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

Rashidizadeh-Kermani, Homa ; Vahedipour-Dahraie, Mostafa; Anvari-Moghaddam, Amjad; Guerrero, Josep M.

Published in:
International Transactions on Electrical Energy Systems

DOI (link to publication from Publisher):
10.1002/2050-7038.12109

Publication date:
2019

Document Version
Accepted author manuscript, peer reviewed version

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

Homa Rashidizaheh-Kermani[*1], Mostafa Vahedipour-Dahraie[1], Amjad Anvari-Moghaddam[2], Josep M. Guerrero[2]

[1] Department of Electrical & Computer Engineering, University of Birjand, Birjand, Iran; vahedipour_m@birjand.ac.ir

[2] Department of Energy Technology, Aalborg University, Aalborg, Denmark; aam@et.aau.dk; joz@et.aau.dk

***Corresponding Author:** Mostafa Vahedipour-Dahraie, vahedipour_m@birjand.ac.ir, **Tel.:** +98-5632732001

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

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

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

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

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

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

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

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	✓	✓	✓	✓	✓

2. STOCHASTIC-BASED DECISION-MAKING PROBLEM OF LSE

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

The proposed decision-making problem of LSE for scheduling of the responsive loads and PEVs has a two-level structure where in the upper level, the LSE aims at maximizing its expected profit from taking part in pool-based short-term electricity market comprising of DA and balancing markets. In this level, scheduled energy exchanges for the next day are specified and then the energy deviations are obtained and compensated in the balancing market. Also, the LSE suggests optimal bids to the PEV owners and end-use customers to encourage them making interactive energy trading. Since, the actions of rival LSEs affect the decision-making of the under-study LSE, the prices offered by rivals are considered by different scenarios.

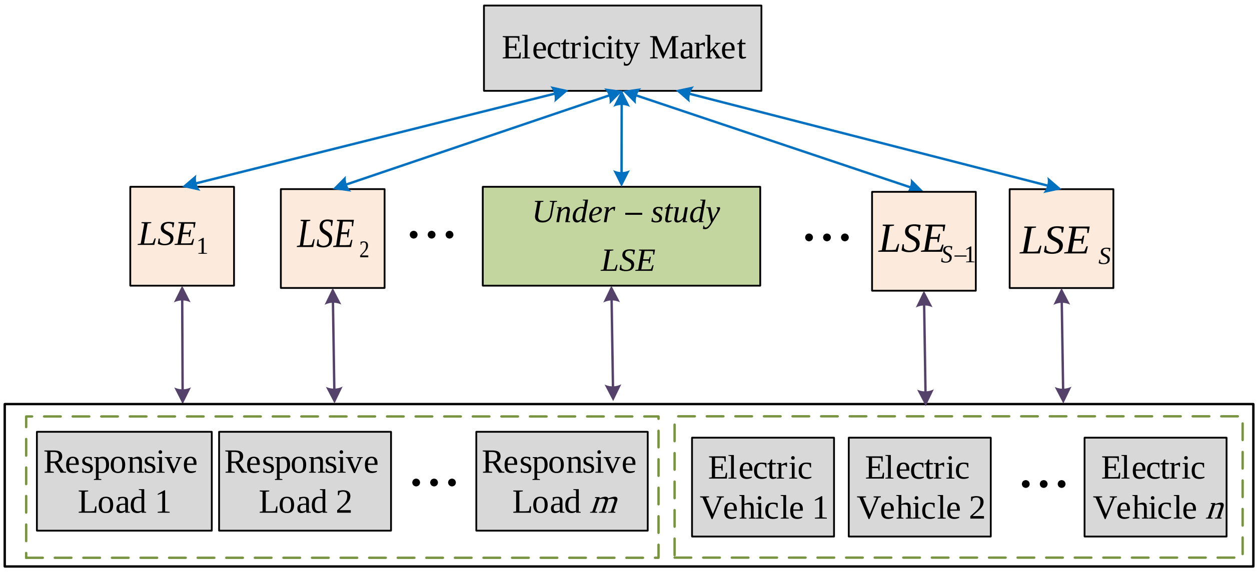


Figure 1. Schematic of the LSE problem.

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

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

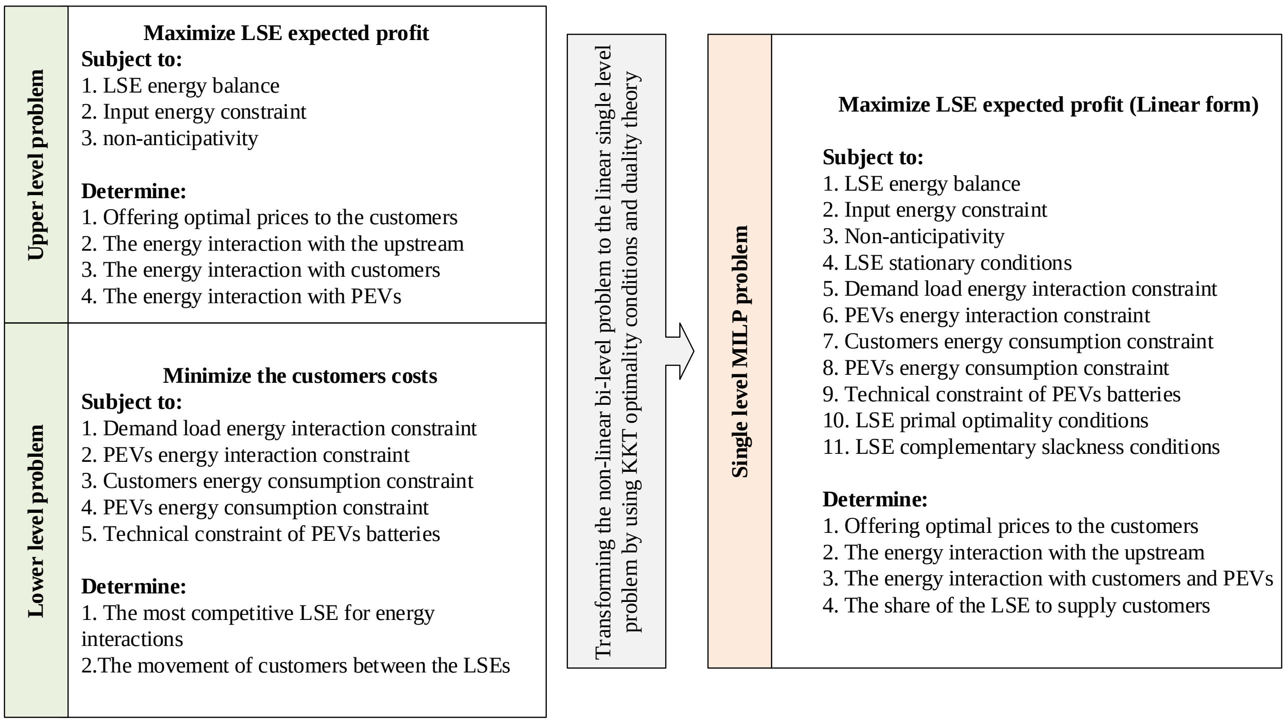


Figure 2. The bi-level framework of decision-making of LSE.

Subject to the following constraints,

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

$$E_{t,\omega}^{D} = E_{t,\omega}^{D_D} \sum_{\xi\in\Xi} \theta_{\xi}^{D} L_{S_0,t,\xi}^{D} \tag{3}$$

$$E_{t,\omega}^{ch} = E_{t,\omega}^{D_{ch}} \sum_{\xi\in\Xi} \theta_{\xi}^{Ch} L_{S_0,t,\xi}^{Ch} \tag{4}$$

$$E_{t,\omega}^{Dis} = E_{t,\omega}^{D_{Dis}} \sum_{\xi\in\Xi} \theta_{\xi}^{Dis} L_{S_0,t,\xi}^{Dis} \tag{5}$$

$$E_{t,\omega}^{DA} = E_{t,\omega'}^{DA} \tag{6}$$

$$E_{t,\omega}^{B^+} \le \overline{P} \tag{7}$$

$$E_{t,\omega}^{B^-} \le \overline{P} \tag{8}$$

Equation (1) indicates the objective function from the under-study LSE perspective. Constraint (2) investigates the energy balance. The under-study LSE contributes to provide the required energy of customers and PEVs based on Constraints (3)-(5). That is the estimated energy supplied by the under study LSE that is equal to the expected value of the demand of the responsive loads and charge/discharge of EVs supplied by the LSE over all rival-LSEs price scenarios. The nonanticipativity is demonstrated in (6) and confirms similar DA bids for equal DA prices at each hour t and scenario ω [27]. The energy transaction in both balancing markets is limited based on constraints (7) and (8), respectively.

3.2 Lower-level Viewpoint

The objective in the lower-level consists of the objectives of customers and PEV owners to minimize the costs of their energy exchange that is explained as bellow:

$$\begin{aligned}
&Minimize \ \ \{\widehat{E}_t^{D}[\mathrm{Pr}^{D}_{s_0,t}\, L^{D}_{s_0,t,\xi} + \sum_{\substack{s\in S\\ s\neq 0}} \mathrm{Pr}^{D}_{s,t,\xi}\, L^{D}_{s,t,\xi}] + \\
&\widehat{E}_t^{Ch}[\mathrm{Pr}^{Ch}_{s_0,t}\, L^{Ch}_{s_0,t,\xi} + \sum_{\substack{s\in S\\ s\neq 0}} \mathrm{Pr}^{Ch}_{s,t,\xi}\, L^{Ch}_{s,t,\xi}] - (\widehat{E}_t^{Dis}[\mathrm{Pr}^{Dis}_{s_0,t}\, L^{Dis}_{s_0,t,\xi} + \sum_{\substack{s\in S\\ s\neq 0}} \mathrm{Pr}^{Dis}_{s,t,\xi}\, L^{Dis}_{s,t,\xi}] + \\
&\sum_{s\in S}\sum_{\substack{s'\in S\\ s'\neq s}} \widehat{E}_t^{D} R^{D}_{s,s'} M^{D}_{s,s',t,\xi} + \sum_{s\in S}\sum_{\substack{s'\in S\\ s'\neq s}} \widehat{E}_t^{Ch} R^{Ch}_{s,s'} M^{Ch}_{s,s',t,\xi} + \sum_{s\in S}\sum_{\substack{s'\in S\\ s'\neq s}} \widehat{E}_t^{Dis} R^{Dis}_{s,s'} M^{Dis}_{s,s',t,\xi}\}
\end{aligned} \tag{9}$$

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

$$L^{\ell}_{s,\xi,t} = U^{\mathrm{int},\ell}_{s,t,\xi} + \sum_{\substack{s'\in S\\ s'\neq s}} M^{\ell}_{s,s',t,\xi} - \sum_{\substack{s'\in S\\ s'\neq s}} M^{\ell}_{s',s,t,\xi} : e^{\ell}_{s,\xi} \tag{10}$$

$$\sum_{\substack{s\in N_s\\ s\neq 0}} L^{\ell}_{s,t,\xi} + L^{\ell}_{s_0,t,\xi} = 1 : w^{\ell}_{\xi} \tag{11}$$

$$L^{\ell}_{s,t,\xi} \geq 0 \tag{12}$$

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

$$\underline{SoC} \leq SoC_{t,\omega} \leq \overline{SoC} : \underline{\mu}^{S}_{t,\omega}, \overline{\mu}^{S}_{t,\omega} \tag{13}$$

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

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

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

$$E^{D_D}_{t,\omega} = E^{D,\text{int}}_{t} + \Delta E^{D}_{t} \tag{16}$$

The benefit of customers can be obtained as:

$$S(E^{D_D}_{t,\omega}) = B(E^{D_D}_{t,\omega}) - E^{D_D}_{t,\omega}.\text{Pr}^{DA}_{t,\omega} \tag{17}$$

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

$$\frac{\partial S(E^{D_D}_{t,\omega})}{\partial E^{D_D}_{t,\omega}} = \frac{\partial B(E^{D_D}_{t,\omega})}{\partial E^{D_D}_{t,\omega}} - \text{Pr}^{DA}_{t,\omega} = 0 \tag{18}$$

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

$$B(E^{D_D}_{t,\omega}) = B^{D,\text{int}}_{t} + \frac{\text{Pr}^{DA,\text{int}}_{t}.E^{D_D}_{t,\omega}}{1+Elas^{-1}_{t,t}} \times [(\frac{E^{D_D}_{t,\omega}}{E^{D,\text{int}}_{t}})^{Elas^{-1}_{t,t}} - 1] \tag{19}$$

Differentiating (20) with respect to $E^{D_D}_{t,\omega}$ gives:

$$\frac{\partial B(E^{D_D}_{t,\omega})}{\partial E^{D_D}_{t,\omega}} = \frac{\text{Pr}^{DA,\text{int}}_{t}}{1+Elas^{-1}_{t,t}} \times [(\frac{E^{D_D}_{t,\omega}}{E^{D,\text{int}}_{t}})^{Elas^{-1}_{t,t}} - 1] + \frac{\text{Pr}^{DA,\text{int}}_{t}.E^{D_D}_{t,\omega}}{1+Elas^{-1}_{t,t}} \times [Elas^{-1}_{t,t}.\frac{1}{E^{D,\text{int}}_{t}}(\frac{E^{D_D}_{t,\omega}}{E^{D,\text{int}}_{t}})^{Elas^{-1}_{t,t}-1}] \tag{20}$$

Substituting (21) into (19) yields:

$$(1+Elas_{t,t}^{-1})\times\frac{\Pr_t^{DA,\text{int}}}{\Pr_{t,\omega}^{DA}}=(\frac{E_{t,\omega}^{D_D}}{E_t^{D,\text{int}}})^{Elas_{t,t}^{-1}}-1+Elas_{t,t}^{-1}.(\frac{E_{t,\omega}^{D_D}}{E_t^{D,\text{int}}})^{Elas_{t,t}^{-1}} \tag{21}$$

$$\frac{\Pr_{t,\omega}^{DA}}{\Pr_t^{\text{int}}}=(\frac{E_{t,\omega}^{D_D}}{E_t^{D,\text{int}}})^{Elas_{t,t}^{-1}}-\frac{1}{1+Elas_{t,t}^{-1}} \tag{22}$$

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

$$E_{t,\omega}^{D_D}=E_t^{D,\text{int}}.(\frac{\Pr_{t,\omega}^{DA}}{\Pr_t^{DA,\text{int}}}+\frac{1}{1+Elas_{t,t}^{-1}})^{Elas_{t,t}} \tag{23}$$

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

$$E_{t,\omega}^{D_D}=E_t^{D,\text{int}}.\prod_{\substack{t=1\\t\neq h}}^{T}(\frac{\Pr_{h,\omega}^{DA}}{\Pr_h^{DA,\text{int}}}+\frac{1}{1+Elas_{t,h}^{-1}})^{Elas_{t,h}} \tag{24}$$

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

$$E_{t,\omega}^{D_D}=E_t^{D,\text{int}}.\exp\sum_{h\in T}Elas_{t,h}.\ln[\frac{\Pr_{h,\omega}^{DA}}{\Pr_h^{DA,\text{int}}}+\frac{1}{1+Elas_{t,h}^{-1}}] \tag{25}$$

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

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

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

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

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

3.3 Combination of Upper and Lower Levels

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 (1). Here, the KKT conditions are applied and to the lower-level problem in (9)–(18) and are merged to the upper-level. Also, by using duality theorem [19], the bilinear terms are substituted with their equivalent statements as bellow:

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

$$\mathrm{Re}v_{t,\omega}^{Ch} = \frac{E_{t,\omega}^{D_{Ch}}}{\widehat{E}_t^{Ch}} \sum_{\xi\in\Xi} \theta_\xi^{Ch} [-\sum_{\substack{s\in S\\ s\neq 0}} \hat{E}_t^{Ch}\, \mathrm{Pr}_{s,t,\xi}^{Ch}\, L_{s,t,\xi}^{Ch} - \sum_{s\in S}\sum_{\substack{s'\in S\\ s'\neq s}} \hat{E}_t^{Ch} R_{s,s'}^{Ch} M_{s,s',t,\xi}^{Ch} + \sum_{s\in S} U_{s,t,\xi}^{\mathrm{int},Ch} e_{s,\xi}^{Ch} + w_\xi^{Ch}] \tag{29}$$

$$\mathrm{Re}v_{t,\omega}^{Dis} = \frac{E_{t,\omega}^{D_{Dis}}}{\widehat{E}_t^{Dis}} \sum_{\xi\in\Xi} \theta_\xi^{Dis} [-\sum_{\substack{s\in S\\ s\neq 0}} \hat{E}_t^{Dis}\, \mathrm{Pr}_{s,t,\xi}^{Dis}\, L_{s,t,\xi}^{Dis} - \sum_{s\in S}\sum_{\substack{s'\in S\\ s'\neq s}} \hat{E}_t^{Dis} R_{s,s'}^{Dis} M_{s,s',t,\xi}^{Dis} + \sum_{s\in S} U_{s,t,\xi}^{\mathrm{int},Dis} e_{s,\xi}^{Dis} + w_\xi^{Dis}] \tag{30}$$

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

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

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

$$\hat{E}_t^{D_\ell}\, \mathrm{Pr}_{s,t,\omega}^{\ell} - e_{s,\xi}^{\ell} - w_\xi^{\ell} \ge 0 \tag{32}$$

$$\hat{E}_t^{D_\ell} R_{s,s'}^{\ell} + e_{s',\xi}^{\ell} - e_{s,\xi}^{\ell} \ge 0 \tag{33}$$

$$\hat{E}_t^{D_\ell}\, \mathrm{Pr}_{s,t,\xi}^{\ell} - e_{s,\xi}^{\ell} - w_\xi^{\ell} \le K_1{}^{\ell} S_{s,\xi}^{L_\ell} \tag{34}$$

$$L_{s,t,\xi}^{\ell} \le K_2^{\ell}[1 - S_{s,\xi}^{L_\ell}] \tag{35}$$

$$\hat{E}_t^{D_\ell} R_{s,s'}^{\ell} + e_{s',\xi}^{\ell} - e_{s,\xi}^{\ell} \le K_1^{\ell} S_{s,s',\xi}^{M_\ell} \tag{36}$$

$$M_{s,s',\xi}^{\ell} \le K_2^{\ell}[1 - S_{s,s',\xi}^{M_\ell}] \tag{37}$$

$$0 \le \underline{\mu}_{t,\omega}^{s} \perp (SoC_{t,\omega} - \underline{SoC}) \ge 0 \tag{38}$$

$$0 \le \overline{\mu}_{t,\omega}^{s} \perp (\overline{SoC}. - SoC_{t,\omega}) \ge 0 \tag{39}$$

$$0 \le \underline{\gamma}_{t,\omega}^{Ch} \perp [SoC_{t,\omega}\Delta t] \ge 0 \tag{40}$$

$$0 \le \overline{\gamma}_{t,\omega}^{Ch} \perp [\overline{SoC}. - SoC_{t-1,\omega} - SoC_{t,\omega}] \ge 0 \tag{41}$$

$$0 \le \underline{\gamma}_{t,\omega}^{Dis} \perp [SoC_{t,\omega}\Delta t] \ge 0 \tag{42}$$

$$0 \le \overline{\gamma}_{t,\omega}^{Dis} \perp [SoC_{t-1,\omega} - SoC_{t,\omega}\Delta t] \ge 0 \tag{43}$$

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 auxiliary variables in obtaining KKT optimality conditions.

4. SIMULATIONS AND NUMERICAL RESULTS

4.1 Case Study

The obtained program is implemented on a test system with four LSEs (i.e., LSE_0, LSE_1, LSE_2 and LSE_3) that supply a number of PEVs and smart responsive loads. LSE_0 is the under-study LSE and the others are considered as rivals. The time horizon for scheduling of LSE is one day with 24 equal hours. Figure 3 illustrates the forecasted demand of both customers and PEVs. The pattern of PEVs demand is obtained based on [14], which represents how demand of PEVs changes during a day. It should be noted that in each time period of the scheduling horizon, only a number of PEVs are connected to the network and can participate in DR program. All the PEVs are supposed to have the same battery capacity of 16kWh and only 20% of them desire to take part in discharge process. The initial *SoC* of PEVs at each scenario as well as the initial hourly demands supplied by each LSE are randomized. Moreover, Figure 4 illustrates the forecasted prices of electricity market that are extracted from Nordpool market [30]. The forecasted errors of each stochastic variable are generated using associated PDF in which the forecasted values are considered as mean values. Here, the PDFs are separated into five discrete intervals with related probabilities. Standard deviation of the responsive loads, PEVs demand, DA and negative balancing market prices forecast errors are considered ±15% [31]. Also, standard deviation of positive balancing prices forecast errors is considered ±5% [32]. In addition, the forecasted prices offered by rival LSEs are extracted from [19] by some modifications. The associated scenarios of rival prices are generated with three segment normal PDF and their forecasted errors are considered ±20% [29]. Finally, the price elasticity of loads is extracted from [33]. The forecasted errors are generated based on 1000 scenarios by using MCS and RWM. After generation of 1000 initial scenarios, *K*-means algorithm is used to reduce the number of scenarios into 45. Afterwards, the selected scenarios are used in the proposed problem and the optimization is executed by CPLEX solver using GAMS software [34] on a PC with 4 GB of RAM and Intel Core i7 @ 2.60 GHz processor.

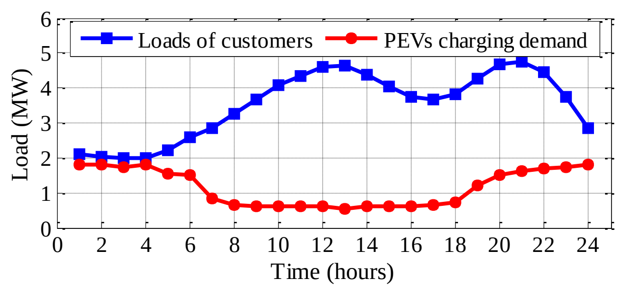


Figure 3. The hourly forecasted loads of customers and charging demand of PEVs.

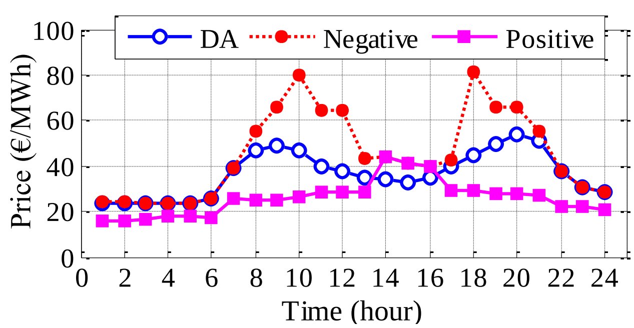
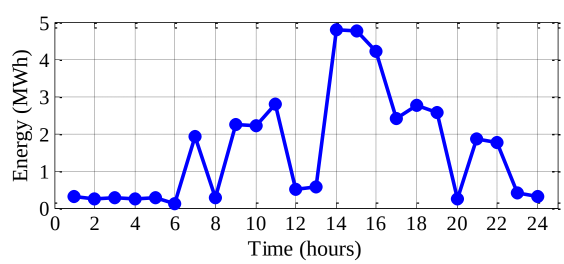


Figure 4. Hourly forecasted electricity price of DA, positive and negative balancing markets.

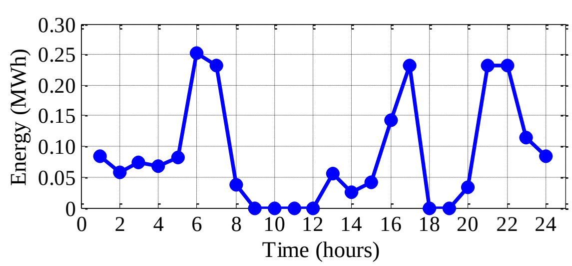
4.2 Numerical Results

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.

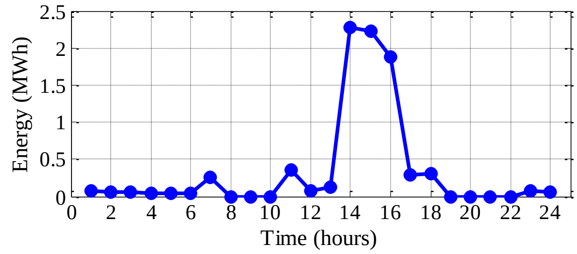
Figure 6 depicts the prices suggested by the under study LSE and the forecasted offering prices of rival LSEs during the scheduling horizon. Here, it is assumed that similar price offering scheme is applied to responsive loads as well as charging PEVs. As can be seen, LSE_0 offers competitive charging 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)

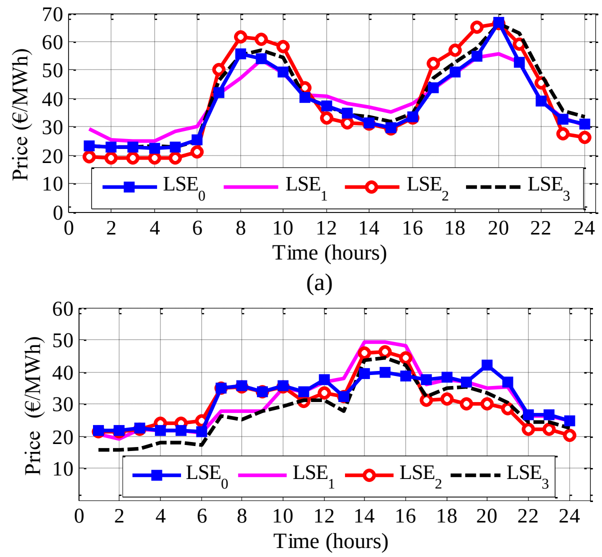


(b)



(c)

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



(a)

(b)

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

The percentages of demand loads together with charging and discharging energies of PEVs supplied by all LSEs are shown in Figure 7. It can be clearly understood that in a competitive environment when the selling price offered by a given LSE is the lowest, its related market share is the highest. To this end, comparing Figure 6 (a) and Figure 7 (a) shows that the under-study LSE is 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 competitive bids. The same procedure happens during 1:00-6:00 when LSE_2 takes the market power. Similar analysis can be made for supplying PEVs' demand by LSEs. However, it is observed from Figure 7 (c), the share of LSE_0 in buying discharge energy from PEVs is high most of the times due to its higher price offers (Figure 6 (b)).

In order to assess the behavior of customers and PEV owners in choosing the LSEs, Table II shows the transferred demand, charge and discharge of PEVs among the LSEs at different sample times. As mentioned before, the loads can be transferred from one LSE to another one based on the offered prices (see equation (10)). Noted that the minus sign indicates a demand transferred in the opposite orientation. As can be seen from the same table, at 4:00 for example, 17.46% of the responsive loads transferred from LSE_0 to LSE_2. Instead, 2.57% and 7.95% of responsive loads will be shifted from LSE_1 and LSE_3 to LSE_0, respectively. Moreover, 20.03% of responsive loads will be transferred from LSE_1 with the highest price to LSE_0 that has the lowest price offers. The results also show that PEVs' owners have the same behavior in choosing their LSE for charging process. However, it should be noted that LSEs which offer the highest discharge incentives are selected by the PEVs owners. Such conditions can be seen at 8:00 when LSE_0 offers the highest discharge incentives which in turn increases its share in negative balancing market. These behaviors simply show that the customers usually track the price signals to choose the most competitive LSE for satisfying both the energy needs and economic objectives. Therefore, in a competitive market, optimal offering strategy of the LSE has a substantial effect on the behavior of customers and PEVs owners in choosing a proper LSE.

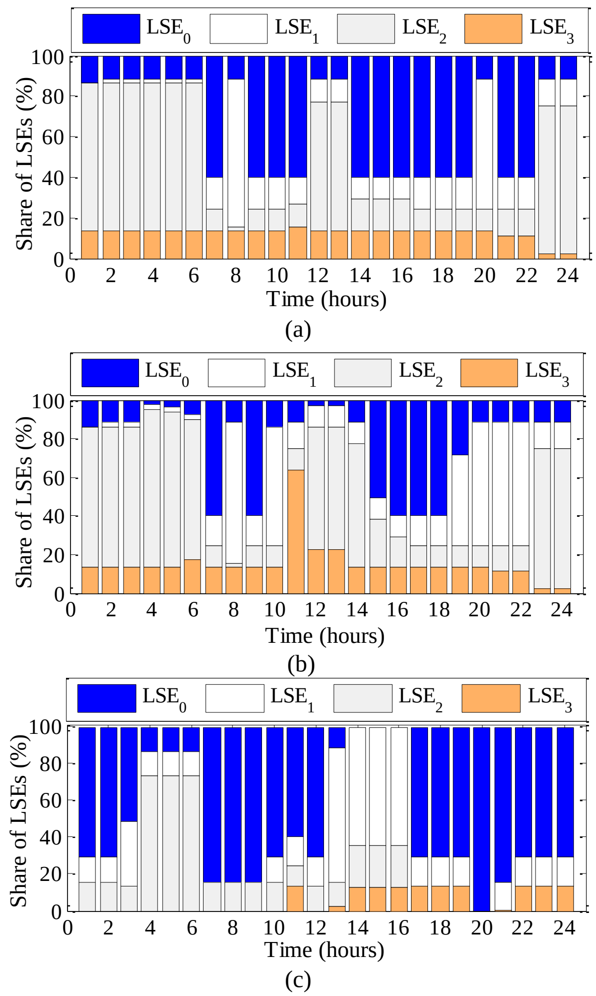


Figure 7. Share of LSEs in supplying (a) customers, (b) charging of PEVs, and (b) discharging of PEVs.

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 LSE1 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

In order to analyze the role of discharge process on the expected profit, revenues and payments of the under-study LSE, Table III is provided. As observed from the table, by increasing the PEVs' participation in the discharging process, revenue of the LSE and its expected profit increases. In other words, the LSE provides more energy from discharge of PEVs and its purchase from costly DA or positive market decreases. For more detailed investigation, the hourly profit of the LSE in three practical levels of PEVs participants in discharge is illustrated in Figure 8. As can be seen, by increasing the share of PEVs in discharging process, the expected profit of the LSE_0 increases usually, especially when the DA and positive market prices are comparatively high. Moreover, the total expected profit of the LSE varies from 135.12 € in without discharge of PEVs to 190.06 € (with a share of 40% in the same market) which denotes an increment of 40.7% in the expected profit. Therefore, PEVs participation in discharge process has a great impact on the expected profit of the LSE in a competitive market.

Table III. Expected profit, revenue and payments of LSE_0 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

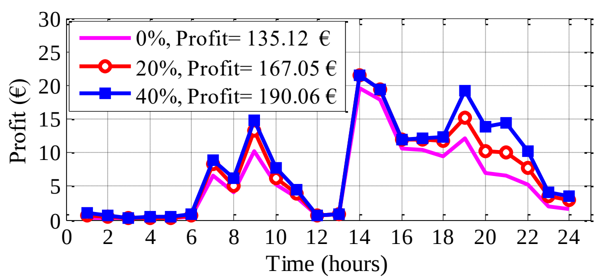


Figure 8. Hourly profit of the under-study LSE in different percentage of PEVs' participation in discharge process.

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

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

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

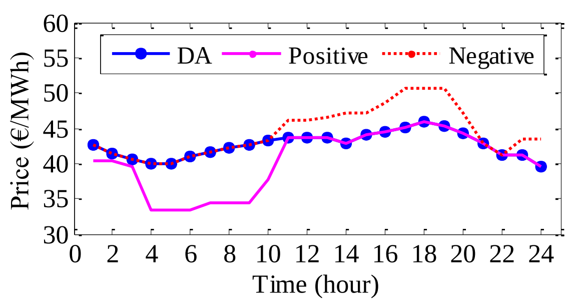


Figure 9. Electricity market prices

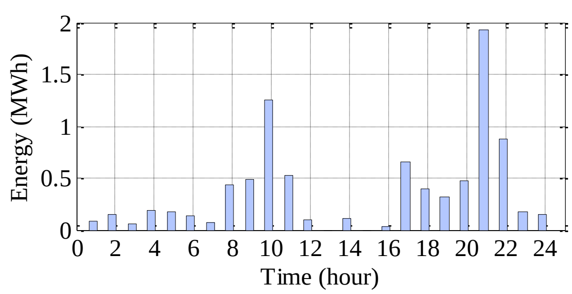


Figure 10. DA energy bidding

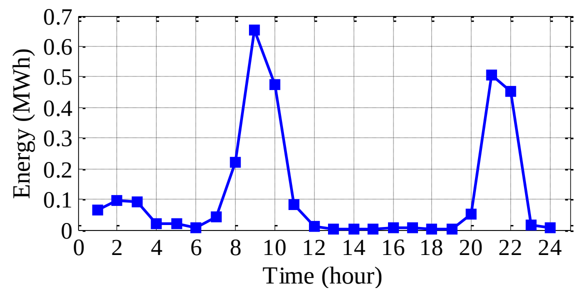


Figure 11. The energy trading in negative balancing market

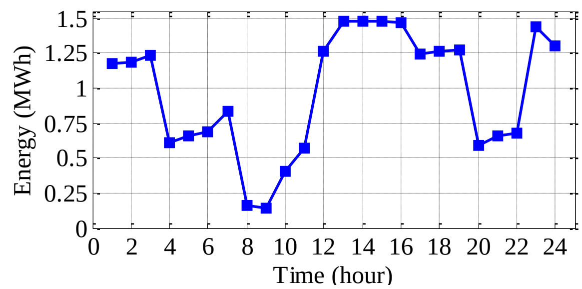
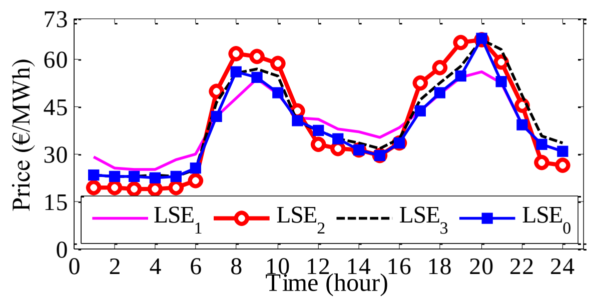
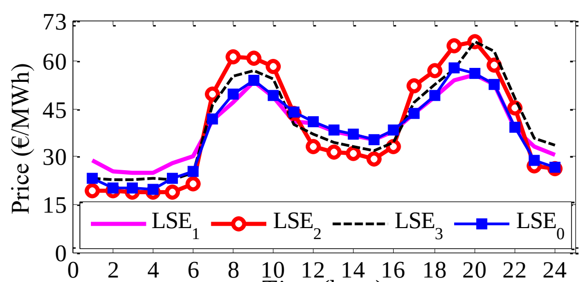


Figure 12. The energy trading in positive balancing market

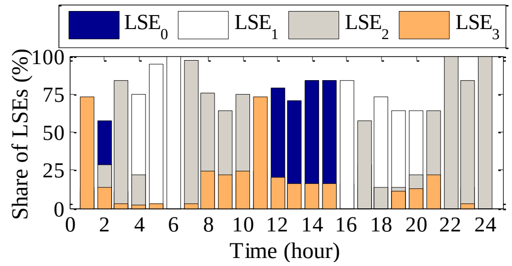


(a)

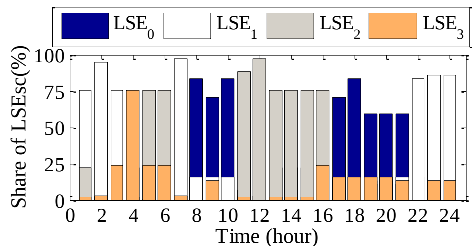


(b)

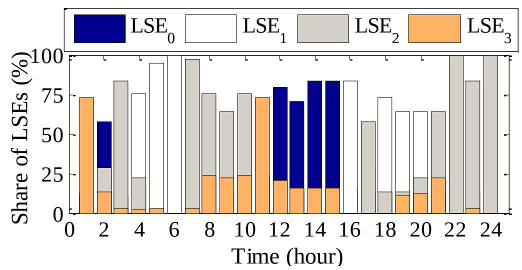
Figure 13. The prices proposed by all LSEs, (a) charging prices, (b) discharging prices.



(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.

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

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.
ξ (Ξ)	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 (%).
$\mathrm{Pr}_{s_0,t}^{\ell}$	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 (€).
$\mathrm{Re}\,v$	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 (%) .
$\overline{\underline{\mu}}^{s}$ / $\overline{\underline{\gamma}}^{Ch/Dis}$	Auxiliary variables of KKT optimality conditions corresponding with technical constraints of PEVs.

Parameters

$Elas_{t,t}(Elas_{t,h})$	The self (cross) elasticity of loads.
E^{Cap}	Capacity of PEV battery (MWh).
$E^{D,\mathrm{int}}$	Initial demand of loads before participating in DR programs (MWh).
$E^{D_{\ell}}$	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).
$\mathrm{Pr}^{B^+}(\mathrm{Pr}^{B^-})$	Prices of positive (negative) balancing market (€/MWh).
Pr^{DA}	Day-ahead market prices (€/MWh).
$\mathrm{Pr}_t^{DA,\mathrm{int}}$	The expected value of DA prices (€).
$\mathrm{Pr}_s^{\ell}(\mathrm{Pr}_{s_0}^{\ell})$	Price signals offered by rival LSEs (€/MWh).

$\overline{P}$ Restriction for energy trading with the network (MWh).

$\underline{SoC}$ ($\overline{SoC}$) Minimum (maximum) limitation of *SoC*.

$U_{s,t,\xi}^{\text{int}\ell}$ 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.

REFERENCES

[1] Vahedipour-Dahraie M, Najafi HR, Anvari-Moghaddam A, and Guerrero JM. Optimal scheduling of distributed energy resources and responsive loads in islanded microgrids considering voltage and frequency security constraints. J. Renewable Sustainable Energy, 2018; 10(2): 025903.

[2] Sharifi R, Anvari-Moghaddam A, Fathi SH, Guerrero JM, Vahidinasab V. Economic demand response model in liberalized electricity markets with respect to flexibility of consumers", IET Gener. Trans. Dist., 2017; 11 (7): pp.4291 – 4298.

[3] Vahedipour-Dahraie M, Anvari-Moghaddam A, and Guerrero JM. Evaluation of reliability in risk-constrained scheduling of autonomous microgrids with demand response and renewable resources. IET Renew. Power Gener., 2018; 12(6): 657-667.

[4] Wang X, and Liang Q. Energy management strategy for plug-in hybrid electric vehicles via bidirectional vehicle-to-grid. IEEE Systems Journal, 2017; 11 (3): 1789 – 1798.

[5] Chen YW, and Chang JM. Fair demand response with electric vehicles for the cloud based energy management service. IEEE Trans. Smart Grid, 2018; 9 (1): 458-468.

[6] Yazdani-Damavandi M, Neyestani N, Shafie-khah M, Contreras J, and.Catalao JPS. Strategic Behavior of Multi-Energy Players in Electricity Markets as Aggregators of Demand Side Resources using a Bi-level Approach. IEEE Trans. Power Systems, 2018; 33 (1): 397–411.

[7] Xu Z, Hu Z, Song Y, and Wang J. Risk-Averse Optimal Bidding Strategy for Demand-Side Resource Aggregators in Day-Ahead Electricity Markets Under Uncertainty. IEEE Trans. Smart Grid, 2017; 8 (1): 96-105.

[8] Nojavan S, Nourollahi R, Pashaei-Didani H, Zare K. Uncertainty-based electricity procurement by retailer using robust optimization approach in the presence of demand response exchange. Electrical Power and Energy Systems, vol. 105, 2019, pp. 237–248.

[9] Fang X, Hu Q, Li F, Wang B, and Li Y. Coupon-Based Demand Response Considering Wind Power Uncertainty: A Strategic Bidding Model for Load Serving Entities. IEEE Trans. Power Syst., 2016; 31(2): 1025 – 1037.

[10] Rahimiyan M, Baringo L, and Conejo AJ. Energy management of a cluster of interconnected price-responsive demands. IEEE Trans. Power Syst., 2014; 29(2): 645–655.

[11] Nasrolahpour E, Kazempour J, Zareipour H, and William D. Rosehart. A Bilevel Model for Participation of a Storage System in Energy and Reserve Markets. IEEE Tran. Sustainable Energy, vol. 9, no. 2, 2018. pp. 582 – 598.

[12] Momber I, Wogrin S, and Román TGS. Retail Pricing: A Bilevel Program for PEV Aggregator Decisions Using Indirect Load Control. IEEE Trans. Power Syst., 2016; 31(1): 464–473.

[13] Xu H, Zhang K, and Zhang J. Optimal Joint Bidding and Pricing of Profit-seeking Load Serving Entity. IEEE Trans. Power Syst., 2018; 33(5): 5427–5436.

[14] Sekizaki S, Nishizaki I, hayashida T. Decision making of electricity retailer with multiple channels of purchase based on fractile criterion with rational responses of consumers. Electrical Power and Energy Systems, 2019, vol. 105, pp. 877–893.

[15] Maharjan S, Zhu Q, Zhang Y, Gjessing S, and Basar T. Dependable demand response management in the smart grid: A Stackelberg game approach. IEEE Trans. Smart Grid, 2013; 4(1): 120–132.

[16] Motalleb M, Ghorbani M. Non-cooperative game-theoretic model of demand response aggregator competition for selling stored energy in storage devices. Applied Energy, 2017; 202: 581–596.

[17] Mahmoudi N, Heydarian-Forushani E, Shafie-khah M, Saha TK, Golshan MEH, Siano P, "A bottom-up approach for demand response aggregators'participation in electricity markets, Electric Power Systems Research, vol. 143, 2017, pp. 121–129.

[18] Hatami A, Seifi H, and Sheikh-El-Eslami M.K. A Stochastic-Based Decision-Making Framework for an Electricity Retailer: Time-of-Use Pricing and Electricity Portfolio Optimization. IEEE Trans. Power Systems, vol. 26, no. 4, pp. 1808-1816, Nov. 2011.

[19] Rashidizadeh-Kermani H, Najafi H, Anvari-Moghaddam A, and Guerrero JM. Optimal Decision-Making Strategy of an Electric Vehicle Aggregator in Short-Term Electricity Markets. Energies, 2018; 11 (9): 1-20.

[20] Rashidizadeh-Kermani H, Vahedipour-Dahraie M, Najafi HR, Anvari-Moghaddam A, and Guerrero JM. A Stochastic Bi-level Scheduling Approach for Participation of EV Aggregators in Competitive Electricity Markets. Appl. Sci., 2017; **7** (10): 1-16.

[21] Guzmán Acuña L, Ramírez Ríos D, Paternina Arboleda C, González Ponzón E. Cooperation model in the electricity energy market using bi-level optimization and Shapley value. Operations Research Perspectives, vol. 5, 2018, pp. 161-168.

[22] Carrión M, Arroyo JM, and Conejo A.J. A Bilevel Stochastic Programming Approach for Retailer Futures Market Trading. IEEE Trans. Power Systems, 2009; 24(3): 1446-1456.

[23] Conti S, Nicolosi R, Rizzo SA, and Zeineldin H.H. Optimal dispatching of distributed generators and storage systems for MV islanded microgrids. IEEE Trans. Power Deliv., 2012; 27 (3): 1243–1251.

[24] Akhavan-Rezai E, Shaaban MF, El-Saadany EF, Karray F. Online Intelligent Demand Management of Plug-In Electric Vehicles

in Future Smart Parking Lots. IEEE Systems Journal, 2016; 10, (2): 483 – 494.

[25] Rashidizadeh-Kermani H, Vahedipour-Dahraie M, Shafie-khah M, Catalão JPS. A bi-level risk-constrained offering strategy of a wind power producer considering demand side resources. International Journal of Electrical Power & Energy Systems, 2019; 104: 562-574.

[26] Arthur D, and Vassilvitskii S. K-means++: The advantages of careful seeding. in Proc. 18th Annu. ACM-SIAM Symp Discrete Algorithms (SODA '07)," New Orleans, LA, USA, 2007; 1027-1035.

[27] Morales JM, Conejo AJ, and Pérez-Ruiz J. Short-Term Trading for a Wind Power Producer. IEEE Trans. Power Sys., 2010; 25(1): 554-564.

[28] Vahedipour-Dahraei M, Najafi HR, Anvari-Moghaddam A, Guerrero JM. Security-constrained unit commitment in AC microgrids considering stochastic price-based demand response and renewable generation. Int. Trans. Electr. Energ. Syst., DOI: 10.1002/etep.2596.

[29] Rashidizadeh-Kermani H, Vahedipour-Dahraie M, Anvari-Moghaddam A, and Guerrero JM. Stochastic risk-constrained decision-making approach for a retailer in a competitive environment with flexible demand side resources. Int. Trans. Electr. Energ. Syst., https://doi.org/10.1002/etep.2719, (2018).

[30] Nordic Electricity, available online: www.nordpool .com, Accessed on 5 September 2016.

[31] N. Rezaei, and M. Kalantar. Economic–environmental hierarchical frequency management of a droop-controlled islanded microgrid. Energy Converse. Manage., 2014; 88: 498-515.

[32] Rezaei N, and Kalantar M. Smart microgrid hierarchical frequency control ancillary service provision based on virtual inertia concept: An integrated demand response and droop controlled distributed generation framework. Energy Converse. Manage., 2015; 92: 287-301.

[33] Vahedipour-Dahraie M, Rashidizadeh-Kermani H, Najafi HR, Anvari- Moghaddam A, and Guerrero JM. Stochastic Security and Risk-Constrained Scheduling for an Autonomous Microgrid with Demand Response and Renewable Energy Resources. IET Renew. Power Gener., 2017; 11(14): 1118-1121.

[34] GAMS (General Algebraic Modeling System) [Computer software]. GAMS Development Corp., Washington, DC.