators with considering DR is proposed in [25] where a risk-constrained scenario-based stochastic programming framework is proposed to deal with various uncertainties. A bi-level strategic scheduling model is proposed in [26] in which the primary objective is to maximize the load serving entity's profit by optimally scheduling energy storage charging/discharging profile. In [27], the interaction between market players in DA and real-time markets is modeled via an incomplete information game theory algorithm. In this study, the uncertain behavior of responsive customers including plug-in EV owners and consumers is modeled and incomplete information game theory is developed. In [26] an optimal decision making program for participating EV aggregators in short term electricity market is proposed without considering discharge of EVs and responsive loads. In [29], a bi-level optimization approach is used, in which the operation problem of the distribution companies and the Independent System Operator are modeled in the upper- and lower-level problems, respectively. Also, the consumers can purchase their required electricity through distribution companies or choose a retailer. In order to compare the highlights and important aspects of this paper Table I is also added to show the contributions of the works in view of existing state of the art literature.

In this work a more completed risk-averse model is presented for decision-making problem of a retailer in a competitive environment. A stochastic model is developed for a retailer to determine the bidding and offering strategies in DA and regulation markets considering both responsive loads and EVs. The stochastic model is formulated as a bi-level problem that includes bi-linear products of decision variables. The upper-level problem represents the expected profit maximization of the retailer considering optimal biding and offering price to the customers while the lower-level problem represents the energy cost minimization for customers and EV owners. By using an equivalent single-level mixed-integer linear formulation based on Karush–Kuhn–Tucker (KKT) optimality conditions and duality theory [21], lower-level of the problem is transferred to the upper-level and solved by mixed integer liner programing (MILP). Moreover, uncertainties on DA prices up/down regulation markets prices, demand of customers' loads and EVs power together with the rival retailers' prices are taken into account through a stochastic programming model. In this study, CVaR index is used to consider the risk that allows the retailer to compare different offering strategies by considering the tradeoff between the expected profit and the low-profit risk. Also, the effect of different risk levels on decision-making of the retailer is studied through appropriate sensitivity analyses. Therefore, the main contributions of this paper can be summarized as bellow:

- A bi-level stochastic framework is provided for decision-making problem of a retailer to decide the optimal level of involvement in DA and regulation markets, as well as to obtain proper bidding strategy under uncertainties,
- A competitive market environment is modeled by considering the reaction of responsive loads and charging and discharging of EVs to the prices offered by the retailers,
- The impact of risk-aversion parameter on the decision making problem of the retailer in a realistic case study is studied and the sensitivity of the retailer's profit to the risk-aversion level in a competitive trading floor is analyzed.

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

Table I. The contribution of literatures in in view of existing state of the art.

Reference	Bi-level modelling	Competitive environment	Risk assessment	Discharge of EVs	Demand response
[13]	-	✓	✓	-	-
[14]	-	✓	-	-	✓
[15]	-	✓	-	✓	-
[17]	-	-	✓	-	✓
[20]	-	-	✓	✓	-
[25]	-	-	✓	-	✓
[26]	✓	-	-	✓	-
[27]	-	✓	-	✓	✓
[28]	✓	✓	✓	-	-
[29]	✓	✓	-	-	✓
This paper	✓	✓	✓	✓	✓

2. Proposed Decision-making Strategy

This study presents a decision-making problem for a retailer in a competitive environment. This problem is formulated as a bi-level programming model. In the upper-level, the retailer determines optimal volume of energy purchasing from DA and regulation markets and the selling prices offered to the clients, so that its expected profit can be maximized. Moreover, the objective of the lower-level is to minimize the clients' costs. Here, it is assumed that the clients including a number of EVs and several industrial loads are equipped with smart energy management controllers (SEMC) and are able to respond to the electricity prices by adjusting their consumption levels to reduce their energy costs. Therefore, based on the offered electricity prices from different retailers, EV owners can change their behaviour and demand level, while SEMC in industrial loads can participate in DR programs, automatically and adjust the customer consumption to reduce energy costs. To this end, SEMC of each industrial load can choose proper retailer by monitoring real-time prices and can switch to the most competitive retailer in short-term scheduling. This is feasible by developing a fast communication media with bidirectional data transfer between the retailers and smart loads and the EV charging stations. It should be noted that the clients have not gotten involved each day in the process, but this act is done by SEMC system and therefore it is not difficult and burdensome in practice for the clients [19].

Based on the offered electricity prices from different retailers, EV owners can change their behavior and demand level, while industrial loads can participate in DR programs and adjust their consumption to reduce energy costs. The framework of the bi-level decision-making problem is illustrated in Figure 1. In energy trading phase, the retailer encounters different uncertainties including prices of DA market, up/down regulation markets, rival retailers' prices as well as demand of customers' and EVs. These uncertainties can be modeled by using scenario generation and reduction techniques. In this study, a proper probability density function (PDF) is used for each stochastic variable to model its forecasting errors [29].

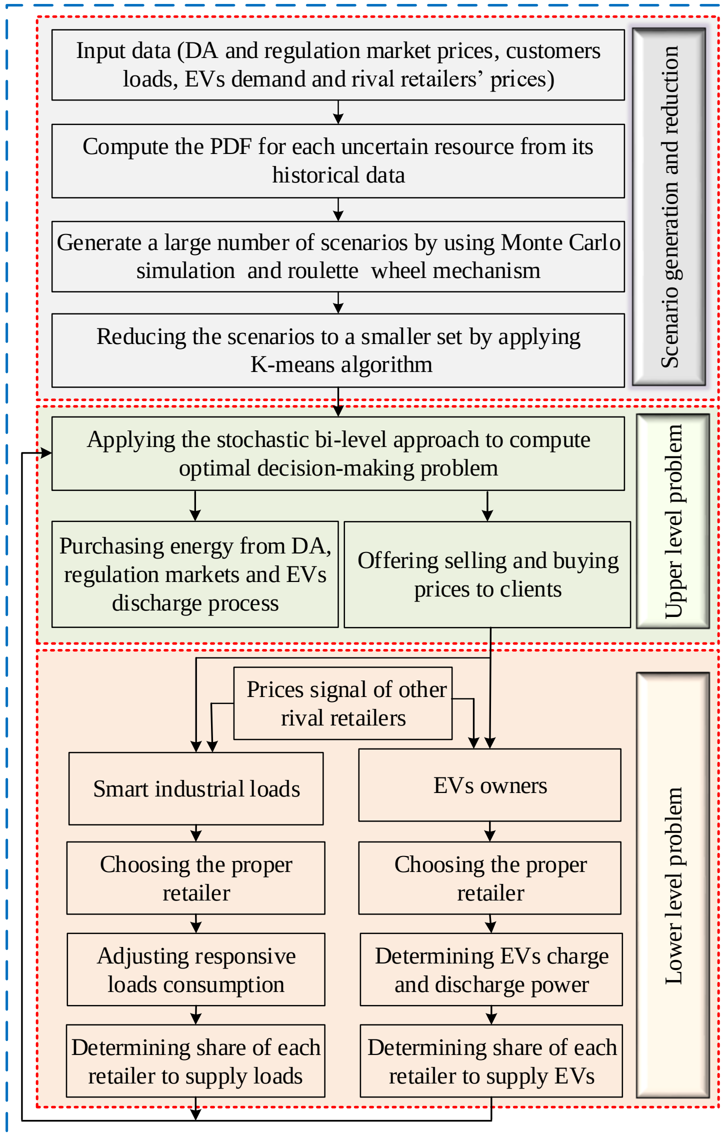

Figure 1. The structure of bi-level decision-making problem for retailer's participation in DA and balancing energy markets.

Monte-Carlo simulation (MCS) and roulette wheel mechanism (RWM) are used to generate a large number of scenarios representing the uncertain parameters based on their corresponding PDFs over the examined period [32]. To mitigate the computational burden of the stochastic programming, K-means algorithm [33] is then used to reduce the number of scenarios into a smaller set providing well enough the uncertainties. The reduced scenarios are applied to the stochastic bi-level model to solve the decision-making problem.

In the upper-level of the problem, the amount of traded energy and the offered prices to the clients would be obtained. Moreover, in this level, offered prices for discharge of EVs is also determined. In the lower-level, the industrial loads and EVs demand choose their retailer based on the offering prices. It should be noted that each industrial customer has some responsive loads that can participate in price based-DR program and adjust their consumption. By implementing DR programs and energy management of EVs, the share of each retailer to supply the industrial loads and EVs demand are determined and apply to the upper-level program. Furthermore, because the retailer encounters different uncertainties in its decision-making problem, it is required to investigate its expected profit in different levels of risk aversion. In this regard, the sensitivity of the retailer's profit to the risk aversion parameter is analyzed.

3. THE FRAMEWORK OF MARKET ENVIRONMENT

Here, a short term trading floor including the DA market, and a real-time energy balancing mechanism is considered. It is assumed that the retailer has no market power capability in either of the aforementioned markets and acts as a price-taker. In this work, competitive environment also denotes a situation where competition concerns the retail level and not by exercising market power in the different trading floors of electricity markets. Also, the objective of retailer is to maximize its expected profits from trading energy in the DA and to minimize the imbalance cost incurred in the regulating market as well as supplying the loads and EVs. Each one of the two markets is cleared through a single auction process as bellow:

- The DA market concerning the whole day d is cleared at 10 A.M. of day d-1. Because of the significant delay between the closure of this market and the beginning of the energy delivery period (14 h), the regulating market is required to take corrective actions to reduce or eliminate the differences between the expected demand and the schedule cleared in the DA market.
- The regulating market ensures the real-time balance between the real-time operation and the last energy program cleared in the DA market. For this reason, the regulating market remains open until 15 min before the delivery hour. Therefore, through this market, energy imbalances are corrected and priced.

In this paper, the bidding strategy of retailer in the DA market is proposed where the retailer submits the required volume of energy to this market. In this stage, decisions are made based on plausible realizations of the stochastic processes including market prices (DA, and regulating prices) and the loads of demand and EVs. Once the DA market price is known for each time period, the retailer decides the amount of energy to sell/buy in/from the regulating market. Then, in second stage, and for every DA market price realization, decisions are made based on plausible scenarios of regulating prices and the required demand of loads and charge/discharge of EVs.

4. RISK-CONSTRAINED STOCHASTIC BI-LEVEL DECISION-MAKING PROBLEM FORMULATION

4.1. Incorporating Risk Management

A risk management criterion is typically used to control the outcome volatility of the problem and avoid undesired profit scenarios due to various uncertainties. In the risk-neutral formulation, only the expected profit is maximized while the achieved optimal expected profit may include high possibility of low profits or even negative profits (losses). Therefore, CVaR as a measurement tool is incorporated to the problem of decision-making of the retailer. Mathematically, CVaR at a given confidence level α, is defined as below, [34]:

$$CVaR = \max_{\xi,\eta_\omega}\left(\xi - \frac{1}{1-\alpha}\sum_{\omega=1}^{\Omega}\pi_\omega . \eta_\omega\right) \tag{1}$$

Subject to:

$$\eta_\omega + profit_\omega - \xi \geq 0; \quad \eta_\omega \geq 0 \tag{2}$$

where, $profit_{\omega}$ stands for the profit in scenario ω, η_{ω} as an auxiliary non-negative variable shows the difference between auxiliary variable ξ and the $profit_{\omega}$ when the $profit_{\omega}$ is smaller than ξ and π_{ω} is the probability of scenario ω.

4.2.Objective Function of the Problem

The objective of the retailer is to maximize its expected profit and minimize the customers' payments confronting with uncertainties. Therefore, a risk-constrained stochastic bi-level structure using CVaR measurement tool is provided to the problem. In this aim, through a risk aversion parameter β as a weighting factor, CVaR is added to the risk-neutral optimization problem. Therefore, the objective function from the retailer's viewpoint is as follows:

$$Maximize \quad \sum_{\omega=1}^{\Omega} \pi_{\omega}.profit_{\omega} + \beta.CVaR \tag{3}$$

where the $profit_{\omega}$ in each scenario ω is defined as:

$$profit_{\omega} = \sum_{\omega\in\Omega} \pi_{\omega} \sum_{t\in T} [(E^{D}_{t,\omega}\rho^{D}_{s_0,t} + E^{Ch}_{t,\omega}\rho^{Ch}_{s_0,t} + E^{B^-}_{t,\omega}\rho^{B^-}_{t,\omega}) - (E^{DA}_{t,\omega}\rho^{DA}_{t,\omega} + E^{B^+}_{t,\omega}\rho^{B^+}_{t,\omega} + E^{Dis}_{t,\omega}\rho^{Dis}_{s_0,t})] \tag{4}$$

The objective function of the upper-level is the sum of the revenues obtained from selling energy to the customers, and EVs and participating in down regulation market, minus purchasing energy from DA and positive balancing markets as well as buying energy from EVs discharging process.

Moreover, the objective of the lower-level of the problem from the customers' viewpoint can be formulated as follow:

$$Minimize \begin{bmatrix} \widehat{E}^{D}_{t}(\rho^{D}_{r_0,t}X^{D}_{r0,t,\xi} + \sum\limits_{\substack{r\in N_r \\ r\neq 0}} \rho^{D}_{r,t,\xi}X^{D}_{r,t,\xi}) \\ +\widehat{E}^{Ch}_{t}(\rho^{Ch}_{r_0,t}X^{Ch}_{r0,t,\xi} + \sum\limits_{\substack{r\in N_r \\ r\neq 0}} \rho^{Ch}_{r,t,\xi}X^{Ch}_{r,t,\xi}) \\ -\widehat{E}^{Dis}_{t}(\rho^{Dis}_{r_0,t}X^{Dis}_{r0,t,\xi} + \sum\limits_{\substack{r\in N_r \\ r\neq 0}} \rho^{Dis}_{r,t,\xi}X^{Dis}_{r,t,\xi}) \end{bmatrix} + \begin{bmatrix} \sum\limits_{r\in N_r}\sum\limits_{\substack{r'\in N_r \\ r\neq r'}} \widehat{E}^{D}_{t}K^{D}_{r,r'}Z^{D}_{r,r',t,\xi} \\ +\sum\limits_{r\in N_r}\sum\limits_{\substack{r'\in N_r \\ r\neq r'}} \widehat{E}^{Ch}_{t}K^{Ch}_{r,r'}Z^{Ch}_{r,r',t,\xi} \\ +\sum\limits_{r\in N_r}\sum\limits_{\substack{r\in N_r \\ r'\neq r}} \widehat{E}^{Dis}_{t}K^{Dis}_{r,r'}Z^{Dis}_{r,r',t,\xi} \end{bmatrix} \tag{5}$$

In the above equation, index *r0* denotes the under-study retailer. The three lines in the left side of equation (5) represent the costs of purchased energy from the under-study and rival retailers for demand loads and charge/discharge of EVs, respectively. The three lines in the right side of the equation represent the reluctance of customers and EV owners to change their retailer for providing their loads, charge and discharge of EVs, respectively.

4.3.Constraints of the Problem

The proposed objective function is subject to the upper-level and lower-level constraints.

1) Upper-level constraints: Constraint (6) denotes the energy balance for each scenario and at each time. In (7)-(9) the share of the under-study retailer to supply loads and EVs' charge/discharge demand are determined. Constraint (10) represents the non-anticipativity that shows identical DA bids have to be made in all scenarios with equal DA prices. Moreover, constraints (11) and (12) represent the limitation of energy trading in positive and negative balancing market, respectively.

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$$E_{t,\omega}^{D} + E_{t,\omega}^{Ch} - E_{t,\omega}^{Dis} = E_{t,\omega}^{DA} + E_{t,\omega}^{B^+} - E_{t,\omega}^{B^-} \tag{6}$$

$$E_{t,\omega}^{D} = E_{t,\omega}^{T_D} \sum_{\xi \in \Xi} \upsilon^{D}(\xi) X_{r_0}^{D}(\xi) \tag{7}$$

$$E_{t,\omega}^{Ch} = E_{t,\omega}^{T_{Ch}} \sum_{\xi \in \Xi} \upsilon^{Ch}(\xi) X_{r_0}^{Ch}(\xi) \tag{8}$$

$$E_{t,\omega}^{Dis} = E_{t,\omega}^{T_{Dis}} \sum_{\xi \in \Xi} \upsilon^{Dis}(\xi) X_{r_0}^{Dis}(\xi) \tag{9}$$

$$E_{t,\omega}^{DA} = E_{t,\omega'}^{DA} \tag{10}$$

$$E_{t,\omega}^{B^+} \le \overline{P} \tag{11}$$

$$E_{t,\omega}^{B^-} \le \overline{P} \tag{12}$$

2) Lower-level constraints: In (13) the share of each retailer to supply demand loads and EVs charge/discharge energies is determined. In (14) the total expected customers demand and charge/discharge loads of EVs is obtained. Constraint (15) denotes that all of the loads and EVs should be supplied by all of the retailers. In (16) and (17) the limitation of variables are presented. Finally, the limitation of energy exchange between retailers and customers is expressed in (18).

$$X_r^{\ell}(\xi) = X_r^{0,\ell}(\xi) + \sum_{\substack{r' \in N_r \\ r' \ne r}} Z_{r',r}^{\ell}(\xi) - \sum_{\substack{r' \in N_r \\ r' \ne r}} Z_{r,r'}^{\ell}(\xi) \tag{13}$$

$$\widehat{E}_t^{\ell} = \sum_{\omega \in \Omega} \pi_{\omega} E_{t,\omega}^{D_{\ell}} \tag{14}$$

$$\sum_{r \in N_r} X_r^{\ell}(\xi) = 1 \tag{15}$$

$$X_r^{\ell}(\xi) \ge 0 \tag{16}$$

$$Z_{r,r'}^{\ell}(\xi) \ge 0, \qquad \forall r, r' \in N_r, r \ne r' \tag{17}$$

$$0 \le E_{t,\omega}^{\ell} \le \overline{P}^{\ell} \tag{18}$$

Moreover, constraints (19)-(22) impose limits on EV battery at each time period that should be considered in the problem [29].

$$SoC_{t,\omega} = SoC_{t-1,\omega} + \eta^{Ch} E_{t,\omega}^{Ch} - \frac{1}{\eta^{Dis}} E_{t,\omega}^{Dis} ,: \lambda_{t,\omega}^{s} \tag{19}$$

$$\underline{SoC} \times E^{Cap} \le SoC_{t,\omega} \le \overline{SoC} \times E^{Cap} : \underline{\mu}_{t,\omega}^{s}, \overline{\mu}_{t,\omega}^{s} \tag{20}$$

$$0 \le \eta^{Ch} \times E_{t,\omega}^{Ch} \le (\overline{SoC} \times E^{Cap}) - SoC_{t-1} : \underline{\gamma}_{t,\omega}^{Ch}, \overline{\gamma}_{t,\omega}^{Ch} \tag{21}$$

$$0 \le \frac{1}{\eta^{Dis}} E_{t,\omega}^{Dis} \le SoC_{t-1,\omega} : \underline{\gamma}_{t,\omega}^{Dis}, \overline{\gamma}_{t,\omega}^{Dis} \tag{22}$$

In addition, there are some of the technical constraints that represent customers' participation in DR programs. In this study, the energy consumption of customers at each hour is determined based on the price signal and their demand elasticity [35]. The customers are encouraged to adjust their energy consumption by shifting and shedding controllable loads. Therefore, the energy consumption changes from E_t^{int} to E_t in period *t* as below:

$$E_t = E_t^{\text{int}} + \Delta E_t \quad (23)$$

The benefit of customers is obtained as bellow:

$$S(E_t) = B(E_t) - E_t .\rho_t^D \quad (24)$$

where, $S(E_t)$ and $B(E_t)$ stand for the benefit and income of customers at period t after implementing DR program. The following criteria should be maximized in order to obtain the benefit of customers [36]:

$$\frac{\partial S(E_t)}{\partial E_t} = \frac{\partial B(E_t)}{\partial E_t} - \rho_t^D = 0 \quad (25)$$

Based on the model represented in [37], the energy consumption of customers at time t is obtained as follows:

$$E_t = E_t^{\text{int}}.\exp \sum_{h \in T} Elas_{t,t}.\ln[\frac{\rho_t^D}{\rho_t^{D,\text{int}}} + \frac{1}{1+Elas_{t,t}^{-1}}] \quad (26)$$

4.4. Equivalent Linear Single-Level Problem

The problem explained above is a nonlinear one due to the bilinear product of terms $E_{t,\omega}^D \rho_{r_0,t}^D$, $E_{t,\omega}^{Ch} \rho_{r_0,t}^{Ch}$ and $E_{t,\omega}^{Dis} \rho_{r_0,t}^{Dis}$ in (4). To derive the single-level formulation, the KKT optimality conditions of the lower-level problem (5) and (13)-(22) are obtained and incorporated in the upper-level problem. Then the bilinear terms are also replaced with their equivalent expressions using the strong duality theorem [26] and [21] as bellow:

$$\operatorname{Re} v_{t,\omega}^D = \frac{E_{t,\omega}^{T_D}}{\hat{E}_t^D} \sum_{\xi \in \Xi} \upsilon^D(\xi) \left[-\sum_{\substack{r \in N_r \\ r \neq 0}} \hat{E}_t^D \rho_{r,t,\xi}^D X_r^D(\xi) - \sum_{r \in N_r} \sum_{\substack{r' \in N_r \\ r' \neq r}} \hat{E}_t^D K_{r,r'}^D Z_{r,r'}^D(\xi) + \sum_{r \in N_r} X_r^{0.D}(\xi) \varepsilon_r^D(\xi) + \phi^D(\xi) \right] \quad (27)$$

$$\operatorname{Re} v_{t,\omega}^{Ch} = \frac{E_{t,\omega}^{Ch}}{\hat{E}_t^{Ch}} \sum_{\xi \in \Xi} \upsilon^{Ch}(\xi) \left[-\sum_{\substack{r \in N_r \\ r \neq 0}} \hat{E}_t^{Ch} \rho_{r,t,\xi}^{Ch} X_r^{Ch}(\xi) - \sum_{r \in N_r} \sum_{\substack{r' \in N_r \\ r' \neq r}} \hat{E}_t^{Ch} K_{r,r'}^{Ch} Z_{r,r'}^{Ch}(\xi) + \sum_{r \in N_r} X_r^{0.Ch}(\xi) \varepsilon_r^{Ch}(\xi) + \phi^{Ch}(\xi) \right] \quad (28)$$

$$\operatorname{Re} v_{t,\omega}^{Dis} = \frac{E_{t,\omega}^{Dis}}{\hat{E}_t^{Dis}} \sum_{\xi \in \Xi} \upsilon^{Dis}(\xi) \left[-\sum_{\substack{r \in N_r \\ r \neq 0}} \hat{E}_t^{Dis} \rho_{r,t,\xi}^{Dis} X_r^{Dis}(\xi) - \sum_{r \in N_r} \sum_{\substack{r \in N_r \\ r' \neq r}} \hat{E}_t^{Dis} K_{r,r'}^{Dis} Z_{r,r'}^{Dis}(\xi) + \sum_{r \in N_r} X_r^{0.Dis}(\xi) \varepsilon_r^{Dis}(\xi) + \phi^{Dis}(\xi) \right] \quad (29)$$

By using KKT conditions and strong duality theorem, the lower-level problem is obtained and is solved as a single-level MILP problem [26]. This equivalent problem includes the objective function of the upper-level, the constraints of both levels and the equivalent expression of lower-level objective function. Therefore, the equivalent single-level linear problem with considering customers objective is represented as follows:

$$Maximize \ \sum_{\omega \in \Omega} \pi_\omega \sum_{t \in T} \begin{bmatrix} (\operatorname{Re} v_{t,\omega}^D + \operatorname{Re} v_{t,\omega}^{Ch} + E_{t,\omega}^{B^-} \rho_{t,\omega}^{B^-}) \\ -(\operatorname{Re} v_{t,\omega}^{Dis} + E_{t,\omega}^{DA} \rho_{t,\omega}^{DA} + E_{t,\omega}^{B^+} \rho_{t,\omega}^{B^+}) \end{bmatrix} + \beta(\xi - \frac{1}{1-\alpha} \sum_{\omega=1}^{\Omega} \pi_\omega.\eta_\omega) \quad (30)$$

It should be noted that the above objective function is subject to constraints (6)-(22) and (27)-(29) as well as those obtained from KKT and duality theory that are presented in Appendix A.

5. Simulation and Numerical Results

5.1. Case Study

A case study based on realistic data from the Nord Pool market [38] is implemented to evaluate the applicability and effectiveness of the proposed methodology. The scheduling horizon is considered one day which is divided into 24 equal time intervals. In the case study, it is assumed that the under-study retailer (Ret_0) competes with three rival retailers (Ret_1, Ret_2 and Ret_3) in order to supply the energy of industrial loads and a number of EVs. The hourly forecasted demand of the customers and EVs are considered as shown in Figure 2. The hourly prices offered by the rival retailers are also modeled by three randomly generated scenarios with different probabilities. For the sake of simplicity, all EVs are assumed to be the same and only 20% of them participate in discharge process. EV owners and responsive loads respond to the price signal based on their price elasticity [37]. The initial *SoC* of EVs at each scenario is randomly generated between 0-1 pu. Also, the initial hourly demands of customers and EVs supplied by each retailer (X_r^0) are also generated randomly. Furthermore, DA and up/down-regulation prices are obtained from the DK-West area in the Nord Pool market during September 2016, and shown in Figure 3.

A number of 1000 initial scenarios are generated using MCS and RWM strategies to model the forecasted errors. Then, K-means algorithm is also implemented to reduce the initial scenarios into a set of 45 selected scenarios that represent well enough the uncertainties. Finally, the reduced scenarios are applied to the proposed decision-making model to maximize the expected profit of the under-study retailer. The optimization is carried out by CPLEX solver using GAMS software [39] on a PC with 4 GB of RAM and Intel Core i7 @ 2.60 GHz processor.

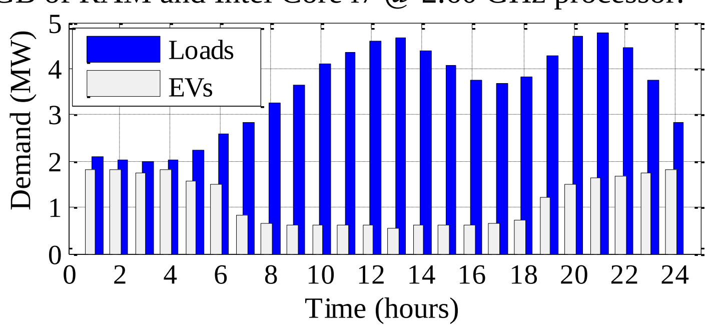


Figure 2. The hourly forecasted demand of the customers' loads and EVs.

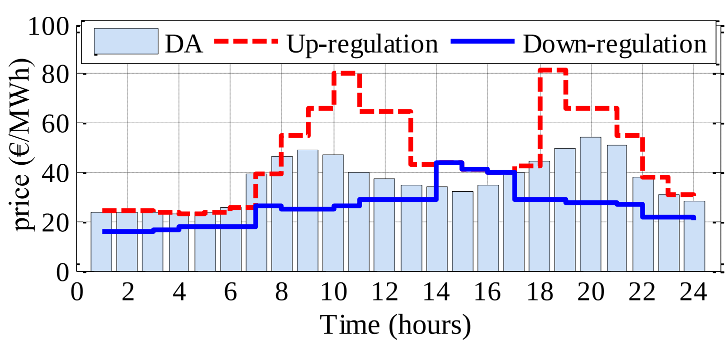


Figure 3. The forecasted electricity prices of DA, up and down regulation markets.

5.2. Numerical Results

The proposed approach is applied to the case study and risk-constrained decision-making of the retailer is analyzed in different modes of EVs operation (grid-to-vehicle (G2V) and V2G) as well as responsive loads participation in DR programs. The expected profit of the under-study retailer

(Ret$_0$) versus CVaR and its standard deviation for different values of β are shown in Figure 4 (a) and (b), respectively. In this study, the confidence level to compute CVaR is considered 95% in all instances. As can be observed, by increasing β the expected profit decreases and CVaR increases in all cases. The maximum profit at the minimum CVaR is attained when the retailer has no risk aversion decision. By increasing β, the expected profit of the retailer decreases, however the average expected profit of the worst-case scenarios increases, thus, the risk exposure is mitigated. The expected profit and CVaR varies from 298.534€ and -39.816€ (for $\beta = 0$) to 246.159€ and -5.953€ (for $\beta = 5$), respectively whichdenotes a reduction of 17.5% in the expected profit and 85.04% increase in the CVaR. The negative CVaR represents that the profit in some scenarios is negative, showing that there is a probability of experiencing financial losses.

It is observed that for lower values of β, the expected profit is not highly dependent on the risk-aversion of the retailer. However, the CVaR increases severely by increasing β. This also implies that a small decrease in the expected profit can be used to reduce efficiently the risk of profit variability. Therefore, based on the efficient frontier profile the retailer can decide its degree of risk-aversion to participate in the competitive electricity markets in different cases. Moreover, as shown in Figure 4 (b), with increasing β, the standard deviation of the retailer's profit decreases. In fact, when the retailer tries to hedge against volatilities, the low probable profits in undesired scenarios are eliminated. But, when the retailer becomes less risk-averse, its profits become more dispersed and far from their expected values.

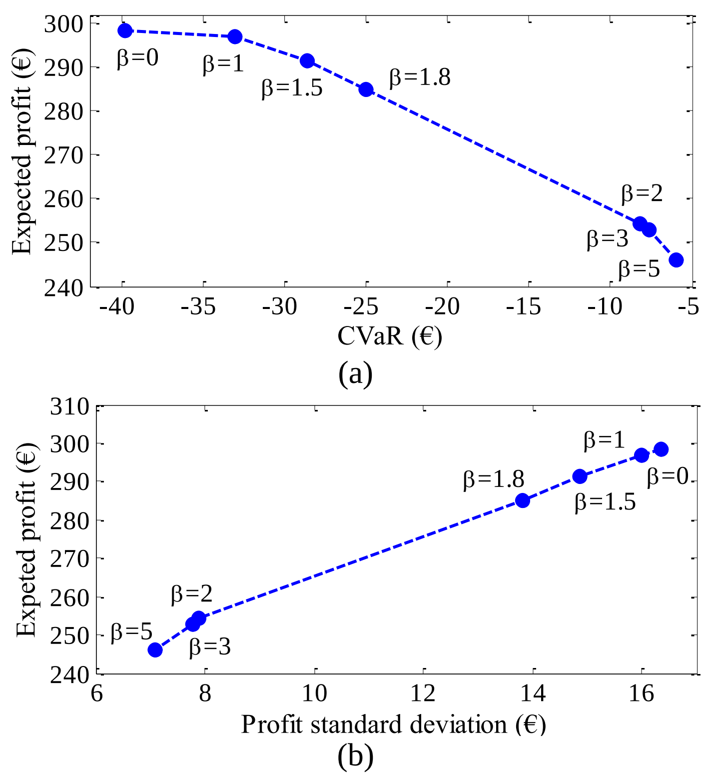
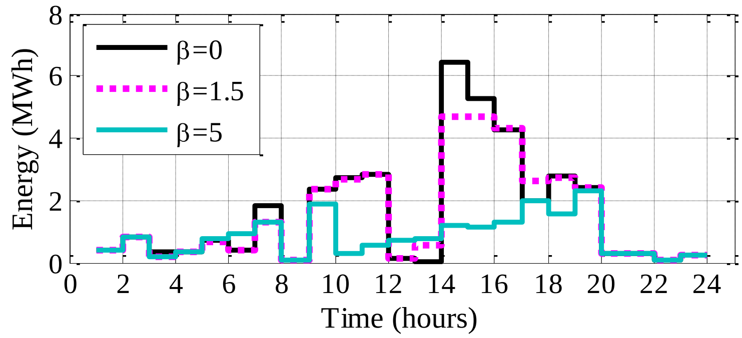


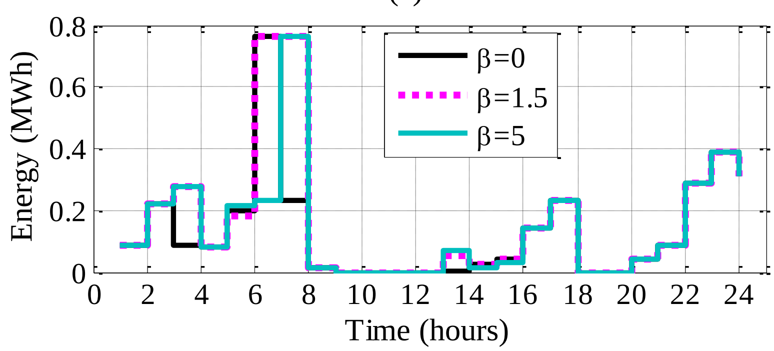
Figure 4. Expected profit of the retailer versus, (a) CVaR, (b) Standard deviation of the expected profit.

The hourly energy purchased by the retailer from the DA and up/down regulation markets for different values of β is shown in Figure 5. The retailer purchases high amount of the required energy from DA market and covers the effects of uncertainties by trading energy in regulation markets. As can be observed, the retailer in the risk-neutral case (β=0) provides most of the customers' energy need from DA market. However, by increasing β, energy procurement from DA market decreases at some hours, especially during 14:00 to 16:00 due to the price volatility in DA market as compared to the regulation markets. In this condition, the retailer needs to compensate the energy deviations in the expensive up-regulation market which in turn imposes further cost of energy provision.

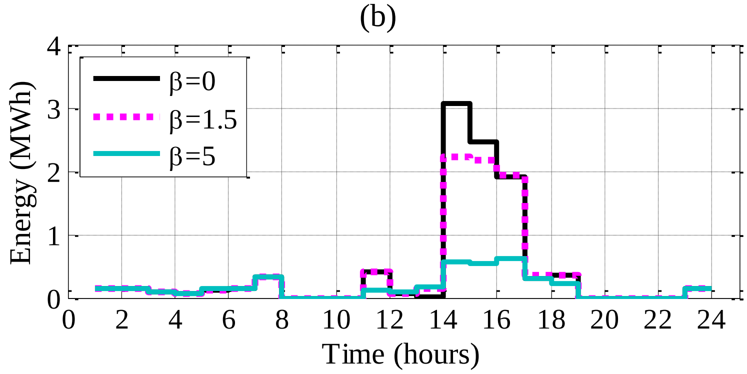
In addition, it is observed from Figure 5 (c) that, by increasing risk aversion factor, the participation of the retailer in down-regulation market decreases to hedge against the volatilities of this trading floor. Also, it is observed that regardless of β values, the retailer bids for load decrement when down-regulation prices are high (from 14:00 to 16:00) to achieve more revenue. In fact, this procedure indicates that the retailer can adapt to hedge against profit volatility with trading less energy in DA market in the hope that energy deviations can be compensated in the up-regulation market with less volatile prices. Moreover, its participation in the volatile down-regulation market mitigates as it behaves more risk-averse.



(a)



(b)



(c)

Figure 5. Energy procurement by the under-study retailer from, (a) DA market, (b) up-regulation market, and (c) down-regulation market.

The hourly charging and discharging prices offered by all the retailers is shown in Figure 6. For the sake of simplicity, the DR tariff and charging prices are the same. As shown, prices offered by retailer 2 are the highest at the peak hours and are the lowest in off-peak periods. Retailer 1 mostly offers moderate prices compared to retailers 2 and 3. As can be seen, the under-study retailer offers competitive prices most of the times to stay in the game for energy exchange. Furthermore, the discharge prices offered by the examined retailer are relatively high to attract more EV owners. In fact, when the markets prices are relatively high, the retailer prefers to purchase energy from the EV owners instead of the expensive market. Likewise, it offers the lowest prices for discharging at some hours especially during 14:00 to 16:00 when the DA and up-regulation markets have low prices (see Figure 3).

In order to investigate the behavior of the retailer encountering uncertain resources, its optimal offering prices in different values of risk-aversion parameter are shown in Figure 7. As observed, by increasing β, the price signals don't vary substantially due to the fact that in a competitive market, an increase in the selling prices offered by a given retailer can easily motivate customers to join other retailers as energy supplier. Therefore, in order to stay in the game, the retailer should not increase the selling price, significantly. However, when it behaves more risk-averse, it increases the selling prices in some hours slightly to compensate the extra cost incurred due to participation in expensive markets. With the same reason, the retailer does not decrease offered discharge prices significantly in order to keep a reasonable market share while making profit.

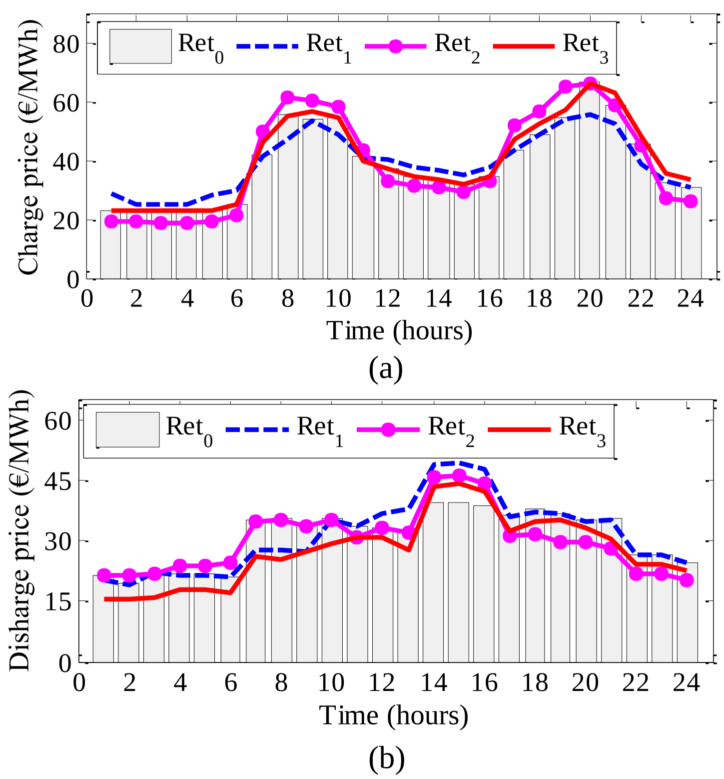
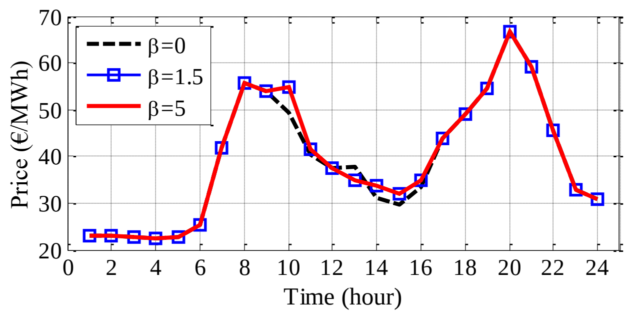


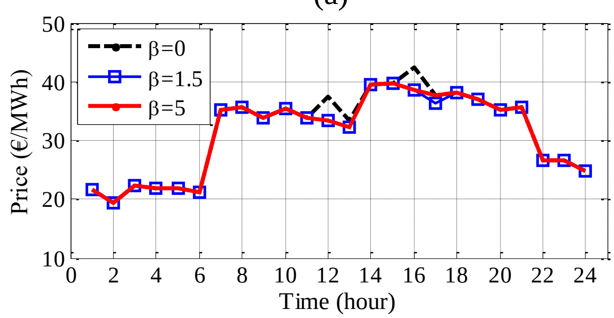
Figure 6. Hourly price signal offered by different retailers, (a) charging prices, and (b) discharging prices.

Figure 8 shows the share of each retailer as a load serving entity in supplying the customers' loads and EVs charge and discharge demand in different values of β during the scheduling horizon. Each sector of the pie charts represents the percentage of the expected value of energy that is supplied by the associated retailer. As it can be seen, by increasing the value of risk-aversion from $\beta = 0$ to $\beta = 5$, the market share of the retailer decreases around 42%. Moreover, when the retailer is more risk-averse, its share in providing charge demand decreases. In other words, by increasing β, the procurement of the retailer from DA market decreases and it purchases more energy from expensive up-regulation market. Consequently, it offers higher charge prices to compensate the payments which in turn lead to lower number of clients and market share.

As mentioned before, the discharge price offered by the under-study retailer is such that to attract the EV owners for discharge process. Therefore, the share of the retailer in purchasing the discharge energy from EVs is the highest (39%). However, when the risk-aversion parameter increases, the offered prices by the retailer for discharging actions decreases slightly which leads to the lower market share.



(a)



(b)

Figure 7. Hourly price signal offered by the retailer in different values of β, (a) charging prices, and (b) discharging prices.

As explained before, with increasing β, the retailer's share decreases in a competitive market. Table II shows the percentage of customers' demand transferred between the retailers for different values of β at two sample hours. It should be noted that the minus sign (-) denotes a demand shift in the opposite direction. As can be observed, for example at 8:00, the transferred percentage of customers and EVs does not change as the value of β increases. That can be as a result of unchanged charge and discharge prices as shown in Figure 7. On the other hand, at 15:00, around 10 % of the responsive loads change the serving entity and go from Ret_1 to Ret_0 in β=0. The same happens in β=5 where a demand transfer of 2.23% happens between Ret_0 and Ret_1.

The EVs' charge and discharge demand transferring among retailers also follows the same pattern. It can be seen that at 15:00, the transferred percentage of EVs' charging load from Ret_0 to Ret_1 increases from 1.01% in β=0 to 3.49% in β=5. In the same manner, the transfer of customers among retailers and different hours can be analyzed.

Table III shows the expected energy exchanged between the retailer and the network in DA and up/down regulation markets in different values of β. As shown, with increasing β from 0 to 5, the retailer's participation in DA and negative balancing market changes from 37.353 and 9.936MWh to 19.651 and 4.013MWh; which shows a reduction of 47.3% and 59.6%, respectively. In other words, when the retailer becomes more risk-averse, it procures less blocks of energy from more volatile markets. Numerical results of Table III also demonstrate that by increasing β from 0 to 1.8, the retailer purchases more energy from up-regulation market (from 3.240MWh to 4.002MWh) which has a more stable nature. However, further increase of the risk-aversion factor, results in less energy purchases from the up-regulation trading floor since the retailer increases the charging price signals and decreases the discharging price offers as shown in Figure 7.

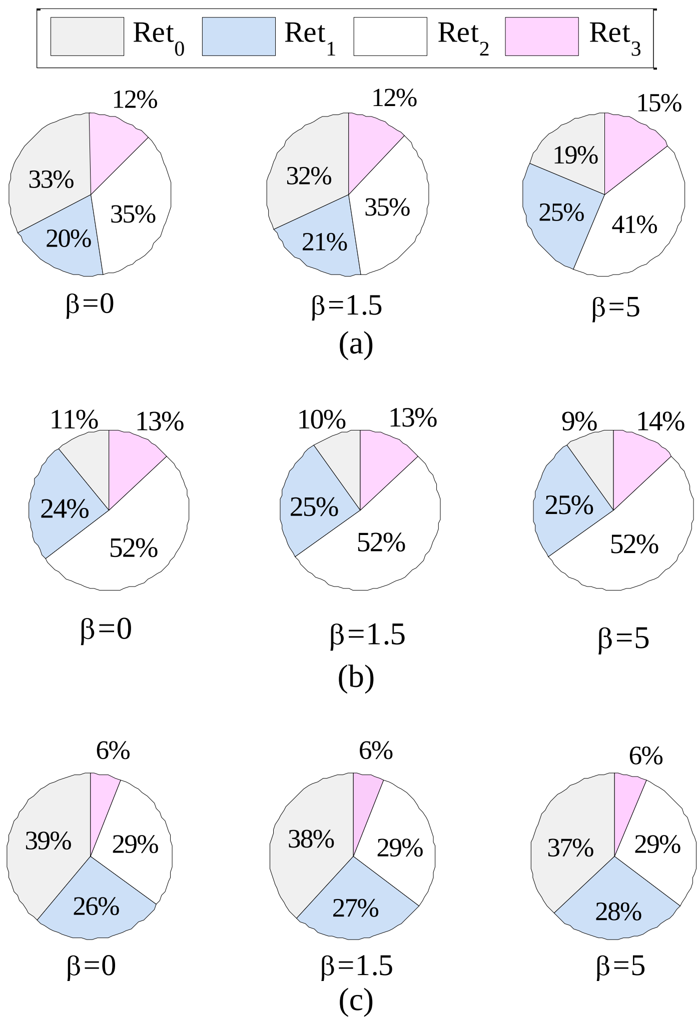


Figure 8. Share of different retailers in supplying demand, (a) demand of customers, (b) charging demand of EVs, and (c) discharging demand of EVs.

Table II. Transferred percentage of customers demand between the retailers in different β

Risk aversion parameter	Options	From Ret_0 to Ret_1	From Ret_0 to Ret_2	From Ret_0 to Ret_3	From Ret_1 to Ret_2	From Ret_1 to Ret_3	From Ret_2 to Ret_3
		At 8:00					
β =0	Responsive loads	18.74	2.11	-9.06	-16.63	-27.8	-11.17
	Charge of PEVs	18.73	2.11	9.06	-16.62	-27.79	-11.17
	Discharge of PEVs	-17.64	-12.62	-30.5	5.02	-12.86	-17.88
β=1.5	Responsive loads	18.73	2.11	-9.06	-16.62	-27.79	-11.17
	Charge of PEVs	18.73	2.18	-9.06	-16.62	-27.79	-11.17
	Discharge of PEVs	-17.64	-12.62	-30.5	5.02	-12.86	-17.88
β=5	Responsive loads	18.74	2.11	-9.06	-16.63	-27.8	-11.17
	Charge of PEVs	18.73	2.11	-9.06	-16.62	-27.79	-11.17
	Discharge of PEVs	-17.65	12.63	-30.51	5.02	-12.86	-17.88
		At 15:00					
β =0	Responsive loads	-9.81	-6.951	-17.87	2.86	-8.06	-10.96
	Charge of EVs	1.01	14.74	-7.04	13.73	-8.05	-21.78
	Discharge of EVs	18.18	9.43	-3.24	-8.75	-21.42	-12.67
β=1.5	Responsive loads	2.23	17.23	-5.77	15	-8	-23
	Charge of EVs	2.23	17.15	-5.83	14.92	-8.06	-22.98
	Discharge of EVs	18.31	9.52	-3.14	-8.79	-21.45	-12.66
β=5	Responsive loads	2.23	17.21	-5.83	14.98	-8.06	-23.44
	Charge of EVs	3.49	18.41	-3.31	14.92	-6.8	-21.72
	Discharge of EVs	18.31	9.52	-3.14	-8.79	-21.45	-12.66

Table III. Expected energy exchanged by the under-study retailer in different markets (in MWh)

β	DA	Up-Regulation	Down-Regulation
0	37.353	3.240	9.936
1	37.080	3.819	9.904
1.5	35.369	4.002	9.017
1.8	33.655	4.002	8.226
2	21.380	3.553	4.433
3	21.223	3.522	4.388
5	19.651	3.499	4.013

6. Conclusions

In this paper a risk-averse bi-level stochastic programming model was proposed for decision-making problem of a retailer in a competitive environment considering different uncertain recourses. In this problem, optimal energy purchasing by the retailer in the DA and regulating markets and its optimal selling prices to the clients was determined on a day scheduling horizon. Due to the uncertainties of markets and rivals' prices as well as the ones associated with demand's behavior, CVaR was incorporated into the optimal scheduling problem to model the risk-averse behavior of the retailer. The nonlinear stochastic bi-level programming problem was transformed into its equivalent single-level problem by using mathematical methods. The proposed strategy was also applied on a realistic case study to show its applicability and effectiveness. The main results of this work can be summarized as fallow:

- The expected profit of a given retailer depends on the risk-aversion level β. It was observed form the simulation results that by increasing β value, the expected profit and its standard deviation decrease while CVaR increases which accordingly denotes that the retailer makes less profits but in a more reliable way.
- In a risk-neutral case (β=0), the retailer tends to meet most of the demanded energy using DA market contracts, but in a risk-averse case (β=5) its energy procurement from DA market decreases. In fact, when β increases, the retailer can adapt to hedge against profit volatility in the presence of a regulation market; trading less energy in DA market in the hope that extra demand can be compensated through regulation markets.
- When β increases, the retailer changes its bidding strategy in a way to increase charge prices and decrease discharge prices to make more profit. However, this action is normally followed by a lower market share which in turn affects the retailer's profit negatively. Therefore, in a competitive environment, considering risk exposure can influence the decision-making of the retailer, substantially.

Future efforts will be mainly focused on the application of the proposed model in larger test systems with more competitive players and investigating the effects of competition among retailers on the system's security and reliability.

Appendix A.

In order to incorporate the upper level and lower level of the problem, the following steps are applied to the problem:

- For a given vector of upper-level variables, the Lagrangian function of the lower-level problem is obtained as bellow:

$$
\begin{aligned}
L = {} & \widehat{E}_t^{D}(\rho_{r_0,t}^{D} X_{r0,t,\xi}^{D} + \sum_{\substack{r\in N_r \\ r\neq 0}} \rho_{r,t,\xi}^{D} X_{r,t,\xi}^{D}) + \widehat{E}_t^{Ch}(\rho_{r_0,t}^{Ch} X_{r0,t,\xi}^{Ch} + \sum_{\substack{r\in N_r \\ r\neq 0}} \rho_{r,t,\xi}^{Ch} X_{r,t,\xi}^{Ch}) + \\
& - \widehat{E}_t^{Dis}(\rho_{r_0,t}^{Dis} X_{r0,t,\xi}^{Dis} + \sum_{\substack{r\in N_r \\ r\neq 0}} \rho_{r,t,\xi}^{Dis} X_{r,t,\xi}^{Dis}) + \sum_{r\in N_r} \sum_{\substack{r'\in N_r \\ r\neq r'}} \widehat{E}_t^{D} K_{r,r'}^{D} Z_{r,r',t,\xi}^{D} + \\
& + \sum_{r\in N_r} \sum_{\substack{r'\in N_r \\ r\neq r'}} \widehat{E}_t^{Ch} K_{r,r'}^{Ch} Z_{r,r',t,\xi}^{Ch} + \sum_{r\in N_r} \sum_{\substack{r\in N_r \\ r'\neq r}} \widehat{E}_t^{Dis} K_{r,r'}^{Dis} Z_{r,r',t,\xi}^{Dis} + \\
& \varepsilon_{r,\xi}^{\ell}(X_r^{\ell}(\xi) - X_r^{0,\ell}(\xi) - \sum_{\substack{r'\in N_r \\ r'\neq r}} Z_{r',r,t,\xi}^{\ell} + \sum_{\substack{r'\in N_r \\ r'\neq r}} Z_{r,r',t,\xi}^{\ell}) + \\
& \phi_{\xi}^{\ell}(\sum_{r\in N_r} X_r^{\ell}(\xi) - 1) + \lambda_{t,\omega}^{s}(SoC_{t,\omega} - SoC_{t-1,\omega} - \eta^{Ch} E_{t,\omega}^{Ch} + \frac{1}{\eta^{Dis}} E_{t,\omega}^{Dis}) + \\
& - \underline{\mu}_{t,\omega}^{s}(SoC_{t,\omega}^{E} - \underline{SoC} \times E^{Cap}) - \overline{\mu}_{t,\omega}^{s}(\overline{SoC} \times E^{Cap} - SoC_{t,\omega}^{E}) + \\
& - \underline{\gamma}_{t,\omega}^{ch}\left[\eta^{ch} \times (E_{t,\omega}^{ch}) \times \Delta t - SoC_{t-1,\omega}^{E}\right] - \overline{\gamma}_{t,\omega}^{ch}\left[\overline{SoC} \times E^{Cap} - SoC_{t-1,\omega}^{E} - \eta^{ch} \times E_{t,\omega}^{ch} \times \Delta t\right] + \\
& - \underline{\gamma}_{t,\omega}^{dch}\left[\frac{1}{\eta^{dch}} \times E_{t,\omega}^{dch} \times \Delta t\right] - \overline{\gamma}_{t,s}^{dch}\left[SoC_{t-1,\omega}^{E} - \frac{1}{\eta^{dch}} \times E_{t,\omega}^{dch} \times \Delta t\right]
\end{aligned}
\tag{A.1}
$$

where, $\underline{\gamma}_{t,\omega}^{ch/dch}, \overline{\gamma}_{t,\omega}^{ch/dch}, \lambda_{t,\omega}^{s},,\ \mu_{t,\omega}^{s},\ \phi_{\xi}^{\ell},\ \varepsilon_{r,\xi}^{\ell}$ are the Lagrangian multipliers.

- In addition to the primal feasibility constraints of the lower level, the KKT necessary optimality conditions of the lower-level problem would be obtained by partial derivative of the Lagrangian function.

$$\frac{\partial L}{\partial X_{r0,t,\xi}^{\ell}} = \hat{E}_t^{\ell} \rho_t^{\ell} - \varepsilon_{r0,\xi}^{\ell} - \phi_{\xi}^{\ell} = 0 \tag{A.2}$$

$$\frac{\partial L}{\partial X_{r,t,\xi}^{\ell}} = \hat{E}_t^{\ell} \rho_t^{\ell} - \varepsilon_{r,\xi}^{\ell} - \phi_{\xi}^{\ell} = 0 \tag{A.3}$$

$$\frac{\partial L}{\partial Z_{r,r',t,\xi}^{\ell}} = \hat{E}_t^{\ell} K_{r,r'}^{\ell} + \varepsilon_{r',\xi}^{\ell} - \varepsilon_{r,\xi}^{\ell} = 0 \qquad \forall r, r' \in N_r, r \neq r' \tag{A.4}$$

$$\frac{\partial L}{\partial SoC_{t,\omega}^{E}} = \lambda_{t,\omega}^{s} - \lambda_{t-1,\omega}^{s} - \underline{\mu}_{t,\omega}^{s} + \overline{\mu}_{t,\omega}^{s} - \underline{\gamma}_{t,\omega}^{ch} - \overline{\gamma}_{t,\omega}^{ch} - \underline{\gamma}_{t,\omega}^{dch} - \overline{\gamma}_{t,\omega}^{dch} = 0 \tag{A.5}$$

- The nonlinear complementary slackness conditions are equivalently expressed as a set of linear constraints as following:

$$\hat{E}_t^{D_\ell} \rho_{r,t,\omega}^{\ell} - \varepsilon_{r,\xi}^{\ell} - \phi_{\xi}^{\ell} \geq 0 \tag{A.6}$$

$$\hat{E}_t^{D_\ell} K_{s,s'}^{\ell'} + \varepsilon_{r,\xi'}^{\ell} - \varepsilon_{r,\xi}^{\ell} \geq 0 \tag{A.7}$$

$$\hat{E}_t^{D_\ell} \rho_{r,t,\xi}^{\ell} - \varepsilon_{r,\xi}^{\ell} - \phi_{\xi}^{\ell} \leq M_1^{\ell} e_s^{X_\ell}(\xi) \tag{A.8}$$

$$X^{\ell}(\xi) \leq M_2^{\ell}[1 - e_s^{X_\ell}(\xi)] \tag{A.9}$$

$$\hat{E}_t^{D_\ell} K_{s,s'}^{\ell} + \varepsilon_{s'}^{\ell}(\xi) - \varepsilon_{s}^{\ell}(\xi) \leq M_1^{\ell} e_{s,s'}^{Z_\ell}(\xi) \tag{A.10}$$

$$Z_{r,r'}^{\ell}(\xi) \leq M_2^{\ell}[1 - e_{s,s'}^{Z_\ell}(\xi)] \tag{A.11}$$

$$0 \leq \underline{\mu}_{t,\omega}^{\ell} \perp (E_{t,\omega}^{\ell}) \geq 0 \tag{A.12}$$

$$0 \leq \overline{\mu}_{t,\omega}^{\ell} \perp (\overline{P} - E_{t,\omega}^{\ell}) \geq 0 \tag{A.13}$$

$$0 \leq \underline{\mu}_{t,\omega}^{s} \perp (SoC_{t,\omega} - \underline{SoC}.E^{Cap}) \geq 0 \tag{A.14}$$

$$0 \leq \overline{\mu}_{t,\omega}^{s} \perp (\overline{SoC}.E^{Cap} - SoC_{t,\omega}) \geq 0 \tag{A.15}$$

$$0 \leq \underline{\gamma}_{t,\omega}^{Ch} \perp [\eta^{Ch}.E_{t,\omega}^{Ch}.\Delta t] \geq 0 \tag{A.16}$$

$$0 \leq \overline{\gamma}_{t,\omega}^{Ch} \perp [\overline{SoC}.E^{Cap} - SoC_{t-1,\omega} - \eta^{Ch}.E_{t,\omega}^{Ch}] \geq 0 \tag{A.17}$$

$$0 \leq \underline{\gamma}_{t,\omega}^{Dis} \perp [\frac{1}{\eta^{Dis}} E_{t,\omega}^{Dis} \Delta t] \geq 0 \tag{A.18}$$

$$0 \leq \overline{\gamma}_{t,\omega}^{Dis} \perp [SoC_{t-1,\omega} - \frac{1}{\eta^{Dis}} E_{t,\omega}^{Dis} \Delta t] \geq 0 \tag{A.19}$$

- Duality theory is applied to the problem as bellow:

$$Maximize\sum_{s\in N_s}\begin{bmatrix}(X^{0}_{r_D t,\xi}\varepsilon^{D}_{r}(\xi)\\ +\phi_D(\xi))+(X^{0}_{r_{ch}t,\xi}\varepsilon^{ch}_{r}(\xi)\\ +\phi_{ch}(\xi))-(X^{0}_{s_{dch},t,\xi}\varepsilon^{dch}_{r}(\xi)\\ +\phi_{dch}(\xi))\end{bmatrix}=$$

$$\hat{E}^{D}_{ch}\left[\rho^{D}_{s_0,t}X^{D}_{0}(t,\xi)+\sum_{\substack{s\in N_s\\ s\neq 0}}\rho^{D}_{s,t,\xi}X^{D}_{s}(t,\xi)+\sum_{s\in N_s}\sum_{\substack{s'\in N_s\\ s'\neq s}}K^{s,s'}_{D}Z^{s,s'}_{D}(t,\xi)\right]+ \tag{A.20}$$

$$\hat{E}^{D}_{ch}\left[\rho^{ch}_{s_0,t}X^{ch}_{0}(t,\xi)+\sum_{\substack{s\in N_s\\ s\neq 0}}\rho^{ch}_{s,t,\xi}X^{ch}_{s}(t,\xi)+\sum_{s\in N_s}\sum_{\substack{s'\in N_s\\ s'\neq s}}K^{s,s'}_{ch}Z^{s,s'}_{ch}(t,\xi)\right]+$$

$$\hat{E}^{D}_{dch}\left[\rho^{dch}_{s_0,t}X^{dch}_{0}(t,\xi)+\sum_{\substack{s\in N_s\\ s\neq 0}}\rho^{dch}_{e,s,\xi}X^{dch}_{s}(t,\xi)+\sum_{s\in N_s}\sum_{\substack{s'\in N_s\\ s'\neq s}}K^{s,s'}_{dch}Z^{s,s'}_{dch}(t,\xi)\right]$$

Also, with considering the following relations:

$$E^{D}_{t,\omega}=E^{T_D}_{t,\omega}\sum_{\xi\in\Xi}\upsilon^{D}(\xi)X^{D}_{r_0}(\xi) \tag{A.21}$$

$$E^{Ch}_{t,\omega}=E^{T_{Ch}}_{t,\omega}\sum_{\xi\in\Xi}\upsilon^{Ch}(\xi)X^{Ch}_{r_0}(\xi) \tag{A.22}$$

$$E^{Dis}_{t,\omega}=E^{T_{Dis}}_{t,\omega}\sum_{\xi\in\Xi}\upsilon^{Dis}(\xi)X^{Dis}_{r_0}(\xi) \tag{A.23}$$

The bilinear product of terms $E^{D}_{t,\omega}\rho^{D}_{r_0,t}$, $E^{Ch}_{t,\omega}\rho^{Ch}_{r_0,t}$ and $E^{Dis}_{t,\omega}\rho^{Dis}_{r_0,t}$ are replaced with their linear expressions as follow:

$$\mathrm{Re}\,v^{D}_{t,\omega}=\frac{E^{T_D}_{t,\omega}}{\hat{E}^{D}_{t}}\sum_{\xi\in\Xi}\upsilon^{D}(\xi)\begin{bmatrix}-\sum_{\substack{r\in N_r\\ r\neq 0}}\hat{E}^{D}_{t}\rho^{D}_{r,t,\xi}X^{D}_{r}(\xi)-\\ [\sum_{r\in N_r}\sum_{\substack{r'\in N_r\\ r'\neq r}}\hat{E}^{D}_{t}K^{D}_{r,r'}Z^{D}_{r,r'}(\xi)-\sum_{r\in N_r}X^{0.D}_{r}(\xi)\varepsilon^{D}_{r}(\xi)+\phi^{D}(\xi)]\end{bmatrix} \tag{A.24}$$

$$\mathrm{Re}\,v^{Ch}_{t,\omega}=\frac{E^{Ch}_{t,\omega}}{\hat{E}^{Ch}_{t}}\sum_{\xi\in\Xi}\upsilon^{Ch}(\xi)\begin{bmatrix}-\sum_{\substack{r\in N_r\\ r\neq 0}}\hat{E}^{Ch}_{t}\rho^{Ch}_{r,t,\xi}X^{Ch}_{r}(\xi)-\\ [\sum_{r\in N_r}\sum_{\substack{r'\in N_r\\ r'\neq r}}\hat{E}^{Ch}_{t}K^{Ch}_{r,r'}Z^{Ch}_{r,r'}(\xi)-\sum_{r\in N_r}X^{0.Ch}_{r}(\xi)\varepsilon^{Ch}_{r}(\xi)+\phi^{Ch}(\xi)]\end{bmatrix} \tag{A.25}$$

$$\operatorname{Re}v_{t,\omega}^{Dis} = \frac{E_{t,\omega}^{Dis}}{\widehat{E}_t^{Dis}} \sum_{\xi\in\Xi} \upsilon^{Dis}(\xi) \begin{bmatrix} -\sum_{\substack{r\in N_r \\ r\neq 0}} \hat{E}_t^{Dis} \rho_{r,t,\xi}^{Dis} X_r^{Dis}(\xi) - \\ [\sum_{r\in N_r} \sum_{\substack{r\in N_r \\ r'\neq r}} \hat{E}_t^{Dis} K_{r,r'}^{Dis} Z_{r,r'}^{Dis}(\xi) - \sum_{r\in N_r} X_r^{0.Dis}(\xi) \varepsilon_r^{Dis}(\xi) + \phi^{Dis}(\xi)] \end{bmatrix} \quad (A.26)$$

Appendix B

In this paper, in order to determine the price of the energy replacing the deviations, a mechanism for imbalance prices is used. Based on this mechanism, a price for the positive energy deviation (lower consumption than the scheduled one) and a price for the negative energy deviation (higher consumption than scheduled one) are settled for each time period. These prices are determined such that to counteract the unplanned deviations, and consequently, they represent the cost of the energy required to be compensated. These prices depend on the sign of the imbalance occurred in the system as follow:

To apply two-price system, as supposed in this paper, the single balancing price ρ_t^B, is split up into two prices for each period including $\rho_t^{B^+}$ and $\rho_t^{B^-}$. The price $\rho_t^{B^+}$ is paid by a balancing responsible party in case it deviates positively by an energy amount denoted by $E_t^{B^+}$. In opposite, the balancing responsible party receives the price $\rho_t^{B^-}$ for the negative energy deviation denoted by $E_t^{B^-}$. In these two-price systems, the difference in DA market price ρ_t^D and balancing price ρ_t^B is taken to obtain what is referred to as the imbalance that is $\rho_t^I = \rho_t^B - \rho_t^{DA}$, therefore, the two prices can be obtained as follows:

$$\rho_t^{B+} = \begin{cases} \rho_t^{RT} & if \rho^I > 0 \\ \rho_t^{DA} & otherwise \end{cases} \qquad \rho_t^{B-} = \begin{cases} \rho_t^{RT} & if \rho^I < 0 \\ \rho_t^{DA} & otherwise \end{cases}$$

Where, ρ_t^{RT} is the real time price. It is rational that those consumers who incur excess consumption than the scheduled one, should pay for it and those who reduce their consumption (or even discharge their EVs) when the system occurs with low production and high consumption, should buy the energy requirement with lower prices (or be paid for the volume of energy injected).

Nomenclature

Sets and indices

$(\cdot)_{t,\omega}$	At time t and scenario ω.
$(\cdot)_{t,\xi}$	At time t and scenario ξ.
Ch (*Dis*)	Charge (Discharge) process.
D	Demand load of customers (MW).
$r, r'(N_r)$	Indices (set) of retailers.
ℓ	Index that represents charge and discharge of PEVs and also demand loads of customers.
ξ (Ξ)	Scenario index (set) of rival retailers' prices.
t (*T*)	Index (set) of time periods.
ω (Ω)	Scenario index (set) of market prices, demand loads and charge/discharge of PEVs.

Variables

e_r^X (e_r^Z)	Auxiliary binary variable used in complementary slackness conditions.

E	The amount of energy supplied by the under-study retailer (MWh).
$E^{B^+}(E^{B^-})$	Energy traded in positive (negative) balancing markets (MWh).
$E_{t,\omega}^{DA}$	Energy traded in day-ahead market (MWh).
K	The cost modelling the reluctance of customers and PEV owners to (go from retailer s to retailer s' (€).
$\mathrm{Re}\,v$	The revenue of the under study retailer (€).
X_r	Percentage of customers supplied by rival retailers.
X_{r0}	Percentage of customers supplied by the under study retailer.
$Z_{r,r'}$	Percentage of customers shifted between the retailers.
$\varepsilon_r(\phi)$	Lagrange multipliers.
SoC	State of charge of PEV.

Parameters

$Elas_{t,t}(Elas_{t,h})$	Self-elasticity (cross-elasticity) of demand of customers.
E^{T_ℓ}	Total demand of customers (MWh).
$\widehat{E}_t$	Total expected demand of customers (MWh).
X_r^0	Initial percentage of loads and PEVs demand supplied by each retailer.
π_ω	Probability of scenario ω .
$\rho^{B^+}(\rho^{B^-})$	Positive (negative) balancing market prices (€/MWh).
ρ^{DA}	Price of day-ahead market (€/MWh).
$\rho_r\,(\rho_{r_0})$	Price signals offered by rival (under study) retailer (€/MWh).
υ_ξ	Probability of scenario ξ .
$\eta^{Ch}(\eta^{Dis})$	Coefficient of charge (discharge) efficiency.
$\underline{SoC}\ (\overline{SoC})$	Minimum (maximum) of *SoC*.
E^{Cap}	Energy capacity of PEV (MWh).
$\overline{P}$	Limitation of maximum energy traded with the network (MWh).

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