

A Bi-level Risk-Constrained Offering Strategy of a Wind Power Producer considering Demand Side Resources

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Abstract

This paper proposes a stochastic decision making problem for a wind power producer (WPP) in the day-ahead (DA) and balancing markets. In this problem, bidding strategy of the WPP in a competitive electricity market and also its participation to supply demand response (DR) and electric vehicle (EV) aggregators is determined to achieve the maximum profit. In this model, DR and EV aggregators are able to choose the most competitive WPP in such a way that their energy payments be minimized in the scheduling horizon. Therefore, the problem is formulated as a stochastic bi-level programming model with conflict objectives of the WPP and the aggregators. Moreover, owing to the uncertainties associated with market prices, offered prices by rival WPPs, demand of DR and EV aggregators, conditional value at risk (CVaR) is applied to the proposed model. The attained stochastic bi-level problem is transformed to a linear stochastic single level problem with equilibrium constraints using Karush–Kuhn–Tucker (KKT) optimality conditions. The proposed model is evaluated on a realistic case study and the impacts of risk-averse behavior and demand response participants on the decision making problem of the WPP are investigated. Numerical results indicate that with increasing DR participants of 0%, 60% and 100%, CVaR of WPP increases 33.81%, 40.79% and 46.99%, respectively. This means that if the loads are more responsive, the WPP tries to control the profit variability due to the uncertainties of loads.

Keywords: demand response, electric vehicle, offering Strategy, risk-constrained, wind power producer.

Nomenclature

Sets and indices

$(\cdot)_{t,s}$ At time t and scenario s .

$(\cdot)_{t,\psi}$ At time t and scenario ψ .

Ch Charge process.

D Index of demand.

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$w, w'(N_w)$	Indices (set) of WPPs.
ℓ	Index that represents responsive loads and charge of EVs.
ψ (Ψ)	Scenario index (set) of rivals' offered prices.
t (T)	Index (set) of time periods.
$s(N_S)$	Scenario index (set) of market prices, demand loads and charge of EVs.

Parameters

$E_{t,t}(E_{t,h})$	Self-elasticity (cross-elasticity) of demand of responsive customers.
$E_{t,s}^{T_\ell}$	Total demand of customers (MWh).
\hat{E}_t	Total expected demand of customers (MWh).
X_w^{init}	Initial percentage of responsive loads and EVs supplied by each WPP.
π_s	Probability of scenario s .
Pr^{B^+} (Pr^{B^-})	Prices of positive (negative) balancing markets (€/MWh).
Pr^{DA}	Price of day-ahead market (€/MWh).
Pr_w	Price signals offered by rival (under study) WPP (€/MWh).
R	The cost modeling the unwillingness of customers and EV owners to go from WPP w to WPP w' (€).
ρ_ψ	Probability of scenario ψ .
η^{Ch}	Coefficient of charge efficiency.
\underline{SoC} (\overline{SoC})	Minimum (maximum) of SoC .
E_{batt}^{Cap}	Energy capacity of EV battery (MWh).
\bar{E}	Limitation of maximum energy traded with the network (MWh).

Variables

E	The amount of energy supplied by the under-study WPP (MWh)
E^{B^+} (E^{B^-})	The amount of energy traded between the WPP and positive (negative) balancing markets (MWh).
E^{DA}	Energy traded between the WPP and day-ahead market (MWh).
Pr_{w_0}	Price signals offered by the WPP (€/MWh).

$\varepsilon_{w,w'} / \phi_{w'}$	Multipliers associated with obtaining KKT conditions.
X_{w_0}	Percentage of customers supplied by the WPP.
$Y_{w,w'}$	Percentage of customers transferred among the WPPs.
X_w	Percentage of customers supplied by rival WPP w .
SOC	State of charge of EV.

1. Introduction

The wind-power capacity installed throughout the world has increased drastically in the last years [1]. This development is facilitated via various subsidies and supportive policies that allowed wind power producers (WPPs) to recover their investment costs in advantageous conditions if compared with conventional producers [2]. However, by increasing wind energy, WPPs encounter with a significant challenge to participate in electricity markets due to the power production uncertainty. To cope with this issue, WPPs provide three main practical solutions including optimal wind trading strategies in short-term markets, a joint operation of WPPs and easily controllable resources and increasing the wind power forecasting accuracy. This study focuses on the first two solutions.

WPPs need to develop optimal trading strategies for their participation in the short-term markets to increase expected profits and to make their investments profitable. This issue is addressed in a large number of references in the technical literature. In [2], an offering optimization model for aggregated WPP and flexible loads in DA electricity markets is proposed in which flexible load is considered as a storage unit that can either cover the imbalances of WPP or recover itself according to electricity price and load curve during various hours. In [4], the offering strategy of wind power is evaluated by price-maker WPPs, but in [5] a strategic bidding model for several price-taker plug-in electric vehicle aggregators that participate in both day-ahead energy and ancillary services markets is assessed without focusing on WPP.

Demand response (DR) as a responsive and cost-effective option can be used to facilitate the integration of wind [6], and makes good opportunity in a joint operation with WPPs. The effect of DR programs on the bidding strategies of WPPs has been investigated from different points of view in several works [6]-[13]. For example, in [6], it is expressed that the WPP is obligated to offer its generation to the DA market. Therefore, its DA forecast errors are compensated using DR. A stochastic multi-layer agent-based model is proposed in [7] in which the wholesale market players including renewable power producers are modeled such that to optimize bidding/offering in the electricity markets without using any risk aversion factor in the model. In [8], a two-stage offering plan is presented in which a WPP participates in the DA market while employing DR to smooth its power variations. Although, in the presented approach the energy trading of WPP is determined for each period, the DR and EV aggregator reaction to choose their energy provider in a competitive market is not addressed. In [10], the positive

benefits of DR on the short-term trading of WPPs are investigated from the WPPs' viewpoint. Also, an offering strategy for a price maker WPP participating in both DA and balancing markets is proposed in [11] in which the penetration of DR resources into smart grids is modeled. A bi-level equilibrium model to study market equilibrium interactions between energy storage and wind and conventional generators is assessed in [12] but the effect of DR is not investigated.

In [13], a framework for trading DR resources has been proposed in a separate intraday market in order to improve the WPPs' profit. Then the problem has been solved from the WPPs' viewpoint. Moreover, in [14], a combined scheduling and bidding strategy has been presented for constructing the DA bidding curve of an electric utility including DR option. In the proposed strategy of this reference, units are dispatched by optimizing the retailer's DR programs. An offering optimization model for aggregated wind power and flexible loads in only DA electricity market is proposed in [15]. A stochastic programming approach for the development of offering strategies for a WPP with considering the uncertainties of electricity market prices is investigated in [16] without using any tool to decrease the unfavorable effect of uncertainties.

In the reviewed literature, although the effect of DR actions is discussed on offering strategy of the WPP, the profit of demand side is not considered. Nevertheless, a few research works have studied offering strategy of WPP from the viewpoint of both WPPs and demand side. Moreover, in the reviewed literature, risk management in WPP offering decision strategies is not considered. However, there are some research works, in which different risk management tools such as conditional-value-at-risk (CVaR) are used to model the profit risk associated with the WPPs offering decisions. For example, authors in [2] propose a multi-stage risk-constrained stochastic model to derive the optimal offering strategy for the participation of WPP in both DA and the balancing markets. A risk-based two-stage stochastic optimization problem for the operation of a microgrid is studied in [17] where the uncertainties of renewable energy resources are modeled using a two-stage stochastic programming while the uncertainties of EVs are not assessed. In addition, CVaR index is used to manage the risk level of the microgrid operator decisions. In [18], a platform is proposed to obtain the best offering strategy for a hybrid power plant consisting of a WPP and DR provider in the power market. In this work DR is used to cover uncertainty of wind power and mitigate the imbalance cost. Also, CVaR is used in this research to limit the risk of profit variability while the goal of lower level of the problem is not paid attention. In [19] a comprehensive stochastic decision making model is proposed for the coordinated operation of WPP and DR aggregators participating in the DA market. In this work, CVaR term has been included in the model to account uncertainty around the true outcomes of DA prices and wind power generation, however, the preferences of DR aggregators to minimize their payments is not addressed. A bi-level problem including a single leader and two followers is formulated in [20] in which the WPP aims to maximize its profit through offering into DA market and clearing the deviation in the balancing trading floor. Also, the DR aggregator is able to sell its DR product to the WPP, other competitors and the DA market. A scheme for joining WPPs with non-wind firms by considering both positive and negative balancing costs is studied in [21] without considering any risk measurement tool. In the reviewed works, although, bidding strategy of the WPP in an uncertain environment is studied, the decision making problem of the WPP with considering the preferences of both DR and

EV aggregators in a competitive market is not addressed. Market clearing in the presence of uncertain responsive loads based on information gap decision theory concept is performed in [22] where responsive loads are considered as reserve providers to participate in the market by offering their price-quantity capacity bids to the reserve market. Also, risk aversion strategies are used to measure related risk/immunity cost. Table 1 addresses a systematically comparison between the contributions of this paper and some of the recent works in the same subject area.

Table 1 The contributions of literatures in view of existing state of the art.

Reference	Bi-level modelling	Competitive environment	Risk assessment	WPP	Demand response
[2]	-	✓	✓	✓	
[6]	-	✓	-	-	✓
[7]	-	✓	✓	✓	-
[9]	-	-	✓	✓	✓
[10]	-	✓	✓	✓	✓
[12]	✓	✓	-	✓	-
[19]	-	-	✓	✓	✓
[20]	✓	✓	-	✓	✓
[21]	✓	-	-	✓	-
This paper	✓	✓	✓	✓	✓

To overcome the mentioned issues, this study proposes an offering and bidding strategy for a WPP in a competitive environment in which the preferences of both DR and EV aggregators is considered in a bi-level problem. The WPP competes with the rivals to supply the DR and EV aggregators such a way that not only maximize its profit, but also minimize the aggregators' costs. In this model, responsive loads of customers and EVs under the jurisdiction of aggregators can adjust their demand based on the real-time prices. Furthermore, The DR and EV aggregators can participate in the DA and balancing markets as well as buy energy from the most competitive WPP. Therefore, in the objective of the upper-level of the problem is to maximize the total expected profit of the WPP through making optimal bidding and offering strategy to the market and demand side resources. In the lower-level of the problem, the optimal scheduling from DR and EV aggregators' point of view is handled considering their minimum costs as the objective. The lower-level problem is transferred to the upper level to obtain the equivalent single-level mixed-integer linear problem based on Karush–Kuhn–Tucker (KKT) optimality conditions and duality theory [23].

The main contributions of this paper are summarized as follows:

- An optimal bidding strategy for the participation of a WPP in DA and balancing markets is proposed in which the behavior of demand side resources is modeled based on a price-based DR program within a bi-level problem.
- A new scheme is presented where WPPs can procure the demand of DR and EV aggregators in a competitive environment. In addition, the impact of different levels of DR participants on the decision making of WPP is studied.
- The risk faced with by WPPs is modeled using CVaR and the effect of risk-aversion behavior of WPP on the prices offered to the aggregators is investigated.

The rest of this paper is arranged as follows: In section 2, the proposed decision making strategy of WPP is explained. In section 3, the proposed problem is formulated. Case studies together with simulation results are presented in section 4. Finally, section 5 draws the conclusions.

2. Problem Framework and Description

2.1. Assumptions

In the proposed methodology some assumptions are considered as follows.

- 1) It is assumed that WPPs submit their energy offers in the DA market while clearing imbalances in the balancing market. Furthermore, WPPs are treated similarly to conventional power plants, being responsible for their bidding strategies and power production variation and subject to financial penalties for generation shortfall [19].
- 2) It is assumed that the customers are equipped with smart energy management controllers and are able to respond to the electricity prices by adjusting their responsive loads to reduce their energy consumption costs. Also, the aggregators can choose proper WPP by monitoring real-time prices and can switch the loads under its jurisdiction to the most competitive WPP in short-term scheduling. This is feasible by developing a fast communication media with bidirectional data transfer between the WPPs and smart loads and the EV charging stations.
- 3) It is assumed that, responsive loads and demand of EVs can participate in price-based DR programs using two general categories including shiftable and sheddable loads [24]. Therefore, DR is modeled through its self- and cross-elasticities, the former accounts for an immediate response to price signals, while the latter refers to the consumer's reaction to the prices in other hours and accounts for load shifting [25].

2.2. Aim and Framework of the Problem

In the proposed methodology, an offering and bidding strategy is developed for a WPP which submits the optimal offers to DA market in the competitive trading floor.

The objective of the WPP is to maximize its profit through its interactions while the objective of DR and EV aggregators is to minimize their payments during scheduling horizon. Moreover, due to the intermittent nature of wind power, market and demand loads, the offered energy by WPP has a degree of uncertainty. Moreover, in a competitive market, it encounters with the forecasting errors of prices offered by the other rival WPPs. In this condition, WPP needs to adjust deviations of DA market in balancing market when the wind generation and other stochastic parameters become more accurate near the real time.

The proposed framework considers that the DR and EV aggregators supply the load under their jurisdiction from a proper WPP. Based on the price signals offered by WPPs, the optimal shares of DR and EV aggregators contracted with WPPs for

each time slot are determined. After determining the volume of DR and EVs aggregators contracted by the WPP, it makes its bids in the DA market.

The WPP faces the uncertainty of several parameters at the time it submits energy bids to the DA market and offering prices to the aggregators such as uncertainty of DA and balancing market prices, rival WPPs' offers, wind power production as well as customers and EVs demands. In order to model the mentioned uncertain resources, a large number of scenarios are generated by using appropriate forecasting tools [26]. Owing to the uncertain resources, risk aversion of the WPP is considered in the model by means of CVaR metric that is coherent, linear, and easy to incorporate in the optimization problems [27].

2.3. Solution Methodology

The WPP bids energy to DA and balancing markets while offers electricity prices to the aggregators under real-time pricing scheme in a competitive environment. In this regard, the WPP faces with the uncertainties involving the power production, client demand and market price forecasts. To this end, plausible realizations of these stochastic parameters should be taken into account. In addition, the level of risk taken by the WPP affects the energy trading in the electricity market. So, the share of WPP in DA and balancing markets may change in various risk levels. The DR share and the behavior of EV owners are the other factors that affect the decisions made by the WPP. The proposed bidding and offering strategy of WPP is formulated as a bi-level programming. In the upper level, the WPP's objective is to maximize its expected profit from bidding energy in short-term electricity trading floor including DA and balancing markets. In this level, scheduled energy exchanges for the next day are determined and then the energy deviations between the scheduled and the production are eliminated through actions performed in the balancing market. Afterwards, as the WPP does not know the prices that will be offered by rival WPPs, it considers them through different scenarios to assess their influence on the offering strategy. Also, due to the optional behavior of DR and EV aggregator, CVaR as a measurement tool is incorporated to the problem.

In the lower level, there are several customers and EV owners who want to supply their required energy from the most competitive WPP. The conflict between the two levels of problem is modeled via a bi-level problem. In this regard, the DR and EV aggregators' response to the prices offered by WPPs as well as competition among rival WPPs are explicitly modeled in the proposed bi-level model. The reaction of DR and EV aggregators as customers consists in determining the demand share supplied by each WPP (including the under study and the rival WPP) such that the expected procurement cost of the DR and EV aggregators is minimized. It should be emphasized that competition among rival WPPs is explicitly modeled in the lower level.

This nonlinear bi-level programming problem should be transformed into an equivalent single-level mixed-integer linear programming problem that can be solved using available commercial branch-and-cut solvers [28]. Therefore, the equivalent single-level form of the proposed scheme is obtained by using KKT optimality conditions. Also, by implementing duality

theory, the bilinear products are replaced by their equivalent expressions. The structure of bidding strategy of the WPP in the DA and balancing energy markets is shown in Fig. 1. Here, the characteristics of the uncertain parameters are taken into account using a set of scenarios. Therefore, forecasting errors of each uncertainty are generated using probability density functions (PDFs) with zero-mean normal distributions as well as the corresponding standard deviations [29]. A large number of scenarios representing each uncertain parameter based on its corresponding PDF are generated using Monte Carlo simulation (MCS) and roulette wheel mechanism (RWM) [30]. Each scenario includes a set of information about hourly DA prices, positive and negative balancing prices, demand loads, EVs charging energy as well as the prices offered by the rival WPPs during the scheduling horizon. Then, to mitigate the computational burden of the stochastic procedure, K-means algorithm [31] as a scenario-reduction technique is used to reduce the number of scenarios into a smaller set representing well enough the uncertainties. Next, the reduced scenarios are applied to the proposed model. Then the equivalent single-level stochastic problem is solved as a mixed-integer linear problem (MILP).

3. Problem Formulation

The proposed model is formulated as a bi-level optimization problem in which in the upper-level problem the bidding energy to the Markets and offering prices to DR and EV aggregators are obtained. Also, in the lower-level of the problem, optimal tradeoff between WPPs and DR/EV aggregators is defined to determine the percentage share of WPPs to supply DR and EVs with the goal of minimizing the costs of customers' energy consumption. Therefore, the objective function of the problem can be formulated from both WPP and demand side viewpoints.

3.1 Formulation from the WPP Viewpoint

The objective of the WPP is maximizing its expected profit which consists of the revenue obtained from selling energy to the DA, positive balancing market, DR and EVs minus the payments in the negative balancing market to cover its contracted agreements.

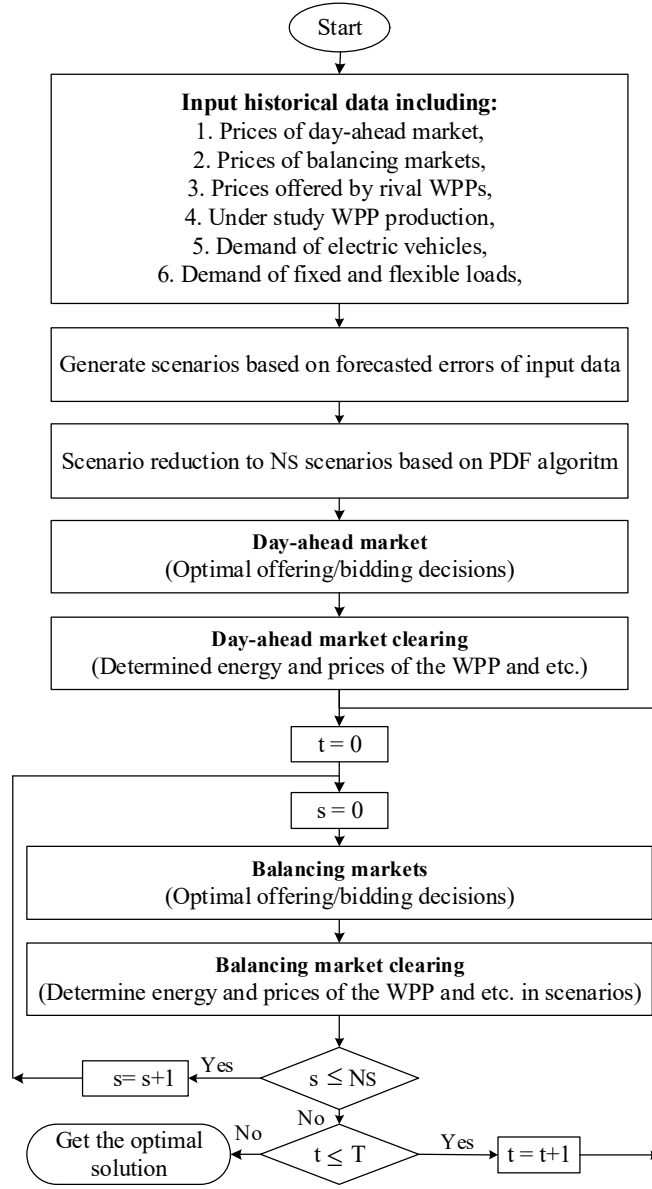


Fig. 1. The structure of bidding strategy of the WPP in DA and balancing energy markets.

$$\begin{aligned}
 & \text{Maximize } \sum \pi_s \sum_{t \in T} [E_{t,s}^D \text{Pr}_{w_0,t}^D + E_{t,s}^{Ch} \text{Pr}_{w_0,t}^{Ch} + E_{t,s}^{DA} \text{Pr}_{t,s}^{DA} + E_{t,s}^{B^+} \text{Pr}_{t,s}^{B^+} - E_{t,s}^{B^-} \text{Pr}_{t,s}^{B^-}] \\
 & \quad + \beta \cdot (\xi - \frac{1}{1-\alpha} \sum_{s=1}^{N_S} \pi_s \cdot \eta_s)
 \end{aligned} \tag{1}$$

Subject to the following constraints:

$$\begin{aligned}
 & \sum_{s \in N_S} \sum_{t \in T} [E_{t,s}^D \text{Pr}_{w_0,t}^D + E_{t,s}^{Ch} \text{Pr}_{w_0,t}^{Ch} + E_{t,s}^{DA} \text{Pr}_{t,s}^{DA} + E_{t,s}^{B^+} \text{Pr}_{t,s}^{B^+} - E_{t,s}^{B^-} \text{Pr}_{t,s}^{B^-}] + \eta_s - \xi \geq 0 \\
 & ; \eta_s \geq 0
 \end{aligned} \tag{2}$$

Where, $\text{Pr}_{w_0,t}^D$, $\text{Pr}_{t,s}^{B^+}$ and $\text{Pr}_{t,s}^{B^-}$ stand for the prices of DA, positive and negative balancing markets, respectively. $E_{t,s}^{DA}$, $E_{t,s}^{B^+}$, $E_{t,s}^{B^-}$ show the amount of energy traded between the WPP and DA, positive and negative balancing markets, respectively. $E_{t,s}^D$ and $E_{t,s}^{Ch}$ state the amount of energy supplied by the under-study WPP for both DR and EV aggregators. $\text{Pr}_{w_0,t}^D$ and $\text{Pr}_{w_0,t}^{Ch}$ stand for the price signals offered by the under study WPP for demand and charge process. π_s shows the probability of scenarios and η_s is an auxiliary nonnegative variable that is equal to the difference between auxiliary variable ξ and the WPP profit when the profit is lower than ξ .

Constraint (3) represents the energy balance at each time slot and scenario.

$$E_{t,s}^D + E_{t,s}^{Ch} = E_{t,s}^{DA} + E_{t,s}^{B^+} - E_{t,s}^{B^-} \quad (3)$$

The share of energy supplied by the under study WPP at each hour t and scenario ψ is given by (4). It is equal to the expected value of the demand supplied by the under study WPP over all rival WPPs price scenarios. It should be mentioned that a different way might be used to evaluate the demand supplied by the under study WPP.

$$E_{t,s}^\ell = E_{t,s}^{T_\ell} \sum_{\psi \in \Psi} \rho_\psi^\ell X_{w_0,\psi}^\ell \quad (4)$$

$X_{w_0,\psi}^\ell$ stands for the percentage of customers supplied by the under study WPP with the probability of ρ_ψ^ℓ .

The non-anticipativity which represents the identical DA bids have to be made in all scenarios with equal DA prices, is provided as below:

$$E_{t,s}^{DA} = E_{t,s'}^{DA} \quad (5)$$

The non-anticipativity denotes that if the realizations of the stochastic processes are identical up to each stage, the values of the decision variables must be then identical up to that stage [36].

Constraint (6) explains the limitation of traded energy in positive and negative balancing market, respectively.

$$E_{t,s}^{B^+/B^-} \leq \bar{E} \quad (6)$$

where, \bar{E} is the limitation of maximum energy traded with the network.

3.2 Formulation from the Customers Viewpoint

The lower-level of the problem explains the energy cost of customers and EV owners which should be minimized. Therefore, the objective function of this level can be formulated as below:

$$\begin{aligned}
& \left[\begin{aligned}
& \{ \widehat{E}_t^D [\text{Pr}_{w_0,t}^D X_{w_0,t,\psi}^D + \sum_{\substack{w \in N_w \\ w \neq 0}} \text{Pr}_{w,t,\psi}^D X_{w,t,\psi}^D] \\
& + \widehat{E}_t^{Ch} [\text{Pr}_{w_0,t}^{Ch} X_{w_0,t,\psi}^{Ch} + \sum_{\substack{w \in N_w \\ w \neq 0}} \text{Pr}_{w,t,\psi}^{Ch} X_{w,t,\psi}^{Ch}] \\
& + \sum_{w \in N_w} \sum_{\substack{w' \in N_w \\ w' \neq w}} \widehat{E}_t^D R_{w,w'}^D Y_{w,w',t,\psi}^D \\
& + \sum_{w \in N_w} \sum_{\substack{w' \in N_w \\ w' \neq w}} \widehat{E}_t^{Ch} R_{w,w'}^{Ch} Y_{w,w',t,\psi}^{Ch} \}
\end{aligned} \right] \quad (7)
\end{aligned}$$

\widehat{E}_t^{DR} and \widehat{E}_t^{Ch} are the total expected demand of DR and charge process. $\text{Pr}_{w,t,\psi}^D$ and $\text{Pr}_{w,t,\psi}^{Ch}$ stand for the DR and charge prices offered by the rival WPPs. The percentage of DR and charge demand that is supplied by the under study WPP are shown by $X_{w,t,\psi}^D$ and $X_{w,t,\psi}^{Ch}$. $R_{w,w'}^D$ and $R_{w,w'}^{Ch}$ are the cost which models the unwillingness of customers and EV owners to go from WPP w to WPP w' . $Y_{w,w',t,\psi}^D$ and $Y_{w,w',t,\psi}^{Ch}$ express the percentage of DR and EVs that transferred among the WPPs.

In the above equation, several WPPs are considered to provide the required energy of DR and EV aggregators that index $w=0$ shows the under-study WPP. The first two lines in (7) express the costs of purchased energy from the under-study WPP and the rivals to supply the demand of DR and EV aggregators. The last two lines express the cost representing the unwillingness of DR and EV aggregators to switch among the WPPs in order to supply their load and charge of the vehicles. Here, it is assumed that DR and EV aggregators are able to monitor the prices offered by WPPs and supply the customers under their jurisdictions by switching their load to the most competitive WPP such that to minimize their energy payments. The reluctance of DR aggregators to switch from WPP w to WPP w' is modeled with $\widehat{E}_t^D R_{w,w'}^D Y_{w,w',t,\psi}^D$. Similarly, term $\widehat{E}_t^{Ch} R_{w,w'}^{Ch} Y_{w,w',t,\psi}^{Ch}$ denotes the switching of EVs demand among WPPs.

For the lower-level objective function, the following constraints are taken into account. Also, the dual variables associated with each constraint are given in front of each constraint.

Constraint (8) discusses the share of each WPP to supply responsive loads and EVs required energy.

$$X_{w,\psi}^\ell = X_{w,\psi}^{init,\ell} + \sum_{\substack{w \in N_w \\ w' \neq w}} Y_{w,w',\psi}^\ell - \sum_{\substack{w' \in N_w \\ w' \neq w}} Y_{w,w',\psi}^\ell : \phi_\psi^\ell \quad (8)$$

where, $X_{w,\psi}^{init,\ell}$ is the initial percentage of responsive loads and EVs supplied by each WPP.

The total expected customers' demand and charge of EVs is obtained by (9).

$$\widehat{E}_t^\ell = \sum_{s \in N_s} \pi_s E_{t,s}^{T_s} \quad (9)$$

$E_{t,s}^T$ is the total demand of customers. Moreover, constraint (10) states that the total demand of DR and EV aggregators should be supplied by the under study and rival WPPs. In fact, the percentage of demand that provided by all WPPs is equal to 100% at each time period.

$$X_{t,w_0,y}^\ell + \sum_{\substack{w \in N_w \\ w \neq w_0}} X_{t,w,y}^\ell = 100\% : \varepsilon_{w,y}^\ell \quad (10)$$

Constraint (11) shows that the *SoC* of EV at time t and in scenario s depends on the *SoC* at time $t-1$ and the charging process. The charging efficiency of EV battery is η^{Ch} .

$$SoC_{t,s} = SoC_{t-1,s} + \eta^{Ch} E_{t,s}^{Ch} : \kappa_{t,\omega}^{Ch} \quad (11)$$

Constraints (12) and (13) express the technical constraints of EV battery.

$$\underline{SoC} E_{batt}^{Cap} \leq SoC_{t,s} \leq \overline{SoC} E_{batt}^{Cap} : \underline{\mu}_{t,\omega}^s, \overline{\mu}_{t,\omega}^s \quad (12)$$

$$0 \leq \eta^{Ch} E_{t,s}^{Ch} \leq (\overline{SoC} E_{batt}^{Cap}) - SoC_{t-1} : \underline{\tau}_{t,\omega}^{Ch}, \overline{\tau}_{t,\omega}^{Ch} \quad (13)$$

$\overline{SoC} E_{batt}^{Cap}$ shows the limitation for the *SOC* of the EVs battery. Moreover, the customers take part in DR programs and adjust their consumption based on their demand elasticity as well as the price signal offered by the WPP. Demand elasticity is defined as the sensitivity of demand to the price signal [32]. To achieve maximum benefit, each customer applies both load shifting and load shedding options and changes its energy consumption (ΔE_t) from E_t^{int} to E_t in period t as:

$$E_t = E_t^{int} + \Delta E_t \quad (14)$$

The benefit of customer k can be calculated as:

$$S(E_t) = B(E_t) - E_t \text{Pr}_{t,s}^{DA} \quad (15)$$

where, $S(E_t)$ and $B(E_t)$ represent benefit and income of customers at period t after implementing DR program. To maximize the benefit of customers, the following criteria must be met [29]:

$$\frac{\partial S(E_t)}{\partial E_t} = \frac{\partial B(E_t)}{\partial E_t} - \text{Pr}_{t,s}^{DA} = 0 \quad (16)$$

Based on the model represented in [29], the energy consumption of customers at time t is obtained as follows:

$$E_t = E_t^{int} \exp \sum_{h \in T} \text{Elas}_{t,t} \ln \left[\frac{\text{Pr}_{t,s}^{DA}}{\text{Pr}_t^{D,int}} + \frac{1}{1 + \text{Elas}_{t,t}^{-1}} \right] \quad (17)$$

$E_{t,s}$ is the elasticity of demand of responsive customers and $\text{Pr}_t^{D,\text{int}}$ is the average of $\text{Pr}_{t,s}^{DA}$. More explanations about the implementation of equation (17) is given in Appendix A.

3.3 Combining Lower Level with Upper Level

After formulating the upper and lower levels independently, the equivalent linear single-level problem is obtained by the objective function in (1) and the constraints in (2)-(6) and (8)-(13) as well as the KKT optimality conditions of the lower level problem and the duality theorem. Also, the bilinear product of terms $E_{t,s}^D \text{Pr}_{w_0,t}^D$ and $E_{t,s}^{Ch} \text{Pr}_{w_0,t}^{Ch}$ are achieved with using strong duality theorem [33] as bellow.

$$E_{t,s}^D \lambda_{w_0,t}^D = \frac{E_{t,s}^{TD}}{\bar{E}_t^D} \sum_{\psi \in \Psi} \rho_{\psi}^D - \left[\begin{array}{l} - \sum_{\substack{w \in N_w \\ w \neq 0}} \hat{E}_t^D \text{Pr}_{w,t,\psi}^D X_{w,\psi}^D \\ - \sum_{\substack{w \in N_w, w' \in N_w \\ w' \neq w}} \hat{E}_t^D R_{w,w'}^D Y_{w,w',\psi}^D \\ + \sum_{w \in N_w} X_{w,\psi}^{\text{init},D} \varepsilon_{w,\psi}^D + \phi_{\psi}^D \end{array} \right] \quad (18)$$

$$E_{t,s}^{Ch} \lambda_{w_0,t}^{Ch} = \frac{E_{t,s}^{TCh}}{\bar{E}_t^{Ch}} \sum_{\psi \in \Psi} \rho_{\psi}^{Ch} - \left[\begin{array}{l} - \sum_{\substack{w \in N_w \\ w \neq 0}} \hat{E}_t^{Ch} \text{Pr}_{w,t,\psi}^{Ch} X_{w,\psi}^{Ch} \\ - \sum_{\substack{w \in N_w, w' \in N_w \\ w' \neq w}} \hat{E}_t^{Ch} R_{w,w'}^{Ch} Y_{w,w',\psi}^{Ch} \\ + \sum_{w \in N_w} X_{w,\psi}^{\text{init},Ch} \varepsilon_{w,\psi}^{Ch} + \phi_{\psi}^{Ch} \end{array} \right] \quad (19)$$

The variables $\varepsilon_{w,\psi}^{\ell}, \phi_{\psi}^{\ell}, \kappa_{t,\omega}^{Ch}, \bar{\mu}_{t,\omega}^s, \underline{\mu}_{t,\omega}^s, \tau_{t,\omega}^{-Ch}$ and $\underline{\tau}_{t,\omega}^{Ch}$ are the Lagrange multiplier associated with the lower level constraints. Appendix B represents more details about combination of the two levels and linearization of the problem.

4. Simulations and Numerical Results

4.1. Case Study

The proposed model is evaluated on realistic data from the Nordic market [34]. Here, the scheduling horizon is considered one day with 24 equal time slots. Four WPPs that capacity of each one is 2.5 MW is considered as under study WPP (i.e., WPP₀) and rivals WPPs (i.e., WPP₁, WPP₂ and WPP₃). The hourly forecasted demand of customers and EVs and also the power of each WPP are considered as shown in Fig. 2. Moreover, in order to illustrate the applicability of the presented model, realistic data prices are used from Nordpool market [34] and the forecasted electricity prices of DA and balancing markets are shown in Fig. 3 [34]. The scenarios related to forecasting errors of wind power generation, market prices as well as prices

offered by rival WPPs are generated with their mean values and standard deviation based on their associated PDF [33]. Forecasted errors of each uncertain parameter are modeled by generating a large enough number of scenarios by implementing Mont Carol simulation (MCS) and Roulette wheel mechanism (RWM). Subsequently, a scenario-reduction technique based on K-means classification method [31] is used to obtain a sufficiently small number of scenarios.

Moreover, the forecasted values of customers' and EVs' demand are extracted from [32] and [33], respectively. It is assumed that the customers' demand is categorized into responsive and non-responsive Loads. Also, it is assumed that only DR and EV have the chance to choose their proper WPP in the competitive environment. The scenarios related to demand of the responsive loads and EVs are correlated to DA prices based on the relation explained in [35] The charging and discharging efficiency is considered 0.95.

The optimization is carried out by CPLEX solver using GAMS software [37] on a PC with 4 GB of RAM and Intel Core i7 @ 2.60 GHz processor.

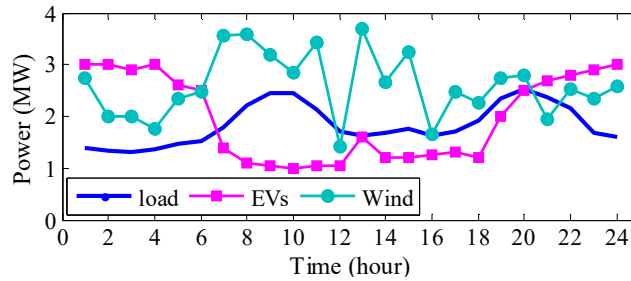


Fig. 2. The hourly forecasted demand of customers and EVs and power of the WPP

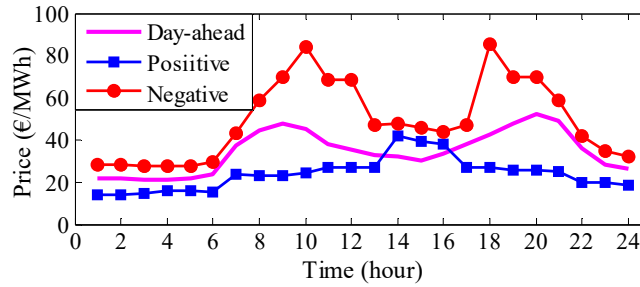


Fig. 3. The forecasted electricity prices of DA, positive and negative balancing markets.

4.2. Numerical Results

In the proposed model, the WPP has the opportunity to reduce the differences between DA energy bids and actual delivery energy time requests in the balancing market. In other words, the WPP sells its excess power to the positive balancing market and also reduces its generation shortage in the negative balancing market. In this process, the WPP decision depends on the DR participants and its risky behavior. In order to investigate the impact of incorporating risk into the decision making problem, Table 1 depicts the expected profit of the WPP versus CVaR in different values of β in 0, 60% and 100% of DR participants. It is assumed that the customers' participation in DR program can be equal to 0% (no DR), 60% (moderate DR adoption) and

100% (large-scale DR adoption) of the total load. Although, 100% of DR participants may not be practical nowadays, analyzing decision making problem of WPP by applying time-varying electricity price structures, coupled with the large-scale adoption of DR actions, can provide a proper view from future smart grids.

It is observed that with increasing DR participant level, the expected profit of the WPP augments. Since, by increasing DR, the aggregator can effectively manage the responsive loads of users and thus the potential to choose its proper WPP based on the offering price signals increases. Therefore, it is probable that more customers refer to the WPP and consequently, its expected profit increases. Additionally, as the loads become more responsive, the WPP tries to control the profit variability due to the uncertainties of loads. For this reason, with increasing DR participants, the values of CVaR term increases.

Moreover, the result shows that by increasing β , the WPP risk exposure is mitigated and its expected profit decreases and the CVaR increases. If β increases from 0 (i.e., risk-neutral case) to 10 (i.e., risk-averse case), the expected profit decreases 1.00%, 1.01%, and 1.52%, and CVaR increases 33.81%, 40.79%, and 46.99% , for 0%, 60% and 100% of DR participants, respectively. In other words, the expected profit is not highly dependent on the risk-aversion of the WPP in all cases. This result means that a small decrease in the expected profit can be used to reduce efficiently the risk of profit variability.

Table 2 provides the optimal offering power derived by the WPP in different values of DR participants and risk aversion parameter β . As it can be observed, in a general trend, in a certain level of DR participants, the total quantity of power offered by the WPP in the DA market decreases as the parameter β grows. This decrease produces an increase in the power traded in the positive balancing market, as this market is less volatile than the DA market. Therefore, the WPP prefers to trade in the balancing market in order to hedge against profit variability at the cost of reducing its average value. Moreover, with increasing β , the WPP decreases its trading energy in the negative balancing market in order to mitigate the costs incurred by the deficit of generation. Furthermore, in the higher values of β ($\beta \geq 2.7$), the profit variability would not occur and as a result the participation of WPP in the DA market is constant, yielding its trades in the balancing market to be fixed.

Table 1 Expected profit versus CVaR (€) in different DR and β .

β	DR=0%		DR=60%		DR=100%	
	Expected profit	CVaR	Expected profit	CVaR	Expected profit	CVaR
0	1851.91	20.05	2189.81	26.35	2419.70	29.24
0.1	1851.91	20.16	2189.80	26.55	2419.60	29.45
0.3	1851.56	22.34	2189.75	26.91	2419.48	30.42
0.5	1851.48	22.55	2189.60	27.0	2419.47	30.53
1	1850.68	23.36	2186.73	30.22	2419.30	30.82
2	1849.20	24.48	2186.03	30.59	2413.70	33.94
2.7	1849.01	24.52	2184.29	31.38	2405.02	37.84
3	1848.80	24.55	2168.27	36.85	2405.02	37.84
5	1848.50	24.65	2167.97	36.96	2383.50	42.83
10	1833.25	26.83	2167.67	37.10	2382.90	42.98

Moreover, the numerical results show that with increasing participation of customers in DR program, the WPP reduces its share in the DA market with the hope of selling energy to the customers and in the positive balancing market to obtain some revenue. Therefore, because the WPP can motivate more loads to purchase their required energy from it in a competitive market, the amount of selling energy to the DA market decreases as DR participants grow.

In low values of DR, the deficit of energy incurred by the WPP is low. But, as the loads become more responsive, the energy requests from the WPP increases. Therefore, it might not be able to procure the amount of energy scheduled in DA market.

Table 2 Energy trading to the network in different values of DR and β .

β	DR=0%			DR=60%			DR=100%		
	DA	Positive	Negative	DA	Positive	Negative	DA	Positive	Negative
0.01	43.05	9.58	5.24	42.48	10.23	5.15	41.88	10.58	5.24
0.1	43.03	9.58	5.24	42.46	10.20	5.15	41.86	10.58	5.24
0.3	42.96	9.64	5.23	42.38	10.27	5.14	41.83	10.58	5.24
0.5	42.94	9.65	5.22	42.35	10.26	5.14	41.82	10.59	5.24
1	42.93	9.67	5.22	42.33	10.28	5.14	41.81	10.61	5.24
2	42.91	9.75	5.20	42.31	10.33	5.13	41.81	10.62	5.23
2.7	42.85	9.76	5.19	42.30	10.40	5.13	41.80	10.63	5.23
3	42.85	9.76	5.19	42.30	10.40	5.13	41.80	10.63	5.23
5	42.85	9.76	5.19	42.30	10.40	5.13	41.80	10.74	5.23
10	42.85	9.76	5.19	42.30	10.40	5.13	41.80	10.74	5.23

The expected cost of DR and EV aggregator with and without considering the collaboration between WPP and aggregator in three sample β is given in Table 3. Jointly considering WPP and the DR aggregator in the bidding process results in a lower volume of costs paid by the aggregator. Therefore, buying energy from WPP is more saving for the aggregator instead of participating in electricity market as shown in Table 3. It is also observed that with collaboration of WPP and aggregator, not only the costs of aggregators would be more decreased, but also, the integration of renewable technologies and the penetration of renewable technologies would be facilitated.

Fig. 4 shows the impact of both risk aversion parameter and DR participants on the expected profit of the WPP. As it is expected, with increasing β , the expected profit of the WPP decreases. That is because the negative scenarios of the profit would be eliminated as the parameter β increases. Also, since the WPP tries to hedge against volatilities of uncertainties, the profits with low probability in unfavorable scenarios are ignored. But, when the WPP has a less risk-averse behavior, it experiences more dispersed profits which are far from the expected one. It is also seen that with integrating DR scheme into the operational model, the WPP obtains more profit compared with the case without considering DR. Therefore, the frontiers

shown in this figure can help the WPP to decide properly its degree of risk-aversion. In fact, because of the increase of DR request, the amount of loads that can select their WPP increases. Therefore, it is more probable that the WPP obtains more benefits.

Table 3. The expected cost of DR and EV aggregator with and without considering the collaboration between WPP and aggregator

β	With collaboration Total costs (€)	With collaboration DR aggregator (€)	With collaboration EV aggregator (€)	Without collaboration Total costs (€)	Without collaboration DR aggregator (€)	Without collaboration EV aggregator (€)
0	4.0451e+03	2.1150e+03	2.0172e+03	4.1222e+03	2.1045e+03	2.0177e+03
1	4.1353e+03	2.1180e+03	2.0173e+03	4.2765e+03	2.2322e+03	2.0443e+03
10	4.1359e+03	2.1161e+03	2.0198e+03	4.2828e+03	2.2384e+03	2.0444e+03

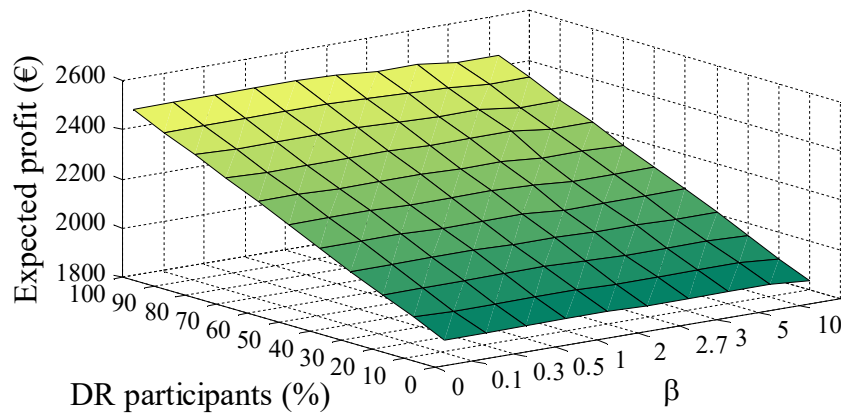


Fig. 4. The expected profit versus DR participation level and parameter β .

In order to assess the effect of risk aversion parameter on the decision making problem by the WPP, its offering prices in different values of β for three levels of DR participants are shown in

Fig. 5. When the parameter β grows the participation of the WPP in positive balancing market increases that it is due to perfect knowledge about the generation of wind power near real-time in order to hedge against volatilities of DA market prices. Although the positive balancing prices are cheaper than the DA prices, in the risk-averse case the WPP tries to exchange energy in the balancing market in the hope that it sells the generation just before the delivery energy time. Therefore, with increasing DR participants from 0% to 100% (

Fig. 5 (a)-(c)), the prices offered by the WPP in peak hours augments. But, due to the competitive environment, with increasing DR, as the WPP becomes more risk-averse; it decreased the prices in off-peak hours in order to attract the customers.

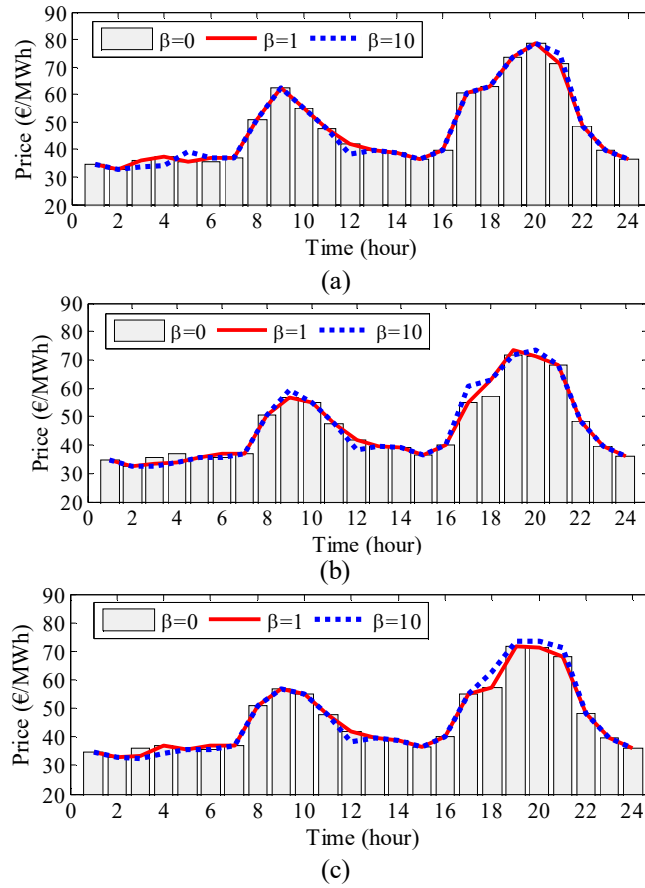


Fig. 5. The price signal offered by the WPP in different values of β (a) Without DR (b) 60% of DR participants and (c) 100% of DR participants.

In this competitive environment, the WPP should compete with other WPPs to attract the customers. Therefore, it offers its price signal such that to motivate the aggregators to purchase their required energy from it. Fig. 6 shows the prices offered by the WPPs in the risk-neutral case (i.e., $\beta = 0$) in 0% and 60% of DR participants. In case of without DR that the all of the loads are non-responsive and can not chooses their proper WPP, the WPP offers the price such that to have high values in peak hours.

In order to assess the effect of DR participants on the decision making problem of the WPP, the case of without DR is considered as a base case in the demand of aggregators is supplied by the WPPs, equally. But, in 60% of DR that 60% of loads are responsive and can choose their WPPs to minimize their payments. Therefore, the WPP offers middle prices to compete with other WPPs, especially at 9:00 and 17:00 to 21:00 in order to motivate the aggregators. Moreover, the results show that when the customer participate in DR program and can choose their WPP based on its offered price, the price offered by the WPP does not increase especially at peak hours to keep the customers.

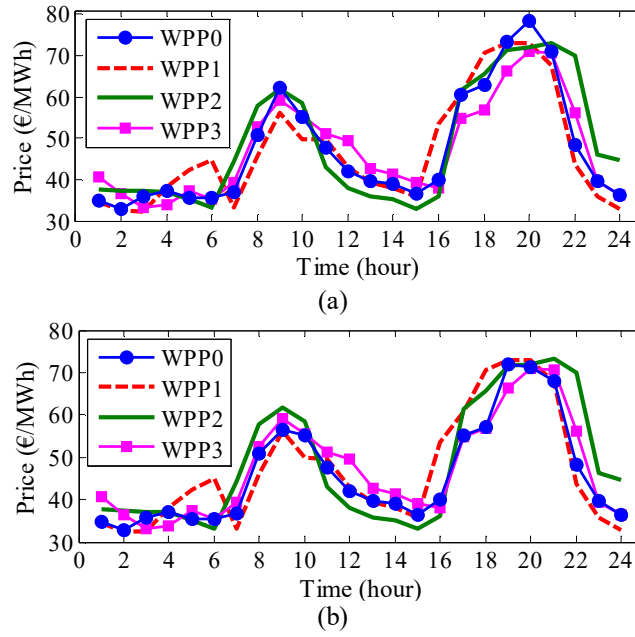


Fig. 6. The price signal offered by WPPs in $\beta = 0$, (a) Without DR and (b) 60% of DR participants.

The share of all WPPs to supply the demand of EVs for $\beta = 0, 1$ and 10 and in different levels of DR participants is depicted in Fig. 7. As it is shown in Fig. 2 the EVs' behavior is in contrast to that of loads. It means that when the demand of customers has a peak value (8:00-11:00 and 18:00-22:00), EVs are used for transportation at those hours and do not request for charge. But, during the night and early in the morning, EVs are connected to the grid and need to charge to be ready for the next-day trip. Since, the rival WPPs offer lower prices than the ones offered by the WPP during early in the morning and night (Fig. 6), the share of the WPP to supply the EVs is lower than the share of all the rivals, especially WPPs 1 and 2, as shown in Fig. 7. Moreover, in all DRs, with increasing β , since the prices offered by the WPP decreases in off-peak hours (See

Fig. 5), it can attract more EV owners as it behaves more risk averse (See Fig. 7 (a)). Also, rivals share to supply EVs' demand depend on their offered prices. For example, when WPP₁ has a low price, especially after 20:00, it supplies a high amount of EVs demand.

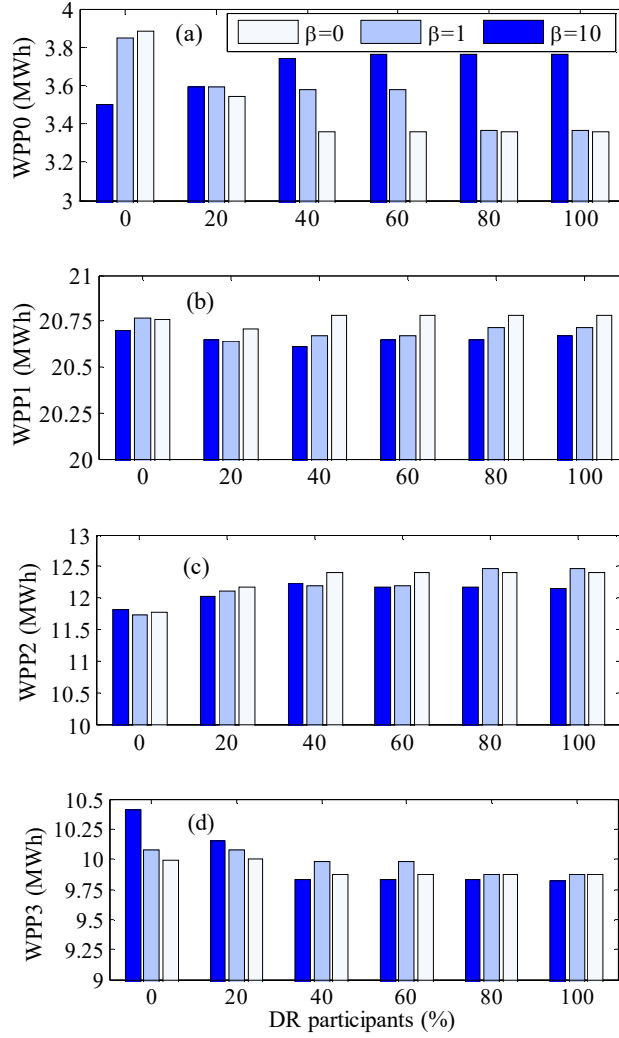


Fig. 7. Share of WPPs to supply the demand of EVs in different levels of DR participants and in three values of parameter β .

Moreover, the share of WPPs to supply the demand of customers for $\beta = 0, 1$ and 10 and in different levels of DR participants is shown in Fig. 8. It should be noted that it is assumed that in case of without DR each of WPPs supplies the demand of aggregators equally (each of them supplies about 11MWh). As observed from this figure, when DR participant is 60% , as the WPP becomes more risk averse, it tries to increase its price signal to compensate its profit losses due to selling in cheap positive balancing market. But, since the market is competitive, the WPP only increases the prices in some periods. Consequently, based on Fig. 8 (a), in $\text{DR}=60\%$, when the WPP is a risk taker (low values of β), it can absorb more demand, because it offers lower prices rather than that of offered by its rivals. But, when it becomes more risk-averse (i.e., $\beta = 10$), it loses some of the loads due to its high prices in some hours. Moreover, when DR participant is grown in 100% and amount of responsive loads augments, in the lower values of β (i.e., $\beta = 0$ and 1) that the price offered by the WPP is low, it can attract more demand (about 11.5MWh). But, as the WPP becomes more risk averse, it offers higher prices in some hours which lead to losing some of its customers. Therefore, as shown in $\beta=10$, the WPP supplies only about 11.2MWh .

In lower values of β , by increasing DR from 0% to 100%, more DR aggregators are willing to supply their demand from the WPP due to its low offering prices. But, for $\beta=10$, it is observed that the amount of demand that the WPP supplied has a variable trend. Because, applying time-varying electricity price structures coupled with the large-scale adoption of DR actions (DR=100%), might create pronounced peaks in the aggregate demand. These peaks might happen during time periods that the WPP offers lower prices than its rivals. Therefore, in $\beta=10$, although the price offered by the WPP increases, an upward trend is shown in DR=100% for demand supplied by the WPP.

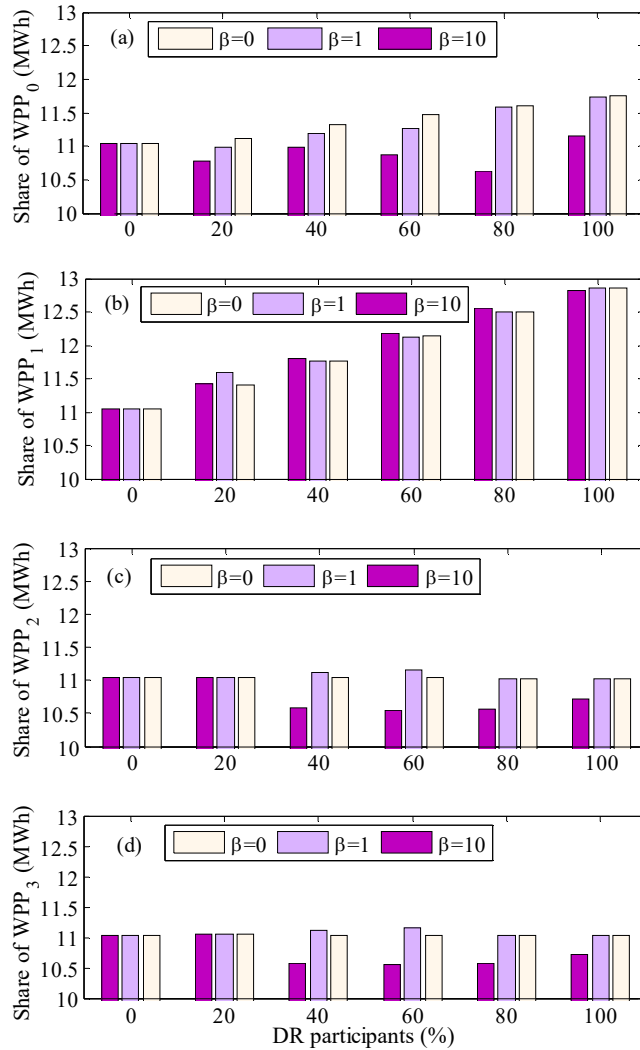


Fig. 8. Share of WPPs to supply the demand of customers in different levels of DR participants and in three values of parameter β .

Table 4 shows the expected profit of all WPPs in different values of DR and different risk aversion factors. It is observed that with increasing DR participants and β , due to occurring new peaks in load profile, the share of the under study WPP increases and as the result, its expected profit augments. Also, the expected profit of the rivals increases; because there are more customers who can choose their WPPs. Moreover, the new peak loads might happen at the time that the price of rivals is low and therefore, with increasing DR, some of the customers might go to the rivals.

Table 4. Expected profit of all WPPs in different DR and different risk aversion factors

DR (%)	β	WPP0	WPP1	WPP2	WPP3
0	0	1851.916	817.048	450.884	461.343
	1	1850.685	817.423	448.449	464.519
	10	1833.259	815.709	451.042	487.633
50	0	2132.174	1078.070	676.051	580.693
	1	2129.813	1074.429	676.093	602.713
	10	2114.207	1087.600	659.854	655.855
100	0	2419.705	1340.034	886.881	709.439
	1	2419.407	1337.521	889.163	710.643
	10	2383.283	1368.970	884.937	810.922

Table 5 shows the transferred percentage of DR and EV aggregators between the WPPs in $\beta=1$ in some sample hours. The negative sign denotes the opposite transfer of aggregators. For example, at 16:00, 2.3% of DR aggregators transfer from WPP₃ to WPP₀.

Fig. 9 depicts the price signal offered by all WPPs in $\beta=1$ and DR=60%. At this hour, based on

Fig. 9, it is seen that WPP₂ offers the lowest price and WPP₁ suggests the highest price. Therefore it is expected that most of DR and EV aggregators choose WPP₂. Based on Table 5, 21.8% of DR aggregators and 23% of EV aggregators transfer from WPP₀ to WPP₂. Also, 19.5% and 20.1% of DR and EV aggregators transfer from WPP₁ to WPP₂. Although, WPP₁ offers the most expensive price at this hour, there are negligible percentages of DR and EV aggregators who choose this WPP. For example, 2.3% and 2.9% transfer from WPP₀ to WPP₁, respectively. Moreover, WPP₃ has low price and about, but 24.1% and 24.7% of DR and EV aggregators move to WPP₂ to find a cheaper WPP. The analysis for the rest hours and parts is the same. Therefore, the under study WPP requires to know the percentage of DR and EV aggregators that may transfer among WPPs to choose the most competitive one.

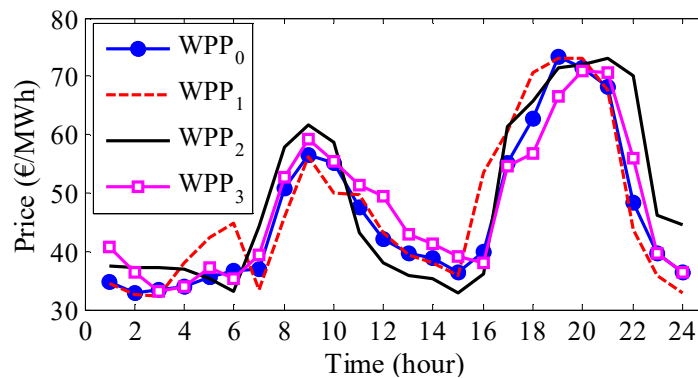


Fig. 9. The price signal offered by all WPPs in $\beta = 1$ and DR=60%.

Table 5. Transferred percentage of DR and EV aggregators between the WPPs in $\beta=1$, DR60%.

DR aggregator						
Hour	From WPP ₀ to WPP ₁	From WPP ₀ to WPP ₂	From WPP ₀ to WPP ₃	From WPP ₁ to WPP ₂	From WPP ₁ to WPP ₃	From WPP ₂ to WPP ₃
3:00	3.4	-0.2	-9.1	-18.09	-26.9	-8.9
8:00	20.8	1	-11.9	-19.83	-32.7	-12.9
12:00	0.2	21.86	-11.5	21.66	-11.7	-33
16:00	2.3	21.8	-2.3	19.5	-4.6	-24.1
20:00	-9.2	-8.5	-19.6	0.7	-10.4	-11.1
22:00	19.9	-0.5	-12.4	-20.4	-32.3	-11.9
24:00	17.96	0.9	-8.2	-17.0	-26.1	-9.1
EV aggregator						
3:00	20.4	2.4	-4	-18.06	-24.4	-6.4
8:00	27.5	4.6	-8.9	-22.9	-36.4	-13.5
12:00	3.5	28.5	-8.2	25	-11.7	-36.7
16:00	2.9	23	-1.7	20.1	-4.6	-24.7
20:00	2.8	3.6	4.5	0.8	1.7	0.9
22:00	27.6	3.3	-8.8	-24.3	-36.4	-12.1
24:00	24.6	4.1	-4.9	-20.44	-29.44	-9

5. Conclusion

This paper proposed a risk-constrained bi-level framework for the offering strategy of a WPP in a competitive market. The upper level represented the WPP profit maximization while the lower-level modeled the minimization of the payments by DR and EV aggregators. To solve the proposed model, the bi-level problem was transformed into a single-level linear programming approach using KKT optimality conditions and duality theory. Also, to cope with the uncertain nature of the problem, CVaR approach was applied to the decision making problem. The proposed model was implemented on a realistic case study and the results demonstrate that:

- A risk-neutral WPP tried to increase its trading energy in the DA market while the risk-averse WPP mitigated its participation in the DA market, and therefore its contribution in the balancing market increased.
- In lower values of β , with increasing DR participants, the share of the WPP to supply the demand of DR aggregators increased. But, with higher values of β and in a high level of DR participants, due to new peaks in the load profile, the share of the WPP increased.
- In lower values of risk aversion factor, with increasing DR, the amount of EVs that the WPP supplied, decreased. But, with higher values of β , as the prices in off-peak were lower, more EVs were motivated to charge their EVs with the considered WPP.

Future efforts will be mainly focused on the application of the proposed model for multi-MGs with different types of consumers (e.g., residential, industrial, and commercial) and incorporate solar power producer to the problem of stochastic decision making of a WPP in the electricity markets.

6. Acknowledgment

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Appendix A

To implement equation 17 in GAMS, the strategy is to use a first order Taylor approximation around the steady state to replace the equations with approximations, which are linear in the log-deviations of the variables. Suppose there is an equation in the form of

$$f(X_t, Y_t) = g(Z_t) \quad (\text{A.1})$$

Where, X_t , Y_t and Z_t are positive variables. To find the linearize form of equation (A.2), if we have

$$\log(f(e^{\log(X_t)}, e^{\log(Y_t)})) = \log(g(e^{\log(Z_t)})) \quad (\text{A.2})$$

Then take the first order Taylor approximation around the steady state ($\log(X)$, $\log(Y)$, $\log(Z)$) and after some calculations, we can write the left hand side as:

$$\log(f(X, Y)) + \frac{1}{f(X, Y)} [f_1(X, Y)X(\log(X_t) - \log(X)) + f_2(X, Y)Y(\log(Y_t) - \log(Y))] = \log(g(e^{\log(Z_t)})) \quad (\text{A.3})$$

Similarly, the right hand side can be linearized as:

$$\log(g(Z)) + \frac{1}{g(Z)} [g'(Z)Z(\log(Z_t) - \log(Z))] \quad (\text{A.4})$$

Equating (A.2) and (A.3) with some calculations yields the following log-linearized equation:

$$[f_1(X,Y)X_{xt} + f_2(X,Y)Y_{yt}] \cong [g'(Z)Z_{zt}] \quad (\text{A.5})$$

Notice that there is a linear equation in the deviations.

Appendix B

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

$$\begin{aligned} L = & \hat{E}_t^D [\text{Pr}_{w_0,t}^D X_{w_0,t,\psi}^D + \sum_{\substack{w \in N_w \\ w \neq 0}} \text{Pr}_{w,t,\psi}^D X_{w,t,\psi}^D] + \hat{E}_t^{Ch} [\text{Pr}_{w_0,t}^{Ch} X_{w_0,t,\psi}^{Ch} + \sum_{\substack{w \in N_w \\ w \neq 0}} \text{Pr}_{w,t,\psi}^{Ch} X_{w,t,\psi}^{Ch}] \\ & + \sum_{\substack{w \in N_w \\ w \neq w'}} \sum_{\substack{w' \in N_w \\ w' \neq w}} \hat{E}_t^D R_{w,w'}^D Y_{w,w',t,\psi}^D + \sum_{\substack{w \in N_w \\ w \neq w'}} \sum_{\substack{w' \in N_w \\ w' \neq w}} \hat{E}_t^{Ch} R_{w,w'}^{Ch} Y_{w,w',t,\psi}^{Ch} \\ & - \sum_{w \in N_w} \phi_\psi^{Ch/D} [X_{w,\psi}^{init,Ch/D} + \sum_{\substack{w \in N_w \\ w' \neq w}} Y_{w,w',\psi}^{Ch/D} - \sum_{\substack{w' \in N_w \\ w' \neq w}} Y_{w,w',\psi}^{Ch/D}] \\ & - \varepsilon_{w,\psi}^{Ch/D} (\sum_{\substack{w \in N_w \\ w \neq w_0}} X_{t,w,\psi}^{Ch/D} - 1) \\ & + \kappa_{t,\omega}^{Ch} (\text{SoC}_{t-1,s} + \eta^{Ch} E_{t,s}^{Ch}) \\ & + \underline{\mu}_{t,\omega}^{ch} (E_{t,\omega}^{ch}) + \overline{\mu}_{t,\omega}^{ch} (\overline{E}^{ch} - E_{t,\omega}^{ch}) \\ & + \underline{\mu}_{t,\omega}^s (\text{SoC}_{t,\omega}^E - \underline{\text{SoC}} \times E^{Cap}) + \overline{\mu}_{t,\omega}^s (\overline{\text{SoC}} \times E^{Cap} - \text{SoC}_{t,\omega}^E) \\ & + \underline{\tau}_{t,\omega}^{Ch} [\eta^{ch} \times (E_{t,\omega}^{ch}) \times \Delta t] + \overline{\tau}_{t,\omega}^{Ch} [\overline{\text{SoC}} \times E^{Cap} - \text{SoC}_{t-1,\omega}^E - \eta^{ch} \times E_{t,\omega}^{ch} \times \Delta t] \end{aligned} \quad (\text{B.1})$$

Then the KKT optimality condition of the lower level problem is obtained by partial derivatives of the 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. The bilinear products of continuous variables are replaced by their equivalent linear expressions.

$$\hat{E}_t^{D,Ch} \text{Pr}_{w_0,t}^{D,Ch} - \phi_\psi^{Ch/D} - \varepsilon_{w_0,\psi}^{Ch/D} \geq 0 \quad (\text{B.2})$$

$$\hat{E}_t^{D,Ch} \text{Pr}_{w,t,\psi}^{D,Ch} - \phi_w^{Ch,D} - \varepsilon_{w,\psi}^{Ch,D} \geq 0, \quad w = 1, 2, \dots, N_w \quad (\text{B.3})$$

$$\hat{E}_t^{Ch,D} R_{w,w'}^{Ch,D} + \varepsilon_{w',\psi}^{Ch/D} - \varepsilon_{w,\psi}^{Ch/D} \geq 0, \quad \forall w, w' \in N_w, \quad w \neq w' \quad (\text{B.4})$$

$$\hat{E}_t^{Ch,D} \text{Pr}_t^{Ch} - \varepsilon_{w_0,\psi}^{Ch,D} - \phi_w^{Ch,D} \leq M_1^{Ch,D} e_0^{X_{Ch,D}} \quad (\text{B.5})$$

$$\hat{E}_t^{Ch,D} \text{Pr}_{w,t,\psi}^{Ch,D} - \varepsilon_{w,\psi}^{Ch,D}(\xi) - \phi_w^{Ch,D} \leq M_1^{Ch,D} e_w^{X_{Ch,D}}, \quad w = 1, 2, \dots, N_w \quad (\text{B.6})$$

$$X_{w,t,\psi}^{Ch,D} \leq M_2^{Ch,D} \left[1 - e_{w,\psi}^{X_{Ch,D}} \right] \quad (\text{B.7})$$

$$\hat{E}_t^{Ch,D} R_{w,w'}^{Ch,D} + \varepsilon_{w,w'}^{Ch/D} - \varepsilon_{w',\psi}^{Ch/D} \leq M_1^{Ch,D} e_{w,w'}^{Y_{Ch,D}}, \quad \forall w, w' \in N_w, w \neq w' \quad (\text{B.8})$$

$$Y_{w,w',\psi}^{Ch/D} \leq M_2^{Ch,D} \left[1 - e_{w,w'}^{Y_{Ch,D}} \right], \quad \forall w, w', w \in N_w, w \neq w' \quad (\text{B.9})$$

$$e_w^{X,CH,D} \in \{0,1\}, \quad \forall w \in N_w \quad (\text{B.10})$$

$$e_{w,w'}^{Y,Ch,D} \in \{0,1\}, \quad \forall w, w', w, w' \in N_w, w \neq w' \quad (\text{B.11})$$

For the rest, only contraction forms of the constraints are given.

$$0 \leq \underline{\mu}_{t,\omega}^s \perp (\underline{SoC}_{t,\omega}^E - \underline{SoC} \times E^{Cap}) \geq 0, \quad \forall t, \forall \omega \quad (\text{B.12})$$

$$0 \leq \overline{\mu}_{t,\omega}^s \perp (\overline{SoC} \times E^{Cap} - \overline{SoC}_{t,\omega}^E) \geq 0, \quad \forall t, \forall \omega \quad (\text{B.13})$$

$$0 \leq \underline{\tau}_{t,\omega}^{Ch} \perp [\underline{\eta}^{Ch} \times (E_{t,\omega}^{Ch}) \times \Delta t] \geq 0, \quad \forall t, \forall \omega \quad (\text{B.14})$$

$$0 \leq \overline{\tau}_{t,\omega}^{Ch} \perp [\overline{SoC} \times E^{Cap} - \overline{SoC}_{t-1,\omega}^E - \overline{\eta}^{Ch} \times E_{t,\omega}^{Ch} \times \Delta t] \geq 0, \quad \forall t, \forall \omega \quad (\text{B.15})$$

$$0 \leq \underline{\gamma}_{t,\omega}^{Ch} \perp [\underline{\eta}^{Ch} \cdot E_{t,\omega}^{Ch} \cdot \Delta t] \geq 0 \quad (\text{B.16})$$

$$0 \leq \overline{\gamma}_{t,\omega}^{Ch} \perp [\overline{SoC} \cdot E^{Cap} - \overline{SoC}_{t-1,\omega}^E - \overline{\eta}^{Ch} \cdot E_{t,\omega}^{Ch}] \geq 0 \quad (\text{B.17})$$

where, $M_1^{Ch,D}$ and $M_2^{Ch,D}$ are large constants and $e_{w,\psi}^{X_{Ch,D}}$ and $e_{w,w'}^{Y,Ch,D}$ are binary variables.

Here, the bilinear product of terms $E_{t,s}^D \text{Pr}_{w_0,t}^D$ and $E_{t,s}^{Ch} \text{Pr}_{w_0,t}^{Ch}$ bring nonlinearities to the problem. Therefore, strong duality theorem [33] is used to replace these terms with their equivalent expressions as bellow.

$$\begin{aligned}
& \text{Maximize } \sum_{\substack{\varepsilon_{w,\psi}, \phi_\psi \\ w \in N_w}} \left[(X_{w,\psi}^{init.D} \varepsilon_{w,\psi}^D + \phi_\psi^D) + (X_{w,\psi}^{init.Ch} \varepsilon_{w,\psi}^{Ch} + \phi_\psi^{Ch}) \right] \\
& = \hat{E}_t^D \left[\text{Pr}_{w_0,t}^D X_{w_0,t,\psi}^D + \sum_{\substack{w \in N_w \\ w \neq 0}} \text{Pr}_{w,t,\psi}^D X_{w,t,\psi}^D + \sum_{\substack{w \in N_w \\ w' \in N_w \\ w' \neq w}} R_{w,w'}^D Y_{w,w',t,\psi}^D \right] \\
& + \hat{E}_t^{Ch} \left[\text{Pr}_{w_0,t}^{Ch} X_{w_0,t,\psi}^{Ch} + \sum_{\substack{w \in N_w \\ w \neq 0}} \text{Pr}_{w,t,\psi}^{Ch} X_{w,t,\psi}^{Ch} + \sum_{\substack{w \in N_w \\ w' \in N_w \\ w' \neq w}} R_{w,w'}^{Ch} Y_{w,w',t,\psi}^{Ch} \right]
\end{aligned} \tag{B.18}$$

From A.1 the bilinear products would be obtained. Then, from the following equations, the

$$E_{t,s}^D = E_{t,s}^{T_D} \sum_{\psi \in \Psi} \rho_\psi^D X_{w_0,\psi}^D \tag{B.19}$$

$$E_{t,s}^{Ch} = E_{t,s}^{T_{Ch}} \sum_{\psi \in \Psi} \rho_\psi^{Ch} X_{w_0,\psi}^{Ch} \tag{B.20}$$

From the above formulations, the bilinear products are replaced with their equivalent expressions:

$$E_{t,s}^D \lambda_{w_0,t}^D = \frac{E_{t,s}^{T_D}}{\hat{E}_t^D} \sum_{\psi \in \Psi} \rho_\psi^D \left[- \sum_{\substack{w \in N_w \\ w \neq 0}} \hat{E}_t^D \text{Pr}_{w,t,\psi}^D X_{w,\psi}^D - \sum_{\substack{w \in N_w \\ w' \in N_w \\ w' \neq w}} \hat{E}_t^D R_{w,w'}^D Y_{w,w',t,\psi}^D + \sum_{w \in N_w} X_{w,\psi}^{init.D} \varepsilon_{w,\psi}^D + \phi_\psi^D \right] \tag{B.21}$$

$$E_{t,s}^{Ch} \lambda_{w_0,t}^{Ch} = \frac{E_{t,s}^{T_{Ch}}}{\hat{E}_t^{Ch}} \sum_{\psi \in \Psi} \rho_\psi^{Ch} \left[- \sum_{\substack{w \in N_w \\ w \neq 0}} \hat{E}_t^{Ch} \text{Pr}_{w,t,\psi}^{Ch} X_{w,\psi}^{Ch} - \sum_{\substack{w \in N_w \\ w' \in N_w \\ w' \neq w}} \hat{E}_t^{Ch} R_{w,w'}^{Ch} Y_{w,w',t,\psi}^{Ch} + \sum_{w \in N_w} X_{w,\psi}^{init.Ch} \varepsilon_{w,\psi}^{Ch} + \phi_\psi^{Ch} \right] \tag{B.22}$$

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