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A Stochastic Bi-Level Decision-Making Framework for a Load-Serving Entity in Day-Ahead and Balancing Markets

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SUMMARY

This paper investigates a stochastic bi-level scheduling model for decision-making of a load serving entity (LSE) in competitive day-ahead (DA) and balancing markets with uncertainties. In this model, LSE as the main interacting player of the market sells electricity to end-use customers and plug-in electric vehicles (PEVs) to maximize its expected profit. Therefore, a two-level decision-making process with different objectives is considered to solve the problem. In one level, the objective is to maximize the LSE's profit by optimally scheduling of responsive loads and PEVs charging/discharging process, while in the other level, the payments of the customers and PEV owners should be minimized in a competitive market. In the proposed decision-making process, to model the uncertainties, market prices, required energy of customers and PEVs as well as the rival LSEs' prices are considered as random variables. The bi-level stochastic problem is then converted into a linear single-level stochastic model with equilibrium constraints by using Karush–Kuhn–Tucker (KKT) optimality conditions as well as duality theory. A case study is implemented to indicate the applicability of the intended model.

Index Terms— Bi-level scheduling, demand response, plug-in electric vehicle (PEV), energy management, load serving entity (LSE).

1. INTRODUCTION

There is an appearing consensus that demand-side management (DSM) can have an active duty in keeping balance between supply and demand in future smart grids [1]. At demand side of a smart restructured power system, responsive loads can not only supply various types of demand response (DR) services such as peak load shifting and ancillary services [2], but also contribute heavily in reduction of operating cost and emission as well as improvement of system reliability [3]. Moreover, plug-in electric vehicles (PEVs) as highly elastic resources at the demand side could make a number of advantages to the future smart grids by their charging and discharging power. Therefore, DSM is more important, especially when the technology such as vehicle-to-grid enables PEVs to work as the grid resources by providing power back to the system [4], [5].

A demand-side aggregator is widely contemplated as an independent load serving entity (LSE), who is responsible for making bids in electricity markets on behalf of a group of customers [6], maximizing their profits and providing their electricity demands [7]. Therefore, LSEs has a substantial duty as a middle agent between end-users and system operator and aggregates customers

43 to take part in the electricity market. In this regard, scheduling strategies for the LSEs has been the
44 subject area of many research works. A robust optimization approach is proposed in [8] to handle
45 market price uncertainty, in which the retailer seeks to minimize the energy procurement costs with
46 only considering DR programs. In [9] a strategic bidding framework for LSE agent has been proposed
47 in which the objective is to maximize LSE's profit by implementing DR programs. In the same work,
48 energy management of PEVs as a significant part of responsive loads has not been considered in the
49 LSE scheduling process. In [10], an energy management system, that simulates the tasks of an LSE,
50 adjusts the price-responsive loads and allows the group of demands to exchange energy at proper
51 periods such that to maximize their utility function. In the mentioned work, the energy management
52 system is not a profit-seeking entity as it is considered in this work. A bi-level complementarity model
53 for a price-maker energy storage system to determine the most beneficial trading actions in pool-
54 based markets, including day-ahead (DA) and balancing settlements is represented in [11]. Also, the
55 uncertainties of the problem are incorporated into the model using a set of scenarios generated. A
56 mathematical program with equilibrium constraints has been provided by [12] to maximize the profit
57 of PEV aggregator and to minimize the PEV owners' costs. In [13], joint bidding and pricing problem
58 of an LSE as a bi-level framework is modeled such that the optimal energy bids and reserve offers
59 that the LSE submits to the wholesale electricity markets as well as its optimal energy and reserve
60 prices in the retail electricity markets are determined simultaneously so as to maximize the LSE's
61 profit. Although, efficient models for LSE scheduling has been presented in [13], competition among
62 the LSEs in the retail market has not been addressed.

63 In most of the reviewed market models, the LSE plays as a middleman for the end-use customers
64 and proposes the energy bids to the independent system operator (ISO). However, in fact the LSE as
65 a mediator can specify prices different from the one defined by the ISO to make profit [14]. On the
66 other hand, since, the electricity industry is changing into a distributed and competitive craft,
67 competition among the market agents is facilitated. In such competitive environment, the interaction
68 between LSEs and customers' responses to the retail prices, should be considered in the operational
69 decision-making of the LSE. So far, there is some works introducing competition into the LSE
70 scheduling problem. Also, authors in [15] propose a Stackelberg game between LSEs and end-use
71 customers to maximize their revenues. However, the effect of PEVs scheduling in decision-making of
72 LSEs is not addressed. A market model has been provided based on game-theoretical implications in
73 [16] where DR aggregators compete against each other to sell energy stored in consumers' storage
74 devices. Therefore, optimal bidding decision for each aggregator to maximize its own payments
75 despite incomplete information in the game and remarkable changes in market circumstance is
76 provided. However, in [16], the tendency towards optimal payments for the energy requirement
77 derived from loads and PEV use for movement is not considered. This matter could highly affect the
78 customer's choice to select the fairest aggregator for its energy requirements. In other words,
79 considering the problem only from LSEs' perspective implies that the role of customers and their
80 reaction to the market prices will be ignored. A decision-making framework based on time-of-use
81 (TOU) price settings and procurement strategies in medium-term planning for a retailer agent with
82 considering the rational responses of consumers to the TOU prices is investigated in [14]. In that
83 study, the competitive environment due to existence of rival retailers is taken into account, although
84 the behavior of PEV owners is neglected in that scheduling problem. A bottom-up model for DR
85 aggregators in electricity markets proposed in [17] which enables a DR aggregator to consider the
86 technical constraints of customers in developing an optimal trading strategy in the wholesale
87 electricity market. Since the DR aggregator needs to be competitive in trading DR on both consumers
88 and wholesale sides, stepwise functions is provided for load shifting and load curtailment programs.

89 However, such functions cannot show the competition nature of the problem completely. A decision-
90 making model, based on stochastic programming, for a retailer is proposed in [18] to determine the
91 sale price of electricity to the customers based on TOU rates.

92 The authors in [19] have partly addressed the issue by proposing a stochastic bi-level approach for
93 the EV aggregator in order to participate in short-term electricity market considering the preferences
94 of EV owners. However, discharge process of EVs and DR participants has not been studied in
95 decision-making process. Similarly, in [20] the authors have presented a scholastic scheduling model
96 for EV aggregators in a competitive market with considering both charging and discharging process
97 of EVs. A cooperation model between a generating company and several marketers is presented in
98 [21] which considers the optimal decision for the generating company and the group of marketers in
99 terms of maximization of their profits, based on bi-level optimization. Nevertheless, the works in [20]
100 and [21] did not address the effect of DR programs.

101 In this study, an efficient framework is provided for decision making of an LSE in a competitive
102 energy market under uncertainties. decision-making problem of LSE is modelled as a stochastic bi-
103 level framework, in which the obtained nonlinear problem is converted into an equivalent single-
104 level mixed-integer linear programming problem by applying Karush–Kuhn–Tucker (KKT)
105 optimality conditions [22] and duality theory. Also, a proper model of responsive loads and PEVs are
106 developed to analyse the effect of their participation in DR programs on decision making of LSE.
107 Compared to the previous works in this area, there exist a number of key contributions in this study.
108 First, a proper bidding strategy for a typical LSE is introduced with considering both PEVs and DR
109 programs from a joint customers' and LSE's points of view. As an extension of the model developed
110 in prior works, this paper also considers a fully competitive energy market under rival LSEs offering
111 prices uncertainties to enhance the market share of the under-study LSE and to determine the optimal
112 level of its participation in DA market, positive and negative balancing markets as well as to derive
113 optimal selling prices offered to customers and PEV owners. In addition, in the proposed strategy,
114 both PEVs charging and discharging process is modelled and optimal offering price of the LSE and
115 its share in discharging process of PEVs is investigated. Table I addresses a systematically
116 comparison between the contributions of this paper and some of the recent works in the same subject
117 area. As can be observed, most of the recent works do not consider the PEVs charging and discharging
118 management in the optimization problems of LSEs, and they mainly investigated impacts of DR
119 programs based on other types of responsive loads [9]. To the best of our knowledge, there are also
120 some limited works addressing the decision-making problem of LSE by considering both PEVs' and
121 customers' participation in DR programs, simultaneously. However, they did not consider
122 competitive trading floor (e.g., [12]). As a whole, the contributions of this paper can be highlighted
123 as:

- 124 • A bi-level decision-making structure for an LSE is proposed to determine the optimal level of
125 participation in the DA market, positive and negative balancing markets, to derive optimal
126 selling prices offered to customers and PEV owners as well as to model the corresponding
127 rational behaviour of those consumers to the offering prices.
- 128 • The impacts of PEVs participants in discharge process on decision-making of the LSE are
129 investigated in a competitive market via the proposed model. Also, efficient load management
130 is implemented through incorporation of DR programs.
- 131 • The reaction of PEV owners and responsive loads to the decisions made by the LSE as well as
132 their preferences is discussed within a fully competitive market model to enhance the market
133 share of the LSE.

134 The rest of the paper is organized as follows: In section 2, the proposed decision-making problem
 135 of the LSE is explained. The problem formulation is given in section 3 and in section 4, the
 136 simulations and numerical results are provided. At last, section 5 draws the conclusions.

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

Reference	Bi-level modelling	Competitive trading floor	DR participation	EVs Charging management	EVs Discharging management
[6]	✓	✓	✓	-	-
[8]	-	-	✓	-	-
[9]	✓	-	✓	-	-
[10]	✓	-	✓	-	-
[11]	✓	✓	-	-	-
[12]	✓	-	✓	✓	✓
[13]	✓	-	✓	-	-
[14]	✓	✓	✓	-	-
[17]	✓	✓	✓	-	-
[15]	-	✓	✓	-	-
[16]	-	✓	✓	-	-
[19]	✓	✓	-	✓	✓
[20]	✓	✓	-	✓	-
This paper	✓	✓	✓	✓	✓

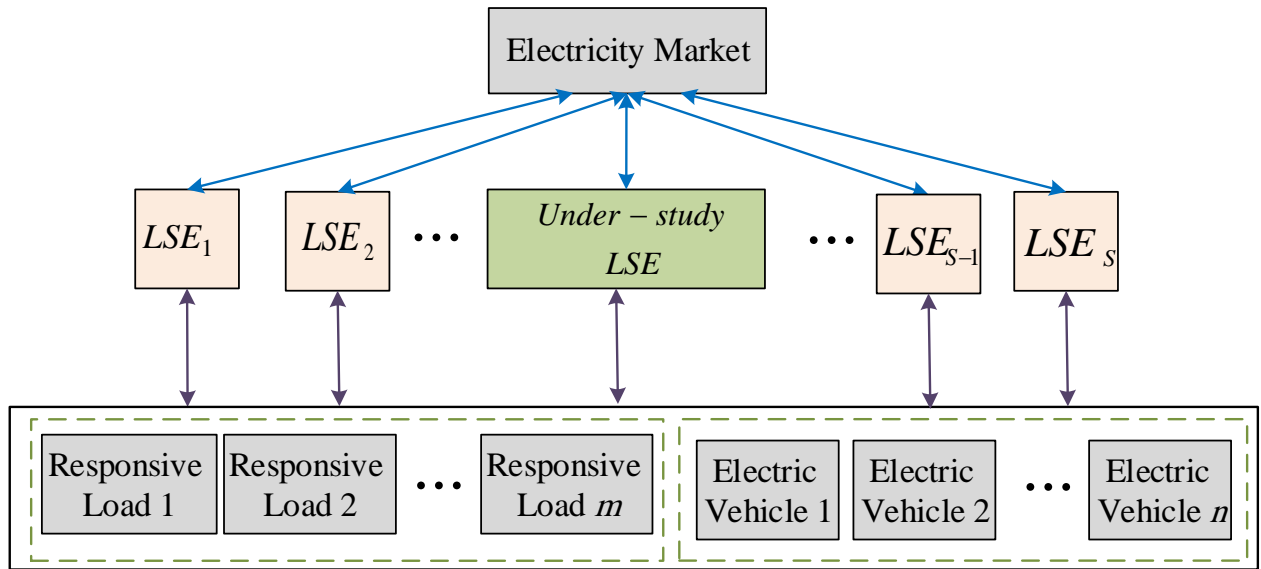
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2. STOCHASTIC-BASED DECISION-MAKING PROBLEM OF LSE

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 141 In a fully competitive electricity market, LSEs play a critical role to fill the gaps between end
 142 customers and wholesale market operators to connect them into an optimal operation framework. As
 143 a profit-seeking organization, the objective of LSEs is to maximize their expected profit considering
 144 the uncertainty from both wholesale market and end-use customers. Naturally, LSEs will have the
 145 motivation to induce the end-use customers' inherent elasticity by offering DR programs, especially
 146 when the system is under stress or close to the next binding constraint, which is termed as a critical
 147 load level. In this paper, a decision-making model is investigated for an LSE that supports some
 148 responsive loads (e.g., controllable residential and industrial loads) and PEVs as depicted in Figure
 149 1. The under-study LSE has a take-or-pay contract [23] to buy energy from DA and balancing markets
 150 while it sells electricity to the customers under real-time pricing scheme in a competitive
 151 environment. Here, it is assumed that the customers have smart energy management devices and can
 152 tune their demand to mitigate their energy consumption costs by responding to the prices offered by
 153 LSEs. Also, they can supply their demand from fair LSE based on the prices offered by each LSE
 154 and can change their LSE in a short-term time span. This is plausible by constructing fast
 155 communication infrastructure with bidirectional data transition among the LSEs and responsive loads
 156 and the PEV parking lots [24]. It should be noted that, responsive loads can take part in price-based
 157 DR programs with common schemes comprising sheddable and shiftable loads [25]. Moreover, PEV
 158 owners can reduce their payments by choosing proper LSE for charging and discharging process.

159 The proposed decision-making problem of LSE for scheduling of the responsive loads and PEVs
 160 has a two-level structure where in the upper level, the LSE aims at maximizing its expected profit
 161 from taking part in pool-based short-term electricity market comprising of DA and balancing markets.
 162 In this level, scheduled energy exchanges for the next day are specified and then the energy deviations
 163 are obtained and compensated in the balancing market. Also, the LSE suggests optimal bids to the
 164 PEV owners and end-use customers to encourage them making interactive energy trading. Since, the

165 actions of rival LSEs affect the decision-making of the under-study LSE, the prices offered by rivals
 166 are considered by different scenarios.
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Figure 1. Schematic of the LSE problem.

In the lower level, there are several customers that should adjust their loads based on offered prices by LSEs and purchase their needed energy through the most appropriate LSE. Moreover, PEVs' owners are willing to buy energy from the LSE with the lowest charging costs or to sell energy through discharging of the batteries, with the highest prices to minimize their total payments. To this end, by using Karush–Kuhn–Tucker (KKT) optimality conditions, the equivalent single-level form of the proposed scheme can be obtained. Moreover, the bilinear products are substituted by their equivalent statements using strong duality theorem. The structure of bi-level decision making for taking part of the LSE in the DA and balancing trading floor is shown in Figure 2.

Here, the realizations of uncertainties are modeled using the scenario generation process based on Monte-Carlo simulations (MCS) and roulette wheel mechanism (RWM). At first the distribution function is separated into different intervals with different standard deviations [19]. Then, each interval is related to a certain probability that is obtained by the probability density functions (PDF) [19]. Each scenario vector includes the information of electricity market, loads of customers, PEVs charging and discharging power and the prices offered by the rivals. Then a specified number of the probable scenarios are chosen precisely using K-means algorithm [26]. Finally, the achieved equivalent single-level stochastic problem is considered as a mixed-integer linear problem (MILP).

3. THE PROPOSED DECISION MAKING FORMULATION

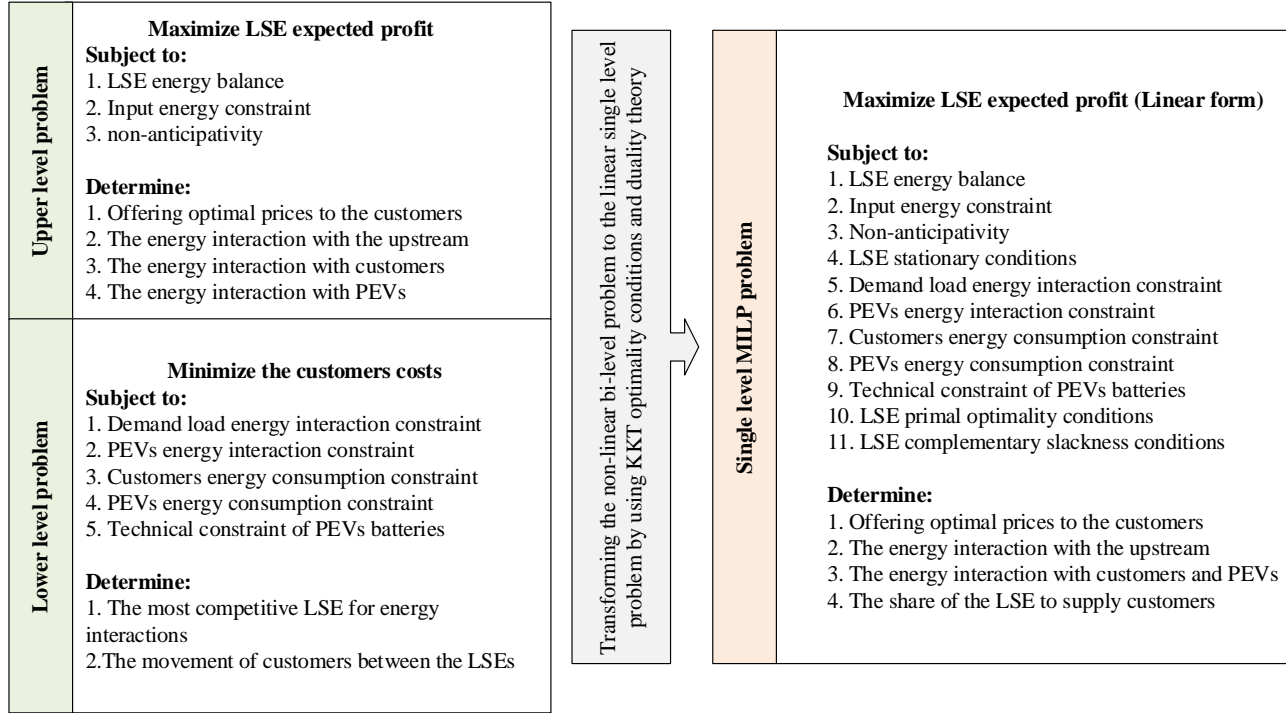
The proposed decision-making problem of LSE is formulated as a stochastic bi-level programming problem and presented in this section.

3.1 Upper-level Viewpoint

In the upper-level, the LSE bids to the electricity market while competing against rival LSEs to offer optimal prices to customers and PEV owners to maximize its expected profit. Therefore, the expected profit includes the income from selling energy to both customers and PEVs and participating

195 in negative balancing market minus the costs due to purchasing energy from DA and positive
 196 balancing markets and buying energy from PEVs in discharging mode. Hence, in the upper-level, the
 197 decision-making of the LSE can be formulated as bellow:

$$\text{Maximize} \left\{ \sum_{\omega \in \Omega} \pi_{\omega} \sum_{t \in T} [(E_{t,\omega}^D \text{Pr}_{s_0,t}^D + E_{t,\omega}^{Ch} \text{Pr}_{s_0,t}^{Ch} - E_{t,\omega}^{Dis} \text{Pr}_{s_0,t}^{Dis} - E_{t,\omega}^{DA} \text{Pr}_{t,\omega}^{DA} - E_{t,\omega}^{B^+} \text{Pr}_{t,\omega}^{B^+} + E_{t,\omega}^{B^-} \text{Pr}_{t,\omega}^{B^-})] \right\} \quad (1)$$



198
 199
 200
 201 Figure 2. The bi-level framework of decision-making of LSE.

202 Subject to the following constraints,

$$E_{t,\omega}^D + E_{t,\omega}^{Ch} - E_{t,\omega}^{Dis} = E_{t,\omega}^{DA} + E_{t,\omega}^{B^+} - E_{t,\omega}^{B^-} \quad (2)$$

$$E_{t,\omega}^D = E_{t,\omega}^{DD} \sum_{\xi \in \Xi} \theta_{\xi}^D L_{S_0,t,\xi}^D \quad (3)$$

$$E_{t,\omega}^{Ch} = E_{t,\omega}^{Dch} \sum_{\xi \in \Xi} \theta_{\xi}^{Ch} L_{S_0,t,\xi}^{Ch} \quad (4)$$

$$E_{t,\omega}^{Dis} = E_{t,\omega}^{Ddis} \sum_{\xi \in \Xi} \theta_{\xi}^{Dis} L_{S_0,t,\xi}^{Dis} \quad (5)$$

$$E_{t,\omega}^{DA} = E_{t,\omega}^{DA} \quad (6)$$

$$E_{t,\omega}^{B^+} \leq \bar{P} \quad (7)$$

$$E_{t,\omega}^{B^-} \leq \bar{P} \quad (8)$$

202 Equation (1) indicates the objective function from the under-study LSE perspective. Constraint (2)
 203 investigates the energy balance. The under-study LSE contributes to provide the required energy of
 204 customers and PEVs based on Constraints (3)-(5). That is the estimated energy supplied by the under
 205 study LSE that is equal to the expected value of the demand of the responsive loads and
 206 charge/discharge of EVs supplied by the LSE over all rival-LSEs price scenarios. The non-

207 anticipativity is demonstrated in (6) and confirms similar DA bids for equal DA prices at each hour t
 208 and scenario ω [27]. The energy transaction in both balancing markets is limited based on constraints
 209 (7) and (8), respectively.

210
 211 **3.2 Lower-level Viewpoint**
 212 The objective in the lower-level consists of the objectives of customers and PEV owners to minimize
 213 the costs of their energy exchange that is explained as bellow:

214

$$\begin{aligned}
 \text{Minimize } \{ & \hat{E}_t^D [\Pr_{s_0,t}^D L_{s_0,t,\xi}^D + \sum_{\substack{s \in S \\ s \neq 0}} \Pr_{s,t,\xi}^D L_{s,t,\xi}^D] + \\
 & \hat{E}_t^{Ch} [\Pr_{s_0,t}^{Ch} L_{s_0,t,\xi}^{Ch} + \sum_{\substack{s \in S \\ s \neq 0}} \Pr_{s,t,\xi}^{Ch} L_{s,t,\xi}^{Ch}] - (\hat{E}_t^{Dis} [\Pr_{s_0,t}^{Dis} L_{s_0,t,\xi}^{Dis} + \sum_{\substack{s \in S \\ s \neq 0}} \Pr_{s,t,\xi}^{Dis} L_{s,t,\xi}^{Dis}]) + \\
 & \left. \sum_{\substack{s \in S \\ s' \neq s}} \sum_{\substack{s' \in S \\ s' \neq s}} \hat{E}_t^D R_{s,s'}^D M_{s,s',t,\xi}^D + \sum_{\substack{s \in S \\ s' \neq s}} \sum_{\substack{s' \in S \\ s' \neq s}} \hat{E}_t^{Ch} R_{s,s'}^{Ch} M_{s,s',t,\xi}^{Ch} + \sum_{\substack{s \in S \\ s' \neq s}} \sum_{\substack{s' \in S \\ s' \neq s}} \hat{E}_t^{Dis} R_{s,s'}^{Dis} M_{s,s',t,\xi}^{Dis} \right\} \quad (9)
 \end{aligned}$$

215 where, s and s' mention the transfer of customers and PEV owners among the LSEs, and index $s=0$
 216 shows the under-study LSE. The payment made by the customers and EV owners to the under-study
 217 and rival LSEs is characterized through the first two lines in (9), respectively. The unwillingness of
 218 both customers and PEV owners to alter their LSE is determined in the third line. In other words, the
 219 last line states the reluctance of customers to switch among LSEs. Since, the prices offered by the
 220 rivals are uncertain to the under-study LSE, it approximates prices offered by the rivals through a set
 221 of scenarios to adjust its selling price to the customers. In this regard, at first, the prices of rivals are
 222 forecasted based on historical data and then the uncertainties of prices offered by all rivals are
 223 extracted based on their corresponding errors, and then normal probability density functions (PDFs)
 224 are calculated based on previous records of the rivals' prices. In this study, PDFs of rivals' prices are
 225 divided into three discrete intervals with different probability levels. Here, the scenarios are generated
 226 based on the hourly price forecasts with a uniform random error of $\pm 10\%$ for hourly rivals' prices
 227 [29]. Then, the selling price of the LSE is computed based on a bi-level stochastic program in which
 228 different uncertainties are investigated via stochastic programming. The obtained price of the LSE is
 229 considered to enable consumers and PEVs' owners to track the price changes and manage their
 230 consumption accordingly. The load management process could be an automatic procedure
 231 implemented through an energy management and automation system. In other words, the proposed
 232 automated DR consists of fully automated signaling from a utility (which is the LSE in our case) to
 233 provide automated connectivity to customer end-use control systems and strategies. It should be noted
 234 that from the practical point of view, a main concern lies on the technological side which reflects
 235 barriers that are related to the advanced systems implementations and associated interfaces between
 236 users and operator. However, with the growth of smart technology these barriers are deemed to be
 237 overcome. Generally, the equations represented LSEs competition in the proposed decision making
 238 framework can be modeled as bellow:

239
 240

$$L_{s,\xi,t}^\ell = U_{s,t,\xi}^{\text{int},\ell} + \sum_{\substack{s' \in S \\ s' \neq s}} M_{s,s',t,\xi}^\ell - \sum_{\substack{s' \in S \\ s' \neq s}} M_{s',s,t,\xi}^\ell : e_{s,\xi}^\ell \quad (10)$$

$$\sum_{\substack{s \in N_s \\ s \neq 0}} L_{s,t,\xi}^\ell + L_{s_0,t,\xi}^\ell = 1 : w_\xi^\ell \quad (11)$$

$$L_{s,t,\xi}^{\ell} \geq 0 \quad (12)$$

241
 242 In order to abbreviate the equations, symbol ℓ is used which refers to the charge/discharge process
 243 of PEVs and demand loads. In other words, in the above formulations, for simplicity of derivation,
 244 index ℓ is used instead of Ch , Dis and D indices. Constraint (10) discusses the contribution of LSEs
 245 to provide energy for both customers and PEVs. It shows the increment and decrement from base
 246 demand in scenario ζ at period t for each LSE. All of the LSEs should supply all the required energy
 247 of loads and PEVs in their jurisdiction based on constraint (11). Constraint (12) represents that the
 248 amount of demand that is provided by each LSE is not negative. Also, technical constraints of PEVs'
 249 batteries are provided as bellow:

$$\underline{SoC} \leq SoC_{t,\omega} \leq \overline{SoC}; \underline{\mu}_{t,\omega}^S, \overline{\mu}_{t,\omega}^S \quad (13)$$

$$0 \leq SoC_{t,\omega} \leq (\overline{SoC} - SoC_{t-1}) : \underline{\gamma}_{t,\omega}^{Ch}, \overline{\gamma}_{t,\omega}^{Ch} \quad (14)$$

$$SoC_{t-1,\omega} - \underline{SoC} \leq SoC_{t,\omega} \leq SoC_{t-1,\omega} : \underline{\gamma}_{t,\omega}^{Dis}, \overline{\gamma}_{t,\omega}^{Dis} \quad (15)$$

250
 251 Constraints (13)-(15) provide the technical constraints of the PEV battery. Dual variables of each
 252 constraint in the lower-level problem are shown right after their corresponding constraints following
 253 a colon that will be used to transform lower-level problem into its dual problem. Moreover, the
 254 responsive loads participate in DR programs and change their energy usage based on the price
 255 suggested by LSEs and the defined elasticity. Demand elasticity is indicated as demand reaction to
 256 the price signal [29]. The customers' energy consumption behavior can be adjusted in response to the
 257 incentives received based on the load level changes and the electricity prices. To achieve maximum
 258 benefit, end-use consumers manage their energy usage pattern in period t from an initial value, $E_t^{D,int}$
 259 to $E_{t,\omega}^{D,D}$ as below:

$$E_{t,\omega}^{D,D} = E_t^{D,int} + \Delta E_t^D \quad (16)$$

261
 262 The benefit of customers can be obtained as:

$$S(E_{t,\omega}^{D,D}) = B(E_{t,\omega}^{D,D}) - E_{t,\omega}^{D,D} \cdot Pr_{t,\omega}^{DA} \quad (17)$$

264
 265 where, $S(E_{t,\omega}^{D,D})$ and $B(E_{t,\omega}^{D,D})$ represent the benefit and income of customers after performing DR
 266 program. The following statement should be met to obtain maximum benefit for customers.

$$\frac{\partial S(E_{t,\omega}^{D,D})}{\partial E_{t,\omega}^{D,D}} = \frac{\partial B(E_{t,\omega}^{D,D})}{\partial E_{t,\omega}^{D,D}} - Pr_{t,\omega}^{DA} = 0 \quad (18)$$

268 In this study, a quadratic utility function, is used to incentivize the participation of responsive loads
 269 in DR programs [30]. Based on the model, the utility of customers is obtained as:

$$B(E_{t,\omega}^{D,D}) = B_t^{D,int} + \frac{Pr_t^{DA,int} \cdot E_{t,\omega}^{D,D}}{1 + Elas_{t,t}^{-1}} \times \left[\left(\frac{E_{t,\omega}^{D,D}}{E_t^{D,int}} \right)^{Ela_{t,t}^{-1}} - 1 \right] \quad (19)$$

270 Differentiating (20) with respect to $E_{t,\omega}^{D,D}$ gives:

$$\frac{\partial B(E_{t,\omega}^{D,D})}{\partial E_{t,\omega}^{D,D}} = \frac{Pr_t^{DA,int}}{1 + Elas_{t,t}^{-1}} \times \left[\left(\frac{E_{t,\omega}^{D,D}}{E_t^{D,int}} \right)^{Ela_{t,t}^{-1}} - 1 \right] + \frac{Pr_t^{DA,int} \cdot E_{t,\omega}^{D,D}}{1 + Elas_{t,t}^{-1}} \times \left[Ela_{t,t}^{-1} \cdot \frac{1}{E_t^{D,int}} \left(\frac{E_{t,\omega}^{D,D}}{E_t^{D,int}} \right)^{Ela_{t,t}^{-1}-1} \right] \quad (20)$$

271 Substituting (21) into (19) yields:

$$(1 + Elast_{t,t}^{-1}) \times \frac{Pr_t^{DA,int}}{Pr_t^{DA}} = \left(\frac{E_{t,\omega}^{D_D}}{E_t^{D,int}} \right)^{Elast_{t,t}^{-1}} - 1 + Elast_{t,t}^{-1} \cdot \left(\frac{E_{t,\omega}^{D_D}}{E_t^{D,int}} \right)^{Elast_{t,t}^{-1}} \quad (21)$$

$$\frac{Pr_{t,\omega}^{DA}}{Pr_t^{int}} = \left(\frac{E_{t,\omega}^{D_D}}{E_t^{D,int}} \right)^{Elast_{t,t}^{-1}} - \frac{1}{1 + Elast_{t,t}^{-1}} \quad (22)$$

272

273 Therefore, the consumption of customers at time t is obtained as follows:

$$E_{t,\omega}^{D_D} = E_t^{D,int} \cdot \left(\frac{Pr_{t,\omega}^{DA}}{Pr_t^{DA,int}} + \frac{1}{1 + Elast_{t,t}^{-1}} \right)^{Elast_{t,t}} \quad (23)$$

274 Additionally, based on cross-elasticity coefficients [30], which are defined as demand sensitivity of
275 the t^{th} period with respect to the price elasticity at h^{th} period, the amount of demand after the DR can
276 be obtained as:

$$E_{t,\omega}^{D_D} = E_t^{D,int} \cdot \prod_{\substack{t=1 \\ t \neq h}}^T \left(\frac{Pr_{h,\omega}^{DA}}{Pr_h^{DA,int}} + \frac{1}{1 + Elast_{t,h}^{-1}} \right)^{Elast_{t,h}} \quad (24)$$

277 By combining (17), (24) and (25) the economic model of load at time t is obtained as:

$$E_{t,\omega}^{D_D} = E_t^{D,int} \cdot \exp \sum_{h \in T} Elast_{t,h} \cdot \ln \left[\frac{Pr_{h,\omega}^{DA}}{Pr_h^{DA,int}} + \frac{1}{1 + Elast_{t,h}^{-1}} \right] \quad (25)$$

278

279 The uncertainties on DA price, positive and negative balancing market prices as well as demand of
280 customers and PEVs are modeled via random variables that are represented using a finite set of
281 scenarios Ω . The vector including market prices and demand is provided as follows:

$$\text{scenario } \omega = \left\{ Pr_{t,\omega}^{DA}, Pr_{t,\omega}^{B^+}, Pr_{t,\omega}^{B^-}, E_{t,\omega}^{T_D}, E_{t,\omega}^{T_{Ch}}, E_{t,\omega}^{T_{Dis}} \right\} \quad (26)$$

282 Each scenario ω has the probability of occurrence $\pi(\omega)$, in such a way that the sum of the
283 probabilities over all scenarios is equal to 1. Therefore, the uncertainty associated with the offering
284 prices of rival LSEs, a set of Ξ scenarios are generated and the vector of each scenario ξ is as
285 bellow:

$$\text{scenario } \xi = \left\{ Pr_{s_0,t}^D, Pr_{s_0,t}^{Ch}, Pr_{s_0,t}^{Dis} \right\} \quad (27)$$

286 The sum of the probabilities over all scenarios of set of Ξ is also 1. Since the first set of scenarios is
287 considered independent of the scenarios associated with the prices offered by the LSEs, the authors
288 distinguish two sets of scenarios to better undersetting problem formulations. However, all
289 scenarios should be combined in problem solving process.

290

291 3.3 Combination of Upper and Lower Levels

292 The above mentioned model consists of nonlinear terms including $E_{t,\omega}^D Pr_{s_0,t}^D$, $E_{t,\omega}^{Ch} Pr_{s_0,t}^{Ch}$ and $E_{t,\omega}^{Dis} Pr_{s_0,t}^{Dis}$ in
293 (1). Here, the KKT conditions are applied and to the lower-level problem in (9)–(18) and are merged
294 to the upper-level. Also, by using duality theorem [19], the bilinear terms are substituted with their
295 equivalent statements as bellow:

296

$$Rev_{t,\omega}^D = \frac{E_{t,\omega}^{D_D}}{\hat{E}_t^D} \sum_{\xi \in \Xi} \theta_\xi^D \left[- \sum_{\substack{s \in S \\ s \neq 0}} \hat{E}_t^D Pr_{s,t,\xi}^D L_{s,t,\xi}^D - \sum_{\substack{s \in S \\ s' \neq s}} \hat{E}_t^D R_{s,s'}^D M_{s,s',t,\xi}^D + \sum_{s \in S} U_{s,t,\xi}^{int,D} e_{s,\xi}^D + w_\xi^D \right] \quad (28)$$

$$\text{Rev}_{t,\omega}^{Ch} = \frac{E_{t,\omega}^{DCh}}{\bar{E}_t^{Ch}} \sum_{\xi \in \Xi} \theta_{\xi}^{Ch} \left[- \sum_{s \in S} \hat{E}_t^{Ch} \text{Pr}_{s,t,\xi}^{Ch} L_{s,t,\xi}^{Ch} - \sum_{s \in S} \sum_{s' \in S, s' \neq s} \hat{E}_t^{Ch} R_{s,s'}^{Ch} M_{s,s',t,\xi}^{Ch} + \sum_{s \in S} U_{s,t,\xi}^{\text{int},Ch} e_{s,\xi}^{Ch} + w_{\xi}^{Ch} \right] \quad (29)$$

$$\text{Rev}_{t,\omega}^{Dis} = \frac{E_{t,\omega}^{DDis}}{\bar{E}_t^{Dis}} \sum_{\xi \in \Xi} \theta_{\xi}^{Dis} \left[- \sum_{s \in S} \hat{E}_t^{Dis} \text{Pr}_{s,t,\xi}^{Dis} L_{s,t,\xi}^{Dis} - \sum_{s \in S} \sum_{s' \in S, s' \neq s} \hat{E}_t^{Dis} R_{s,s'}^{Dis} M_{s,s',t,\xi}^{Dis} + \sum_{s \in S} U_{s,t,\xi}^{\text{int},Dis} e_{s,\xi}^{Dis} + w_{\xi}^{Dis} \right] \quad (30)$$

297
 298 Afterwards, the single-level MILP problem is obtained which includes the objective function of the
 299 upper-level, the constraints and limitations of both upper- and lower-levels and the statement which
 300 equals to the objective function of the lower-level indicated as bellow:

$$\text{Maximize} \sum_{\omega \in \Omega} \pi_{\omega} \sum_{t \in T} [(\text{Rev}_{t,\omega}^D + \text{Rev}_{t,\omega}^{Ch} + P_{t,\omega}^{B-} \text{Pr}_{t,\omega}^{B-}) - (\text{Rev}_{t,\omega}^{Dis} + E_{t,\omega}^{DA} \text{Pr}_{t,\omega}^{DA} + E_{t,\omega}^{B+} \text{Pr}_{t,\omega}^{B+})] \quad (31)$$

302
 303 Also, this objective function is limited with the constraints (2)-(8), (10)-(15), (25) and the constraints
 304 that achieved from applying KKT and duality theory. It should be noted that after obtaining the upper-
 305 level and lower-level problem formulation independently, Lagrange function of the lower-level is
 306 achieved. The KKT optimality condition of the lower-level problem is obtained by partial derivatives
 307 of the Lagrange function. Accordingly, the lower-level problem is incorporated to the upper-level
 308 and the bi-level problem is formed. Finally, a conversion to the equivalent single-level linear
 309 optimization form is applied. Also, the bilinear products of continuous variables are replaced by their
 310 equivalent linear expressions. Bellow, only the abbreviation form of the constraints are represented.
 311 The constraints that are introduced in the form of $0 \leq a \perp b \geq 0$ denote the nonlinear form of
 312 $a \geq 0; b \geq 0; -ab \geq 0$.

$$\hat{E}_t^{Di} \text{Pr}_{s,t,\omega}^{\ell} - e_{s,\xi}^{\ell} - w_{\xi}^{\ell} \geq 0 \quad (32)$$

$$\hat{E}_t^{Di} R_{s,s'}^{\ell} + e_{s',\xi}^{\ell} - e_{s,\xi}^{\ell} \geq 0 \quad (33)$$

$$\hat{E}_t^{Di} \text{Pr}_{s,t,\omega}^{\ell} - e_{s,\xi}^{\ell} - w_{\xi}^{\ell} \leq K_1^{\ell} S_{s,\xi}^{L_{\ell}} \quad (34)$$

$$L_{s,t,\xi}^{\ell} \leq K_2^{\ell} [1 - S_{s,\xi}^{L_{\ell}}] \quad (35)$$

$$\hat{E}_t^{Di} R_{s,s'}^{\ell} + e_{s',\xi}^{\ell} - e_{s,\xi}^{\ell} \leq K_1^{\ell} S_{s,s',\xi}^{M_{\ell}} \quad (36)$$

$$M_{s,s',\xi}^{\ell} \leq K_2^{\ell} [1 - S_{s,s',\xi}^{M_{\ell}}] \quad (37)$$

$$0 \leq \underline{\mu}_{t,\omega}^s \perp (\text{SoC}_{t,\omega} - \underline{\text{SoC}}) \geq 0 \quad (38)$$

$$0 \leq \overline{\mu}_{t,\omega}^s \perp (\overline{\text{SoC}} - \text{SoC}_{t,\omega}) \geq 0 \quad (39)$$

$$0 \leq \underline{\gamma}_{t,\omega}^{Ch} \perp [\text{SoC}_{t,\omega} \Delta t] \geq 0 \quad (40)$$

$$0 \leq \overline{\gamma}_{t,\omega}^{Ch} \perp [\overline{\text{SoC}} - \text{SoC}_{t-1,\omega} - \text{SoC}_{t,\omega}] \geq 0 \quad (41)$$

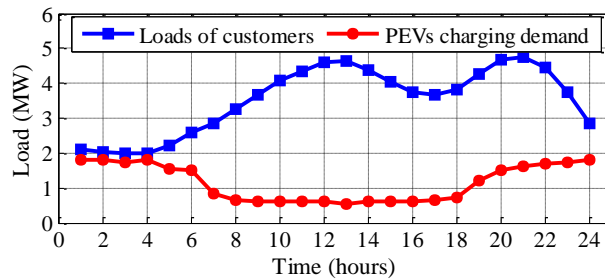
$$0 \leq \underline{\gamma}_{t,\omega}^{Dis} \perp [\text{SoC}_{t,\omega} \Delta t] \geq 0 \quad (42)$$

$$0 \leq \overline{\gamma}_{t,\omega}^{Dis} \perp [\text{SoC}_{t-1,\omega} - \text{SoC}_{t,\omega} \Delta t] \geq 0 \quad (43)$$

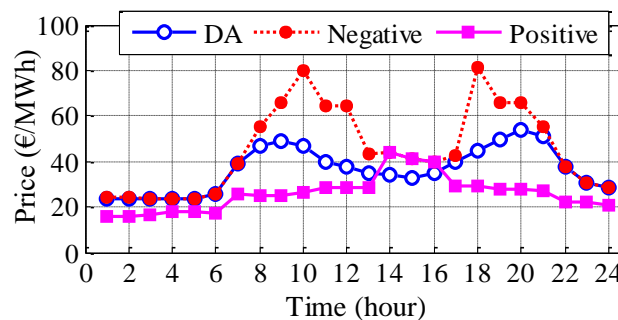
314
 315 where, K_1^{ℓ} and K_2^{ℓ} are selected such that the problem remains optimal. $\underline{\gamma}_{t,\omega}^{Ch/Dis}$, $\overline{\gamma}_{t,\omega}^{Ch/Dis}$, $\underline{\mu}_{t,\omega}^s$ and $\overline{\mu}_{t,\omega}^s$ are
 316 auxiliary variables in obtaining KKT optimality conditions.

317 4. SIMULATIONS AND NUMERICAL RESULTS

318 *4.1 Case Study*
 319 The obtained program is implemented on a test system with four LSEs (i.e., LSE₀, LSE₁, LSE₂
 320 and LSE₃) that supply a number of PEVs and smart responsive loads. LSE₀ is the under-study LSE
 321 and the others are considered as rivals. The time horizon for scheduling of LSE is one day with 24
 322 equal hours. Figure 3 illustrates the forecasted demand of both customers and PEVs. The pattern of
 323 PEVs demand is obtained based on [14], which represents how demand of PEVs changes during a
 324 day. It should be noted that in each time period of the scheduling horizon, only a number of PEVs
 325 are connected to the network and can participate in DR program. All the PEVs are supposed to have
 326 the same battery capacity of 16kWh and only 20% of them desire to take part in discharge process.
 327 The initial *SoC* of PEVs at each scenario as well as the initial hourly demands supplied by each LSE
 328 are randomized. Moreover, Figure 4 illustrates the forecasted prices of electricity market that are
 329 extracted from Nordpool market [30]. The forecasted errors of each stochastic variable are generated
 330 using associated PDF in which the forecasted values are considered as mean values. Here, the PDFs
 331 are separated into five discrete intervals with related probabilities. Standard deviation of the
 332 responsive loads, PEVs demand, DA and negative balancing market prices forecast errors are
 333 considered $\pm 15\%$ [31]. Also, standard deviation of positive balancing prices forecast errors is
 334 considered $\pm 5\%$ [32]. In addition, the forecasted prices offered by rival LSEs are extracted from [19]
 335 by some modifications. The associated scenarios of rival prices are generated with three segment
 336 normal PDF and their forecasted errors are considered $\pm 20\%$ [29]. Finally, the price elasticity of loads
 337 is extracted from [33]. The forecasted errors are generated based on 1000 scenarios by using MCS
 338 and RWM. After generation of 1000 initial scenarios, *K*-means algorithm is used to reduce the
 339 number of scenarios into 45. Afterwards, the selected scenarios are used in the proposed problem and
 340 the optimization is executed by CPLEX solver using GAMS software [34] on a PC with 4 GB of
 341 RAM and Intel Core i7 @ 2.60 GHz processor.
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343
 344 Figure 3. The hourly forecasted loads of customers and charging demand of PEVs.
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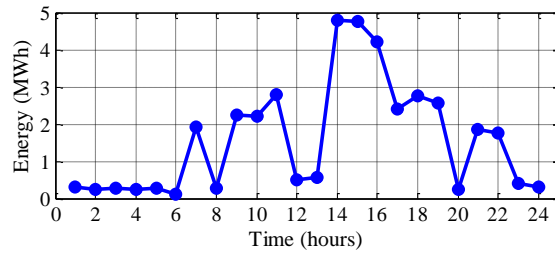
346
 347 Figure 4. Hourly forecasted electricity price of DA, positive and negative balancing markets.
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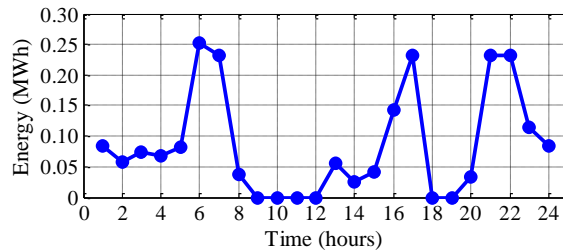
4.2 Numerical Results

The profiles of the expected energy procured by the under-study LSE from DA, positive and negative balancing markets, following the proposed optimization strategy, are obtained and shown in Figure 5. As it is observed, the LSE purchases a major part of the needed energy from DA market and mitigates the outcomes of different uncertain resources by trading energy in balancing market. In some periods, especially at peak hours when the prices of positive balancing market are very high, the LSE purchases most of the required energy from DA market. Therefore, its contribution in positive balancing market is very low (even zero in some time slots) as observed from Fig. 5 (b). Moreover, when the prices of negative balancing market are relatively high (e.g., 14:00-16:00 based on Figure 4), the LSE bids for load reduction in negative balancing market to achieve more profit.

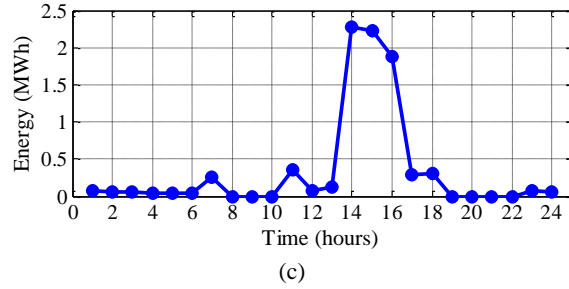
Figure 6 depicts the prices suggested by the under study LSE and the forecasted offering prices of rival LSEs during the scheduling horizon. Here, it is assumed that similar price offering scheme is applied to responsive loads as well as charging PEVs. As can be seen, LSE_0 offers competitive charging prices at all hours to attract more customers. In fact, in a competitive market, a decrease in offered price can be a way of increasing the amount of responsive loads and PEVs that are supplied. Moreover, the bid prices offered by LSE_0 in most hours are high enough to attract more PEV owners for discharging process. To get better insight into this bidding strategy, the charge price signal offered by the under-study LSE is evaluated in some hours. For example, from 1:00 to 6:00 when the market prices and demand loads are low, LSE_0 offers moderate prices to remain in the game. Moreover, from 9:00 to 12:00, or at 18:00 and 19:00, although the market prices are high (Figure 4), LSE_0 offers lower charging prices to keep more customers interested in energy purchases. Moreover, the prices offered by the under-study LSE for discharging of PEVs are shown in Figure 6 (b). During these hours LSE_0 tries to purchase energy from the PEVs' owners, and not from the market, with high prices. However, it proposes the lowest discharging rates at 14:00-16:00, in which the DA and positive balancing prices are also relatively low.



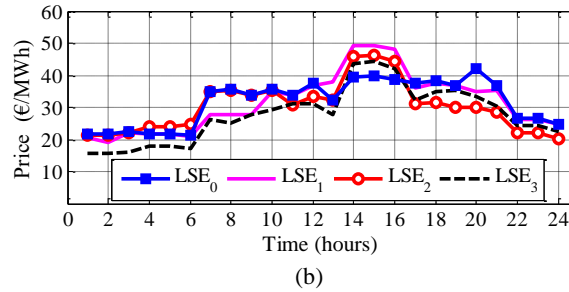
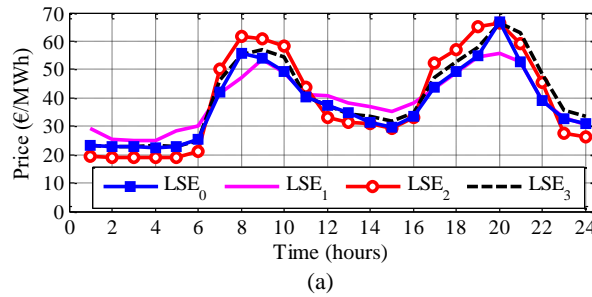
(a)



(b)



376 Figure 5. Behavior of the under-study LSE in different markets, (a) DA market, (b) positive
 377 balancing market, and (c) negative balancing market.

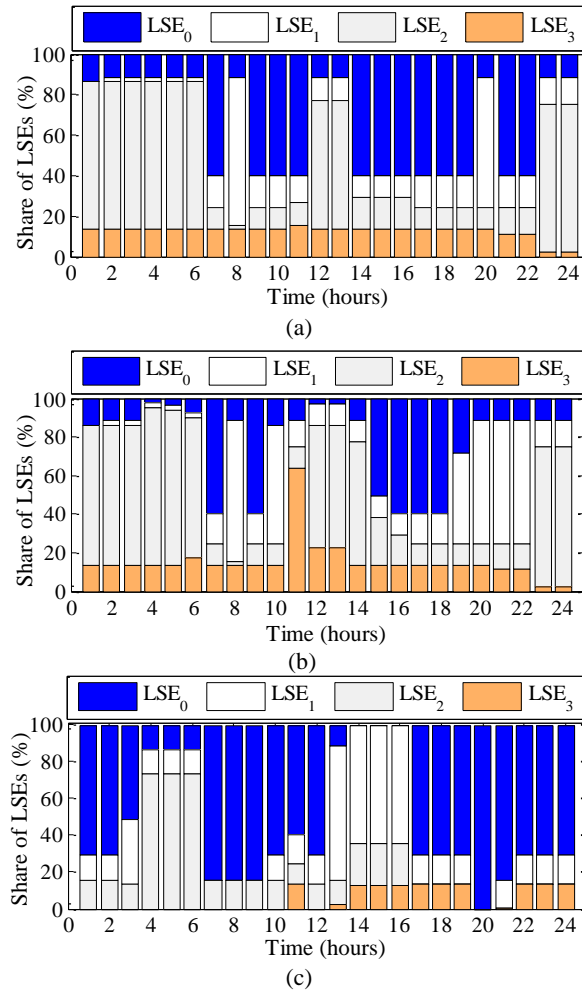


380 Figure 6. The prices proposed by all LSEs, (a) charging prices, (b) discharging prices.

381
 382 The percentages of demand loads together with charging and discharging energies of PEVs
 383 supplied by all LSEs are shown in Figure 7. It can be clearly understood that in a competitive
 384 environment when the selling price offered by a given LSE is the lowest, its related market share is
 385 the highest. To this end, comparing Figure 6 (a) and Figure 7 (a) shows that the under-study LSE is
 386 the dominant player of market at 7:00, 9:00-11:00, 14:00-19:00, 21:00 and 22:00 due to its most
 387 competitive bids. The same procedure happens during 1:00-6:00 when LSE₂ takes the market power.
 388 Similar analysis can be made for supplying PEVs' demand by LSEs. However, it is observed from
 389 Figure 7 (c), the share of LSE₀ in buying discharge energy from PEVs is high most of the times due
 390 to its higher price offers (Figure 6 (b)).

391 In order to assess the behavior of customers and PEV owners in choosing the LSEs, Table II shows
 392 the transferred demand, charge and discharge of PEVs among the LSEs at different sample times. As
 393 mentioned before, the loads can be transferred from one LSE to another one based on the offered
 394 prices (see equation (10)). Noted that the minus sign indicates a demand transferred in the opposite
 395 orientation. As can be seen from the same table, at 4:00 for example, 17.46% of the responsive loads
 396 transferred from LSE₀ to LSE₂. Instead, 2.57% and 7.95% of responsive loads will be shifted from
 397 LSE₁ and LSE₃ to LSE₀, respectively. Moreover, 20.03% of responsive loads will be transferred from
 398 LSE₁ with the highest price to LSE₀ that has the lowest price offers. The results also show that PEVs'

399 owners have the same behavior in choosing their LSE for charging process. However, it should be
 400 noted that LSEs which offer the highest discharge incentives are selected by the PEVs owners. Such
 401 conditions can be seen at 8:00 when LSE₀ offers the highest discharge incentives which in turn
 402 increases its share in negative balancing market. These behaviors simply show that the customers
 403 usually track the price signals to choose the most competitive LSE for satisfying both the energy
 404 needs and economic objectives. Therefore, in a competitive market, optimal offering strategy of the
 405 LSE has a substantial effect on the behavior of customers and PEVs owners in choosing a proper
 406 LSE.
 407



408 Figure 7. Share of LSEs in supplying (a) customers, (b) charging of PEVs, and (b) discharging of
 409 PEVs.
 410

411 Table II. Transferred percentage of demand, charge and discharge of PEVs among the LSEs.

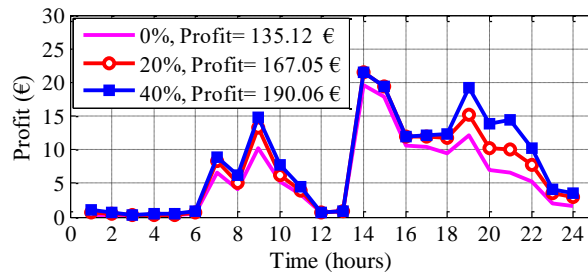
Options	From LSE ₀ to LSE ₁	From LSE ₀ to LSE ₂	From LSE ₀ to LSE ₃	From LSE ₁ to LSE ₂	From LSE ₁ to LSE ₃	From LSE ₂ to LSE ₃
	At 4:00					
Responsive loads	-2.57	17.46	-7.95	20.03	-5.38	-25.41
Charge of PEVs	-0.27	22.06	-5.65	22.33	-5.38	-27.71
Discharge of PEVs	-0.31	16.94	-11.78	17.25	-11.47	-28.72
At 8:00						

Responsive loads	18.73	2.11	-9.06	-16.62	-27.79	11.17
Charge of PEVs	18.5	2.46	19.63	-16.62	-27.75	11.17
Discharge of PEVs	-17.65	-12.63	-30.51	5.02	-12.86	-17.88
At 15:00						
Responsive loads	-9.82	-6.95	-17.88	2.87	-8.06	10.93
Charge of PEVs	-7.57	-2.46	-15.63	5.11	-8.06	13.17
Discharge of PEVs	18.3	9.517	-3.14	-8.783	-21.44	-12.657

413
 414 In order to analyze the role of discharge process on the expected profit, revenues and payments of
 415 the under-study LSE, Table III is provided. As observed from the table, by increasing the PEVs'
 416 participation in the discharging process, revenue of the LSE and its expected profit increases. In other
 417 words, the LSE provides more energy from discharge of PEVs and its purchase from costly DA or
 418 positive market decreases. For more detailed investigation, the hourly profit of the LSE in three
 419 practical levels of PEVs participants in discharge is illustrated in Figure 8. As can be seen, by
 420 increasing the share of PEVs in discharging process, the expected profit of the LSE₀ increases usually,
 421 especially when the DA and positive market prices are comparatively high. Moreover, the total
 422 expected profit of the LSE varies from 135.12 € in without discharge of PEVs to 190.06 € (with a
 423 share of 40% in the same market) which denotes an increment of 40.7% in the expected profit.
 424 Therefore, PEVs participation in discharge process has a great impact on the expected profit of the
 425 LSE in a competitive market.

426
 427
 428
 429 Table III. Expected profit, revenue and payments of LSE₀ in different percentage discharge of PEVs.

Percentage discharge of PEVs	Expected profit	Revenue of discharge	Revenue of DR	Payments to the network	Payments for discharging
0%	137.55	86.68	1257.49	-1196.02	0.00
10%	153.57	133.49	1263.92	-1196.42	-47.42
20%	167.05	187.81	1263.92	-1191.53	-93.15
30%	179.18	224.45	1263.92	-1179.20	-129.99
40%	190.06	273.40	1263.92	-1177.82	-169.44
50%	200.71	306.27	1263.92	-1170.26	-199.21
60%	209.27	312.74	1263.92	-1159.30	-208.09
70%	218.42	346.98	1356.90	-1249.94	-235.53
80%	226.30	371.45	1430.77	-1316.45	-259.47
90%	232.42	371.45	1430.77	-1311.65	-258.16
100%	237.00	371.45	1430.77	-1313.38	-251.84



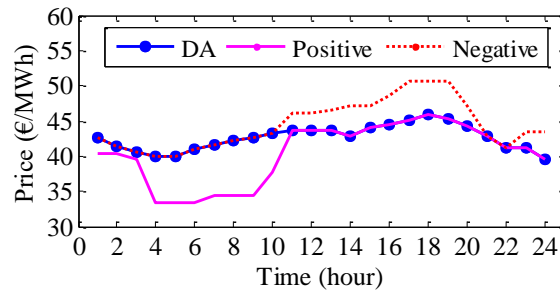
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 435 Figure 8. Hourly profit of the under-study LSE in different percentage of PEVs' participation in
 436 discharge process.

437
 438 To further analyze the effectiveness of the proposed approach, other case studies implemented
 439 here. To this end, the proposed strategy is applied in situations where different DA or balancing
 440 market pricing schemes may be realized in a given day (each with 24h) in a year as shown in Figure
 441 9. Figure 10 shows the DA energy bidding profiles. As seen from Figure 10, the LSE tends to supply
 442 loads; i.e., buying low energy bids during off-peak periods (e.g., 1:00–7:00 during midnight to
 443 morning) and high energy bids during peak periods (e.g., 17:00–22:00). The energy imbalances are
 444 compensated in regulating market as shown in Figure 11 and Figure 12. As seen, the lack of energy
 445 to supply the loads specifically during peak hours could be compensated easily by buying energy and
 446 the surplus energy generated from discharge process can be sold to obtain some revenues.

447 Figure 13 shows the offering prices of all LSEs during scheduling horizon for DR, charge and
 448 discharge processes. As can be seen, the pattern of price signal offered by the under-study LSE is
 449 affected by the one offered by competitors. Also, if the rivals' discharge price is assumed to be the
 450 same as the one offered for charge process, the pattern of price signal offered by the under-study LSE
 451 is affected by the one offered by competitors as in Figure 13. It should be noted that the proposed
 452 architecture is valid for different pricing schemes which relates to different internal data.

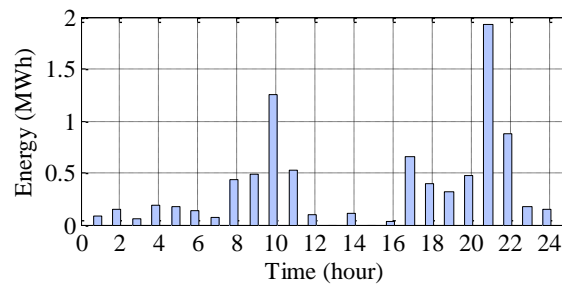
453 Figure 14, provides the percentage of loads and EVs to be supplied by all LSEs. As observed, the
 454 customers choose the LSE with the lowest prices for energy purchases while they tend to augment
 455 their revenues by selling energy to the LSE with the highest bids. So, it can be concluded that different
 456 behaviors of rivals (in terms of pricing) could affect the pattern of price offered by the under-study
 457 LSE.

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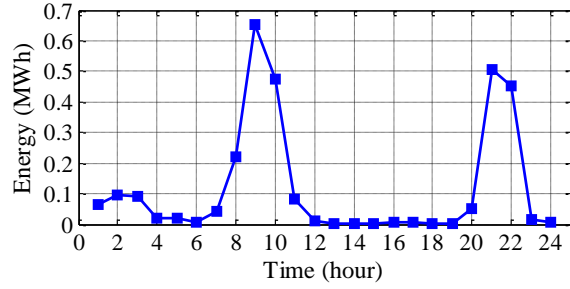
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Figure 9. Electricity market prices



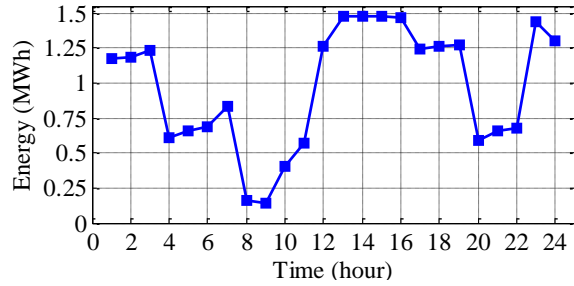
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Figure 10. DA energy bidding



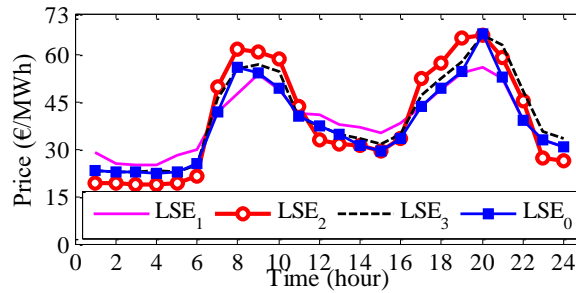
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Figure 11. The energy trading in negative balancing market

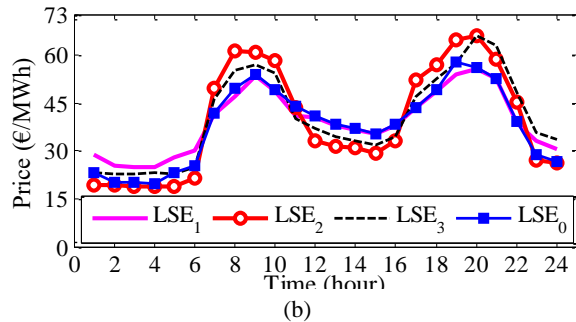


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Figure 12. The energy trading in positive balancing market

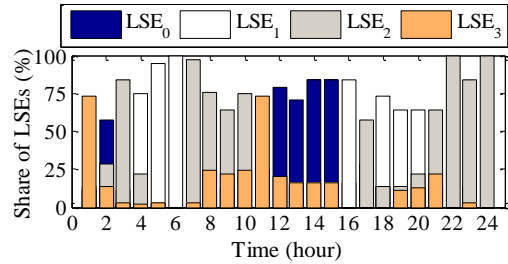


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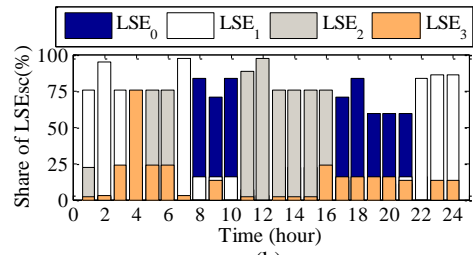


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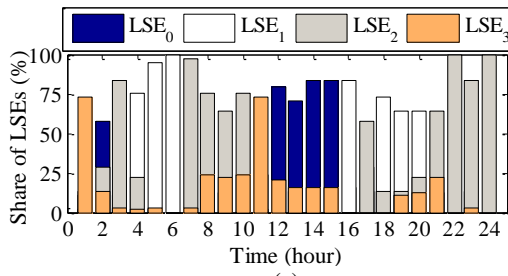
Figure 13. The prices proposed by all LSEs, (a) charging prices, (b) discharging prices.



(a)



(b)



(c)

Figure 14. Share of LSEs in supplying (a) customers, (b) charging of PEVs, and (b) discharging of PEVs.

5. CONCLUSION

This paper investigated a stochastic bi-level scheduling strategy for an LSE in a competitive environment. The uncertainties related to the market prices, demand loads, charging/discharging power of PEVs and the prices suggested by rival LSEs were simulated via stochastic programming. The obtained nonlinear bi-level problem was converted into an equivalent single-level mixed-integer linear programming problem by applying KKT optimality conditions and duality theory. Finally, the proposed scheduling framework was applied to a case-study. The numerical outcomes demonstrated that:

- The LSE participates in DA and balancing markets to procure energy for serving loads in a competitive market. However, this participation should be complemented by an appropriate bidding strategy to be profitable.
- When the prices of DA and positive balancing markets are relatively high, an optimal strategy for the LSE is to motivate PEV owners for discharge process to participate in negative balancing market. In this way the LSE would feed the loads through PEVs discharging instead of buying from the expensive DA and positive balancing markets.

- 503 • In a competitive market, the customers usually select the most competitive LSE to trade with. In
 504 other words, they buy energy through the cheapest one and selling energy to the one(s) with the
 505 highest price offers to meet their objectives.

506

507 **Nomenclature**

Sets and indices

$(\cdot)_{t,\omega}$	At time t and scenario ω .
$(\cdot)_{t,\xi}$	At time t and scenario ξ .
$D/Ch/Dis$	Index of demand of customers/Charge/Discharge mode.
$s, s'(N_S)$	Indices (set) of LSEs.
$t(T)$	Index (set) of time periods.
$\omega(\Omega)$	Scenario index (set) related to market prices, customers' loads and charge/discharge process.
$\xi (\Xi)$	Index (set) for scenarios of rival LSEs.

ℓ The sign that shows the index of both responsive loads and EVs charge/discharge process.
 $a \perp b$ Complementarity conditions between a and b .

Variables

$E^{D/Ch/Dis}$	Energy supplied by the under-study LSE (MWh).
$E^{B^+} (E^{B^-})$	Energy exchanged in positive (negative) balancing markets (MWh).
E^{DA}	Energy purchased from day-ahead market (MWh).
$e_s(w)$	Lagrange coefficient.
ΔE_t^D	Energy deviation from the base case once participating in DR programs (MWh)
L_s^ℓ	Percentage of loads supplied by rival LSEs (%).
$L_{s_0}^\ell$	Percentage of loads supplied by the under-study LSE (%).
$M_{s,s'}^\ell$	Percentage of loads transferred among the LSEs (%).
$Pr_{s_0,t}^\ell$	Selling price offered by the under-study LSE to the customers (€/MWh).
R	The cost models the unwillingness of customers and PEV owners to change their LSE (€).
$Re v$	The revenue obtained by the under study LSE (€).
$S_s^X (S_s^Z)$	Binary variable for complementary slackness conditions.
$S(B)$	The benefit and income of customers after performing DR program (€).
SOC	State of charge of PEV (%).
$\bar{\mu}^s / \bar{\gamma}^{-Ch/Dis}$	Auxiliary variables of KKT optimality conditions corresponding with technical constraints of PEVs.

Parameters

$Elast_{i,t} (Elast_{i,h})$	The self (cross) elasticity of loads.
E^{Cap}	Capacity of PEV battery (MWh).
$E^{D,int}$	Initial demand of loads before participating in DR programs (MWh).
E^{D_t}	Total demand required (MWh).
\hat{E}_t	The expected demand (MWh).
$K_{1,2}^\ell$	Constants to obtain equivalent linear expressions of lower level problem.
$p^{Ch/Dis}$	Charged (discharged) power (MWh).
$Pr^{B^+} (Pr^{B^-})$	Prices of positive (negative) balancing market (€/MWh).
Pr^{DA}	Day-ahead market prices (€/MWh).
$Pr^{DA,int}$	The expected value of DA prices (€).
$Pr_s^\ell (Pr_{s_0}^\ell)$	Price signals offered by rival LSEs (€/MWh).

\bar{P}	Restriction for energy trading with the network (MWh).
$\underline{SoC} (\overline{SoC})$	Minimum (maximum) limitation of SoC .
$U_{s,t,\xi}^{int,\ell}$	Primary percentage of loads and PEVs that is supplied by each LSE s .
π_{ω}	Probability of scenario ω .
θ_{ξ}	Probability of scenario ξ .

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